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Towards safe human–machine interaction in remotely controlled ships: A system-theoretic risk analysis framework

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ABSTRACT

With the rapid advancement of Maritime Autonomous Surface Ships (MASS), the complexity of onboard automation and remote operations has significantly increased, placing greater demands on the safety and reliability of Human-Machine Interaction (HMI). Ensuring safe navigation under varying levels of autonomy requires a structured and comprehensive assessment of HMI-related risks. This study proposes a novel risk-informed safety framework for HMI in remotely controlled MASS, particularly those operating at Degree of Autonomy 2 (DoA2). By integrating Systems-Theoretic Process Analysis (STPA) with the Human Factors Analysis and Classification System (HFACS), the framework systematically identifies unsafe interactions, causal factors, and control structure vulnerabilities across multiple functional levels. The approach captures both technical failures and human factors, offering a holistic view of HMI safety. A case study of DoA2 ships demonstrates the applicability and effectiveness of the proposed STPA-HFACS framework in visualising unsafe scenarios and tracing their root causes. The findings highlight key areas for risk mitigation through targeted technological improvements and enhanced operator training. This research contributes a structured methodology for MASS HMI safety assessment and provides practical guidance for risk management in semi-autonomous ship operations.

1. Introduction

Maritime Autonomous Surface Ships (MASS) represent a transformative development in the maritime industry, offering the promise of enhanced operational efficiency and reduced human error (Munim, 2019). The integration of automation and advanced technologies in MASS aims to mitigate navigational risks and improve maritime safety by minimising human-related incidents (Ramos et al., 2020; Liu et al., 2025). However, increasing autonomy also introduces new and unpredictable safety concerns, underscoring the importance of robust safety analysis throughout the development and deployment of MASS (Wrobel et al., 2016).

To support the safe implementation of MASS, the International Maritime Organization (IMO) has classified MASS into four Degrees

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of Autonomy (DoA), providing a framework for further study and regulatory development (IMO, 2021). Among these, DoA2 and DoA3 vessels, commonly referred to as remotely controlled ships, have drawn considerable attention due to their transitional nature between conventional manned operations and fully autonomous navigation (Cheng et al., 2023; Yang et al., 2024). These vessels rely on Remote Operation Centres (ROCs), introducing more complex and frequent Human-Machine Interactions (HMI), particularly in DoA2 systems where operators are responsible for continuous monitoring and direct control.

Despite growing research into MASS safety, much of the existing literature focuses on macro-level risks, such as navigational hazards (Chou et al., 2022; Fu et al., 2023; Zhang and Zhang, 2023) and system failures (Chaal et al., 2020; Chang et al., 2021; Glomsrud and Xie, 2019; Utne et al., 2020; Wróbel et al., 2018a; Zhang et al., 2020). At the macro level, however, the nuanced risk factors embedded within HMI systems, especially those involving human cognitive and organisational dimensions, remain insufficiently explored (Zhang et al., 2021a). Traditional risk assessment methodologies, such as component-based failure analysis, may overlook latent risks arising from human behaviour, decision-making, or organisational structures (Leveson, 2011).

Recent research on HMI safety in autonomous ships has focused primarily on specific HMI scenarios (Cheng et al., 2023; Fan and Yang, 2023; Liu et al., 2022). This is largely due to the difficulty of simultaneously addressing both task-level and cognitive-level human factors within complex HMI systems. As a result, a more systematic and integrated approach is needed to fully understand the risks associated with HMI in MASS and their impact on operational safety.

System-Theoretic Process Analysis (STPA) is a widely used safety analysis method grounded in systems theory and cybernetics. It is effective for examining the safety of complex systems by focusing on structural and functional design, rather than solely on component failures. Applying STPA to MASS HMI enables risk analysis from a control perspective, identifying unsafe actions and control flaws in system design (Mallam et al., 2020). However, while STPA can detect task-level safety issues, it is limited in capturing deeper cognitive-level risks (Porathe et al., 2018; Ramos et al., 2019). To address this gap, the Human Factors Analysis and Classification System (HFACS) offers a complementary approach. HFACS systematically identifies and categorises human error across multiple levels, including cognitive processes, supervision, and organisational factors (Wrobel et al., 2021).

This study introduces a novel framework that combines STPA and the HFACS. STPA, grounded in systems theory and cybernetics, enables a holistic safety assessment by identifying unsafe interactions and control flaws within complex systems. By integrating these approaches, this study proposes an STPA-HFACS framework that captures both task-level and cognitive-level human factors affecting HMI in DoA2 MASS. This study makes three key contributions:

(1) Bridging the cognitive gap in human factors analysis.
This study highlights often-overlooked cognitive-level human factors, such as unsafe supervision, decision errors, and organisational issues, by integrating HFACS into the analysis of MASS HMI. It offers a dual-perspective understanding of operator interaction, encompassing both task execution and cognitive processes.
(2) Establishing a holistic framework for HMI risk evaluation.
A dynamic safety control structure is proposed, allowing for the identification of latent hazards in operator-system interactions. This framework captures the feedback loop between operator control actions and system behaviour, enabling comprehensive risk diagnosis in MASS HMI systems.
(3) Integrating STPA and HFACS for systematic risk management.
The fusion of STPA and HFACS provides a scalable methodology for evaluating HMI safety at both macro and micro levels. A case study on DoA2 remotely controlled ships validates the framework's effectiveness and highlights actionable recommendations for enhancing HMI safety through technological upgrades and targeted training.

The structure of the paper is outlined as follows: Section 2 presents a comprehensive review of MASS HMI safety and the application of STPA in the MASS domain. Section 3 outlines the proposed STPA-HFACS framework. Section 4 presents a case study on DoA2 MASS. Section 5 discusses the results and uncertainty analysis. Finally, Section 6 concludes the study and outlines directions for future research.

2. Literature review

This section provides a literature review on the safety-related research related to MASS. Section 2.1 reviews studies concerning the HMI safety of MASS, including cooperative navigation, human error analysis, and system-theoretic approaches. Section 2.2 focuses on fault and failure analysis methods, particularly the application and evolution of the STPA framework. Lastly, Section 2.3 identifies key research gaps in the existing literature.

2.1. Research on HMI safety of MASS

With the rapid development of autonomous ship technologies, safety concerns regarding HMI have become increasingly prominent (Cotfas et al., 2023; Hwang et al., 2024). Ensuring the reliability of HMI is essential to support autonomous or unmanned navigation under varying degrees of autonomy. Existing research on HMI safety in MASS mainly clusters around three thematic areas: (1) human–machine cooperative navigation, (2) human error prediction and assessment, and (3) system-theoretic modelling of interactive behaviours.

Human–machine cooperative navigation examines how humans and intelligent systems interact effectively in navigational tasks (Longo et al., 2023). With the emergence of the ROC and remote operators as a new occupational role, novel collaborative methods

have been proposed (Jovanović et al., 2024). While these methods offer improvements in efficiency, they also introduce new safety challenges (Saha, 2023). Liu et al. (2022) reviewed challenges in human–machine cooperation and emphasised the foundational role of human involvement in MASS. Veitch and Alsos (2022) highlighted the risk of over-reliance on automation, arguing that while AI may replace certain functions, human operators remain central to safe operation. Fan et al. (2021) further proposed a four-step risk framework validated through case studies to assess cooperative navigation safety.

Human error–focused studies employ probabilistic and fuzzy logic models to identify and mitigate operator mistakes (Cotfas et al., 2023; Palbar Misas et al., 2024). For example, Liu et al. (2021) predicted operational errors via the HMI interface using the Success Likelihood Index Method (SLIM) and Interval Type-2 Fuzzy Sets (IT2FS) to address decision uncertainty. Zhang et al. (2020) evaluated the probability of human error aboard autonomous cargo vessels using the Technique for Human Error Rate Prediction (THERP) and Bayesian Network (BN) models, illustrating the significance of identifying human error patterns within collaborative systems.

System-theoretic modelling approaches provide a structural lens to analyse interactive safety (Guo et al., 2024; Yang et al., 2024). Building on STPA principles, Fan and Yang (2023) developed a dynamic HMI model for accident analysis and cognitive support. Cheng et al. (2023) applied STPA to evaluate ROC safety under multiple autonomy scenarios, demonstrating its ability to uncover interaction-level risks. Tang et al. (2022) compared HMI characteristics across autonomy levels, showing how intelligent algorithms influence decision-making behaviours. Such methods offer a holistic view of the system's feedback loops and response mechanisms.

Beyond the maritime sector, empirical studies in other autonomous domains provide valuable insights for enhancing HMI safety assessment. In the automotive field, extensive research on human–automation collaboration in autonomous vehicles has demonstrated that excessive trust, mode confusion, and cognitive overload remain critical barriers to safe operation (Oviedo-Trespalacios et al., 2016). Similarly, studies on unmanned aerial vehicles reveal that delayed feedback, poor interface transparency, and inadequate adaptive automation can significantly impair operator situation awareness (Pongsakornsathien et al., 2025). These findings collectively underscore that effective HMI design must not only optimise task execution but also address cognitive resilience and workload management.

Although there have been some forward-looking studies in other fields, few maritime studies have yet incorporated these cross-domain lessons into MASS HMI frameworks. Compared with these domains, maritime HMI studies remain limited in addressing how cognitive demands and trust dynamics shape operational safety. This study addresses this thematic gap by explicitly linking unsafe control actions to cognitive and organisational precursors, thus aligning MASS HMI research with evolving priorities in autonomous system safety.

2.2. Research on fault failure methods of MASS

In research utilising the STPA method, scholarly attention has predominantly centred on two key dimensions: (1) the application of STPA to establish the preliminary system architecture of MASS and to conduct systematic safety assessments, and (2) the validation of the methodology through case studies specifically designed to reflect operational scenarios relevant to MASS. STPA has become a cornerstone methodology in MASS safety research (Zhou et al., 2020). Grounded in systems theory, STPA facilitates a holistic understanding of system operations by emphasising the complex interactions among system components (Cheng et al., 2023). This approach enables researchers to identify potential hazards and propose effective prevention and mitigation strategies (Kristensen et al., 2024). For instance, systems theory helps establish risk evolution models, simulate system behaviour under various operational conditions, and suggest optimisation measures for safety improvement (Li et al., 2023a). Wróbel et al. (2018b) applied STPA to a theoretical MASS safety model, identified key safety enhancements, and proposed design recommendations. Rokseth et al. (2019) identified operational hazards and potential losses associated with accidents and verified corresponding safety strategies through a combination of case studies and simulator-based testing. Similarly, Wróbel et al. (2020) developed a preliminary safety control structure using STPA principles, highlighting the need for further research to address unresolved safety issues. Chaal et al. (2020) proposed a hierarchical MASS structure based on STPA, incorporating seafarer experience and existing MASS knowledge. This framework emphasised the value of operator input in shaping MASS functionality and ensuring safe offshore operations.

As MASS technologies continue to evolve, new systems and operational scenarios give rise to novel and often unforeseen risks (Chae et al., 2020). Traditional STPA methods face limitations when addressing such emerging challenges, including incomplete system coverage and inadequate adaptability. Consequently, ongoing refinement of safety assessment methods is essential to address evolving risks effectively (Qiao et al., 2023). Enhancements may involve expanding the analytical scope to include more subsystems and interactions (Khastgir et al., 2021), improving methodological robustness for complex system environments (Johansen and Utne, 2024), and refining analysis results to better inform policy and system design (Carreras Guzman et al., 2021).

Furthermore, several extended STPA-based methods have been proposed. Zou (2018) tested STPA's feasibility for DoA4 MASS operating systems by establishing a scenario-based risk estimation framework and comparing it with other methodologies. Glomsrud and Xie (2019) introduced an integrated STPA method for MASS, emphasising closed-loop control structures for safety. Utne et al. (2020) advanced a framework for real-time MASS risk modelling by linking STPA outputs to Bayesian Belief Networks (BBNs), paving the way for autonomous supervisory control systems. Zhou et al. (2021) introduced a STPA-based analysis methodology that Synthesizes Safety and Security (STPA-SynSS), which integrates safety and cybersecurity analysis by identifying hazards and revealing causal mechanisms, offering a unified approach to safety and security in MASS operations.

To enhance the capture of human-related causal factors in maritime safety, insights can be drawn from integrated applications of STPA and HFACS in other safety-critical domains. In road traffic safety, Dong et al. (2024) developed a STAMP–HFACS framework by embedding HFACS classifications into the STAMP process model, thereby facilitating structured traceability from unsafe acts to systemic root causes and offering diagnostic depth beyond standalone STPA. Similarly, in the aviation domain, Lower et al. (2018)

incorporated HFACS levels explicitly into STPA's control structure, enabling the identification of high-level interactions, particularly latent conditions and supervisory deficiencies, often overlooked in conventional STPA outputs. Further advancing this integration, Li et al. (2019) devised a hybrid HFACS–STAMP framework for rail transit, synthesising HFACS's hierarchical taxonomy of human error with STAMP's control-theoretic reasoning. This approach bridges the analytical gaps of both methods: STAMP's limited representation of managerial influences and HFACS's descriptive rather than explanatory focus on human error.

This section reviews how STPA has been employed to model system architectures, identify hazards, and enhance safety. It further discusses the limitations of conventional STPA in addressing emerging risks and surveys recent methodological refinements. The emergence of hybrid frameworks has strengthened the capacity not only to identify unsafe acts and conditions but also to trace their underlying causes across supervisory and organisational layers. These developments motivate the present study's adoption of an integrated STPA–HFACS mapping structure, which supports a multi-level causal analysis beyond the scope of standard STPA.

2.3. Research gaps

Based on the reviewed literature, the following key research gaps have been identified to align with the contributions of this study:

(1) Insufficient focus on cognitive-level human factors: While human factors are acknowledged as critical in ensuring the safety of HMI in MASS, current studies tend to overlook the cognitive dimensions, such as the preconditions for unsafe actions, inadequate supervision, and organisational influences. This lack of attention limits the depth and accuracy of risk assessments in MASS HMI systems.
(2) Lack of dynamic and holistic risk modelling approaches for HMI systems: Existing analyses often treat MASS HMI as static systems, failing to account for the dynamic nature of human-system interactions. There is a need for comprehensive models that consider the feedback loops and evolving interactions between operators and automated systems to identify risks more effectively.
(3) Limited integration of system-level and human-factor methodologies: Although STPA has been widely used for analysing system-level risks in MASS, its limitations in addressing human cognitive and organisational factors remain unresolved. Conversely, HFACS offers a structured classification of human errors but lacks system-level risk modelling. A gap exists in combining these two complementary approaches into a unified framework that captures both macro- and micro-level safety concerns in MASS HMI.

This study aims to bridge these gaps by proposing an integrated STPA-HFACS framework that enables a comprehensive, dynamic, and human-centred risk analysis for remotely operated MASS.

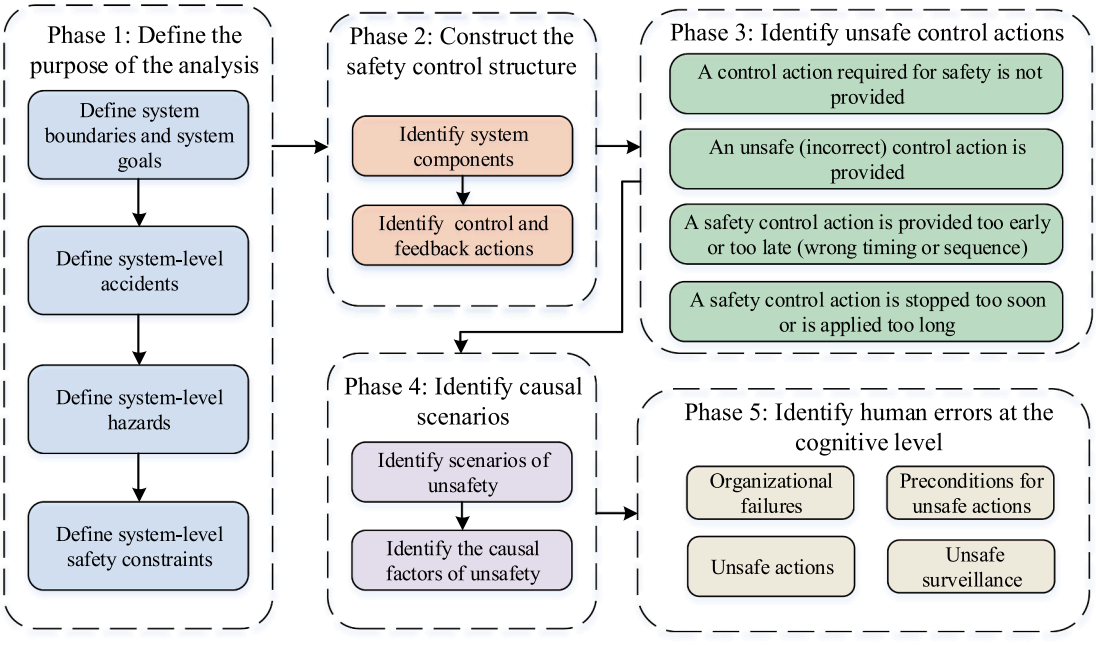

Fig. 1. The proposed framework in this study.

3. The proposed framework and methodology

3.1. The proposed framework

This study proposes an integrated framework that combines STPA and HFACS to systematically assess safety risks in HMI within MASS. The framework systematically integrates both system-level and human-level risk factors by leveraging the strengths of STPA and HFACS. Specifically, STPA is used to identify Unsafe Control Actions (UCAs) and associated system hazards, while HFACS enables the identification of human error pathways and organisational deficiencies. The methodology comprises several key steps: defining system-level hazards, constructing safety control structures, identifying UCAs along with their Causal Scenarios (CSs), and extending the analysis to include cognitive-level human errors. This layered integration ensures a systematic understanding of the interactions between human operators and autonomous systems in MASS. The proposed framework is illustrated in Fig. 1.

3.2. STPA-HFACS integration method

The operation of MASS involves the coordination of multiple complex subsystems, where unsafe interactions among components can pose significant safety risks. To address these challenges, STPA, developed from the System-Theoretic Accident Model and Processes (STAMP), has been applied in various high-risk industries such as aerospace (Wilkinson et al. (2012), and more recently in modelling safety for autonomous ships (Sulaman et al., 2019; Wróbel et al., 2018a). Unlike traditional accident models that focus on component failures, STPA reconceptualises safety as a control problem. It emphasises the identification of unsafe interactions within system control loops and the enforcement of Safety Constraints (SC) (Chaal et al., 2020).

Although STPA is well-suited for identifying technical and systemic risks, it has limited capability in analysing human and organisational causes of unsafe actions (Zhou et al., 2020). To address this limitation, HFACS is introduced as a systematic human reliability analysis method. Rooted in Reason's "Swiss Cheese Model" (Shappell and Wiegmann, 2000), HFACS classifies human error into four hierarchical levels: (1) organisational influences, (2) unsafe supervision, (3) preconditions for unsafe acts, and (4) unsafe acts. This structure facilitates the identification of latent failures that are often hidden within organisational processes or supervisory practices.

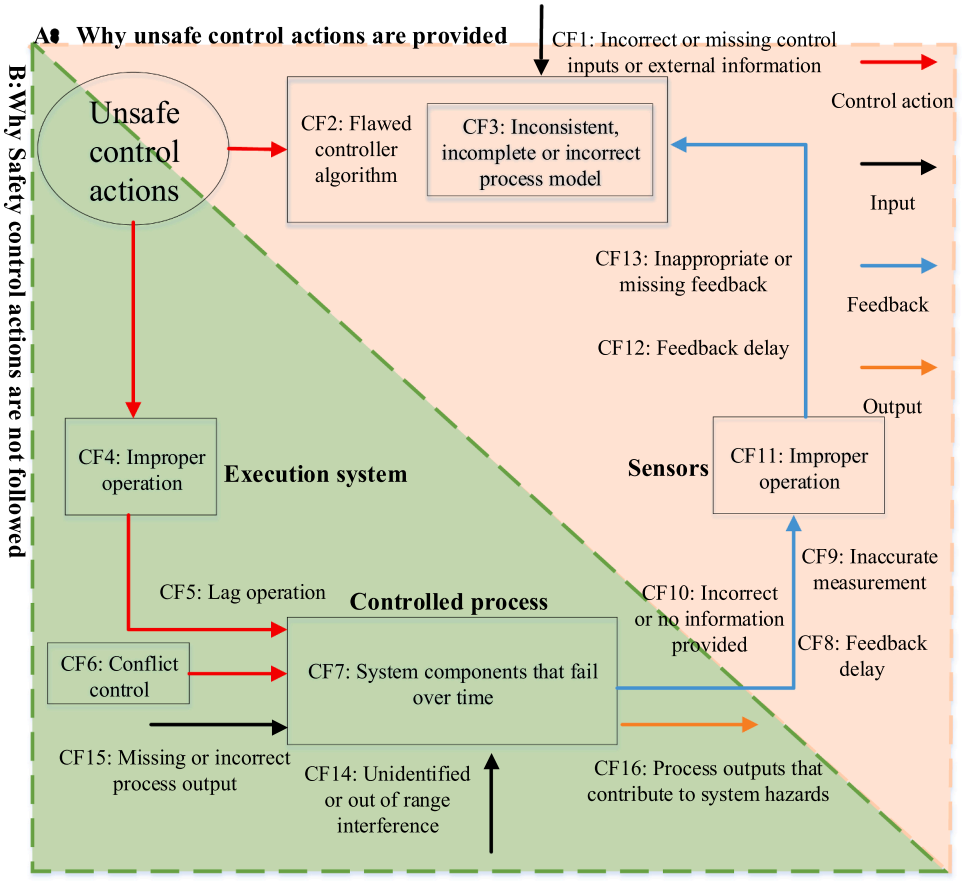

Fig. 2. The schematic diagram of the STPA-HFACS framework for CSs analysis.

The integrated STPA-HFACS approach enhances the systematic risk assessment in MASS by bridging technical system analysis with human reliability analysis. Specifically, UCAs identified through STPA are further examined using HFACS to determine their cognitive, supervisory, and organisational causes. This integrated framework enables the identification of both design-related hazards and human performance issues, fostering a holistic safety assessment.

The STPA-HFACS integration consists of five analytical phases:

Phase 1: Define the safety control structure. This phase involves identifying potential system-level Accidents (A), system-level Hazards (H), and the SC required to prevent these hazards.

Phase 2: Construct the safety control structure. A closed-loop safety control architecture is developed to map control actions, feedback loops, and system components, facilitating the identification of interactions that could lead to unsafe conditions.

Phase 3: Identify UCAs. UCAs are defined as control actions that violate safety constraints in a specific environment and lead to risk. These can be categorised into four types:

(1) Control actions required for safety are not provided.

(2) Unsafe or incorrect control actions are provided.

(3) Control actions are applied at inappropriate times or in incorrect sequences.

(4) Control actions are applied for too long or terminated too early.

Phase 4: Identify CSs. In this stage, unsafe Causal Factors (CFs) and their associated scenarios that may lead to the occurrence of UCAs are systematically analysed.

Phase 5: Identify human errors at the cognitive level. Drawing on the HFACS framework, human errors associated with the identified UCAs are classified according to the four HFACS levels, allowing for the identification of systemic and cognitive precursors to unsafe actions.

A critical component of the integrated framework is the analysis of CSs. As illustrated in Fig. 2, this process incorporates four key system dimensions: control actions, feedback, input, and output. These elements collectively capture decision-making processes, information flow dynamics, and the monitoring and adjustment of operational outcomes.

Two fundamental questions guide this stage of analysis:

(1) Why are UCAs issued?

(2) Why are safe control actions not executed as intended?

By addressing these questions, the STPA-HFACS framework enables the identification of latent risks such as communication breakdowns, feedback delays, insufficient procedural clarity, or cognitive overload. This holistic understanding of technical and human interactions is critical for informing the design of targeted safety interventions and enhancing the operational resilience of MASS.

To bridge the analytical strengths of system-theoretic and human-factor perspectives, this study proposes a stepwise integration of

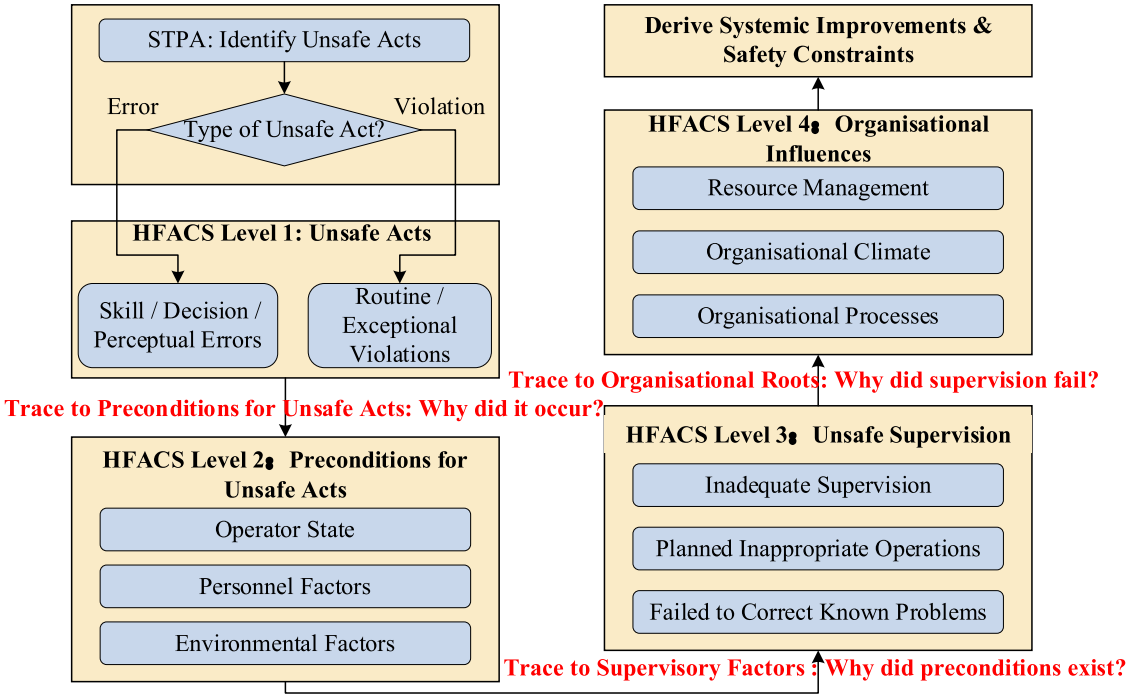

Fig. 3. STPA-HFACS integrated causal analysis flowchart.

STPA and HFACS. The objective is to move beyond isolated UCAs and systematically uncover their latent supervisory and organisational causes. Fig. 3 presents the integrated causal flowchart that illustrates this mapping process. The UCAs identified through STPA serve as direct inputs to the HFACS taxonomy. Each UCA is first classified under HFACS Level 1 (Unsafe Acts) according to its error or violation type. Subsequently, these unsafe acts are traced downward to Level 2 (Preconditions for Unsafe Acts), which examines operator states, human–machine coordination issues, and environmental factors that contribute to the unsafe event. The analysis then proceeds to Level 3 (Unsafe Supervision), identifying supervisory deficiencies such as inadequate monitoring, improper operational planning, or delayed corrective actions. Finally, Level 4 (Organisational Influences) reveals deeper systemic roots, including resource allocation policies, organisational culture, and procedural weaknesses.

This mapping enables a hierarchical reasoning process that complements the system-level view of STPA by exposing latent cognitive, supervisory, and organisational factors that are often unobservable through control-structure analysis alone. In essence, STPA defines what unsafe interaction occurred, while HFACS explains why it occurred at multiple human and organisational levels.

For instance, a STPA-identified UCA, such as "The operator provides a collision-avoidance command too late through the HMI" is initially categorised as a decision-making lapse resulting in delayed intervention (HFACS Level 1). This error is then traced to Level 2: Preconditions, where the operator's situational awareness is found degraded due to information overload and interface clutter. At Level 3: Unsafe Supervision, this error can be attributed to inadequate simulator training and insufficient monitoring of operator workload during remote operations. Further, at Level 4: Organisational Influences, the root cause lies in resource allocation policies that prioritise system throughput over ROC design and fatigue management. Through this hierarchical tracing, the STPA-HFACS integration reveals human or organisational factors that would remain unaddressed under a purely STPA-based approach.

3.3. Functional foundations for applying the STPA–HFACS framework to MASS HMI

To effectively apply the proposed STPA–HFACS framework for HMI risk analysis in MASS, it is essential to first understand the functional characteristics of both the human operator and the MASS system, as well as their interaction process. This section serves as a conceptual bridge between the general framework introduced in Section 3.1 and the integrated analysis method in Section 3.2. It

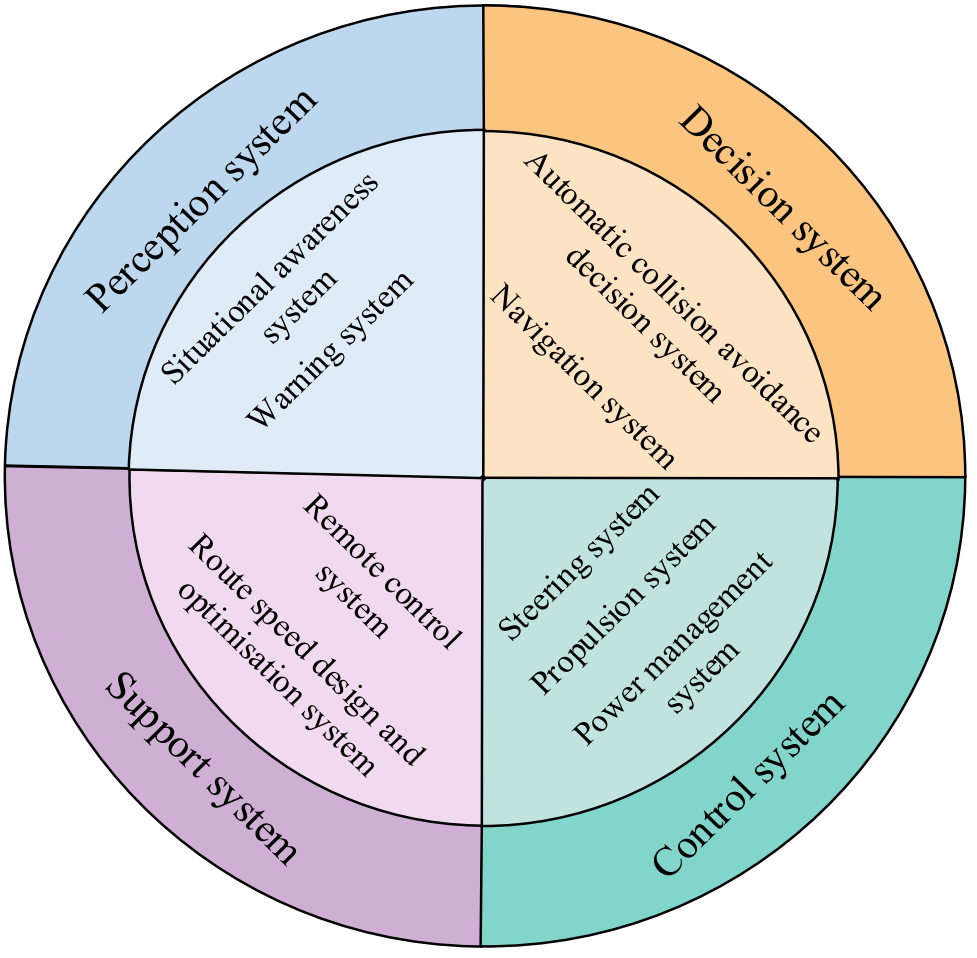

Fig. 4. Functional subsystems and roles within the MASS architecture.

achieves this by mapping the key components of the HMI system to corresponding analysis dimensions. The following subsections provide foundational insights into: (1) the functional roles of the human operator, (2) the core structure and capabilities of the MASS system, and (3) the interaction processes between the human operator and machine during MASS navigation.

3.3.1. *Framework for the interaction function of the operator*

Understanding the nature of operator interactions with MASS is essential for analysing the human role in safety-critical operations. Unlike pre-programmed automation, human operators rely on dynamic judgment, cognitive flexibility, and contextual interpretation, making their interactions with autonomous systems inherently more complex (Zhang et al., 2021b). Within the context of MASS HMI, operator activities can be analysed on two interrelated levels: task execution and cognitive processing.

At the task level, operator interaction comprises three primary stages:

(1) Task recognition (e.g., interpreting alerts or sensor readings),
(2) Decision-making (e.g., evaluating possible responses and selecting appropriate actions),
(3) Execution and monitoring (e.g., issuing control commands and observing system feedback).

These stages align closely with the UCAs identified in STPA, especially in scenarios involving omitted, mistimed, or improperly sequenced actions.

Beyond task-level execution, cognitive factors such as situational awareness, mental workload, and decision-making accuracy play a critical role in HMI safety. Operators, particularly those in ROCs, rely heavily on system-provided data. Any delay, distortion, or overload of information may impair judgment and increase the likelihood of human error. These cognitive dimensions map directly to the "preconditions for unsafe acts" and "unsafe supervision" categories in HFACS.

Therefore, for a robust STPA–HFACS analysis, both the observable operator tasks and the latent cognitive processes must be systematically modelled and evaluated (Fan and Yang, 2023).

3.3.2. *Functional architecture of the MASS system*

The MASS system consists of multiple subsystems that collectively perform perception, decision-making, support, and control

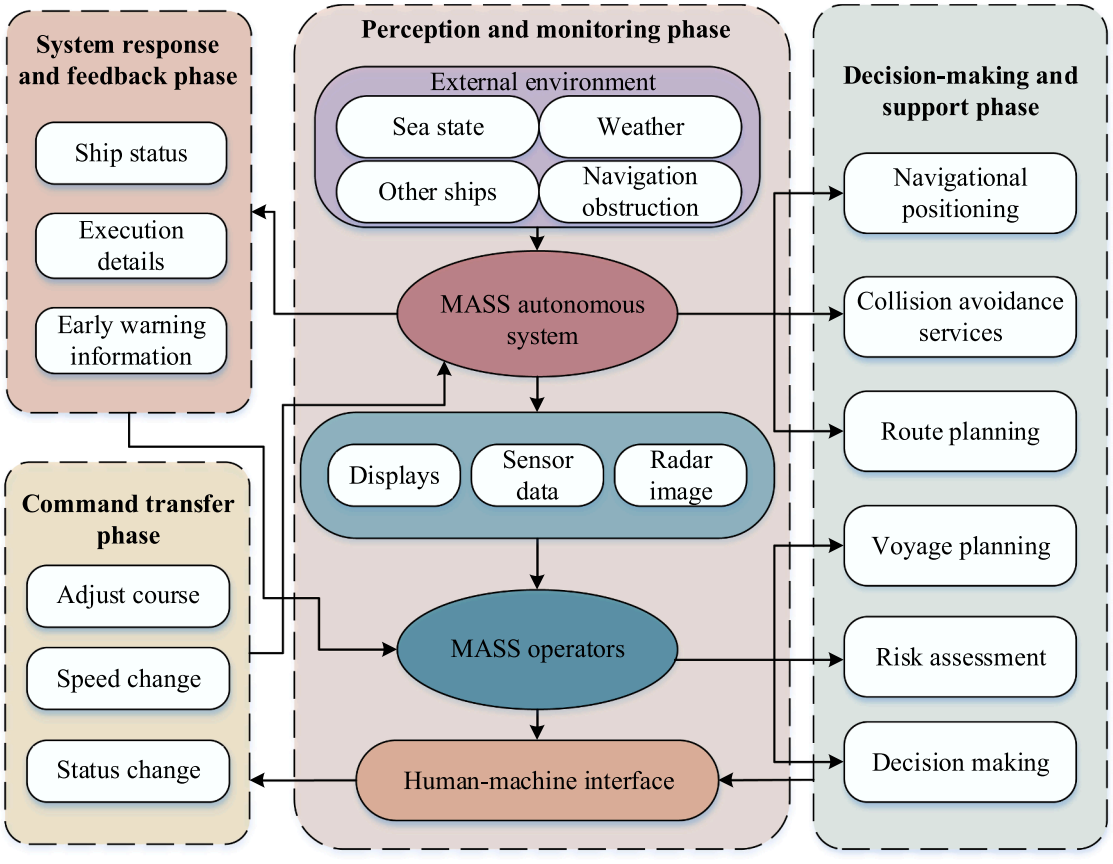

Fig. 5. The MASS HMI process and operator–system interaction phases.

functions. A clear understanding of this architecture is fundamental for building the STPA safety control model and identifying critical interaction points between human operators and system components (Tao et al., 2024).

Based on classifications from major maritime authorities (LLOYD'S, 2017; Bureau Veritas, 2017), the MASS system can be categorised into four main subsystems, as illustrated in Fig. 4.

(1) Perceptive subsystem: Responsible for situational awareness and hazard detection, this subsystem utilises various onboard sensors to monitor equipment conditions, vessel motion, and the surrounding environment. It also includes diagnostic and alarm functionalities.
(2) Decision-making subsystem: Comprising automatic collision avoidance and navigation systems, it integrates environmental and ship-specific data to generate optimal routing plans based on positioning, environmental input, and mission-specific goals.
(3) Support subsystem: Includes modules for route and speed optimisation, as well as remote control. It provides necessary decision support, monitors system reliability, and evaluates both hardware and software performance to ensure navigational safety and vessel seaworthiness.
(4) Control subsystem: Manages ship propulsion, steering, and power. It ensures the vessel's course and speed are controlled efficiently while maintaining system integrity through real-time power management.

Effective coordination among these subsystems is facilitated by a reliable onboard Local Area Network (LAN) within the ship, enabling seamless communication and data exchange. Furthermore, real-time connectivity with ROCs and other ships is supported through satellite and radio communication technologies, which are vital for safe and autonomous operations.

3.3.3. HMI process in MASS

The interaction process between human operators and the MASS system can be viewed as a continuous feedback loop involving four phases: perception, decision-making, execution, and system response. Understanding this loop is key to mapping control actions and feedback flows, key components of the STPA causal analysis and HFACS classification. The detailed process of MASS HMI is illustrated in Fig. 5.

The MASS HMI process is divided into four phases (Huang et al., 2020).

(1) Perception and monitoring: The MASS system collects environmental and vessel data through sensors and displays it to the operator (e.g., radar imagery, weather, and obstacle detection).
(2) Decision-making and support: Based on the data, the operator plans routes, assesses risks, and makes navigational decisions, supported by system-generated information such as position tracking and collision avoidance suggestions.
(3) Command execution: The operator issues commands through a user interface (e.g., course corrections or speed changes). These commands must be timely and precise to ensure safe implementation.
(4) System response and feedback: The system executes the given commands and provides real-time feedback (e.g., changes in speed or heading, updated status displays), keeping the operator informed and engaged.

Each phase of this interaction loop involves both control actions and feedback mechanisms, which are critical in identifying potential failure points in the STPA safety model. Furthermore, these phases highlight possible sources of human error, ranging from misinterpretation of data to delayed or inappropriate control actions, each of which can be systematically categorised using the HFACS taxonomy.

This section establishes the foundational understanding necessary for applying the STPA–HFACS methodology to HMI safety analysis in MASS. By detailing the roles of human operators, the structure of the MASS system, and the interaction process between them, this section links system functionality and human behaviour to the analytical constructs of the framework. This integrated perspective enhances both the depth and practical relevance of the proposed risk analysis approach.

4. Case study: HMI safety analysis for DoA2 MASS

This section examines the safety analysis of the HMI in the context of DoA2 MASS. The study follows the steps defined in the proposed STPA–HFACS framework. It begins by establishing the purpose of the analysis, including the definition of system-level accidents, hazards, and safety constraints. Next, a safety control structure is constructed to provide a foundation for identifying risk scenarios. UCAs are then identified for both the MASS operator and the autonomous system, emphasising potential critical failures. Finally, CSs and human factors are analysed to establish links between operator interactions, system-level risks, and potential failure paths. The implementation of the STPA–HFACS framework in this case study is supported by structured expert consultation. A panel of five domain experts contributed to the identification of system-level hazards, unsafe control actions, and causal factors. Detailed background information of the experts and their roles in the study is provided in Appendix Table A.

4.1. Define the purpose of the analysis

4.1.1. Define system-level accidents

Before conducting a detailed safety analysis, it is essential to define the analysis objective, including the boundaries and functions of the system under investigation. In this case study, the system boundary is defined as a DoA2 MASS that operates with a minimal

onboard crew and is capable of remote navigation. The primary objective of the system is to reduce risks associated with HMI while supporting both the safe deployment of autonomous functionality and the preservation of operator oversight.

Accordingly, Table 1 outlines the potential system-level accidents associated with the HMI of DoA2 MASS. These accidents reflect losses involving human safety, vessel integrity, environmental impact, operational effectiveness, and broader deployment feasibility.

4.1.2. Define system-level hazards

The STPA–HFACS framework is grounded in the principle that accidents are not solely attributable to isolated component failures but frequently arise from unsafe interactions among system elements. In the context of MASS, the overall system is designed to operate within predefined safety constraints enforced by its subsystems. When these constraints are violated, particularly under worst-case operational conditions, hazardous states may emerge that can escalate into accidents.

It is important to underscore, however, that system-level hazards do not invariably culminate in accidents. For example, an autonomous navigation system may erroneously execute an unintended turn. While this constitutes a failure at the system level, it only poses a genuine hazard if it occurs in close proximity to another vessel or a navigational obstacle. Consequently, effective hazard identification requires not only an assessment of the system's functional boundaries but also careful consideration of the operational contexts in which failures may occur.

Fig. 5 illustrates the system boundary applied in this analysis, encompassing the interactions among the operator, the MASS system, and the external environment. Within this boundary, Table 2 summarises the principal system-level hazards, each of which has the potential to precipitate one or more of the accidents identified earlier in the study.

Each of these hazards can be mapped to one or more system-level accidents listed in Table 1. For example, the hazard of collision may lead to A_1 (injury or fatality), A_2 (damage or cargo loss), A_3 (environmental harm), or A_4 (mission failure). Similarly, the hazard of H_5 (unmanned operation) may reduce operational redundancy and diminish the system's capacity to respond effectively to unexpected situations, thereby increasing the risk of both A_4 and A_5.

4.1.3. Define system-level SC

Following the identification of system-level hazards, corresponding SC must be established. These constraints serve as essential design principles that must be enforced to prevent hazards from developing into accidents. Accidents typically occur only when such constraints are violated or inadequately maintained. Well defined and effectively implemented SC ensure the system remains within acceptable operational limits and avoids transitioning into unsafe states.

Table 3 presents the system-level SC for DoA2 MASS. These constraints specify the required behaviours and operating conditions necessary to prevent hazards, or to enable their timely detection and mitigation. Particular emphasis is placed on the rapid recognition of hazards and the execution of responsive corrective actions, both of which are critical for preserving system safety.

4.2. Construct the safety control structure

The safety control structure for MASS HMI is developed based on established system architecture models and insights from previous studies (Chaal et al., 2020; Wróbel et al., 2018a; Zhou et al., 2021). Fig. 6 illustrates the safety control structure tailored to the HMI context. In contrast to the process-oriented flow described in Section 3.3.3, this diagram emphasises the control and feedback relationships among key system components involved in command execution. While it does not provide a detailed breakdown of operator tasks or system internal logic, the structure includes critical operational roles such as the MASS operator, control systems, sensors, communication interfaces, execution systems, the ROC, and environmental elements. In this diagram, red arrows represent control actions, while blue arrows denote feedback loops. Items marked with an asterisk (*) are further explained in Fig. 6.

4.3. Identify UCAs

UCAs are defined as actions issued by controllers within the system that may lead to potentially hazardous system states. In addition to explicitly unsafe commands, UCAs can also arise from unintentional system behaviours that result from limitations in functionality or performance, thereby contributing to system-level hazards (Leveson and Thomas, 2018).

Drawing upon the safety control structure developed in Section 4.2, a total of 10 control actions and 14 feedback mechanisms are identified and detailed in Appendix Table B. The identification of UCAs is grounded in the evaluation of each control action using the four standard STPA guidewords: (1) not provided when required, (2) provided incorrectly, (3) provided too early, too late or out of sequence, and (4) applied too long or stopped too soon.

Table 1
The system-level accidents for DoA2 MASS.

Number	System-level accidents
A_1	Loss of life or injury to the operator or other personnel involved.
A_2	Damage to the hull and/or loss of onboard cargo or contents.
A_3	Environmental pollution or damage resulting from operational incidents.
A_4	Mission failure of the autonomous navigation system, even without physical damage or casualties.
A_5	Reduced the likelihood of successful MASS introduction and acceptance.

Table 2
The system-level hazards for DoA2 MASS.

Number	System-level hazards
H_1	MASS collisions with other ships, objects, terrain, and various obstacles [$A_1/A_2/A_3/A_4/A_5$].
H_2	Critical incidents such as grounding, sinking, or onboard fire [$A_1/A_2/A_3/A_4/A_5$].
H_3	MASS deviation from its intended navigational course [A_4/A_5].
H_4	Failure of MASS navigation systems to adhere to international maritime conventions and COLREGs [A_4/A_5].
H_5	Lack of onboard crew presence, increasing risk in emergency or ambiguous situations [A_4/A_5].

Table 3
The system-level SC for DoA2 MASS.

Number	System-level SC
SC_1	MASS is required to autonomously avoid collisions with other ships, objects, terrain, and various obstacles.
SC_2	MASS is required to autonomously prevent accidents such as running aground, sinking, or catching fire.
SC_3	MASS is required to adhere to a predetermined navigational route.
SC_4	MASS is required to adhere to applicable maritime international conventions and COLREGs.
SC_5	MASS is required to ensure that it is not left unmanned.

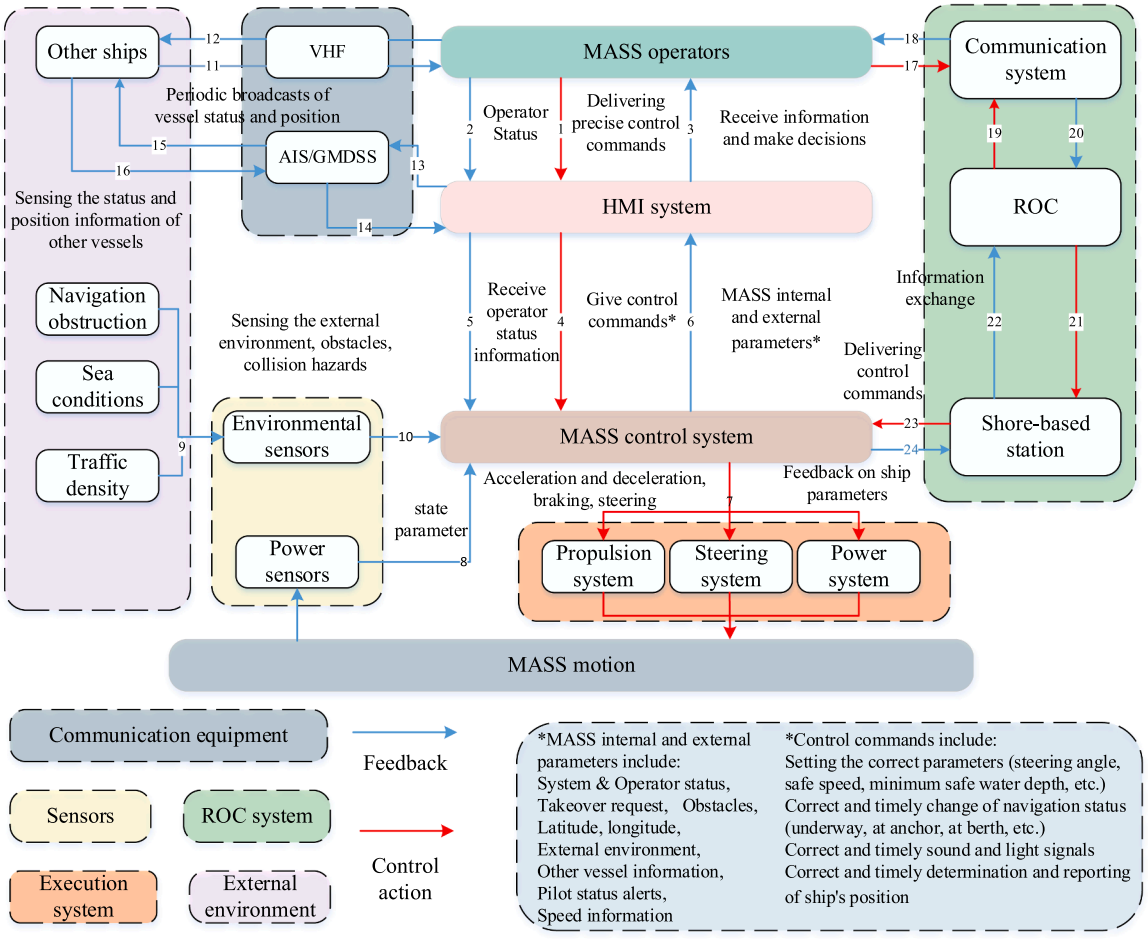

Fig. 6. Safety control structure for MASS HMI.

While feedback mechanisms do not directly constitute UCAs, they are critical components within closed-loop control systems. Inaccurate, missing, or delayed feedback can significantly impair decision-making processes, thereby contributing indirectly to the emergence of UCAs.

4.3.1. UCAs involving the MASS operator

This subsection analyses the role of the MASS operator within the identified control loops using the HMI safety control structure. The MASS operator functions as a key controller, interfacing with various subsystems, including the HMI interface, the Very High Frequency (VHF) communication system, Automatic Identification System (AIS), Global Maritime Distress and Safety System (GMDSS) and the ship-to-shore communication link Table 4.

Key operator control processes include:

(1) Receiving commands from the ROC through the ship-to-shore communication system and manipulating the HMI system to adjust the ship's state in real-time.
(2) Monitoring internal and external ship parameters through data transmitted by onboard controllers, and making operational decisions using information presented via the HMI to ensure the ship's safety and stability.
(3) Exchanging navigational information with nearby vessels via the VHF system and maintaining real-time communication to uphold navigational safety and regulatory compliance.

Among the identified control-feedback actions, Actions 1, 12, and 18 are directly initiated by the operator. Failures in these actions, whether in terms of timing, content, or omission, may result in UCAs. In contrast, Actions 17 and 11 represent inputs received from external controllers, specifically the ROC and nearby vessels, respectively. Action 3 constitutes a critical feedback mechanism that the operator must accurately interpret. Any delays, inaccuracies, or misinterpretations in processing this feedback can adversely affect the operator's situational awareness, judgment and decision-making ability.

Based on these control-feedback loops, the corresponding UCAs have been systematically identified and are summarised in Table 5.

4.3.2. UCAs involving the MASS system

This section analyses potential UCAs originating from the MASS system. To ensure consistency and facilitate clear differentiation, the HMI and associated control subsystems are treated collectively as a unified controller. This distinction enables a clearer comparison between UCAs stemming from human operators and those from system components Table 6.

Under this framework, the MASS system functions as a controller within a feedback control loop, issuing commands to and receiving information from multiple subsystems. The core control-feedback loop involves the actuation system, onboard sensors, the shore-based station, and the human operator. The primary responsibilities assigned to the MASS system are summarised as follows:

(1) Sensor management: Receives data on environmental and ship state information from onboard sensors, configuring them to operate in accordance with the current sailing conditions.
(2) Actuator control: Commands the actuation system to align with the ship's current state, ensuring performance reliability, manoeuvrability, and low emissions.
(3) Interaction with shore-based station: Processes operational instructions from the shore-based station and provides periodic feedback on the ship's status, ensuring timely and effective execution of control instructions.
(4) Operator monitoring and support: Receives the operator's instructions, monitors their status and action, offers real-time feedback on status parameters, and issues alarms for operational violations or fatigue.

Control actions such as Actions 4, 5, and 6 represent internal communication between the HMI and control subsystems, whereas Actions 7 and 24 reflect direct system-initiated control commands. Feedback channels such as Actions 8/10/14 and 2 are crucial for informing the system's decisions and maintaining safe operations. Any delays, omissions, or misinterpretations within these control or feedback processes may contribute to the emergence of UCAs. Actions 13 reflect transmitting navigational status and safety information via AIS/GMDSS, enabling external situational awareness for nearby ships.

Based on the control loops established in Phase 2, the specific UCAs associated with the MASS system functioning as a controller are summarised in Table 7.

4.4. Identify CSs and human factors

CSs outline triggering factors, or CFs, that can give rise to UCAs and subsequent hazards. When identifying CSs for UCAs within the

Table 4
The operator control actions and feedback for DoA2 MASS.

Action ID	Description
1	Applying precise control commands to HMI systems.
11	MASS operators receive periodic status and position broadcasts from nearby vessels via VHF, supporting situational awareness and collision avoidance.
17	Receive control commands from the ROC via the ship-to-shore communication system.
12	MASS operators transmit navigational status and safety information via VHF or AIS, enabling external situational awareness for nearby ships.
18	Provide real-time feedback to the ROC via the communication system.
3	Receive information on internal and external parameters of the ship transmitted by the control system.
2	The system monitors and reports operator status information in real time.

Table 5
The UCAs for DoA2 MASS operators acting as controllers.

Action ID	Not providing causes hazard	Providing causes hazard	Too early, too late, out of order causes hazard	Applied too long, stopped too soon, causes hazard
1	UCA-1: The control is not provided to HMI system when the MASS encountered a situation requiring a change in its navigation status [H_1, H_2,H_3,H_4]	UCA-2: The faulty control is provided to HMI system when the MASS encountered a situation requiring a change in its navigation status [H_1,H_2,H_3,H_4]	UCA-3: The control is provided too late or too early to HMI system when the MASS encountered a situation requiring a change in its navigation status [H_1,H_2,H_3,H_4]	UCA-4: The control stopped too soon to HMI system when the MASS encountered a situation requiring a change in its navigation status [H_1,H_2,H_3,H_4]
12	UCA-5: The operator fails to broadcast navigational status or safety information to nearby ships when communication via VHF is required [H_1,H_2,H_3,H_4]	UCA-6: Incorrect or misleading information is transmitted to nearby ships during VHF communication [H_1,H_2,H_3,H_4]	UCA-7: Information is transmitted too early, too late, or in the wrong sequence during VHF communication, leading to potential misunderstanding [H_1,H_2,H_3,H_4]	UCA-8: Information broadcast via VHF is terminated prematurely or continued unnecessarily, resulting in loss of situational awareness [H_1,H_2, H_3,H_4]
18	UCA-9: The control is not provided to ROC when communication via the communication system is required [H_1,H_2,H_3]	UCA-10: The faulty control is provided to ROC when communication via the communication system is required [H_1,H_2,H_3]	UCA-11: The control is provided too late to ROC when communication via the communication system is required [H_1,H_2,H_3]	N/A
3	UCA-12: The operator fails to receive information on the ship's internal and external parameters when monitoring of the rotational speed of the ship's mechanical components and the ship's health is required [H_1,H_2,H_3]	N/A	UCA-13: Information on the ship's internal and external parameters is received too late by the operator when monitoring of the rotational speed of the ship's mechanical components and the ship's health is required [H_1,H_2,H_3]	N/A

Table 6
The system control actions and feedback for DoA2 MASS.

Action ID	Description
4	The HMI system applies the received control commands to the control system.
7	Precise control is applied by the controller to the execution system.
5	The control system receives operator status information monitored by the HMI system.
6	Ship parameters, operator status alarms, and other information are fed back to the HMI system by the control system.
23	Control commands are received from the shore-based base station.
13	MASS system transmits navigational status and safety information via AIS/GMDSS, enabling external situational awareness for nearby ships.
8/10/14	Data is received from each sensor or AIS/GMDSS.
24	Ship's status parameters are periodically fed back to shore-based base stations.
3	Internal and external status parameters, as well as alarms, are reported to the operator.
2	Operator status and behaviour are monitored in real time by the system.

HMI of MASS, it is essential to consider two categories of loss scenarios: (i) why UCAs are issued and (ii) why prescribed safety control actions are not executed. For example, when an operator issues a control command that results in a UCA, three causal pathways should be examined: the control command itself may be erroneous (e.g., due to poor decision-making); input or output information may be delayed or incorrect; or the feedback received from the system may be inaccurate or misleading.

The analysis advances by systematically examining the CFs associated with UCAs under both human-operated and system-controlled conditions. The STPA–HFACS framework is employed to structure and categorise these factors, with particular attention to cognitive deficiencies such as reduced situational awareness, misperception, over-reliance on automation, and decision fatigue. These cognitive-level issues are then linked to higher-level causal sources, including organisational failures, supervisory shortcomings, and design-related limitations.

The subsequent sections present detailed CSs related to operator behaviours and autonomous system responses. This analysis establishes a foundation for uncovering latent safety threats and provides actionable insights for strengthening future safety measures in MASS operations.

4.4.1. CSs and human factors related to MASS operators

The causal analysis of UCAs initiated by MASS operators begins with the identification of deficiencies in both input/feedback and control action selection processes. When the operator functions as the controller within the HMI feedback loop, UCAs may arise due to inaccurate or delayed information, decision-making errors, or improper command execution. Table 8 summarises the detailed CFs contributing to these operator-induced UCAs under the DoA2 MASS context.

Beyond system- and interface-related factors, cognitive aspects of operator performance significantly influence the emergence of UCAs. As MASS systems advance towards greater autonomy, operators are increasingly required to interpret complex system states and manage multi-source inputs under dynamic and often stressful conditions. In high-workload scenarios or environments characterised by ambiguity, cognitive failures such as diminished situational awareness, fatigue, or attentional lapses may compromise operational

Table 7
The UCAs for DoA2 MASS system acting as controllers.

Action ID	Not providing causes hazard	Providing causes hazard	Too early, too late, out of order causes hazard	Applied too long, stopped too soon, causes hazard
7	UCA-14: The control is not provided to the execution system when the MASS encounters a situation requiring a change in its navigation status [H_1, H_2, H_3, H_4]	UCA-15: The faulty control is provided to the execution system when the MASS encounters a situation requiring a change in its navigation status [H_1, H_2, H_3, H_4]	UCA-16: The control is provided too late or out of order to execution when the MASS encounters a situation requiring a change in its navigation status [H_1, H_2, H_3, H_4]	UCA-17: The control stopped too soon in execution when the MASS encountered a situation requiring a change in its navigation status [H_1, H_2, H_3, H_4]
24	UCA-18: The control is not provided to ROC when communication via a shore-based base station is required [H_1, H_2, H_3, H_4]	UCA-19: The faulty control is provided to ROC when communication via a shore-based base station is required [H_1, H_2, H_3, H_4]	UCA-20: The control is provided too late to ROC when communication via a shore-based base station is required [H_1, H_2, H_3, H_4]	UCA-21: The control stopped too soon to ROC when communication via a shore-based base station is required [H_1, H_2, H_3, H_4]
8/10/14	UCA-22: The information is not received by the controller when MASS sensors detect changes in the ship or external environment [H_1, H_2, H_3]	UCA-23: The information is processed incorrectly by the controller when MASS sensors detect changes in the ship or the external environment [H_1, H_2, H_3]	UCA-24: The information is too late to be received by the controller when MASS sensors detect changes in the ship or external environment [H_1, H_2, H_3]	N/A
2	UCA-25: The operator's status is failed to detect by the controller in cases of operational violations or operator fatigue, among other conditions [H_1, H_2, H_3]	UCA-26: The operator's status is processed incorrectly by the controller in cases of operational violations or operator fatigue, among other conditions [H_1, H_2, H_3]	UCA-27: The operator's status is too late to detect by the controller in cases of operational violations or operator fatigue, among other conditions [H_1, H_2, H_3]	N/A

Table 8
The detailed CFs of operators UCAs for DoA2 MASS.

Control deficiencies	Input and feedback	Control action selection
The operator CFs of DoA2 MASS	CF1: The HMI system provides inadequate or missing information regarding the ship's internal and external parameters. CF2: The HMI system displays incorrect information about the ship's status. CF3: Signals presented by the HMI system are delayed, overly brief, or overly uniform. CF4: Failure of the ship-to-shore communication system or VHF. CF5: Delays in receiving control commands from the ROC. CF6: The ROC issues incorrect or maliciously altered control commands. CF7: Other ships provide misleading or insufficient information to MASS. CF8: Communication delays from other ships to MASS.	CF9: The HMI system failed to execute the operator's control instructions and instead responds to inputs from another controller. CF10: Physical failure or malicious damage affecting the HMI system and its components. CF11: Operators lack experience with HMI systems and reporting to the ROC and other ships, leading to operational uncertainty. CF12: Malfunctions in the HMI system or defective algorithms lead to unsuccessful operations. CF13: Delays in the structural response of the HMI execution module. CF14: An incorrect operational process in the HMI system leads to operational failure. CF15: Signal overloads within the HMI system induce confusion or decision delays in operators. CF16: External interference disrupts the execution of commands issued by the HMI system.

effectiveness and trigger unsafe control behaviours.

Using the STPA-HFACS framework, these cognitive deficiencies are further categorised into structured human factor levels, as summarised in Table 9.

According to the STPA-HFACS classification, personal attributes, task contexts, and technological interfaces are typically grouped under "preconditions for unsafe actions." Oversight-related deficiencies fall within the category "unsafe supervision", while structural, managerial, or resource-based issues are treated as "organisational failures." Unsafe actions directly linked to perception, decision-

Table 9
STPA-HFACS analysis of human factors in DoA2 MASS operators.

Level	Human factors
Preconditions for unsafe actions	CF17: Operator is in a suboptimal physical or mental condition. CF18: Operator exhibits limited situational awareness. CF20: Operator lacks sufficient professional skills, leading to delayed task execution. CF21: Operator experiences information overload. CF22: Operation failure arises from an insecure or unstable network environment. CF23: Adverse physical or organisational environments result in failed actions.
Unsafe supervision	CF19: Inadequate supervisory oversight of operator behaviour and performance.
Organizational failures	CF24: Inequitable task allocation or unclear responsibilities within the operator team cause task execution failure.

making, or execution, when not appropriately mitigated, are ultimately identified as UCAs in Phase 3 of the STPA-HFACS analytical process.

4.4.2. CSs related to the MASS system

This section presents CSs analysis results for UCAs in scenarios where the MASS system, comprising the HMI and its control subsystems, functions as the controller. Unlike operator-driven scenarios, UCAs attributable to the MASS system primarily originate from internal system deficiencies, interface faults, sensor or actuator anomalies, or communication disruptions.

The analysis is categorised into three domains: (1) input and feedback-related deficiencies, (2) control action execution failures, and (3) internal system faults and algorithmic limitations. Table 10 summarises the identified CFs contributing to these system-induced UCAs under the DoA2 MASS context.

A comparative assessment of the operator- and system-level CSs reveals clear distinctions. Many operator-related UCAs are frequently linked to external or organisational influences, such as cognitive workload, insufficient training, or environmental stressors. Conversely, system-induced UCAs tend to stem from technical limitations, internal processing delays, or hardware/software failures.

From a systems theory standpoint, environmental disturbances alone do not constitute hazards. Instead, Hazards emerge when the system fails to detect, interpret, or respond effectively to such disturbances. Although MASS systems are largely insulated from psychological or organisational variables, their capacity to ensure safe and stable operation is inherently dependent on the maturity of their technological architecture, the reliability of components, and the robustness of embedded algorithms.

5. Discussion

5.1. Discussion of results

5.1.1. Discussion of UCAs

The analysis of UCAs in MASS HMI reveals that a single control action can result in multiple, distinct failure modes involving both onshore operators and autonomous systems. In the complex control system, each interaction between components constitutes a control function, and UCAs frequently emerge from deficiencies within these functions. It is therefore essential not only to ensure that required control actions are issued, but also that they are accurate, timely, and contextually appropriate (Leveson, 2011).

Among the identified UCAs, those involving failure to control the system (e.g., UCA-1), untimely override of automated control (e.g., UCA-4), and misinterpretation of sensor fusion outputs (e.g., UCA-12) are particularly concerning. These UCAs are recurrently associated with DoA2 and DoA3 configurations, where situational awareness is degraded due to spatial–temporal separation of human supervisors from vessel operations. Their significance lies in the fact that they represent not only interface design flaws but also deeper cognitive and organisational issues.

Furthermore, these high-risk UCAs are often interrelated through cascading failure paths. For instance, a failure to recognise automation faults may delay manual intervention, which—when combined with interface ambiguity, this sequence can culminate in a critical loss of vessel control. These interdependencies underscore the necessity for multi-layer mitigation strategies, including redundancy, context-sensitive decision support, and adaptive alarm prioritisation.

In line with Leveson's system theory, UCAs must be proactively mitigated via design-time interventions. Specifically, system designers should: (1) eliminate or reduce potential hazards to an acceptable level during both the design and operational phases, and (2) assess the feasibility and effectiveness of mitigation strategies prior to finalising the system architecture (Wróbel et al., 2018b).

In addition, for UCAs stemming from shared or overlapping control structures, especially in closed-loop MASS environments, preventing control conflicts and coordination breakdowns is critical. Practical solutions include enhancing software algorithms, streamlining authority delegation protocols, and enforcing periodic HMI audits (Valdez Banda et al., 2019).

Finally, redundancy also serves as a key mitigation strategy, especially for critical components. While cost constraints may limit its application, redundancy often proves to be the most pragmatic and effective safeguard for maintaining operational continuity in

Table 10
The detailed CFs for UCAs of DoA2-MASS system.

Input and feedback	Control action selections	Other CSs
CF25: The operator provides incorrect, insufficient, or missing information. CF26: Sensor signal delays. CF27: Missing or erroneous sensor feedback. CF28: Faulty sensor function. CF29: Delay in control instructions issued by the ROC. CF30: Incorrect or maliciously tampered instructions from the ROC.	CF31: Failure of the system or sensor to execute issued instructions. CF32: Physical failures or malicious damage affecting actuators, sensors, or components. CF33: Defective algorithms in the execution system or sensors. CF34: Delayed response from the execution system or sensor. CF35: Conflicting commands obstruct proper execution. CF36: Ageing or degradation of execution system components. CF37: External interference during execution of control instructions.	CF38: Faults in the control algorithm of the MASS system. CF39: Systemic or component failure over time. CF40: Delayed system-level response. CF41: Invalid or erroneous command processing. CF42: Technological limitations compromise the MASS system's functional integrity.

complex autonomous systems (Fan and Yang, 2022).

5.1.2. Discussion of CFs

By applying the STPA–HFACS framework to DoA2 MASS, this study identified a range of CFs leading to UCAs. These factors are categorised into five primary categories: human factors (e.g., CF17), system deficiencies (e.g., CF10), environmental factors (e.g., CF22), managerial factors (e.g., CF24), and scientific or technological limitations (e.g., CF42). This classification aligns with established risk taxonomies in maritime safety literatures (Fan et al., 2020; Xia et al., 2023).

Among them, CF17, CF24, and CF10 are most frequently implicated in the causal chains of high-risk UCAs. These CFs are critical because they expose vulnerabilities that are often invisible to traditional safety assessments, which treat human error or technical failure in isolation. For example, CF17 ("mental overload") predisposes operators to decision latency or errors in interpreting sensor data, especially in multitasking contexts typical of MASS supervision. CF24 ("unclear task allocation") undermines situational clarity, especially when roles are divided between crew members, shore control centres, and autonomous modules. These human and managerial CFs are rarely independent; instead, they reinforce one another, leading to compound risk scenarios.

For system-related UCAs, technical failures remain the predominant cause, reinforcing the need for rigorous engineering, algorithm robustness, and system reliability. In contrast, human-induced UCAs are primarily attributable to cognitive errors, particularly in DoA2 and DoA3 configurations, where operators are geographically or functionally separated from the systems they oversee. Enhancing operator training and improving situational awareness are therefore critical for risk mitigation in real-world MASS deployments (Man et al., 2018).

Lastly, the discussion of CFs reinforces that addressing only technical resilience (e.g., sensor robustness and fail-safe architecture) is insufficient for MASS safety. Organisational policies, operator preparedness, and cross-domain coordination must be treated as risk-bearing elements in their own right and integrated into the system safety lifecycle (Li et al., 2023b).

5.2. Uncertainty

One of the primary sources of uncertainty in applying the STPA–HFACS framework to MASS HMI lies in the inherent complexity and evolving nature of the underlying system architecture. This challenge has prompted extensive research efforts in recent years to refine MASS system models using STPA, with the goal of reducing uncertainty through continuous data collection and iterative modelling (Chaal et al., 2020; Wróbel et al., 2018b; Zhou et al., 2021).

The rapid evolution of MASS technologies and their associated human-machine interface introduces additional layers of uncertainty, particularly as new functionalities and control paradigms are developed. To address this challenge, a cyclical, adaptive approach is recommended, comprising the following steps:

(1) Regular updates to the system framework to reflect technological changes.
(2) Rigorous safety assessments of the updated model using structured methods such as STPA–HFACS.
(3) Development of forward-looking, innovation-driven recommendations.
(4) Implementation of technically and operationally feasible mitigation strategies.

Another major source of uncertainty stems from the qualitative nature of STPA–HFACS analysis. While the framework is effective in identifying failure modes and mapping causal pathways, it lacks the capacity for quantitative estimation of failure probabilities or associated risk magnitudes. In operational contexts, system components vary considerably in terms of both their likelihood of failure and the severity of potential consequences. Bridging this methodological gap requires the integration of empirical datasets and simulation-based evidence into the STPA–HFACS process. Such enhancements would enable more rigorous, data-informed evaluations of risk and improve the framework's utility for complex, safety-critical systems such as MASS systems (Wrobel et al., 2021).

5.3. The scalability of the framework

Although this study focuses on DoA2, the proposed system-theoretic framework exhibits strong potential for extension to higher autonomy degrees, particularly DoA3. In a DoA3 scenario, the onshore operator typically transitions to a supervisory-only role, with most navigational decisions delegated to onboard autonomy and remote automation systems. Under such conditions, the control-feedback structure would be adjusted to reflect the reduced frequency of direct human intervention, and the emergence of new UCAs would focus on issues (e.g., delayed supervisory, trust misalignment, and human-out-of-the-loop hazards). The control-action mapping and hazard identification procedures outlined in this study can be adapted to include these shifts, allowing the framework to maintain scalability and analytical rigour across different autonomy degrees.

Furthermore, this framework can be extended to mixed-traffic environments, where MASS and conventional ships operate concurrently. In such settings, communication delays, protocol mismatches, and ambiguous situational interpretations can give rise to emergent hazards. By incorporating external manned vessels as interacting agents and mapping their influence on the MASS control structure, the framework could support the analysis of inter-ship coordination risks, enhancing its value for real-world deployment in transitional maritime environments.

6. Conclusion

This study introduces a comprehensive safety analysis framework for HMI in DoA2 MASS. The framework is developed by defining operator roles at both task and cognitive levels and synthesising insights from classification society standards together with field-based investigations of key system functions. This conceptual foundation enables the application of the STPA–HFACS methodology, which facilitates systematic hazard identification, the construction of a safety control structure, and the classification of UCAs and their associated CFs.

The analysis reveals that ensuring HMI safety in MASS requires more than robust technical controls and automation. Verification must also address operator expertise, organisational practices, and the cognitive demands placed on humans within highly automated environments. Cognitive lapses such as diminished situational awareness, misperception, or decision fatigue significantly increase operational risk, while limited technological maturity and the scarcity of empirical data further complicate safety evaluation.

By applying the STPA–HFACS framework, this study demonstrates how unsafe interactions between human and system elements can propagate through subsystems to influence accident outcomes. The approach explicitly links SC to system-level hazards and accidents, offering insights into how deficiencies in control structures escalate into risks. In contrast to traditional risk assessment methods, STPA–HFACS generates detailed CSs that capture the mechanisms underlying accidents, particularly those rooted in human cognitive performance. These insights provide decision-makers with a structured and visual tool for risk assessment and targeted safety improvements.

Nevertheless, reliance on qualitative analysis remains a limitation. To strengthen reliability, future research should integrate empirical data collection with quantitative methods such as probabilistic modelling and simulation-based evaluations. Interdisciplinary collaboration will also be essential to refine the approach and extend its applicability.

Beyond MASS applications, the proposed framework contributes to the broader understanding of human–system interaction in autonomous maritime operations. Its methodological innovations are transferable to conventional ship safety management and to other high-stakes domains where human–automation interaction is critical, offering a foundation for both wide adoption and continuous enhancement of safety-critical systems.

Data availability

Data will be made available on request.

CRediT authorship contribution statement

Zhiwei Zhang: Writing – original draft, Visualization, Software, Methodology. **Xinjian Wang:** Writing – review & editing, Validation, Supervision, Resources, Funding acquisition, Conceptualization. **Zhengjiang Liu:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Data curation. **Huanhuan Li:** Writing – review & editing, Supervision, Methodology, Investigation, Conceptualization. **Zaili Yang:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Jin Wang:** Writing – review & editing, Supervision, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The author Jin Wang is an Associate Editor for *Autonomous Transportation Research* and was not involved in the editorial review or the decision to publish this article. 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.

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Appendix A

Table A
Background information of experts involved in STPA–HFACS analysis.

Expert ID	Job title	Working experience	Service years	Reason for employment

(*continued on next page*)

Table A (*continued*)

Expert ID	Job title	Working experience	Service years	Reason for employment
E1	Associate professor	Specialises in maritime autonomous systems and STPA risk modelling	5 years	To ensure methodological soundness of STPA application in MASS HMI
E2	Senior lecturer	Focused on human factors in maritime navigation systems	3 years	To provide insights on HMI design and human error causal chains
E3	Professor	Expert in complex network theory and system safety	17 years	To assess the technical validity of CN-based MASS risk network construction
E4	Professor	Specialises in maritime safety and risk research	15 years	To provide support from a risk perspective and ensure academic consistency
E5	Industry-academic expert	Former ship officer, now working on MASS system integration in academia	20 years	To offer practical insight into realistic MASS operational risks

Appendix B

Table B
List of control actions and feedback.

Action ID	Description
1	Applying precise control commands to HMI systems.
2	The system monitors and reports operator status information in real time.
3	Receive information on internal and external parameters of the ship transmitted by the control system.
4	The HMI system applies the received control commands to the control system.
5	The control system receives operator status information monitored by the HMI system.
6	Ship parameters, operator status alarms, and other information are fed back to the HMI system by the control system.
7	Precise control is applied by the controller to the execution system.
8/10/14	Data is received from each sensor or AIS/GMDSS.
9	The ship's external environment is sensed by environmental sensors.
11	Other ships communicate with MASS via VHF, and the operator monitors the system in real-time.
12	Communicate with other ships via VHF and provide real-time updates on our ship's status.
13	MASS system transmits navigational status and safety information via AIS/GMDSS, enabling external situational awareness for nearby ships.
15	Control commands are transmitted to other ships by the communication system.
16	The status of other ships is fed back to the communications system.
17	Receive control commands from the ROC via the ship-to-shore communication system.
18	Provide real-time feedback to the ROC via the communication system.
19/20	Information exchange between ROC and the communication system.
21/22	Information exchange between ROC and the shore-based station.
23	Control commands are received from the shore-based base station.
24	Ship's status parameters are periodically fed back to shore-based base stations.

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