Tao, J, Liu, Z, Wang, X, Cao, Y, Matthews, C and Yang, Z

Advanced modelling for team collaborative decision making analysis on maritime autonomous surface ships using team cognitive work analysis

Regional Studies in Marine Science 90 (2025) 104477

Contents lists available at ScienceDirect

Regional Studies in Marine Science

journal homepage: www.elsevier.com/locate/rsma

Advanced modelling for team collaborative decision making analysis on maritime autonomous surface ships using team cognitive work analysis

Juncheng Tao [a], Zhengjiang Liu [a], Xinjian Wang [a,b,c,d,e,*], Yuhao Cao [b], Christian Matthews [b], Zaili Yang [b,**]

[a] Navigation College, Dalian Maritime University, Dalian 116026, PR China
[b] Liverpool Logistics, Offshore and Marine (LOOM) Research Institute, Liverpool John Moores University, Liverpool L3 3AF, UK
[c] State Key Laboratory of Maritime Technology and Safety, Dalian 116026, PR China
[d] Seafarers Research Institute, Dalian Maritime University, Dalian 116026, PR China
[e] Key Laboratory of Navigation Safety Guarantee of Liaoning Province, Dalian 116026, PR China

ARTICLE INFO

Keywords:
Maritime safety
Maritime autonomous surface ships
Team collaboration
Cognitive work analysis
Complex networks

ABSTRACT

The emerging Maritime Autonomous Surface Ships (MASS) significantly challenges team collaboration in the maritime sector. Although significant progress has been made, current research lacks a holistic analytical approach to MASS operational teams, with most studies focusing on isolated aspects. To address this gap, a two-step framework is developed to model and analyse MASS team tasks from a system-wide perspective. Firstly, a team cognitive work analysis and an improved hierarchical task analysis are conducted, clarifying the division of responsibilities and information transmission paths. Secondly, a task network is constructed using complex network theory, and key topological characteristics are extracted. Thirdly, eight types of node importance ranking methods are employed, including three based on individual indicators and five based on hybrid algorithms, along with robustness analysis based on deliberate attacks to quantitatively identify critical nodes from different perspectives and analyse their roles in team tasks. Finally, Boolean algebra is applied to integrate the results of the node rankings, and a susceptible infected model is utilised to validate the validity of ranking results, allowing for prioritisation of critical nodes. The results demonstrate that targeted attacks based on betweenness centrality cause the network to collapse rapidly, with reachability dropping sharply once 16.7 % nodes fail. The entire system becomes nearly non-functional when 54.2 % nodes fail. The decline in reachability slows after 25 % nodes fail, indicating diminishing marginal impact. This study contributes to the development of a holistic framework for analysing team tasks of MASS, with future work exploring dynamic modelling and weighted interdependencies across broader maritime scenarios.

1. Introduction

With the advancements in the global shipping industry and intelligent techniques, developing and deploying Maritime Autonomous Surface Ships (MASS) are emerging as a significant trend in modern maritime transportation (Aydin et al., 2025). The emergence of MASS aims to enhance shipping efficiency, reduce operational costs, and decrease accidents caused by human errors.

Despite advancements that have facilitated efficiency, they also introduce new challenges and issues, such as the development and modification of relevant legal frameworks (Jovanović et al., 2024; Stępień, 2023), training standards (Palbar Misas et al., 2024), humanitarian considerations (Wahlström et al., 2015), software design (Gomola and Bouwer Utne, 2024), path planning (Shu et al., 2024, 2023), and collision avoidance algorithms (Gan et al., 2025b; Gil et al., 2022) for autonomous ships. Among these emerging issues, although properties of traditional human factors are subject to change, they still remain the primary concern affecting maritime safety (Gan et al., 2025a, 2023; Li et al., 2025). A key reason is attributed to the management and design challenges of remote ship operation (Tao et al., 2024). Specifically, the shift to remote operation significantly impacts various aspects of ship operation, including workflows (Storkersen, 2021), resource

* Corresponding author at: Navigation College, Dalian Maritime University, Dalian 116026, PR China.
** Corresponding author.
E-mail addresses: wangxinjian@dlmu.edu.cn (X. Wang), Z.Yang@ljmu.ac.uk (Z. Yang).

https://doi.org/10.1016/j.rsma.2025.104477
Received 25 February 2025; Received in revised form 10 July 2025; Accepted 4 September 2025
Available online 5 September 2025

management (Goerlandt, 2020), and emergency operation procedures (Zhang et al., 2020). Moreover, as the Degree of Autonomy (DoA) changes, the distribution of ship systems undergoes a gradual transition from a centralised configuration on ships to a shared configuration between ships and the shore (Man et al., 2018). This transition alters the roles and team sizes involved in operations (Sezer et al., 2024), inevitably leading to task reallocation and new routes for information transmission.

From a traditional ship operations perspective, primary tasks of humans include navigation, steering, communication, propulsion, power, cargo handling, passenger service, maintenance and repair work, etc. (Cao et al., 2025a; Wang et al., 2025). These tasks still remain essential in the operation of MASS (Aydin et al., 2025). However, in some cases, some heavy and repetitive tasks can be independently completed or supported by autonomous systems, yet still heavily rely on human decision-making and intervention. As the findings from Rødseth and Burmeister (2015), it indicated that failures in interactions with other ships, detection and classification of small to medium size objects, propulsion system, and extreme adverse weather are unacceptable risks for autonomous ships, requiring human intervention, particularly in decision-making and monitoring. Therefore, human teams are still recognised as the primary contributors to ensuring the ship safety, which is no exception in MASS (Tao et al., 2024).

Further to this, within a team on board or on shore, collaboration always serves as a necessary approach to operating ships promptly and smoothly, especially in emergency situations (Fan et al., 2024). However, efficient team collaboration is not always achievable. Potential issues like ambiguous responsibility divisions, failed task designs, and ineffective information transmission can all impact the efficiency of team task execution (Seeber et al., 2020). Particularly, the problems may be amplified in a MASS team due to the long-distance communication, hybrid and dynamic environment and requirements for timeliness. Specifically, ambiguous responsibility divisions directly affect the efficiency and smoothness of team collaboration. In scenarios containing autonomous ships with different degrees of autonomy, clear responsibility divisions between onboard team and shore-based team are necessary to operate a ship without conflicts (Lynch et al., 2024). Such authoritative definitions and clear standards for responsibilities and tasks of each are still lacking. Secondly, inadequate task design further impairs execution. Tao et al. (2024) reviewed 62 existing MASS-related literatures from the perspectives of risk influential factors and risk analysis methods. It emphasized that the prevention of developmental defects during the design phase is key to minimizing the need for later human interference. There are some shortcomings in this study: Ramos et al. (2020) used System-Theoretic Process Analysis (STPA) and Bayesian Networks to achieve supervisory risk control through online risk models, but their contributions were not sufficiently clarified in the review study. Unlike the design and planning of routine task, standardised task procedures for MASS are crucial for both on board team and shore-based team to respond in an orderly manner to unexpected events and enhance team response efficiency. Delivering such an efficient and complete procedure is difficult for task designers (Ramos et al., 2020). Thirdly, ineffective information transmission can lead to information asymmetry and misunderstandings among team members, affecting decisions and actions. This involves not only the information interactions within and between systems but also each system's situation awareness, such as whether team members are aware of the task execution status, main objectives of their tasks, and potential limitations of operational system. Especially in MASS teams, the collaborative decision-making process also involves real-time spatiotemporal information sharing, decision coordination, and task allocation, ensuring that all members possess adequate cognitive performance (DeFranco et al., 2011). Currently, achieving such an efficient collaborative decision-making within MASS teams also remains challenging.

In addition to the above persistent practical difficulties, the current research likewise lacks comprehensive methods for analysing MASS operational teams as an integrated whole. Research on task analysis for MASS primarily focuses on individual sub-tasks of remote operators (Ramos et al., 2020), reliability assessments of the targeted DoA (Sezer et al., 2024), competency requirements (Li et al., 2019), and human-machine cooperation (Fan et al., 2025). Although these studies emphasise the impact of individual sector on the safety of MASS to some extent and contribute valuable insights on team collaboration, task designs, and information transmission, the systemic uncertainties inherent in collaborative decision-making are overlooked. This fragmented perspective limits the ability to support task allocation and coordination in real operational settings. Therefore, there is a clear need for a holistic and structured analytical framework that captures the uncertainties within the complete team or system.

In fact, analytical models for the task design within systems or teams have been developed but still remain limited applications in the emerging MASS. For instance, Cognitive Work Analysis (CWA) is a formative analysis method (Vicente, 1999), designed to understand the interactions involved in human activities in complex socio-technical systems, with a particular focus on those requiring complex thought processes and decision-making abilities (Oosthuizen and Pretorius, 2013). The fundamental premise of CWA is the decomposition of tasks into various cognitive components, aiming to gain a deeper comprehension of the knowledge, skills, and decision-making processes required for performing tasks. This process provides an overview of how the system works rather than specifying the exact work content of the system. So far, this approach has been widely used in various fields (Suleiman, 2022).

A systematic review reveals that while the autonomy of MASS endows them with immense potential in the maritime domain, it also poses challenges for team collaboration. Meanwhile, current research exhibits a need to incorporate an innovative and comprehensive analytical framework to thoroughly explore the team collaborative decision-making within a complete MASS operational system. To address these gaps, this study proposes a two-step team collaboration decision analysis framework applicable to MASS. The specific contributions are as follows:

(1) Qualitative analysis is newly conducted based on existing concepts and task scenarios of MASS. Specifically, the Team Work Domain Analysis (TWDA), which divides team responsibilities from a macro perspective, includes a five-layer abstract structure and demonstrates shared responsibilities and physical constraints within the team. The Team-Hierarchical Task Analysis (Team-HTA) further subdivides and deconstructs the macro tasks defined in the task scenarios to provide as many decision-making behaviours as possible. The Team Control Task Analysis (TConTA) is employed to analyse these independent decision-making behaviours, providing a decision wheel model that includes the decision ladder, decision path, and task process, which demonstrates the flow in the decision-making. Therefore, this incorporated part provides a theoretical basis for responsibility division and qualitative task analysis applicable to MASS, which deeply explores human-system team collaboration.

(2) Subsequently, complex network theory is deployed to quantitatively analyse team tasks. Based on the decision wheel model, complex network modelling explicitly visualises its intricate structure. Further to this, systematic multi-dimensional analyses are utilised for the first time to assess the critical nodes in the MASS system. Of these, three individual indicators and five state-of-the-art hybrid algorithms are applied to rank all tasks. These measures are selected for their proven effectiveness in capturing different aspects of a network, such as connectivity strength, information flow efficiency, and the mediating role of nodes. This approach provides a comprehensive evaluation of the impact on entire system, rather than focusing solely on a single part of the team. Based upon the ranking results, a system robustness analysis is pioneered to determine those critical activities in task design of MASS teams during scenarios that require extensive information transmission and interaction.

The remainder of this study is organised as follows. Section 2 provides an overview of the methods and theories used in this study. Section 3 details the process of constructing a complex network for team tasks using these methods. Section 4 presents the results of complex network analysis. Section 5 discusses the results. Section 6 concludes this study.

2. Methodology

Fig. 1 illustrates the team collaborative decision-making analysis framework consisting of two main parts, qualitative model construction and quantitative network analysis. The content and the employed methods and models are detailed in the ensuing sections.

2.1. Team-HTA

The HTA generally comprises three parts: Task decomposition, task description, and task flow verification (Shepherd, 1998). The overall task is broken down into multiple subtasks, which is a top-down process that forms a hierarchical structure. Compared to the HTA, Team-HTA focuses on the activities carried out by team members, requiring a clear division of different task executors, the actions taken, and the media used. Referring to the heuristic steps of HTA as outlined by Stanton (2006), a structured interview with experts will be conducted. Experts are instructed to use the "what if" approach as a discussion standard and employ fault assumption analysis methods to validate the preliminarily established team task process.

2.2. Team cognitive work analysis

TCWA can iteratively analyse and progressively understand the various constraints constituting the work system through five stages (Kant, 2017). These constraints comprise the work domain, individual tasks and goals, individual strategies, social and organizational constraints, as well as personal qualifications and abilities. These five stages can be used individually or in combination. In this study, the first two stages are adopted, namely TWDA and TConTA, given that they are particularly well-suited for the analysis of functional and task-level constraints in team-based operations. Comparatively, those unemployed later stages, which involve more detailed social and organizational analysis, are deemed less relevant to the focus of this study, which emphasises task interactions and decision-making within MASS teams. Thus, TWDA and TConTA provide the necessary depth to model the operational behaviour and decision processes without overcomplicating the scope of analysis.

2.2.1. Team work domain analysis

To model these task divisions and interactions, TWDA utilises an Abstract Hierarchy Model (AHM) which divides the system into five abstract levels: Functional purpose, abstract function, generalized function, physical function, and physical form (Chen et al., 2019). Firstly, to collect the available data to populate the AHM, a hybrid approach is employed, combining insights from existing literatures, trial materials, and semi-structured interviews with relevant experts to provide objective data from multiple sources. Secondly, the connections between nodes at different levels follow the principles of mean-end links and the why-what-how triad (McLean et al., 2021). The mean-end links principle is used to construct the framework of team work domain model. The why-what-how triad approach is used to link and verify the relationships between nodes across five abstract levels. Finally, the AHM is divided based on the responsibilities of team members and showcases the shared goals, values, and constraints during task execution. In this model, the overlapping areas of different colours represent the shared aspects among team members. It is worth noting that the work domain model is not an exact description of the tasks within the team, but rather a collection of potential behaviours within the task scenario.

2.2.2. Team control task analysis

The decision ladder illustrates the information processing sequence of a single independent event in team tasks, capturing the cognitive states and behaviours during the event. Fig. 2(a) shows the basic template of the decision ladder. In this template, square nodes represent information processing, while circular nodes represent knowledge states. The alternating triggering of information processing and knowledge states forms a directed linear sequence of information processing steps in the independent event. The basic template of the decision ladder depicts a standardized procedure of information processing in an independent event. However, this is not an absolute depiction of the actual information processing sequence. In reality, there may involve various decision shortcuts. In this study, a scenario is projected where a helmsman on a traditional ship takes action upon receiving a steering command to illustrate the decision shortcuts, shown on Fig. 2(b). The decision shortcut is indicated by a red dashed line. The steering command is a signal for helmsman and the node “Activation” is triggered. Due to the characteristics of helmsman’s responsibilities, the steering command must be executed unconditionally. Therefore, a decision shortcut is established from the node “alert”, bypassing the node “Definition of task”, where the task is defined as the execution of steering command. This leads to the formulation of procedures and, ultimately, the decision is executed. The information processing sequence for this independent event is “Activation”, “Definition of task”, “Formulate procedures”, and “Execute”.

It is worth noting that individual control tasks and responsibilities within team tasks are influenced by the nature of team collaboration (Ashoori and Burns, 2013). A single decision ladder of independent

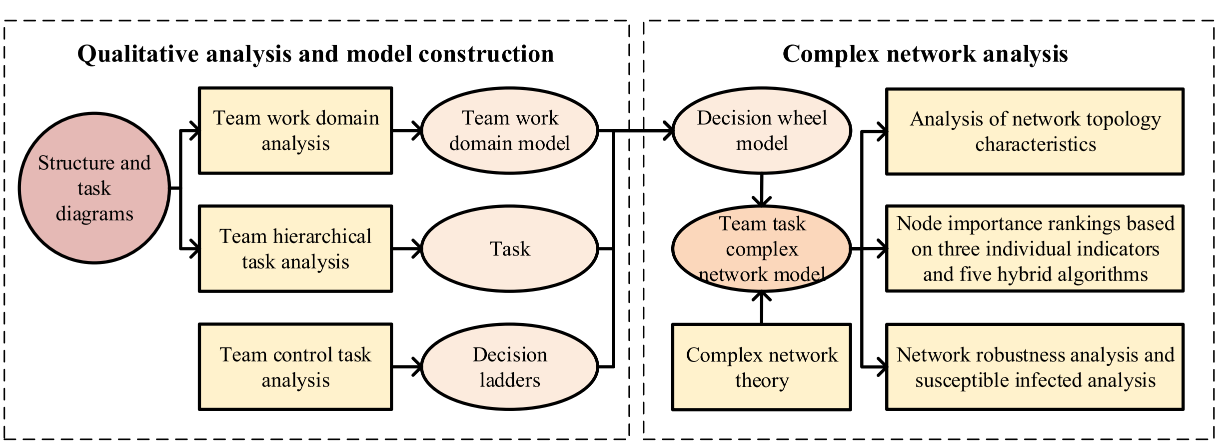
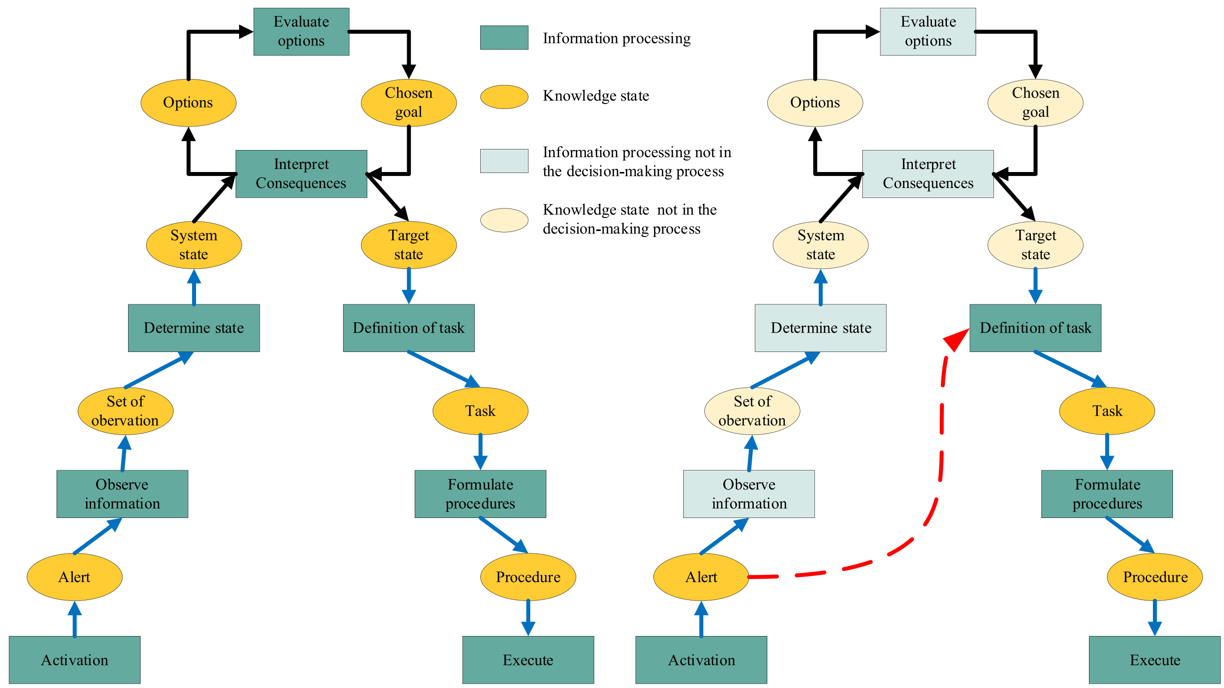


Fig. 1. The proposed framework for team collaborative decision-making analysis.



(a) The basic template for decision ladder (b) The modified decision ladder for decision shortcuts

Fig. 2. Basic template for decision ladder and modified decision ladder for decision shortcuts.

event cannot fully reflect the information flow of team collaborative decision-making. The decision wheel model extends the decision ladder by combining the decision ladders of team members and linking interactions between independent events to effectively address this problem. The layout of decision ladders in the decision wheel model follows two main principles: the geographical distribution of team members and the distribution of their respective sub-teams.

2.3. Network modelling based on complex network theory

This study uses complex network theory to visualize the team tasks. The constructed network shares the same structural characteristics as the team tasks model. The topological characteristics of the complex network reflect the complexity and vulnerability inherent in team tasks.

2.3.1. Construction of network model for team tasks

The decision wheel model illustrates the process of team collaboration and individual decision-making. However, the decision wheel model, characterised by its overly large and complex steps, does not facilitate the intuitive and systematic analysis of critical flows and significant independent events within team tasks. Therefore, in this study, the decision wheel model is mapped into a complex network model for further systematic analyses. The process of executing team tasks is regarded as a network composed of independent events, represented as $TiG = (N, E)$ (Cao et al., 2025b). Among them, the task units in the decision wheel model are treated as nodes, and N represents the set of all independent event nodes. Each node is a subset composed of the executor, physical media, and action. The set of nodes in the network is shown as Eq. (1):

$$N = \{n_1, n_2, \cdots, n_u \cdots, n_m\} \tag{1}$$

where m is the total number of task units.

$$n_u = (R_w, Act) \tag{2}$$

where w is the index of members in the team, R_w represents the w^{th} task executor. Act represents the action taken. n_u is the u^{th} node, also represents the task that task executor R_w preform Act. The directed connections between task units in the decision wheel model are treated as edges, and E represents the set of all directed edges, as shown in Eq. (3):

$$E = \{e_1, e_2, \cdots, e_u \cdots, e_l\} \tag{3}$$

where l is the total number of edges. e_u represents the edge from node n_i to node n_j. The constructed network model for team tasks is represented as Eq. (4):

$$T = \begin{array}{c c} & \begin{array}{cccc} n_1 & n_2 & \cdots & n_m \end{array} \\ \begin{array}{c} n_1 \\ n_2 \\ \vdots \\ n_m \end{array} & \begin{bmatrix} (c_{11}) & (c_{12}) & \cdots & (c_{1m}) \\ (c_{21}) & (c_{22}) & \cdots & (c_{2m}) \\ \vdots & \vdots & & \vdots \\ (c_{m1}) & (c_{m2}) & \cdots & (c_{mm}) \end{bmatrix} \end{array} \tag{4}$$

where $c_{ij} = 1$ and $i \neq j$ represents there is an edge between node n_i and node n_j. $c_{ij} = 0$ and $i \neq j$ represents there is no edge between node n_i and node n_j.

2.3.2. Network topology characteristics

In the constructed team task network, topological characteristics are the most intuitive indicators for illustrating task properties (Cao et al., 2024). Several topological characteristics are introduced.

The degree of a node, which is the sum of its in-degree and out-degree, and the clustering coefficient, which reflects the closeness of connections between nodes and the influence of nodes, are key indicators describing the connectivity and collaboration characteristics of the sub-tasks within the team tasks (Wang et al., 2023). Degree centrality provides a direct measure of a node's local importance based on its connectivity, while closeness centrality measures the proximity between nodes through quantifying the average path length from a node to all other nodes in the network (Shi et al., 2024). Betweenness centrality highlights the role of nodes in facilitating information flow.

2.3.3. Node importance ranking methods based on hybrid algorithms

In complex network theory, the degree of a node indicates the quantity of information it transmits, while the clustering coefficient reflects the local connectivity characteristics of that node (Feng et al., 2025). Relying solely on either may lead to biases, as a node with high degree and clustering coefficient does not necessarily imply high centrality or importance within the entire network. In order to obtain a more accurate understanding of node importance within the network, five types of node importance ranking methods based on hybrid algorithms are introduced, as shown in Table 1. Through the result analysis of three based on individual indicators and five based on hybrid algorithms, these methods essentially examine the source of key nodes influencing team tasks (Niu et al., 2021).

2.3.4. Network robustness analysis method

The robustness of a network measures its capacity to maintain functionality and structure under disturbances. The robustness of team task network reflects the team's ability to remain stable, safe, and effective in response to emergency situations. This study examines network robustness under deliberate attacks and compares it with random attacks. Deliberate attacks subjectively target critical or vulnerable nodes in the network based on network topology characteristics and the results of node importance rankings.

Additionally, reachability is chosen as a metric to evaluate network robustness. In complex network theory, reachability measures the connectivity and information dissemination capability between nodes (Feng et al., 2025). If one node can be accessed from another node through a sequence of edges, then the two nodes are considered to be reachable. In the context of team tasks, the concept of a start node and an end node is predefined. The paths from any node within the task network to the end node are regarded as the complete execution of the task. Robustness analysis based on reachability evaluates how these attributes change after an attack. The reachability matrix is as demonstrated in Eq. (5):

$$RP = \begin{bmatrix} rp_{11} & \cdots & rp_{1m} \\ \vdots & & \vdots \\ rp_{m1} & \cdots & rp_{mm} \end{bmatrix} \tag{5}$$

where rp_{ij} represents the reachability from node n_i to node n_j. If node n_i can reach node n_j, then$rp_{ij} = 1$; otherwise, $rp_{ij} = 0$. The overall reachability of network can be calculated as in Eq. (6):

$$R = \frac{1}{m(m-1)} \sum_{i \neq j} rp_{ij} \tag{6}$$

After an attack, the reachability of network changes. Through comparing the reachability before and after the attack, the robustness of the network can be calculated as in Eq. (7):

$$RL = \frac{R_a}{R_b} \tag{7}$$

where R_a is the reachability of network after the attack. R_b is the reachability of network before an attack.

2.3.5. Node importance validation model

This study applied the epidemic spreading model to validate the effectiveness of critical nodes, aiding in understanding how disruptions or important information can influence network performance and task execution. Common epidemic spreading models include the Susceptible-Infected (SI) model and the Susceptible-Infected-Recovered (SIR) model. In team task networks, the SI model is applicable for scenarios where the spread of information, errors, or failures is continuous as the tasks progress. Therefore, it can be used to validate the validity of critical nodes selected by different ranking methods in this study. There exists two states of nodes: Susceptible (S) and Infected (I) (Zhou et al., 2006). The relationship between the number of nodes in each state as shown in Eq. (8):

$$Sn(t) + In(t) = m \tag{8}$$

Table 1
The detailed information about hybrid algorithms.

No.	Ranking methods	Description	Basic principle	Reason for selection
1	Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) centrality	Node importance ranking based on TOPSIS centrality integrates degree centrality, closeness centrality, and betweenness centrality to provide a more comprehensive analysis, yielding results that provide insights into the network topology and the roles of nodes.	The normalization of degree centrality, closeness centrality, and betweenness centrality ensures all input centralities are on the same scale. Through calculating the Euclidean distances to the positive ideal solution and negative ideal solution, the relative closeness to the ideal solution is obtained to rank the nodes.	The ability to capture the dimensions of comprehensive evaluation on network structure.
2	Hyperlink-Induced Topic Search (HITS) algorithm	The HITS algorithm was proposed by Kleinberg (1999) for webpage ranking, aimed at providing more accurate searches. Node importance ranking based on HITS algorithm identifies the dual role as both sources and receivers of information within the network.	The HITS algorithm revolves around two fundamental concepts: Hubs and authorities. The iterative update and normalization steps of the hub and authority values are repeated until the hub and authority values converge on stable values.	Their abilities to capture the dimensions of information propagation and authority analysis.
3	PageRank algorithm	The PageRank algorithm, proposed by Google's founders, was originally designed for ranking web pages. The core idea is that the importance of a webpage is determined not only by the number of pages linking to it but also by the quality and importance of those linking pages.	The PageRank algorithm assigns an initial value to each node in the network, which is updated iteratively. The PageRank value of each node is distributed evenly among the nodes it links to.	
4	Gravity model	The gravity model originates from Newton's law of universal gravitation to explain the gravitational interaction between objects,	The gravity model equates the degree of nodes to quality and the distance between nodes to path length to identify the crucial nodes,	Their abilities to capture the dimensions of information attraction and transmission efficiency.

(continued on next page)

Table 1 (*continued*)

No.	Ranking methods	Description	Basic principle	Reason for selection
		reflecting the local and global features within the network.	particularly those with high connectivity and close proximity (Li et al., 2021a).	
5	Mutual Information (MI)	The MI is a fundamental concept in information theory that quantifies the shared information between two random variables.	MI exhibits the properties of non-negativity and symmetry. The property of non-negativity indicates if there is an edge between any two nodes, then there exists MI between them.	

where $Sn(t)$ and $In(t)$ are number of susceptible and infected nodes at time t. Each infected node will spread the infection to their directly connected nodes in an infection rate. The transmission formula is as demonstrated in Eq. (9):

$$\frac{dIn(t)}{dt} = \phi I(t)\left(\frac{Sn(t)}{m}\right) \tag{9}$$

where ϕ is the infection rate. The number of infected nodes over time is as demonstrated in Eq. (10):

$$In(t) = \frac{m}{1 + \left(\frac{m-1}{In(0)}\right)e^{-\phi t}} \tag{10}$$

where $In(0)$ is the initial number of infected nodes.

3. Team task network model construction

Gathering comprehensive information about the MASS team is a preliminary step in the team collaborative decision-making analysis for MASS. The first sub-section introduces the teamwork concept of MASS and the associated specific task scenarios. In the last three sub-sections, the team collaborative decision-making analysis is undertaken using the methods proposed in Section 2.

3.1. Background of the MASS team concept

Before exploring how the MASS team is constituted and what tasks humans need to perform, it is essential to clarify how humans are involved in the operation of MASS. Existing literatures on the teamwork concept and real-ship trials of MASS provides relevant information.

Specifically, Liu et al. (2022) highlighted that the task assignment mode, aligned with traditional navigation practices, remains more feasible than remote control due to the current limits of autonomous technology. In this mode, shore-based operators directly give the course and speed orders to the ship-based controllers. Sezer et al. (2024) and Fan et al. (2024) validated this through reliability analysis and risk assessment, while Johansen et al. (2023); Johansen and Utne (2022), (2024) introduced a STPA control structure dividing the system into different parts, i.e., human supervisor in Remote Operation Centre (ROC), Supervisory Risk Controller (SRC), Autonomous Navigation System (ANS), Autonomous Machinery Management System (AMMS), as well as navigation sensors, machinery and propulsion system. However, most studies (BahooToroody et al., 2022; Rødseth and Wennersberg, 2023) focus on Degree of Autonomy 3 (DoA 3) MASS, where team interactions are simpler and geographically concentrated, leaving Degree of Autonomy 2 (DoA 2) MASS team structures less examined. This inconsistency results in varying definitions of MASS teams across studies, requiring a clear context to be established before any meaningful analysis.

3.1.1. The selection of conceptual structure

To further determine the operational models for MASS, two conceptual structures introduced by Shiokari et al. (2024) need to be discussed as follows. Overall, both concept structures involve a master in ROC and a crew on board. The primary distinction between two structures is that in the first conceptual structure, the master can remotely manoeuvre the ship through the Autonomous Ship System (ASS) in the ROC, whereas in the second conceptual structure, the ASS is on board. In the first structure, the centralized control in the ROC reduces the need for onboard automation, making it more suitable for analysing the interaction between the human teams. The first conceptual structure adopted by Shiokari et al. (2024) for hazard identification based on detailed Structure and Task (ST) diagrams of manoeuvring tasks in four operational phases. In this structure, these ST diagrams demonstrate the static information about the functioning of the MASS teams for given scenarios, outlining the sub-tasks of each component, the information required to execute those sub-tasks, and the information interactions between components. The static structure composed of static information describes the physical and functional aspects of systems, driven by tasks or objectives.

The first conceptual structure developed by Shiokari et al. (2024) is selected as the basis, and Fig. 3 illustrates the conceptual structure of MASS used in this study. Among them, a master is assigned to the ROC and a crew to the ship, which forms the human team of MASS. Moreover, the ROC is equipped with the Autonomous Operation System (AOS), Operational Design Domain-Monitoring System (ODD-MS), Weather Information Display System (WIDS), and Cargo Condition Monitoring System (CCMS), together with the equipment onboard, such as Autonomous Operation Information Display System (AOIDS), Ship Manoeuvring System (SMS), and some data acquisition systems for sensors and actuators. For simplicity, the data acquisition systems for sensors, actuators, and the ship manoeuvring system are collectively referred to as the SMS since there is no human involvement in the processes between these components.

Therefore, based on the identified structure, the function of each sector is as follows: The ASS proposes manoeuvring plans, which are executed upon human approval and transmitted to the SMS. The SMS is directly controlled by Information Gathering and Transmission System (IGTS). In this operational mode, the ship is solely controlled by the master and ASS. The master relies heavily on the information provided by the ASS and is responsible for the approval of manoeuvring plans. When necessary, the master has to manually modify the manoeuvring plans or activate the system to make adjustments. The crew is responsible for monitoring the dynamics of ship and its surrounding environment, reporting any suspicious situations to the master, and responding to alarms. The crew cannot directly operate the ship. The ASS is responsible not only for formulating and transmitting the manoeuvring plans to the ship but also for presenting all necessary information to the master. IGTS acts as the executor of manoeuvring plans. In addition to receiving and executing the manoeuvring plans, it also relays necessary information to the ROC and the crew.

3.1.2. The selection of task scenarios

The selection of task scenarios for this study follows several key principles: highlighting the complexity of intra-team information exchanges, presenting situations likely to lead to human errors, and ensuring scenarios are easily conceptualized and understood by experts. For instance, a scenario referred to the study of Man et al. (2018) is selected to simulate human intervention in emergency situations. This scenario is designed to reflect real-world maritime operational conditions, where ships frequently encounter crossing situations that require human decision-making for collision avoidance. Specifically, the

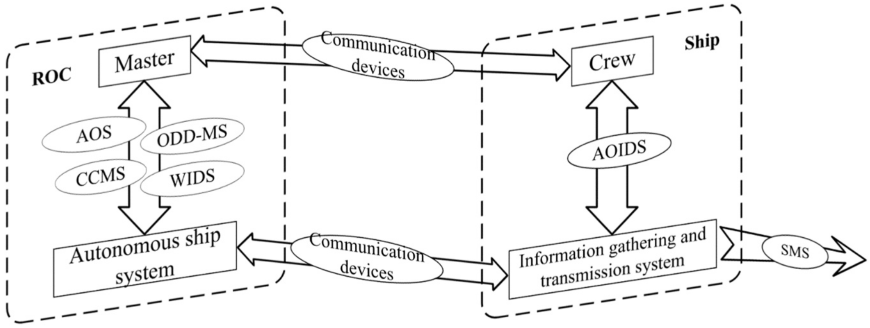


Fig. 3. The approved conceptual structure of MASS.

defined simulation scenario and relevant parameters are as follows:

"Target ship 'Amandla' from the port side of own ship will cross ahead, leading to a crossing situation. The initial manoeuvring plan of own ship is supposed to hold its course and speed until the Distance Closest Point of Approach (DCPA) is 1.5 nautical miles, with Time to Closest Point of Approach (TCPA) is 30 min" (Man et al., 2018).

Given the above conditions, three subsystems in the team are responsible for determining the hazards: The master in ROC, the crew onboard, and the ASS in ROC. The trigger event for this scenario, with referencing to study of Ramos et al. (2019), is defined as the determination of potential hazard by one of these subsystems. During the hazard determination phase, three primary initial scenarios may occur:

Scenario 1: The ASS successfully detects the potential hazard and presents a new solution to the crew and master for the human team to confirm.

Scenario 2: The ASS fails to detect the potential hazard, but the onboard crew identifies it and reports it to the master.

Scenario 3: The ASS fails to detect the potential hazard, but the master identifies it and inputs the information into the ASS.

3.2. *Step 1: construction of team work domain model*

Clarifying the team's shared goals and individual responsibilities is a key step to forming the foundation for establishing the entire task network and is also a prerequisite for TCWA. To achieve this goal, the AHM is developed.

The development and validation of the AHM for MASS team initially involved six experts from the academic and industry fields, specializing in human factors in maritime operations and technologies for ship intelligent collision avoidance, listed as Expert No. 1–6, and detailed in Table A1 in the Appendix A. The model is constructed through a top-down method. Initially, the background of this study is introduced to the experts. Information from Section 3.1 is used to pre-populate some nodes to help the experts better understand and complete the AHM. During the semi-structured interviews, the following but not limited questions are raised to gather detailed information about the team's tasks:

- What is the overall purpose of team tasks?
- What are the priority purposes?
- Who is involved in the task and what are their respective responsibilities?
- What systems are involved in the task?
- How will the tasks be executed and completed in real situations?

Based on the output of AHM, which outlines work demands independent of specific contexts (Elix and Naikar, 2020), these questions aim to understand the details of the tasks and obtain information about the five abstract levels of work domain model.

Finally, for the validation and analysis of the nodes and connections in the AHM, a brainstorming session is conducted through the why-what-how triad. The experts review the composition of each level and the connections between each node according to the principles of mean-

Table 2
Structure of the team work domain model.

Five levels of AHM	Nodes	Crew (on ship)	Master (on shore)	ASS (on shore)	IGTS (on ship)
Functional purpose level	Emergency intervention	✓	✓	✓	✓
	Safe navigation operations	✓	✓	✓	✓
	Efficient navigation operations		✓	✓	✓
Abstract function level	Timeliness	✓	✓	✓	✓
	Effectiveness	✓	✓	✓	✓
Generalized function level	Environmental perception	✓			✓
	Supervision of the ship and its surroundings	✓	✓	✓	✓
	Information interaction	✓	✓	✓	✓
	Risk assessment	✓	✓	✓	
	Development of manoeuvring plans		✓	✓	
	Command and control		✓	✓	
Physical function level	Obtaining ship condition information	✓	✓	✓	✓
	Obtaining environment information	✓	✓	✓	✓
	Obtaining traffic information	✓	✓	✓	✓
	Communication	✓	✓	✓	
	Navigational control		✓	✓	
	Data acquisition and transmission			✓	✓
	Data analysis			✓	
Physical Form level	Autonomous operation system		✓	✓	
	Operational Design Domain-Monitoring System		✓	✓	
	Weather information display system		✓	✓	
	Cargo condition monitoring system		✓	✓	
	Autonomous operation information display system	✓			✓
	Ship manoeuvring system			✓	✓
	Communication device	✓	✓	✓	✓

end links and the why-what-how triad.

As shown in Table 2, ensuring the safe navigation of the ship is a common goal of the team, and this shared goal is crucial to the effective and timely completion of team tasks (McComb, 2017). Specifically, the priority of functional purposes remains unchanged regardless of the task execution status. Individual roles and responsibilities within the team may vary depending on the specific task. Fig. 4 presents the work domain model developed for this scenario. The overlapping parts in different colours represent the shared functions among team members. At the abstract functional level, timeliness and effectiveness are criteria for all team members and systems to execute tasks. Timeliness emphasises the urgency of emergency response and safety assurance actions, while effectiveness focuses on completing tasks within limited time and resources (Zhang et al., 2025). The distribution of responsibilities within the team is more clearly illustrated by the division of components in the three levels below the work domain model.

3.3. Step 2: decomposition and restructuring of team tasks

Since the decomposition and restructuring of MASS team tasks benefit from the operational experience of traditional ship teams, two additional experts with experience in the field of marine navigation and ship management, Expert No.7–8 in Table A1 in the Appendix A, are incorporated into the group. The expert group is invited to further decompose the tasks according to the roles of the master, crew, ASS, and IGTS. The specific task units for team members in each scenario are identified using Team-HTA. In each scenario, both the proactive actions taken by ASS and the absence of such actions, necessitating master to alter the manoeuvring plan manually are considered. Therefore, the start and end events of task process are established. The task process begins with the identification of target ship and ends when own ship and target ship are no longer in a dangerous situation.

Moreover, using TConTA, a detailed decomposition of the decision-making process for each task unit is provided, illustrating the decision activities and decision shortcuts in the tasks. The task units and information processing steps are shown in Table 3. Since ASS and IGTS are software and hardware systems of MASS, their information processing is limited to the activation and execution phases. This is because, although these systems are capable of information collection, processing, and decision-making, their internal operations are fully automated and rely entirely on system performance.

As a final point, it is worth noting that the descriptions of the task units are phrased as actively as possible during brainstorming sessions. For example, "The master receives the manoeuvring plan from ODD-MS" is revised to "ASS provides the manoeuvring plan to the master through ODD-MS." This change is made for two reasons: the master is a passive recipient in this task unit without a decision-making process, and using a passive voice could lead to misunderstandings about the actual execution of the task.

3.4. Step 3: results visualisation

The decision wheel model is established based on the position of task units, decision activities, and information processing steps on the decision ladder (as shown in Table 3), which demonstrates the interaction structure. Each step of the interaction activity is displayed in the decision wheel model through directed links. However, the decision wheel model is inherently complex due to the large number of links involved. To ensure clarity, only a portion of the directed links are presented in the decision wheel model, as shown in Fig. 5. More details about the directed links between task units are listed in Table A2 in the Appendix A.

For clarity, the arrows are colour-coded to match the preceding task units. The position of task units in decision ladder signifies the type of information output from the executors to the next. The numbering of directed links between task units does not indicate their sequence in the task process.

The task units are considered as nodes and the links between nodes are regarded as edges (Niu et al., 2021). Based on this, a simplified network model for team tasks in the specific scenario is established using Eqs. (1) and (3), as shown in Fig. 6.

4. Quantitative analysis based on complex network analysis

The following subsections delve into the results of topology characteristics, three individual centrality indicators, five hybrid algorithms, and robustness analysis, demonstrating how nodes' characteristics contribute to the team task performance.

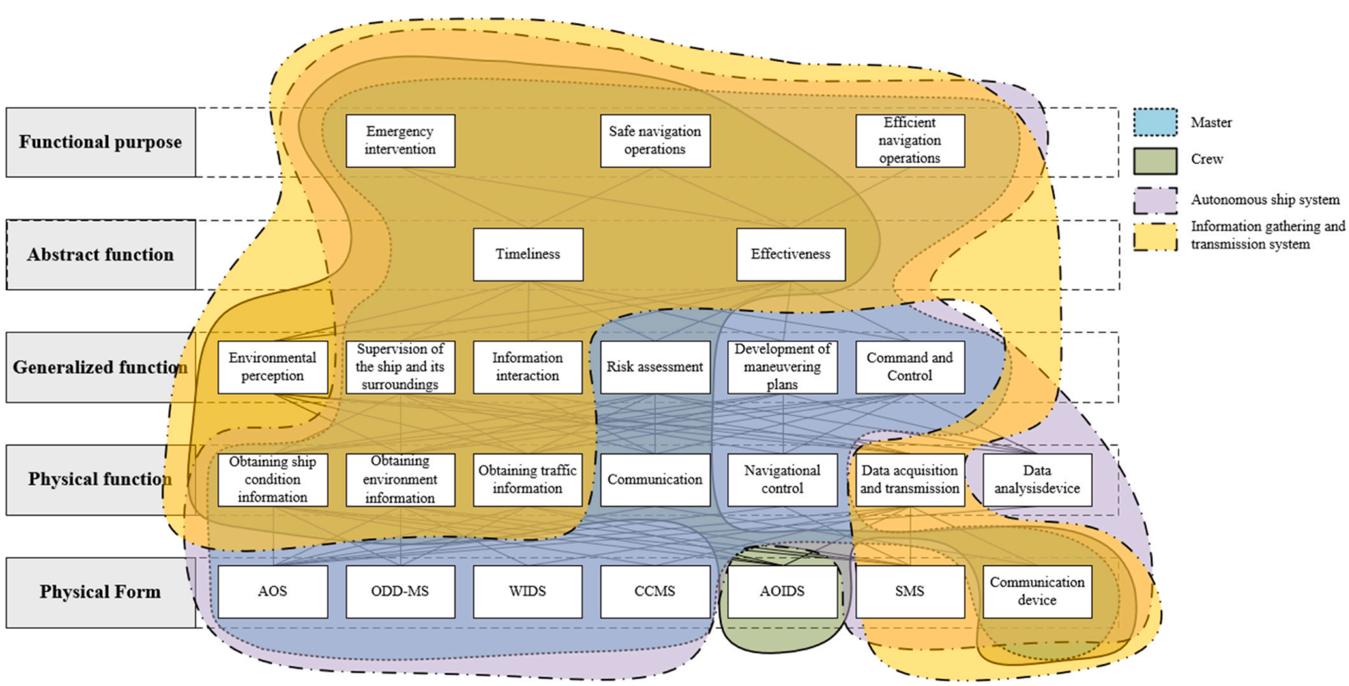


Fig. 4. Work domain model of MASS team.

Table 3
Task units and information processing steps.

No.	Units	Description			Information processing steps involved
		Executor	Physical media	Task	
1	I1	IGTS	SMS	IGTS detects target ship.	Activation and execute.
2	A1	ASS	AOS	ASS determines that it constitute a dangerous situation.	Activation and execute.
3	A2	ASS	AOS	ASS determines that it doesn't constitute a dangerous situation.	Activation and execute.
4	A3	ASS	Communication device	ASS interacts with target ship for information.	Activation and execute.
5	A4	ASS	AOS	ASS generates manoeuvring plans.	Activation and execute.
6	A5	ASS	ODD-MS	ASS displays the manoeuvring plans to the master.	Activation and execute.
7	M1	Master	ODD-MS	Master approves the execution of manoeuvring plans.	Activation, observe information, determine state, interpret consequences, formulate procedure, and execute.
8	A6	ASS	Communication device	ASS transmits the manoeuvring plans to IGTS.	Activation and execute.
9	I2	IGTS	SMS	IGTS executes the manoeuvring plans.	Activation and execute.
10	C1	Crew	AOIDS	Crew determines that it constitute a dangerous situation.	Activation, observe information, determine state, interpret consequences, evaluate options, definition of task, formulate procedure, and execute.
11	C2	Crew	Communication device	Crew communicates with the master.	Activation, definition of task, formulate procedure, and execute.
12	M2	Master	ODD-MS	Master determines that it constitute a dangerous situation.	Activation, observe information, determine state, interpret consequences, evaluate options, definition of task, formulate procedure, and execute.
13	M3	Master	Communication device	Master interacts with target ship for information.	Activation, definition of task, formulate procedure, and execute.
14	M4	Master	ODD-MS	Master manually activates the ASS to generate new manoeuvring plans.	Activation, observe information, determine state, interpret consequences, definition of task, formulate procedure, and execute.
15	I3	IGTS	AOIDS	IGTS displays the manoeuvring plans to the crew.	Activation and execute.
16	M5	Master	ODD-MS	Master vetoes the execution of manoeuvring plans generated by ASS.	Activation, observe information, determine state, interpret consequences, evaluate options, definition of task, formulate procedure, and execute.
17	M6	Master	AOS	Master manually develops manoeuvring plans.	Activation, observe information, determine state, interpret consequences, evaluate options, definition of task, formulate procedure, and execute.
18	M7	Master	Communication device	Master communicates with the crew.	Activation, definition of task, formulate procedure, and execute.
19	C3	Crew	AOIDS	Crew determines that it doesn't constitute a dangerous situation.	Activation, observe information, determine state, interpret consequences, evaluate options, definition of task, formulate procedure, and execute.
20	M8	Master	ODD-MS	Master determines that it doesn't constitute a dangerous situation.	Activation, observe information, determine state, interpret consequences, evaluate options, definition of task, formulate procedure, and execute.
21	A7	ASS	ODD-MS	ASS transmits the alerts to the master.	Activation and execute.
22	A8	ASS	Communication device	ASS transmits the alerts to the IGTS.	Activation and execute.
23	I4	IGTS	AOIDS	IGTS transmits the alerts to the crew.	Activation and execute.
24	I5	IGTS	Communication device	IGTS transmits the alerts to the ASS.	Activation and execute.

4.1. Results analysis based on topology characteristics

The network model for team tasks in this study comprises 24 nodes and 115 edges, as shown in Fig. 6. From an intuitive perspective, the complexity of a network is primarily determined by the number of nodes and edges it contains. The more nodes in a network, the larger the network becomes. The more edges a network has, the more frequent information transfer.

4.1.1. Results analysis based on in-degree, out-degree and degree

The information on in-degree, out-degree and degree of the nodes in the network are shown in Fig. 7(a).

- Node M3 has the highest in-degree, followed by M2, M7, M4, and M8.

Nodes with high in-degree undertake the integration of information and resources during task execution, thereby supporting the smooth progression of tasks. Practically, these nodes occur more frequently in the task process, implying that they occupy important positions in connection and coordination. This is reflected in two main aspects. The high number of paths passing through these nodes indicates a high dependency of task execution on them. The reasons for directing towards these nodes are more direct and explicit. It is worth noting that all nodes with high in-degree fall within the scope of responsibilities assigned to the master.

- Node A1 has the highest out-degree, followed by A3, A7, I5, and M7.

The out-degree of nodes represents the quantity of information, resources, support, or influence that the node provides to other nodes. Nodes with high out-degree play a critical guiding and coordinating role in the task process, significantly affecting task progression. It is worth noting that most nodes with high out-degree fall within the scope of responsibilities assigned to the ASS.

- Node M7 has the highest degree, followed by M3, A7, A3, A1, M5, and C2.

Nodes with high degree serve as critical hubs, which occupy central positions within the network. Most fall within the scope of responsibilities assigned to the ASS and master, particularly concerning the information exchange within and between the team and the target ships.

4.1.2. Results analysis based on clustering coefficient

Fig. 7(b) illustrates the clustering coefficients of nodes in the network:

- Nodes A5, M6, M5, and M4 have the highest clustering coefficient.

Nodes with high clustering coefficient form tightly knit groups or communities. From the distribution of clustering coefficient, it is evident that nodes with high clustering coefficient are involved in the manual generation and review of manoeuvring plans. The clustering coefficient

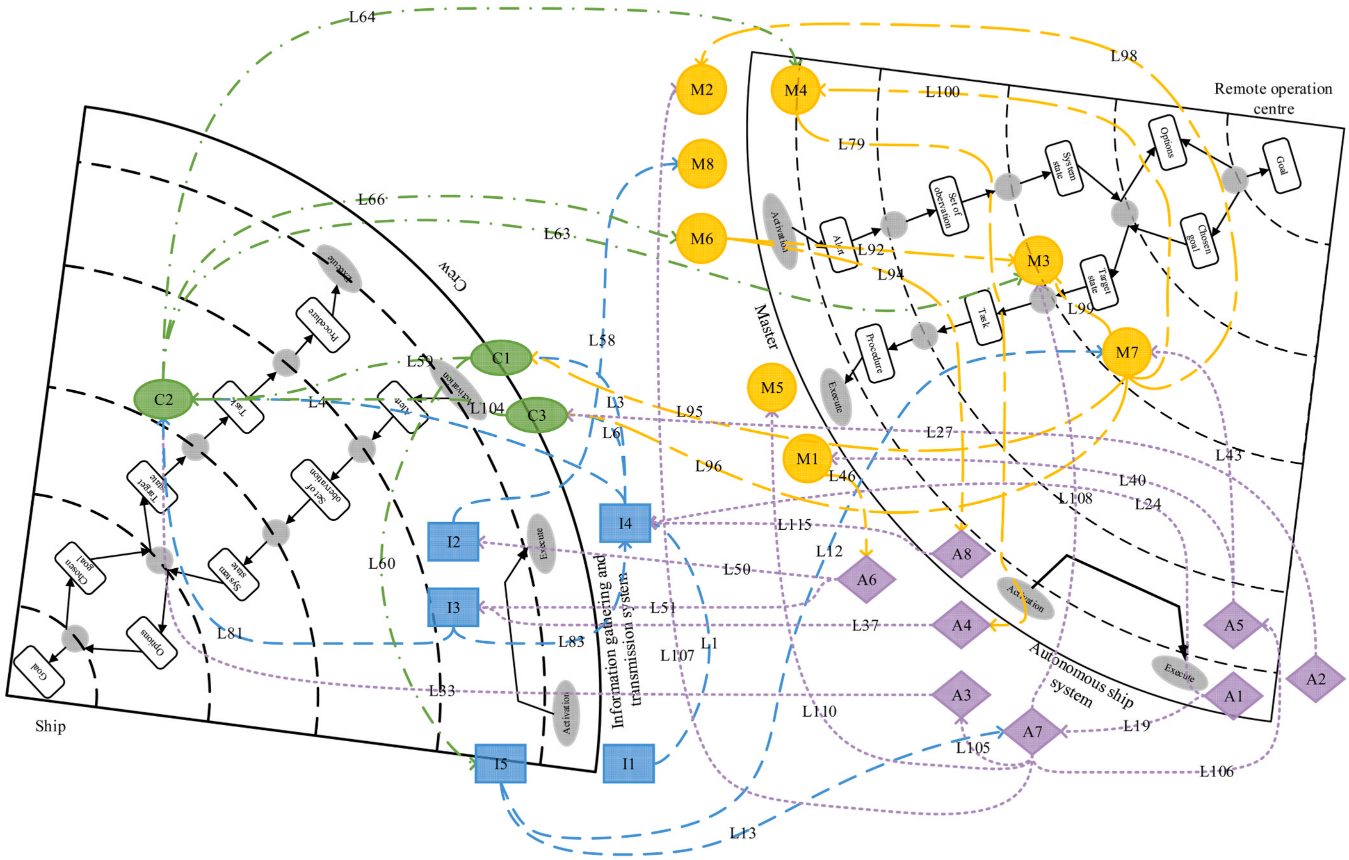


Fig. 5. Example version of decision wheel model for team tasks.

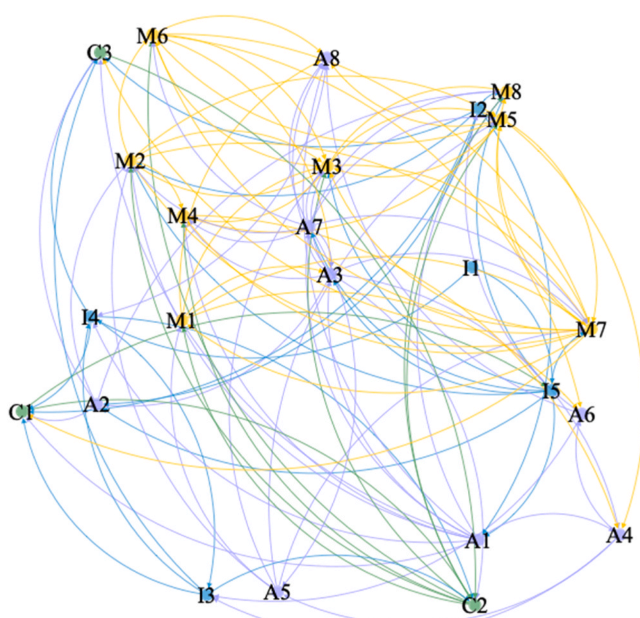


Fig. 6. The network model for team tasks in the specific scenario.

of node I1 is 0, which indicates that the task of detecting target ships dominates the information transmission and task execution, with minimal influence from adjacent nodes.

- The average clustering coefficient is calculated as $C_T = 0.252$.

The average clustering coefficient of the network for team tasks shows that the network has a low degree of clustering. Most nodes do not have direct connections with one another, implying the mutual influence of sub-tasks is not significant, and there is no apparent factional nature. The critical nodes in the network perform a critical linking function in facilitating the progress of team tasks.

4.2. Results analysis based on three types of individual centrality indicators

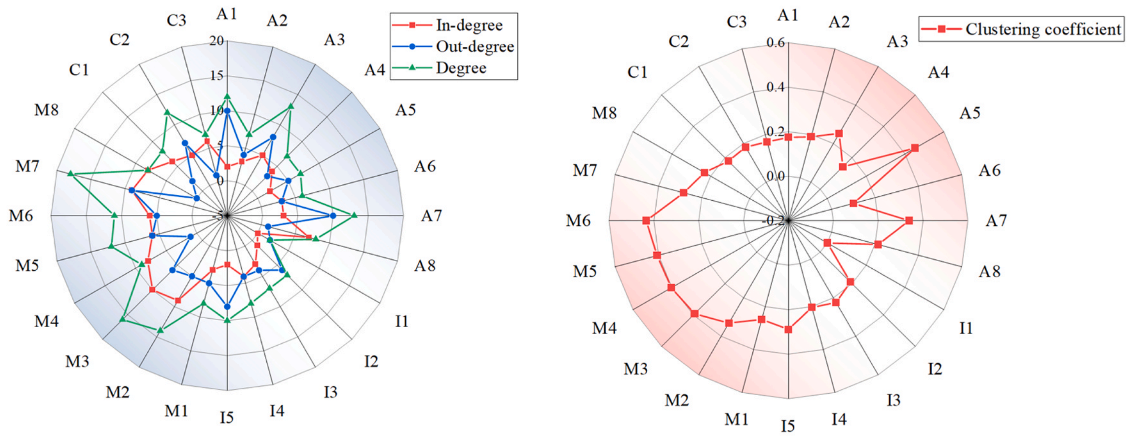
The distribution of degree centrality, closeness centrality, and betweenness centrality is shown in Fig. 8:

- Node M7 has the highest degree centrality, followed by M3, M2, A3, and A7.

- Nodes M2 and M3 have the highest closeness centrality, followed by M4, C3, and M5.

The distribution trends in Fig. 8 show that degree and closeness centrality share a similar distribution. This may be attributed to both degree and closeness centrality being more sensitive to the local topological characteristics. The highest closeness centrality in nodes M2 and M3 highlights the essential capability that must be possessed by the master to promptly disseminate information and make timely decisions. A relatively high closeness centrality in nodes M4, C3, M5, M7, and C1 emphasizes the pivotal role of the master and crew in guaranteeing prompt response to human intervention scenarios. For example, node M5 introduces new directions for the task flow, directly affecting ship safety and its efficiency in navigating the route. Concurrently, the diversity and complexity of information place higher demands on the capabilities of master, as their decisions must take into account for numerous real-time factors and potential risks. Node M5 with high closeness centrality reflects its central role in emergency response and risk management. However, it is worth noting that the network model for team tasks in this case is specific to the given scenario.

- Node C2 has the highest betweenness centrality, followed by M7,



(a) The distribution of degree (b) The distribution of clustering coefficient

Fig. 7. The distribution of network topology characteristics.

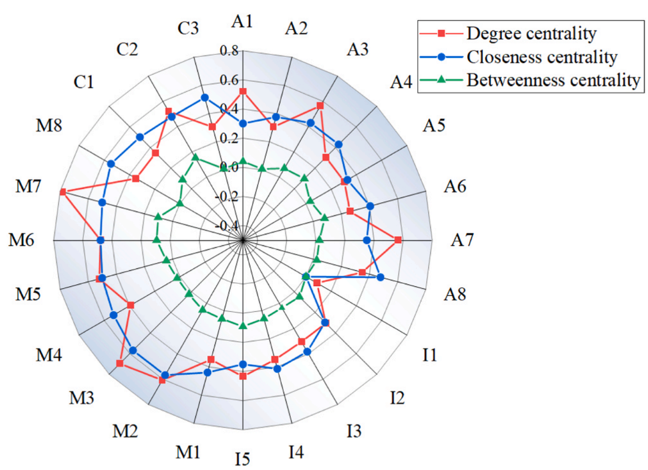


Fig. 8. The distribution of three types of individual indicators.

A4, M6, and A6.

The analysis based on betweenness centrality shows significant differences from those based on degree and closeness centrality, with only node M7 consistently appearing as a critical node across all three centrality measures. Meanwhile, nodes at the edge of network, such as node M8, may be endowed with lower betweenness and closeness centrality. However, this doesn't imply that these nodes lack intermediary roles in information interaction, resource transmission, or influence dissemination.

4.3. Results analysis based on hybrid methods

The results of node importance rankings based on hybrid methods are summarized and listed in Table 4.

4.3.1. TOPSIS centrality

- Node M7 has the highest TOPSIS centrality, followed by C2, M6, M2, and A3.

Nodes M7, C2, M6, M2, and A3 are identified as the top five critical

Table 4
The results of node importance rankings based on hybrid methods.

Rank	TOPSIS centrality		HITS algorithm				Gravity model		PageRank algorithm		Mutual Information	
	Nodes	Value	Nodes	Hub value	Nodes	Authority value	Nodes	Value	Nodes	Value	Nodes	Value
1	**M7**	0.811	**A7**	0.108	**M3**	0.101	**A7**	135.167	**C2**	0.091	**M1**	0.291
2	**C2**	0.780	**M7**	0.093	**M2**	0.094	**I5**	127.132	**M3**	0.065	**M3**	0.265
3	**M6**	0.659	**A1**	0.081	**M4**	0.091	**A1**	123.167	**A4**	0.065	**C2**	0.233
4	**M2**	0.650	**C2**	0.081	**M7**	0.086	**A3**	116.639	**I4**	0.061	**I4**	0.218
5	**A3**	0.623	**M3**	0.074	**M8**	0.086	**M7**	113.778	**M7**	0.058	**C3**	0.208
6	M3	0.612	I5	0.073	M6	0.070	C2	99.486	M4	0.054	I2	0.177
7	C1	0.591	A3	0.066	M5	0.068	M1	96.722	I3	0.051	M2	0.186
8	M5	0.579	M5	0.065	A8	0.061	M5	96.694	M6	0.050	A8	0.185
9	I5	0.572	M2	0.062	A3	0.051	M6	95.972	M2	0.050	A1	0.182
10	A4	0.559	A5	0.057	C1	0.042	A5	95.111	M5	0.048	I5	0.164
11	M1	0.508	M1	0.047	C3	0.042	M3	94.889	M8	0.046	A2	0.151
12	M4	0.501	M6	0.047	M1	0.033	I2	93.361	A8	0.045	A6	0.143
13	A6	0.497	I2	0.046	A7	0.032	M2	90.889	C1	0.045	A4	0.142
14	I4	0.492	A2	0.039	A4	0.031	A2	68.257	C3	0.045	A3	0.139
15	A7	0.491	I3	0.017	A2	0.027	I3	67.208	A6	0.040	M5	0.133
16	A1	0.474	I4	0.015	A1	0.017	I4	66.208	I5	0.030	M7	0.132
17	A8	0.469	A6	0.010	A5	0.016	C1	62.903	M1	0.029	I3	0.125
18	M8	0.467	A4	0.005	C2	0.015	I1	59.294	A5	0.028	M4	0.120
19	C3	0.448	M4	0.005	I4	0.015	A4	58.090	A3	0.027	C1	0.119
20	I3	0.418	C1	0.002	A6	0.014	A6	54.438	I2	0.019	M6	0.115
21	I2	0.389	I1	0.002	I3	0.004	C3	41.720	A2	0.017	M8	0.114
22	A5	0.381	C3	0.002	I2	0.001	A8	31.588	A7	0.015	A7	0.105
23	A2	0.374	A8	0.002	I5	0.000	M4	29.444	A1	0.014	I1	0.079
24	I1	0.000	M8	0.000	I1	0.101	M8	0.000	I1	0.008	A5	0.069

nodes in team tasks, once again underscoring the significant role of the master, particularly in communication and situational assessment.

4.3.2. HITS algorithm

The dual nature of hubs and authorities highlights the multifaceted roles of nodes in terms of information sources and reception.

- Node A7 has the highest hub value, followed by M7, A1, C2, and M3.

Multiple critical nodes are connected to node M7, including various information interaction and decision-related nodes. Its high hub value indicates that it is a critical information source, capable of effectively conveying information to decision-makers and initiating emergency responses promptly. Node M7, connected to the majority of nodes that fall within the scope of responsibilities assigned to the master, reflects the central role of communication among the master and crew.

- Node M3 has the highest authority value, followed by M2, M4, M7, and M8.

In the network, node M3 receives links from multiple hubs, making it a critical information receiving node, capable of obtaining key information and making corresponding decisions. The primary task of node M2 is to determine if it constitutes a dangerous situation, receiving links from various perception nodes. Its high authority value indicates that node M2 is a critical decision-related node, responsible for gathering information and conducting risk assessments for subsequent actions. It is worth noting that node M7 ranks highly in both hub and authority values, highlighting its importance in both sourcing and receiving information.

4.3.3. Gravity model

- Node A7 has the highest gravity centrality, followed by I5, A1, A3, and M7.

Among the nodes with high gravity centrality, three fall within the scope of responsibilities assigned to the ASS, involving situational assessment, transmission of alerts, and interaction with target ships. The high attractiveness of situational assessment raises critical issues regarding decision criteria, such as determining thresholds for modifying manoeuvring plans to ensure navigation safety and the urgency level at which the ASS must seek direct intervention from humans. This issue pertains to quantifying acceptable risk standards during the ASS design, including the definition of thresholds for triggering alarms in collision scenarios such as TCPA, DCPA, ship domain (Szłapczyński et al., 2024), collision avoidance dynamic critical area (Gil, 2021). This consideration extends beyond the spatial and temporal dimensions of detectable objects to include uncertainty prediction, which is beyond the scope of this study.

4.3.4. PageRank algorithm

- Node C2 has the highest PageRank value, followed by M3, A4, I4, and M7.

The PageRank algorithm, based on link relationships and transmission probabilities between nodes, highlights C2, M3, A4, I4, and M7 as critical nodes. It is reasonable to conclude that nodes C2 and I4 are particularly significant for information transmission due to their higher PageRank values. These two nodes connect to multiple important downstream nodes, serving as key channels for information flow. Nodes with high PageRank values underscore the importance of cross-geographical information transmission, which increases the complexity of information interaction, introducing more potential failures and making the network more vulnerable to attacks. From the perspective of team task analysis, these failures may occur in tasks primarily focused on interactions with target ships and communications among team members. Effective communication directly impacts task coordination and execution, while interactions with target ships determine adjustments to manoeuvring plans and risk response strategies. Enhancing the efficiency of information exchange will significantly improve the stability of the team task network in this scenario, although it is challenging. This necessitates timeliness for communication devices, aligning with the abstract functions in the team work domain model. On one hand, sharing consistent communication protocols and terminology within the team establishes standardized processes for accurate information transmission and understanding. On the other hand, adding more nodes and paths capable of transmitting the same information increases the redundancy of nodes and paths. This provides multiple communication channels, ensuring information transmission even if one node or edge fails.

4.3.5. Mutual information

- Node M4 has the highest information quantity, followed by A8, C3, C1, and M2.

Node importance ranking based on MI is an emerging and effective method for assessing dependencies and information sharing among nodes. Nodes M4, A8, C3, C1, and M2 are identified as having the highest levels of information sharing. Among them, nodes C1, C3, and M2 are primarily involved in determining dangerous situations. Decisions made by the master and crew regarding dangerous situations represent critical turning points. This is related to the resource consumption inherent in decision-making. During task execution, evaluations and response strategies of the master, crew, and ASS at different stages not only determine adjustments to the manoeuvring plans but also affect the safety and efficiency of the mission. Node M4, as a subsequent trigger task, continues to rely significantly on the effectiveness and timeliness of information, as shown in the abstract function level of the team work domain model. If thresholds are triggered, the master needs to decide whether to adopt the manoeuvring plans provided by the ASS or proceed with further manual intervention. This process involves the assessment of current data and the consideration of potential future variables, such as weather conditions, other ships' movements, and turning trajectory of own ship (Gil et al., 2024).

4.4. Robustness analysis

The robustness of networks reflects the impact of node failures on overall network performance during team tasks. This study uses deliberate attacks based on degree centrality, closeness centrality, betweenness centrality, TOPSIS centrality, HITS algorithm, gravity model, PageRank, and MI to disrupt the network for team tasks, and adopts random attacks to verify the validity of node importance rankings. Fig. 9 illustrates changes in the reachability of the complex network under different deliberate attacks and random attack strategies.

Compared to deliberate attacks, random attacks are less efficient in destroying network robustness. From the results of deliberate attacks, regardless of the algorithm used, the network tends to collapse rapidly as the number of failed nodes increases, with a notable decline in the

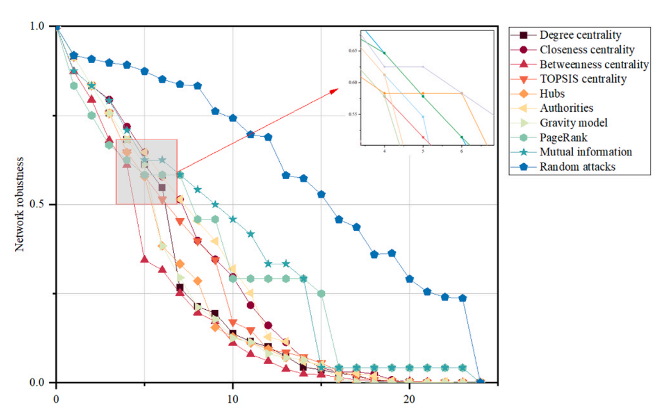


Fig. 9. The results of network robustness analysis under deliberate attacks and random attacks.

network's reachability. In general, critical nodes within the network significantly affect the overall performance of the network for team tasks, indicating poor redundancy of the network structure. Low average clustering coefficient also proves it. In such situation, the network becomes fragmented, and communication paths are disrupted, severely impairing task coordination and execution. The lack of alternative paths or substitutable nodes reveals a structural vulnerability and insufficient fault tolerance, suggesting a low level of topological redundancy (Kim et al., 2015). This phenomenon aligns with the findings in previous research on complex networks, which indicate that networks with scale-free or centralized structures are particularly vulnerable to targeted attacks on high-centrality nodes (Berche et al., 2009). In the context of MASS team tasks, this also implies that the system's ability to sustain operations under stress is highly dependent on a few key roles or decision-making points, making the system more fragile (Massari et al., 2023).

Furthermore, deliberate attacks based on betweenness centrality lead to a faster collapse of the network, with a notable decline in reachability when the number of failed nodes reaches 16.7 %. This suggests that the network's capacity to maintain connectivity between critical tasks is significantly compromised early on, as nodes with high betweenness centrality play crucial intermediary roles. When the number of failed nodes reaches 54.2 %, the network model collapses almost completely, suggesting the removal of additional crucial intermediary nodes results in a breakdown of the entire system, disrupting the overall functionality of the network. Deliberate attacks based on the gravity model and degree centrality show a notable decline in reachability when the number of failed nodes reaches 25 %. For most of deliberate attacks, the trend of declining reachability becomes gradually slower when the number of failed nodes reaches 6, implying the remaining nodes have less impact on the network's overall reachability. The network model collapses almost completely when the number of failed nodes reaches 15 or 16. Therefore, the top six critical nodes are selected as the cross-validation results based on multiple node importance rankings.

This study employs a Boolean algebra approach to cross-validate the top six critical nodes selected from multiple node importance rankings. Each node is evaluated using a Boolean condition, where the ranking positions across different algorithms serve as binary variables: if a node ranks first, it receives the highest value of 5, second receives 4, and so on. The Boolean aggregation of these values determines the most critical nodes by considering their presence across rankings as a logical "true" for highly ranked nodes and "false" otherwise. The six nodes that satisfy this Boolean aggregation with the highest scores are node M7, M3, C2, M2, A7, and M4, most of which fall within the master's scope of responsibility.

4.5. Critical node validation

To verify the effectiveness of the method and the importance of selected nodes, the SI model is applied to evaluate the nodes in team task network again. In the SI model, each node is treated as an infection source to evaluate the efficiency of transmission across the network. The results indicate that the five nodes with the highest Boolean aggregation scores, namely M7, M3, C2, M2, and A7, infect 50 % of the network nodes within just 3 time steps, as shown in Table 5. In contrast, most other nodes require 5 or more time steps to reach the same level of spread, which indicates significantly faster initial propagation efficiency for the critical nodes. However, when simulating infection spread across the entire network, all nodes show a similar rate of full-network transmission, suggesting that while critical nodes accelerate initial influence distribution, the network as a whole exhibits homogeneity in total transmission capacity. This finding underscores the prominent role of critical nodes in maintaining network responsiveness and the effectiveness of task coordination at early stages of information spread (Lee et al., 2019).

Table 5
The number of infected nodes over time.

Time step	M7	M3	C2	M2	M4	A7	A1	A2	A3	A4	A5	A6	A8	I1	I2	I3	I4	I5	M1	M5	M6	M8	C1	C3
0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	3	3	3	3	1	3	4	2	2	2	2	2	1	2	1	2	2	2	2	2	2	1	1	1
2	8	6	9	7	1	5	7	2	3	3	2	3	1	3	3	5	3	3	5	4	5	2	2	1
3	**12**	**12**	**12**	**13**	1	10	**13**	3	4	6	3	7	1	3	3	11	4	4	8	7	9	5	2	2
4	16	13	16	17	1	**12**	15	6	7	10	8	11	1	5	9	**15**	6	5	11	10	**13**	6	3	3
5	18	16	16	20	2	17	18	10	11	**15**	9	**14**	2	8	**12**	17	9	8	**12**	**15**	19	11	4	6
6	19	20	17	21	7	21	21	**14**	**15**	22	**16**	19	4	9	15	20	**12**	9	20	18	21	**18**	7	9
7	22	22	19	22	**13**	22	23	20	19	23	19	20	7	**14**	17	22	15	**15**	21	21	22	20	10	**12**
8	22	22	20	23	16	22	24	23	21	23	22	22	11	17	20	24	17	18	23	23	23	23	**14**	16
9	23	22	22	23	16	24	24	24	22	23	23	24	**12**	19	23	24	21	19	23	24	24	23	20	21
10	24	23	23	24	18	24	24	24	23	24	23	24	15	19	24	24	23	21	24	24	24	23	22	24

5. Discussion and implications

5.1. Discussion on the team tasks

The team collaborative decision-making analysis in this study reveals critical insights, particularly concerning task efficiency and team coordination.

5.1.1. The impact of information and resources receivers on task efficiency

The results of node importance rankings based on MI, authority values, degree centrality, and closeness centrality show the importance of node M2, M3, and M4. In the task scenarios of this study, the concentration of information flow toward the ship master highlights the centralised role of the ship master in task coordination and situational awareness. Communication with target ships and crew, as well as operations within the ROC involving ODD-MS, are primary avenues for acquiring key information and resources. Therefore, this imposes requirements on Human-Machine Interaction (HMI) in ROC. The quantification of information requirements for the ship master may provide specific criteria for the situational awareness required in HMI. Notably, tasks where the ship master approves the execution of manoeuvring plans generated by the ASS and interacts with target ship represent the most information-intensive processes identified in this study. These tasks, in contrast to other tasks, also highlight the need for human oversight in critical decision-making processes. The involvement of the ship master is essential for addressing uncertainties.

Additionally, explicit empirical rules are more common in maritime teams. The ship master, as the primary decision-maker, frequently makes decisions on the information provided by sub-teams and their own observations. However, in an autonomous ship simulation experiment, Chan et al. (2023) pointed out that most candidates were unable to identify failures due to excessive trust in autonomous systems. Therefore, the ship master may face over reliance on autonomous systems in the process of acquiring information and resources. This highlights the significance of information exchange between the ship master and crew, even when the ASS is capable of providing sufficient references for decision-making.

5.1.2. The impact of information and resource sources on task efficiency

The results of node importance rankings based on hub value, gravity centrality, and PageRank value show the importance of node A1, A7, and A3. The ASS performs the central role in transferring information and resources to other nodes in team tasks. The high out-degree of Node A1 also underscores its importance at the beginning of the task process. The ASS transmits critical information and resources to multiple nodes through the determination of dangerous situations, which directly affects the direction of the team task, as well as the judgment and intervention of human team. These information transmission paths serve a coordinating function in cross-node communication and decision-making, influencing the execution of multiple subsequent tasks. Nodes related to the transmission of alerts are also identified in the analysis of hub value distribution. These nodes are considered critical to enhancing overall task efficiency in the design and redesign of team tasks.

In addition to this, human tasks involved nodes M7, C2, and M3, are also identified as key sources of information in the results of node importance rankings based on degree value, betweenness centrality, and TOPSIS centrality. This may be due to the fact that even if the system of MASS is advanced enough, some tasks may still rely on human knowledge. This knowledge may be difficult for computers to handle (Sadraey, 2018).

5.1.3. The impact of ROC on team coordination

The tasks in ROC facilitate the rapid dissemination of decision-related information and the coordination of activities within team. Due to their extensive connections with multiple other nodes, the ROC rapidly gathers information and resources from various sources and effectively distributes them to the activities that need them. In this scenario, the ROC undertakes the integration and distribution of information and resources during task execution. The high connectivity of nodes in ROC endows them with considerable influence in the decision chain. This emphasizes the role of HMI in team tasks, which suggests that designing intuitive HMI systems for the master's tasks is essential to enable efficient information processing (Tao et al., 2025). The interface should present critical information in a visually organized, intuitive layout, minimizing cognitive load and enabling rapid decision-making. Among them, the nodes associated with the manoeuvring plans constitute a relatively dense local network. This can be attributed to the need for fast, efficient, and parallel information dissemination at this time to support modifications to the plans, which is identified as a key function that should be easily accessible, with alerts and critical data clearly highlighted to draw attention instantly. The ASS and master need to interact more frequently and closely with the relevant team members to ensure the effectiveness, feasibility, and executability of plans.

Correspondingly, effective team collaboration hinges on the leader's ability to coordinate the division of labour and cooperation among multiple sub-teams, ensuring a unified effort toward task completion. The local network, where the leader's task units are most concentrated, often features the most intensive events and interactions. This high level of activity is critical for creating an environment where both the machines and humans can operate within their respective domains while achieving objectives that would be unattainable independently.

From the robustness analysis, the network's reachability declines rapidly with the removal of a few critical nodes, particularly those identified through betweenness centrality. It is evident that the network is highly dependent on a small subset of nodes for maintaining overall connectivity and task coordination. The network for team tasks displays a relatively low level of redundancy, which suggests a lack of resilience. Each member is assigned a specific role within their respective responsibilities, emphasizing their indispensability in team collaboration which is crucial for the development of training frameworks that align with the evolving demands of MASS operations.

5.2. Discussion on the modelling process

The conceptual structure used in this study is derived from the definitions and scenarios of MASS described in published literature. Based on this limited information, the team work domain model is established using the WDA to describe the responsibilities of team members. Although the team work domain model clearly delineates the shared and exclusive responsibilities of team members, it is typically static and macroscopic, focusing solely on the static information of the team structure. Additionally, the work domain model is based on certain simplified assumptions or constraints, which may not adequately capture the complexity and interdependencies of the team tasks.

In fact, tasks are not only individual responsibilities but are interrelated components driving operational processes and decision-making. In the team task network, tasks are defined for specific goals and operational scenarios. Task priorities, resource allocation, and decision strategies may change in real-time based on these specific goals and scenarios. While this flexibility is crucial for enhancing the resilience and efficiency of operations, especially in timely responding to unforeseen events and new threats, overly broad task objectives are not conducive to detailed analysis. Therefore, this study defines several scenarios and establishes the complete decision wheel model to demonstrate team activities in a defined scenario. However, as task complexity increases, the decision wheel model becomes increasingly cumbersome and difficult to read. From this, complex network theory is introduced.

Similar to the work domain models, network models are often based on assumed static, homogeneous nodes, and linear edges to represent relationships and structures within the system. From the perspective of model establishment, the simplification of information exchange and the definition of scenarios in this study cannot fully reflect the diversity of real-world systems. The environment of MASS in reality is dynamically changing, with demands, environmental conditions, and interactions among team members evolving over time. Real-time information such as traffic, environmental, and ship condition information also needs to be continuously obtained by team members. The importance of real-time information acquisition in team tasks remains uncertain. This aspect is not adequately reflected, despite its illustration of key information interactions among members. Additionally, while the objective of this study is not to perfectly reproduce the real world, the consideration of multiple main scenarios will facilitate a more adequate demonstration of the risks inherent to team tasks.

From an analytical perspective, the established network for team tasks is a directed, unweighted network. The complexity of tasks and the degree of interdependence among tasks are not considered in this study. As task complexity increases, situational awareness at the human and team levels tends to decline (Li et al., 2021b). This often necessitates greater human input to achieve the desired outcome, which results in a sudden increase in mental workload and a state of overload (Wu et al., 2017). As task interdependence increases, coordination needs among different tasks also tend to increase. It is foreseeable that human performance will decline in highly complex tasks, affecting the smooth execution of tasks.

6. Conclusion and future work

This study focuses on team collaborative decision-making problems of MASS. A two-step team collaborative decision-making analysis framework applicable to MASS is proposed, offering a feasible research approach for the task analysis of MASS teams. The analysis reveals the significance of critical nodes in team tasks from various aspects. Specifically, the ship master plays a central role in acquiring key information and resources, especially in tasks requiring human oversight, as over-reliance on autonomous systems can pose risks. The autonomous ship system is crucial for information transfer, particularly in detecting hazards and issuing alerts, though some tasks still depend on human expertise. The remote operation centre efficiently coordinates team activities, leveraging its high connectivity to manage decision-making and task adjustments. However, the network's vulnerability to the failure of key nodes highlights the need for improved redundancy and resilience to maintain task efficiency and operational stability, as well as the prominent role of these nodes in information spread at the early stages of task execution which is indicated in the analysis of susceptible infected model.

Despite the achievements of this study, there are still some limitations and issues that need further research. The introduction of dynamic complex network theory can simulate the evolution of team tasks over time, exploring the impact of task demands and environmental changes on team collaborative decision making. Moreover, applying this framework to a broader range of maritime tasks will further reveal the patterns of team collaborative decision-making under different task types and operational modes, providing a holistic perspective for the design and optimization of maritime autonomous surface ships systems. Last but not least, future research can emphasize the complexity of individual task nodes and the interdependencies among these nodes, aiming to construct network models with both node and edge weights. Sensitivity analysis can be employed to detail how individual tasks impact overall performance.

CRediT authorship contribution statement

Zhengjiang Liu: Writing – original draft, Validation, Supervision, Funding acquisition, Conceptualization. **Juncheng Tao:** Writing – original draft, Validation, Methodology, Investigation, Conceptualization. **Zaili Yang:** Writing – review & editing, Validation, Supervision, Methodology, Funding acquisition, Formal analysis. **Christian Matthews:** Writing – review & editing, Validation, Investigation, Conceptualization. **Yuhao Cao:** Writing – review & editing, Validation, Resources, Investigation, Formal analysis, Conceptualization. **Xinjian Wang:** Writing – original draft, Supervision, Methodology, Funding acquisition, Formal analysis, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work is financially supported by the National Natural Science Foundation of China [Grant no. 52101399; 52301409], and the MarRI-UK Core Project [Grant Agreement No. MarRI-UK_CORE_2024_02]. This work was also supported by the European Union Horizon 2020 European Research Council Consolidator Grant program [TRUST Grant No. 864724].

Appendix A

Table A1
The information of experts participating in semi-structured interviews

NO.	Type of affiliations	Professional position	Professional experience (years)	Areas of Expertise	Contribution to the semi-structured interview
1	University	Professor/Chief officer	40	Maritime law and policy development, human factors in maritime operations	The construction and validation of AHM model and the decomposition and restructuring of team tasks
2	University	Professor	26	Maritime law and policy development, accident analysis, emergency evacuation, human factors in maritime operations	The construction and validation of AHM model and the decomposition and restructuring of team tasks
3	Research institute	Senior Engineer	21	Technologies for ship intelligent collision avoidance	The construction and validation of AHM model and the decomposition and restructuring of team tasks
4	University	Postdoc researcher	8	Human factors in maritime operations	The construction and validation of AHM model and the decomposition and restructuring of team tasks

(*continued on next page*)

Table A1 (*continued*)

NO.	Type of affiliations	Professional position	Professional experience (years)	Areas of Expertise	Contribution to the semi-structured interview
5	Research institute	Senior Engineer	17	Accident analysis, human factors in maritime operations, technologies for ship intelligent collision avoidance	The construction and validation of AHM model and the decomposition and restructuring of team tasks
6	Public sector	Senior Engineer	15	Technologies for ship intelligent collision avoidance	The construction and validation of AHM model and the decomposition and restructuring of team tasks
7	Shipping company	Second officer	7	Maritime navigation, ship management	Decomposition and restructuring of team tasks
8	Shipping company	Captain	19	Maritime navigation, ship management	Decomposition and restructuring of team tasks

Table A2
The information of directed links between task units in the team work domain model

Links	Starting task units	End task units	Links	Starting task units	End task units	Links	Starting task units	End task units
L1	I1	I4	L40	A5	M1	L79	M4	A4
L2	I1	I5	L41	A5	M5	L80	I3	C1
L3	I4	C1	L42	A5	M3	L81	I3	C2
L4	I4	C2	L43	A5	M7	L82	I3	C3
L5	I4	I3	L44	A5	M2	L83	I3	I4
L6	I4	C3	L45	M1	A3	L84	M5	A4
L7	I5	A1	L46	M1	A6	L85	M5	M3
L8	I5	A2	L47	M1	M3	L86	M5	M4
L9	I5	A3	L48	M1	M7	L87	M5	M6
L10	I5	M2	L49	M1	A8	L88	M5	M7
L11	I5	M3	L50	A6	I2	L89	M5	A8
L12	I5	M7	L51	A6	I3	L90	M6	A3
L13	I5	A7	L52	A6	A8	L91	M6	A6
L14	I5	M8	L53	I2	A1	L92	M6	M3
L15	A1	A3	L54	I2	A2	L93	M6	M7
L16	A1	A4	L55	I2	C1	L94	M6	A8
L17	A1	M4	L56	I2	M2	L95	M7	C1
L18	A1	A8	L57	I2	C3	L96	M7	C3
L19	A1	A7	L58	I2	M8	L97	M7	M1
L20	A1	C3	L59	C1	C2	L98	M7	M2
L21	A1	M8	L60	C1	I5	L99	M7	M3
L22	A1	C1	L61	C2	M1	L100	M7	M4
L23	A1	M2	L62	C2	M2	L101	M7	M5
L24	A1	I4	L63	C2	M3	L102	M7	M6
L25	A2	C1	L64	C2	M4	L103	M7	M8
L26	A2	M2	L65	C2	M5	L104	C3	C2
L27	A2	C3	L66	C2	M6	L105	A7	A3
L28	A2	M8	L67	C2	M8	L106	A7	A5
L29	A3	A4	L68	M2	M3	L107	A7	M2
L30	A3	A7	L69	M2	M4	L108	A7	M3
L31	A3	A8	L70	M2	M5	L109	A7	M4
L32	A3	A2	L71	M2	M6	L110	A7	M5
L33	A3	C2	L72	M2	M7	L111	A7	M6
L34	A3	M3	L73	M3	M2	L112	A7	M7
L35	A3	M4	L74	M3	M4	L113	A7	M8
L36	A3	M7	L75	M3	M5	L114	A7	A8
L37	A4	I3	L76	M3	M6	L115	A8	I4
L38	A4	A5	L77	M3	M7			
L39	A4	A6	L78	M3	M8			

Data availability

Data will be made available on request.

References

Ashoori, M., Burns, C., 2013. Team cognitive work Analysis:Structure and control tasks. J. Cogn. Eng. Decis. Mak. 7 (2), 123–140. https://doi.org/10.1177/1555343412445577.

Aydin, M., Sezer, S.I., Akyuz, E., Gardoni, P., 2025. Improved Z-number based Bayesian network modelling to predict cyber-attack risk for maritime autonomous surface ship (MASS). Appl. Soft Comput. 180, 113416. https://doi.org/10.1016/j.asoc.2025.113416.

BahooToroody, A., Abaei, M.M., Banda, O.V., Kujala, P., De Carlo, F., Abbassi, R., 2022. Prognostic health management of repairable ship systems through different autonomy degree; from current condition to fully autonomous ship. Reliab. Eng. Syst. Saf. 221, 108355. https://doi.org/10.1016/j.ress.2022.108355.

Berche, B., von Ferber, C., Holovatch, T., Holovatch, Y., 2009. Resilience of public transport networks against attacks. Eur. Phys. J. B 71 (1), 125–137. https://doi.org/10.1140/epjb/e2009-00291-3.

Cao, W., Wang, X., Feng, Y., Zhou, J., Yang, Z., 2025a. Improving maritime accident severity prediction accuracy: A holistic machine learning framework with data balancing and explainability techniques. Reliab. Eng. Syst. Saf. 266, 111648. https://doi.org/10.1016/j.ress.2025.111648.

Cao, W., Wang, X., Li, J., Zhang, Z., Cao, Y., Feng, Y., 2024. A novel integrated method for heterogeneity analysis of marine accidents involving different ship types. Ocean Eng. 312, 119295. https://doi.org/10.1016/j.oceaneng.2024.119295.

Cao, Y., Xin, X., Wang, X., Wang, J., Yang, Z., 2025b. Multi-objective resilience-oriented optimisation for the global container shipping network against cascading failures. Transp. Res. A: Policy Pract. 200, 104659. https://doi.org/10.1016/j.tra.2025.104659.

Chan, J.P., Pazouki, K., Norman, R.A., 2023. An experimental study into the fault recognition of onboard systems by navigational officers. J. Mar. Eng. Technol. 22 (2), 101–110. https://doi.org/10.1080/20464177.2022.2143312.

Chen, Y.Y., Fang, W.N., Niu, K., Liu, H.J., 2019. Accessible design of railway vehicle based on cognitive work analysis. IEEE Intelligent Transportation Systems Conference. IEEE-ITSC), Auckland, NEW ZEALAND, Oct 27-30, pp. 1607–1612.

DeFranco, J.F., Neill, C.J., Clariana, R.B., 2011. A cognitive collaborative model to improve performance in engineering teams—A study of team outcomes and mental model sharing. Syst. Eng. 14 (3), 267–278. https://doi.org/10.1002/sys.20178.

Elix, B., Naikar, N., 2020. Designing for adaptation in Workers' individual behaviors and collective structures with cognitive work analysis: case study of the diagram of work organization possibilities. Hum. Factors 63 (2), 274–295. https://doi.org/10.1177/0018720819893510.

Fan, C., Bolbot, V., Montewka, J., Zhang, D., 2024. Advanced Bayesian study on inland navigational risk of remotely controlled autonomous ship. Accid. Anal. Prev. 203, 107619. https://doi.org/10.1016/j.aap.2024.107619.

Fan, S., Shi, K., Weng, J., Yang, Z., 2025. Letting losses be lessons: Human-machine cooperation in maritime transport. Reliab. Eng. Syst. Saf. 253, 110547. https://doi.org/10.1016/j.ress.2024.110547.

Feng, Y., Wang, H., Xia, G., Cao, W., Li, T., Wang, X., Liu, Z., 2025. A machine learning-based data-driven method for risk analysis of marine accidents. J. Mar. Eng. Technol. 24 (2), 147–158. https://doi.org/10.1080/20464177.2024.2368914.

Gan, L., Gao, Z., Zhang, X., Xu, Y., Liu, R.W., Xie, C., Shu, Y., 2025a. Graph neural networks enabled accident causation prediction for maritime vessel traffic. Reliab. Eng. Syst. Saf. 257, 110804. https://doi.org/10.1016/j.ress.2025.110804.

Gan, L., Li, X., Yan, T., Song, L., Xiao, J., Shu, Y., 2025b. Intelligent ship path planning based on improved artificial potential field in narrow inland waterways. Ocean Eng. 317, 119928. https://doi.org/10.1016/j.oceaneng.2024.119928.

Gan, L., Ye, B., Huang, Z., Xu, Y., Chen, Q., Shu, Y., 2023. Knowledge graph construction based on ship collision accident reports to improve maritime traffic safety. Ocean Coast. Manag. 240, 106660. https://doi.org/10.1016/j.ocecoaman.2023.106660.

Gil, M., 2021. A concept of critical safety area applicable for an obstacle-avoidance process for manned and autonomous ships. Reliab. Eng. Syst. Saf. 214, 107806. https://doi.org/10.1016/j.ress.2021.107806.

Gil, M., Kozioł, P., Wróbel, K., Montewka, J., 2022. Know your safety indicator – a determination of merchant vessels bow crossing range based on big data analytics. Reliab. Eng. Syst. Saf. 220, 108311. https://doi.org/10.1016/j.ress.2021.108311.

Gil, M., Krata, P., Kozioł, P., Hinz, T., 2024. A multiparameter simulation-driven analysis of ship turning trajectory concerning a required number of irregular wave realizations. Ocean Eng. 299, 117293. https://doi.org/10.1016/j.oceaneng.2024.117293.

Goerlandt, F., 2020. Maritime autonomous surface ships from a risk governance perspective: interpretation and implications. Saf. Sci. 128, 104758. https://doi.org/10.1016/j.ssci.2020.104758.

Gomola, A., Bouwer Utne, I., 2024. A novel STPA approach to software safety and security in autonomous maritime systems. E31483 Heliyon 10 (10). https://doi.org/10.1016/j.heliyon.2024.e31483.

Johansen, T., Blindheim, S., Torben, T.R., Utne, I.B., Johansen, T.A., Sørensen, A.J., 2023. Development and testing of a risk-based control system for autonomous ships. Reliab. Eng. Syst. Saf. 234, 109195. https://doi.org/10.1016/j.ress.2023.109195.

Johansen, T., Utne, I.B., 2022. Supervisory risk control of autonomous surface ships. Ocean Eng. 251, 111045. https://doi.org/10.1016/j.oceaneng.2022.111045.

Johansen, T., Utne, I.B., 2024. Human-autonomy collaboration in supervisory risk control of autonomous ships. J. Mar. Eng. Technol. 23 (2), 135–153. https://doi.org/10.1080/20464177.2024.2319369.

Jovanović, I., Perčić, M., BahooToroody, A., Fan, A., Vladimir, N., 2024. Review of research progress of autonomous and unmanned shipping and identification of future research directions. J. Mar. Eng. Technol. 23 (2), 82–97. https://doi.org/10.1080/20464177.2024.2302249.

Kant, V., 2017. Revisiting the technologies of the old: a case study of cognitive work analysis and nanomaterials. Cogn. Technol. Work 19 (1), 47–71. https://doi.org/10.1007/s10111-016-0397-8.

Kim, Y., Chen, Y.-S., Linderman, K., 2015. Supply network disruption and resilience: a network structural perspective. J. Oper. Manag. 33-34, 43–59. https://doi.org/10.1016/j.jom.2014.10.006.

Kleinberg, J.M., 1999. Authoritative sources in a hyperlinked environment. J. ACM 46 (5), 604–632. https://doi.org/10.1145/324133.324140.

Lee, C.-H., Tenneti, S., Eun, D.Y., 2019. Transient dynamics of epidemic spreading and its mitigation on large networks. Proceedings of the Twentieth ACM International Symposium on Mobile Ad Hoc Networking and Computing. Association for Computing Machinery, Catania, Italy, pp. 191–200.

Li, Y., Duan, Z., Liu, Z. Study on risk-based operators' competence assessment of maritime autonomous surface ships. *5th International Conference on Transportation Information and Safety (ICTIS)*, Liverpool, ENGLAND, Jul 14-17, 2019, pp. 1412-1417.

Li, H., Shang, Q., Deng, Y., 2021a. A generalized gravity model for influential spreaders identification in complex networks. Chaos Solitons Fractals 143, 110456. https://doi.org/10.1016/j.chaos.2020.110456.

Li, P.-c, Wang, Y.-x, Chen, J.-h, Luo, Z.-h, Dai, L.-c, 2021b. An experimental study on the effects of task complexity and knowledge and experience level on SA, TSA and workload. Nucl. Eng. Des. 376, 111112. https://doi.org/10.1016/j.nucengdes.2021.111112.

Li, T., Wang, X., Zhang, Z., Feng, Y., 2025. A novel feature engineering method for severity prediction of marine accidents. J. Mar. Eng. Technol. 24, 1–16. https://doi.org/10.1080/20464177.2025.2469336.

Liu, J., Aydin, M., Akyuz, E., Arslan, O., Uflaz, E., Kurt, R.E., Turan, O., 2022. Prediction of human-machine interface (HMI) operational errors for maritime autonomous surface ships (MASS). J. Mar. Sci. Technol. 27 (1), 293–306. https://doi.org/10.1007/s00773-021-00834-w.

Lynch, K.M., Banks, V.A., Roberts, A.P.J., Radcliffe, S., Plant, K.L., 2024. What factors May influence decision-making in the operation of maritime autonomous surface ships? A systematic review. Theor. Issues Ergon. Sci. 25 (1), 98–142. https://doi.org/10.1080/1463922X.2022.2152900.

Man, Y., Weber, R., Cimbritz, J., Lundh, M., MacKinnon, S.N., 2018. Human factor issues during remote ship monitoring tasks: an ecological lesson for system design in a distributed context. Int. J. Ind. Ergon. 68, 231–244. https://doi.org/10.1016/j.ergon.2018.08.005.

Massari, G.F., Giannoccaro, I., Carbone, G., 2023. Team social network structure and resilience: a complex system approach. IEEE Trans. Eng. Manag. 70 (1), 209–219. https://doi.org/10.1109/TEM.2021.3058237.

McComb, S.A., 2017. Shared mental models and their convergence 1. Macrocognition in teams. CRC Press, pp. 34–50.

McLean, S., Read, G.J.M., Ramsay, K., Hogarth, L., Kean, B., 2021. Designing success: applying cognitive work analysis to optimise a para sport system. Appl. Ergon. 93, 11. https://doi.org/10.1016/j.apergo.2021.103369.

Niu, K., Fang, W., Song, Q., Guo, B., Du, Y., Chen, Y., 2021. An evaluation method for emergency procedures in automatic metro based on complexity. IEEE Trans. Intell. Transp. Syst. 22 (1), 370–383. https://doi.org/10.1109/TITS.2019.2958115.

Oosthuizen, R., Pretorius, L. Establishing a methodology to develop complex sociotechnical systems. *2013 IEEE International Conference on Industrial Technology (ICIT)*, Cape Town, South Africa, Feb 25-28, 2013, pp. 1477-1482.

Palbar Misas, J.D., Hopcraft, R., Tam, K., Jones, K., 2024. Future of maritime autonomy: cybersecurity, trust and mariner's situational awareness. J. Mar. Eng. Technol. 23 (3), 224–235. https://doi.org/10.1080/20464177.2024.2330176.

Ramos, M.A., Thieme, C.A., Utne, I.B., Mosleh, A., 2020. Human-system concurrent task analysis for maritime autonomous surface ship operation and safety. Reliab. Eng. Syst. Saf. 195, 106697. https://doi.org/10.1016/j.ress.2019.106697.

Ramos, M.A., Utne, I.B., Mosleh, A., 2019. Collision avoidance on maritime autonomous surface ships: operators' tasks and human failure events. Saf. Sci. 116, 33–44. https://doi.org/10.1016/j.ssci.2019.02.038.

Rødseth, Ø.J., Burmeister, H.-C., 2015. Risk assessment for an unmanned merchant ship. TransNav Int. J. Mar. Navig. Saf. Sea Transp. 9 (3), 357–364. https://doi.org/10.12716/1001.09.03.08.

Rødseth, Ø.J., Wennersberg, L.A.L. A criticism of proposed levels of autonomy for mass. *The 33 th European Safety and Reliability Conference (ESREL2023)*, Southampton, UK, Sep 3-8, 2023, pp. 2854-2860.

Sadraey, M.H. Manned-unmanned aircraft teaming. *2018 IEEE Aerospace Conference*, Big Sky, MT, USA, Mar 3-10. 2018, pp. 1-12.

Seeber, I., Bittner, E., Briggs, R.O., de Vreede, T., de Vreede, G.-J., Elkins, A., Maier, R., Merz, A.B., Oeste-Reiß, S., Randrup, N., Schwabe, G., Söllner, M., 2020. Machines as teammates: a research agenda on AI in team collaboration. Inf. Manag. 57 (2), 103174. https://doi.org/10.1016/j.im.2019.103174.

Sezer, S.I., Ahn, S.I., Akyuz, E., Kurt, R.E., Gardoni, P., 2024. A hybrid human reliability analysis approach for a remotely-controlled maritime autonomous surface ship (MASS- degree 3) operation. Appl. Ocean Res. 147, 103966. https://doi.org/10.1016/j.apor.2024.103966.

Shepherd, A., 1998. HTA as a framework for task analysis. Ergonomics 41 (11), 1537–1552. https://doi.org/10.1080/001401398186063.

Shi, J., Liu, Z., Feng, Y., Wang, X., Zhu, H., Yang, Z., Wang, J., Wang, H., 2024. Evolutionary model and risk analysis of ship collision accidents based on complex networks and DEMATEL. Ocean Eng. 305, 117965. https://doi.org/10.1016/j.oceaneng.2024.117965.

Shiokari, M., Itoh, H., Yuzui, T., Ishimura, E., Miyake, R., Kudo, J., Kawashima, S., 2024. Structure model-based hazard identification method for autonomous ships. Reliab. Eng. Syst. Saf. 247, 110046. https://doi.org/10.1016/j.ress.2024.110046.

Shu, Y., Xiong, C., Zhu, Y., Liu, K., Liu, R.W., Xu, F., Gan, L., Zhang, L., 2024. Reference path for ships in ports and waterways based on optimal control. Ocean Coast. Manag. 253, 107168. https://doi.org/10.1016/j.ocecoaman.2024.107168.

Shu, Y., Zhu, Y., Xu, F., Gan, L., Lee, P.T.-W., Yin, J., Chen, J., 2023. Path planning for ships assisted by the icebreaker in ice-covered waters in the Northern sea route based on optimal control. Ocean Eng. 267, 113182. https://doi.org/10.1016/j.oceaneng.2022.113182.

Stanton, N.A., 2006. Hierarchical task analysis: developments, applications, and extensions. Appl. Ergon. 37 (1), 55–79. https://doi.org/10.1016/j.apergo.2005.06.003.

Stępień, B., 2023. Can a ship be its own captain? Safe manning of autonomous and uncrewed vessels. Mar. Policy 148, 105451. https://doi.org/10.1016/j.marpol.2022.105451.

Storkersen, K.V., 2021. Safety management in remotely controlled vessel operations. Mar. Policy 130, 104349. https://doi.org/10.1016/j.marpol.2020.104349.

Suleiman, A.M., 2022. Determining the prerequisites for effective workplace inspection by the occupational safety and health regulatory authority using cognitive work analysis. Int. J. Occup. Saf. Ergon. 28 (3), 1403–1418. https://doi.org/10.1080/10803548.2021.1893023.

Szłapczyński, R., Szłapczyńska, J., Gil, M., Życzkowski, M., Montewka, J., 2024. Holistic collision avoidance decision support system for watchkeeping deck officers. Reliab. Eng. Syst. Saf. 250, 110232. https://doi.org/10.1016/j.ress.2024.110232.

Tao, J., Liu, Z., Wang, X., Cao, Y., Zhang, M., Loughney, S., Wang, J., Yang, Z., 2024. Hazard identification and risk analysis of maritime autonomous surface ships: a systematic review and future directions. Ocean Eng. 307, 118174. https://doi.org/10.1016/j.oceaneng.2024.118174.

Tao, J., Liu, Z., Wang, X., Wang, J., Rao, S., Yang, Z., 2025. Team task complexity analysis in MASS operation using a fuzzy TOPSIS method. Ocean Eng. 329, 121140. https://doi.org/10.1016/j.oceaneng.2025.121140.

Vicente, K.J., 1999. Cognitive work analysis: toward safe, productive, and healthy computer-based work. CRC press.

Wahlström, M., Hakulinen, J., Karvonen, H., Lindborg, I., 2015. Human factors challenges in unmanned ship operations – insights from other domains. Procedia Manuf. 3, 1038–1045. https://doi.org/10.1016/j.promfg.2015.07.167.

Wang, X., Cao, W., Li, T., Feng, Y., Uğurlu, Ö., Wang, J., 2025. An integrated multidimensional model for heterogeneity analysis of maritime accidents during different watchkeeping periods. Ocean Coast. Manag. 264, 107625. https://doi.org/10.1016/j.ocecoaman.2025.107625.

Wang, J., Wang, X., Feng, Y., Cao, Y., Guo, Z., Liu, Z., 2023. Assessing the connectivity reliability of a maritime transport network: a case of imported crude oil in China. J. Mar. Sci. Eng. 11 (8), 1597. https://doi.org/10.3390/jmse11081597.

Wu, Y., Miwa, T., Uchida, M., 2017. Using physiological signals to measure operator's mental workload in shipping – an engine room simulator study. J. Mar. Eng. Technol. 16 (2), 61–69. https://doi.org/10.1080/20464177.2016.1275496.

Zhang, Z., Liu, Z., Zhou, Z., Wang, X., Majumdar, A., Cao, Y., Yang, Z., 2025. Time prediction of human evacuation from passenger ships based on machine learning methods. Transp. Res. A: Policy Pract. 200, 104644. https://doi.org/10.1016/j.tra.2025.104644.

Zhang, M., Zhang, D., Yao, H., Zhang, K., 2020. A probabilistic model of human error assessment for autonomous cargo ships focusing on human-autonomy collaboration. Saf. Sci. 130, 104838. https://doi.org/10.1016/j.ssci.2020.104838.

Zhou, T., Liu, J.-G., Bai, W.-J., Chen, G., Wang, B.-H., 2006. Behaviors of susceptible-infected epidemics on scale-free networks with identical infectivity. Phys. Rev. E 74 (5), 056109. https://doi.org/10.1103/PhysRevE.74.056109.