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Hazard identification and risk analysis of maritime autonomous surface ships: A systematic review and future directions

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ABSTRACT

Despite the progress in autonomous ship technology, unknown risks persist in the design, operation, and regulation of maritime autonomous surface ships. A comprehensive literature review for hazard identification and risk analysis method of maritime autonomous surface ships is currently lacking. Based on a database of 62 relevant literatures, this study presents the distribution of relevant literatures by journal, year of publication, country or region of authorship, and institution. To gain further insights into the research hotpots and the frequently neglected risk influential factors, the literatures are classified into four groups based on the categories of risk influential factors, and a comprehensive list of risk influential factors is compiled. Based on this, the research content is analysed with respect to human factors, ship-related factors, environmental factors, and technology factors. Furthermore, statistical analysis is conducted on 23 literatures related to systematic risk analysis of maritime autonomous surface ships in terms of data sources and risk analysis methods, noting that researchers commonly utilize datasets and a combination of risk analysis methods. This study not only contributes to the understanding of the current status and challenges in hazard identification and risk analysis of maritime autonomous surface ships but also provides potential future research directions.

1. Introduction

The concept of Maritime Autonomous Surface Ships (MASS) was officially recognized during the 98th Maritime Safety Committee (MSC) and formally proposed at the 99th MSC in 2017 (Jovanović et al., 2024). In the continuous development of ship automation, the research and development of MASS have been expedited (Johansen and Utne, 2024). The widespread implementation of MASS is expected to move the maritime industry into a new era, yielding benefits encompassing maritime safety (Hogg and Ghosh, 2016), human resources (Ghaderi, 2019), transportation efficiency (Burmeister et al., 2014), transportation costs (Porathe, 2016), and environmental protection (Munim, 2019). Despite these benefits, concerns are still growing regarding the safety of MASS, as experts warn that more complex and advanced systems may introduce unforeseen risks (Guo et al., 2024; Montewka et al., 2018). Consequently, the safety of MASS is a critical issue for its operation. In fact, the concept, system, and technology of MASS are still in the discussion stages of research and development, while the advancement of autonomous technology is still in its nascent phase (Longo et al., Forthcoming). Thus, the practical implementation of MASS faces numerous challenges (Fan et al., 2024b). To gain insights into these challenges, a comparative analysis with research achievements in aviation, forestry, cars, subway systems, space operations, military, and cranes was conducted by Wahlstrom et al. (2015), which outlined

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human factors challenges associated with autonomous and remote operations within the maritime field. Additionally, Wu et al. (2020) conducted simulations of collision scenarios involving MASS to investigate its potential in reducing ship collision incidents. Moreover, significant attention has been directed towards the challenges and future directions of existing technologies for MASS, such as autonomous decision-making technology (Chae et al., 2020), human-machine cooperative navigation technology (Liu et al., 2022a, 2023), communication technology (Omitola et al., 2018; Wróbel et al., 2021b), and path planning algorithms (Li and Yang, 2023; Ozturk et al., 2022).

Formal Safety Assessment (FSA) recommended by the International Maritime Organization (IMO Maritime Safety Committee, 2007) is a safety analysis method consisting of five steps: hazard identification, risk analysis, identification of risk control options, cost-benefit assessment, and decision-making and recommendations (Fang et al., 2024; Wang, 2001). Hazard identification and risk analysis play a crucial role in FSA. Given their significance in promoting maritime safety, hazard identification and risk analysis are expected to emerge as indispensable components in the realm of safety research for MASS (Liu et al., Forthcoming). However, compared to the rapid progress in autonomous technologies, advancements in hazard identification and risk analysis of MASS are relatively slow (Fan et al., 2024a). Several literature reviews have reviewed and summarized the work in this field. Thieme et al. (2018) utilized system engineering methods to derive nine standards that risk models for MASS should adhere to. The applicability of traditional ship risk models for MASS based on these standards was evaluated. Their findings revealed that existing traditional ship risk models cannot be directly applied to risk analysis of MASS. Similarly, Zhou et al. (2020) utilized system engineering methods to derive 12 system safety requirements and 10 evaluation criteria for hazard analysis methods applicable to MASS. The study examined 29 commonly used hazard analysis methods across 269 papers published over the past 50 years, with System-Theoretic Process Analysis (STPA) identified as an effective hazard analysis method for systematic safety assessment in the design phase. Both studies aimed to extract insights for MASS risk analysis from studies of traditional ships and offer new perspectives in the field. Furthermore, some researchers have conducted comprehensive reviews and analysis from the perspective of MASS safety design, considering multiple factors. Fan et al. (2020) identified risk influencing factors in the operational phases of Degree of Autonomy 3 (DoA3) MASS, developing a risk index framework with four-layer indexes of human, ship, environment and technology. The framework provided a basis for risk analysis of remotely controlled MASS. Veitch and Alsos (2022) conducted a comprehensive review and analysis of MASS safety design methodology, synthesizing 42 studies on human supervision and control of MASS. The study not only summarized the current research status but also identified research gaps, emphasizing challenges that need to be addressed in the design and regulation of MASS. Similarly, Li et al. (2023) conducted a review of relevant literatures on the technical reliability of MASS from 2015 to 2022, utilizing a scientometric approach to provide prospects for MASS reliability analysis. The review focused on aspects such as reliability software failure, collision avoidance, communication and human factors, and mechanical reliability and maintenance. Chaal et al. (2023) conducted a comprehensive literature review on the risk, safety, and reliability of autonomous ships. The study focused on the research hotspots and potential research directions from the macro perspectives of research topics, publication information, and collaborative networks. It leaves research gaps on the analysis of classification and induction of research content and methodology from a micro perspective in the field.

In general, the current review still has several issues with the comprehensiveness of hazard identification and risk analysis. From the perspective of hazard identification, the aforementioned literatures lack a systematic and comprehensive process for identifying hazards in the design, operation, and regulation of MASS. Essential components that affect the safety of MASS, such as the impact of laws and regulations, software failures, network delays, maritime regulation, and other factors, have been overlooked to varying degrees. From the perspective of risk analysis, most of the aforementioned studies primarily concentrate on potential hazards and technical barriers encountered during the design phase. However, due to the broad scope of MASS safety, analysing the entire system solely from the perspective of design, operation, and regulation alone fails to capture the complex interactions between Risk Influential Factors (RIFs), which may underestimate the impact of such effects on the whole. Therefore, it is imperative to conduct a more comprehensive literature review, encompassing hazard identification and risk analysis for MASS, with a specific focus on RIFs and the risk analysis methods in this field. In light of the aforementioned background, the primary contributions of this study to the field are as follows.

1) A systematic approach is utilized to collect and analyse the latest literatures in the field of MASS hazard and risk analysis to create a database. Each selected piece of literatures is individually reviewed and analysed to extract the synergies and classify them accordingly.
2) A bibliometric analysis is conducted on the literatures within the database to map the distribution of journal, year of publication, country or region of authorship, and institution. This analysis provides an overview of the state of the art in the hazard identification and risk analysis method of MASS.
3) RIFs are extracted from the literatures in the database to generate a risk list, which is subjected to statistical analysis. This analysis highlights the research hotspots in current studies, presents the prevailing views of researchers on MASS safety, and identifies research content that is currently missing or lacking.
4) Special attention is given to the data sources and methods utilized for systematic risk analysis of MASS. The study examines the datasets, risk analysis methods, particularly from a quantitative analysis perspective, all of which provide valuable insights into the future direction of research in this field.

The remainder of this study is presented below. Section 2 outlines the literature search strategy, providing statistics and analysis of the distribution of relevant literatures by published journal, year of publication, country or region of authorship, and institution, respectively. Section 3 describes the classification strategy, identifying the main RIFs from relevant literatures. Section 4 discusses and analyses the data sources and risk analysis methods utilized in systematic risk analysis of MASS. Section 5 presents the main findings from statistical analysis and provides future research directions. Finally, Section 6 offers a comprehensive summary of the entire study.

2. Literature search and selection

Inspired by literatures of Filom et al. (2022); Rawson and Brito (2022); Yang et al. (2019); Cao et al. (2023); this study utilizes literature search, manual screening, and data visualization to extract, filter, integrate, classify, refine, and perform trend analysis on the existing literature related to the risk analysis of MASS.

2.1. Data collection

Firstly, Web of Science (WOS) is selected as the data source of the literature search. The WOS Core Collection comprises the world's leading academic journals, books, and proceedings across various fields. Books and proceedings are kept because the MASS risk studies are emerging, and many new findings are presented in the forms of book chapters and conference proceedings. Secondly, the time span of this search is set from January 2010 to November 2022 to ensure the timeliness of the results. Before 2010, there were few studies on MASS in the literature. Then, to accurately identify relevant literatures in the database, "MASS" and "risk" are selected as the search criteria. The following search formulas are utilized for searching in the core collection:

TS = ("*maritime autonomous surface ship**" OR "*unmanned ship**" OR "*intelligent ship**" OR "*smart ship**" OR "*autonomous ship**") AND TS = ("*safe**" OR "*risk**" OR "*accident**" OR "*incident*" OR "*hazard**").

The search formula consists of two sets of keywords. The first set includes "maritime autonomous surface ships*", "unmanned ships*", "intelligent ships*", "smart ships*", and "autonomous ship*", which narrow the search to the literature related to autonomous ships. The second set includes "safe*", "risk*", "accident*", "incident", and "hazard*", which narrow the search to the literatures related to safety and risk. The symbol "*" denotes multiple forms of the same keyword interpretation. To ensure that the search results include all of the literatures related to MASS and safety in the core collection, two sets of keywords are linked by the Boolean operator "AND" and keywords within each set are linked by the Boolean operator "OR". The search was concluded in November 2022, yielding 992 results using the aforementioned strategy.

2.2. Review criteria

To ensure the high relevance of the database, a meticulous review of the search results is conducted on an article-by-article basis. The criteria to be adopted are as follows.

1) Titles and abstracts are examined to confirm that they contain relevant content related to MASS. The inclusion criteria are that the research focuses on MASS or that the findings can be applicable to MASS.
2) Literature that merely includes terms such as MASS, automation process, and risk analysis as part of the background or introduction is manually excluded.
3) The remaining literature is analysed based on its research content. Literature is retained if it involves a systematic risk analysis of MASS or an analysis of the specific risk influential factors pertaining to MASS.

The aim of the search is to acquire research concerning hazard identification and risk analysis of MASS in the areas of design, operation, and regulation, that is, the subject of the selected literatures is limited to the category associated with the keywords in Section 2.1. A portion of the initial search results, which focuses on enhancing the safety of MASS through technological advancements, is manually excluded. It is worth noting that although "safe" is one of the aims of these literatures, the process of hazard identification or risk analysis is the missing part of these literatures. For example, there are some literatures about collision avoidance techniques, trajectory planning methods, and decision-making algorithm of MASS. On the one hand, these literatures primarily revolve around real-time collision risk assessment and have a strong thematic focus. On the other hand, these literatures predominantly concentrate on enhancing algorithms and improving techniques rather than identifying, analysing, and prioritizing risks in collision avoidance, trajectory planning, and autonomous decision-making. As a result, these

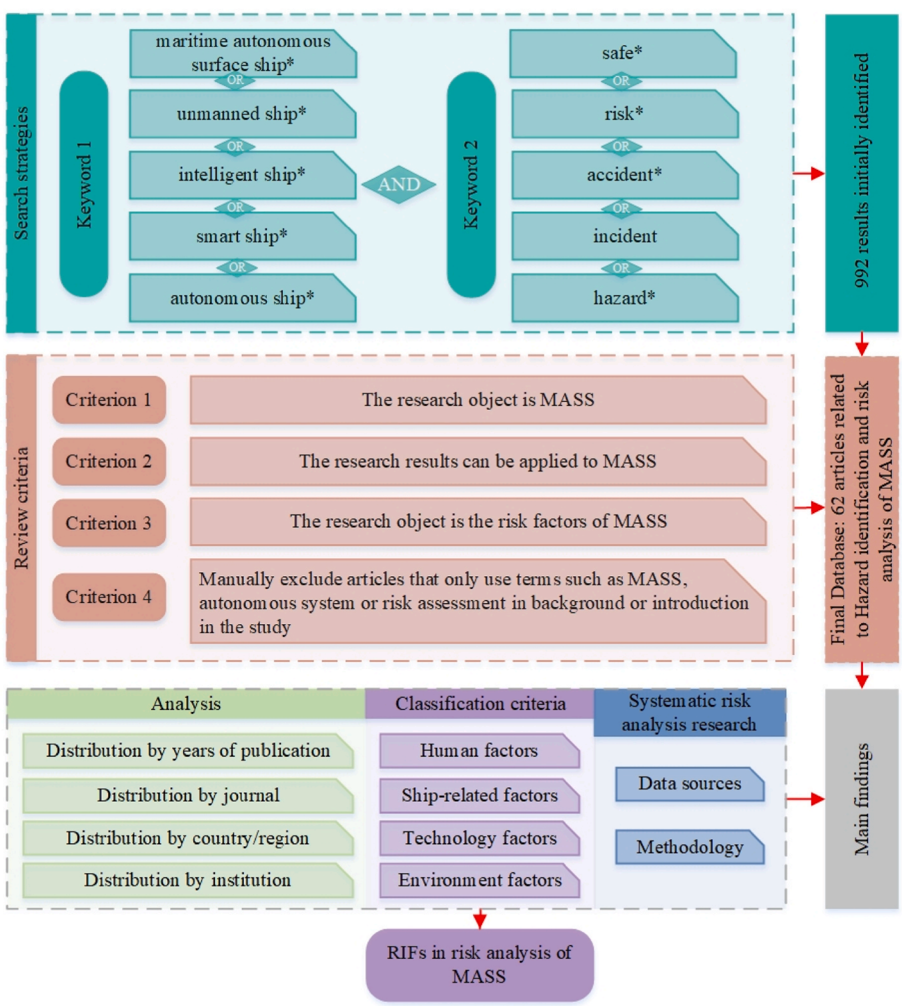

Fig. 1. The search and review framework.

literatures are not highly relevant to the subsequent research content, and will not be reiterated in this study. However, it is worth noting that literatures exploring changes in ship collision risk due to the operation of MASS and assessing risk in collision scenarios have been retained.

Finally, 62 papers are retained through a manual screening process in terms of the research methods, research subjects, and scope of application. This process leads to the establishment of the final database. The specific search and review criteria are depicted in Fig. 1.

2.3. Analysis of the overall literature

This section offers comprehensive statistics of research in the field of hazard identification and risk analysis of MASS. A systematic data analysis approach will be utilized to examine all literatures in the final database in terms of the distribution by journal, year of publication, country or region, and institution.

2.3.1. Distribution by journal

An analysis of the journals is conducted, and the results show that the relevant papers were published across 28 different journals or conference proceedings. Table 1 lists the six journals that have published more than two cumulative papers in this field. Reliability Engineering & System Safety (RESS), Safety Science (SS), and Ocean Engineering (OE) are the top three journals in terms of the number of papers published, which lead the field with around 42%. The followers are Applied Sciences-Basel (ASB), Proceedings of the Institution of Mechanical Engineers Part O - Journal of Risk and Reliability (P I MECH ENG O - J RIS), and Journal of Marine Science and Engineering (JMSE), each with 4 papers in these journals. The majority of these journals fall within the Engineering and “Operations Research & Management Science” fields, although they originate from interdisciplinary fields such as engineering, oceanography, and management science.

The metric of average publication year serves as an indicator of a journal’s acceptance and interest within the literature, revealing the development stage of a scientific subject (Cao et al., 2023). An average publication year is calculated by averaging the first published online dates of all papers, which includes the year and month of publication. Only the year and month of these dates are retained. For ease of calculation and to retain the accuracy of the results, this study averages the published month after dividing them by 12 and adding it to the published years. The integer part of the final calculated result is taken as the year and the decimal part multiplied by 12 is taken as the month. In the case of P I MECH E NG O-J RIS, for example, the first published online dates of the four papers are “August 4, 2017″, “July 12, 2021″, " October 15, 2021″, “October 26, 2021". They are processed as 2017.67, 2021.58, 2021.83, 2021.83. The average value is 2020.73. The integer part is 2020 and the decimal part is 0.73, which translates to a month of 8.76, rounded to September. If there is a large difference in the average publication year of journals within the same field, it represents that journals with an earlier average publication year have not been interested in research in the field in recent years. However, it is undeniable that they attracted more researchers’ attention in the early years and laid a solid foundation for the development of the field. Meanwhile, in contrast, journals with a later average publication year have shown more interest in the field. As can be seen in Table 1, all of these journals have an average publication year of 2020 or later, indicating that the field is developing rapidly and that researchers are increasingly interested in this emerging field. Consequently, it is evident that hazard identification and risk analysis of MASS is an interdisciplinary research area that is still in the nascent stage of development.

Table 1
Top six journals related to risk analysis of MASS.

No.	Name	Number of publications (Nop)	Average publication year	Research Areas
1	RESS	9	2020 Jul	Operations Research & Management Science, Engineering
2	SS	9	2020 Nov	Operations Research & Management Science, Engineering
3	OE	8	2020 Oct	Engineering, Oceanography
4	ASB	4	2020 Oct	Chemistry, Materials Science, Physics, Engineering
5	P I MECH ENG O-J RIS	4	2020 Sep	Operations Research & Management Science, Engineering
6	JMSE	4	2021 May	Oceanography, Engineering

2.3.2. Distribution by year of publication

A visual analysis of year of publication is conducted, and the results show that from 2015 to 2022, each of six journals published more than 4 papers in this field cumulatively. Fig. 2 presents the Nop in these six journals year by year. As an emerging technology, the research achievements of MASS are not as extensive as traditional ships in general. The earliest literature in this field dates back to 2015 (Wahlstrom et al., 2015). Prior to 2017, there was relatively less academic attention to this field. However, from 2017 to 2022, the relevant publications received significant academic attention and showed significant growth, accounting for approximately 90% of the total publications. The burst of papers in 2020 is due to the SS’s special issue on autonomous vessel safety. In general, the tendency of MASS risk/safety research is increasing in the past years.

2.3.3. Distribution by country/region

The publications in the final database have been classified based on the country or region of authorship. Fig. 3 presents the statistical results for the top 13 countries or regions. It is worth noting that some publications may have multiple authors, and these authors may be affiliated with different institutions across various countries. Therefore, in the statistics, if a publication has multiple authors, their respective countries or regions of affiliation are included. If there are repeated countries or regions among the authors within a publication, these similar entries are consolidated, and only one count is recorded. If an author has multiple affiliations across different countries or regions, each affiliation is included. Consequently, following the above strategy, the cumulative number of publications exceeds 62. The result reveals that researchers from Norway, Finland, China, and Poland have contributed the highest

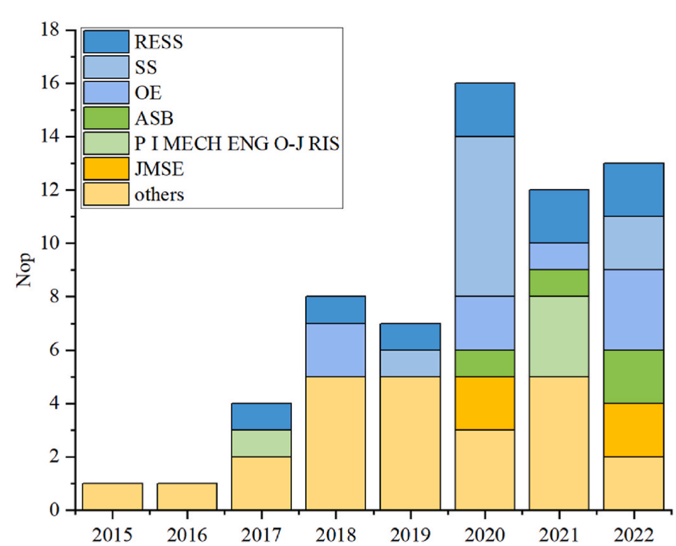

Fig. 2. Distribution by year of publication.

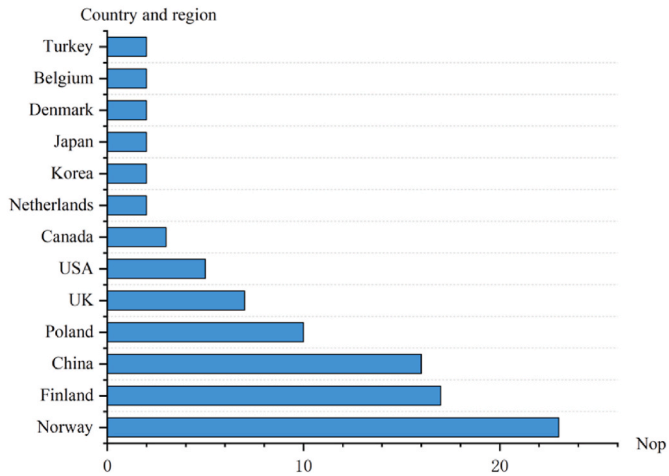

Fig. 3. The top 13 countries and regions with the most publications to risk analysis of MASS.

number of publications.

2.3.4. Distribution by institution

Fig. 4 presents the top seven institutions with the highest number of publications in this field. Utilizing the same statistical method, the Norwegian University of Science and Technology (NTNU) stands out as the most productive institution, have contributed to a total of 15 publications. It is followed by Aalto University (Aalto), Wuhan University of Technology (WUT), Gdynia Maritime University (GMU), Satakunta University of Applied Sciences (SAMK), University of California, Los Angeles (UCLA), and Dalian Maritime University (DLMU).

3. Risk influential factors in risk analysis of MASS

This section presents a detailed analysis of studies conducted on different RIFs, utilizing the RIFs categories encompassed in the literature as classification criteria. The objective is to facilitate a more intuitive understanding of the primary research directions and approaches in this field.

In the risk analysis of traditional ships, the four fundamental factors utilized to identify risk sources are "human, ship, management, and environment" (Fu et al., 2021; Wang et al., 2023). However, upon further investigation, this study adopts the RIFs categories of "human factors, ship-related factors, management factors, environmental factors, and technology factors" as referenced in Luo et al. (2022) and "Guide for traffic safety risk assessment of intelligent navigation of ships: General rules" published by Chinese Institute of Navigation. However, management factors are typically considered a subset of human factors, and there is limited literature available concerning the analysis of management factors within the existing literature. Consequently, in this study, the analysis of management factors is classified under human factors.

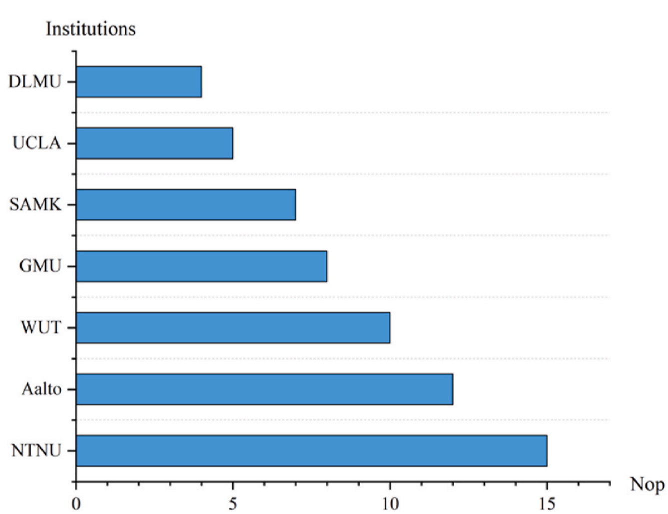

Fig. 4. The top institutions participating in the publication of literature.

The literatures within the final database undergoes a statistical analysis based on four classification criteria: "human factors, ship-related factors, environmental factors, and technology factors" with reference to the classification criteria outlined by Fan et al. (2020) and Luo et al. (2022). The classification is applied after macroscopic examination and simplification of the RIFs. The classification criteria, along with the extracted RIFs and Nop are presented in Table 2.

The following classification strategy is utilized to determine the distribution of RIFs studies across four categories.

1). If the review of a paper indicates that it only examined one type of RIF, it will be assigned to the corresponding RIF category. Additionally, the relevant RIF will be extracted, and one point will be attributed to the corresponding RIF. For instance, if a paper examined factors affecting condition of operators, it will be

Table 2
List of RIFs of MASS.

Classification criteria	No.	RIFs	Nop
Human factors	H_1	Situation awareness	22
	H_2	Condition of operator(s)	16
	H_3	Experience and training	15
	H_4	Competence of operator(s)	13
	H_5	Human-machine interface (HMI) design	13
	H_6	Transitions of control	11
	H_7	Hardware or software development defects	11
	H_8	Maritime supervision	10
	H_9	Automation-induced trust issue	9
	H_{10}	Information overload	7
	H_{11}	Communication	5
	H_{12}	Bridge resource management	4
	H_{13}	Humanitarianism	3
	H_{14}	Manning	2
Ship-related factors	S_1	Reliability of hardware	23
	S_2	Maintenance of hardware	14
	S_3	Reliability of software and algorithms	13
	S_4	fail-to-safe mechanism	7
	S_5	Cargo management	7
	S_6	Maintenance of software	6
	S_7	Maintainability	5
	S_8	Ship conditions including Ship stowage, Tonnage and age, and Structure and performance	4
Environmental factors	E_1	Natural environment	20
	E_2	Traffic environment	16
	E_3	Legal Environment	14
	E_4	Cyber environment	11
	E_5	Security environment	10
	E_6	Work environment	6
Technology factors	T_1	Autonomous perception technology	29
	T_2	Reliability of Information and Communication Technologies (ICT)	20
	T_3	Cybersecurity	18
	T_4	Sufficient redundancy	14
	T_5	Decision-making technology	13
	T_6	Ship-control technology	9
	T_7	Autonomous navigation technology	7
	T_8	Monitoring technology	6
	T_9	Delays of networks	6
	T_{10}	Connectivity of networks	6
	T_{11}	Self-diagnosis technology	4
	T_{12}	Positioning technology	4

classified under human factors studies. Simultaneously, one point will be added to Criterion H_2 in Table 2.

2). If the review of a paper indicates that it examined multiple types of RIFs, it will be assigned to the respective multiple RIF category. Additionally, each relevant RIF will be extracted, and one point will be allocated to each corresponding RIF. For instance, if a paper examined RIFs related to both technology factors and human factors, it will be classified under both technology factors studies and human factors studies. Likewise, one point will be added to each of the corresponding RIFs.

Since some papers have examined more than one category of RIFs, the total count will exceed 62. The classification results demonstrate that the technology factors studies comprise the highest number with 39, followed by human and environmental factors studies with 37 and 33 respectively, while ship-related factors studies are the least with 23.

3.1. Human factors

Will the growing Degree of autonomy (DoA) lead to the elimination of the human factor, and can autonomous technology enhance navigation safety? These issues have been the subject of early research investigating the human factors of MASS. In fact, it is evident that human factors remain crucial in the overall system (Veitch and Alsos, 2022). Human factors persist even in systems widely regarded as reliable (Man et al., 2018). Furthermore, there is no guarantee that the influence of human factors on navigation safety can be completely eliminated. The application of autonomous technology has transformed the role of humans in the operational loop as the core of ensuring the system's safety. Humans transit from active operators to passive monitors of the autonomous system, are responsible for tasks like monitoring, remote controlling, and emergency handling of the vessel. Table 3 presents a summary of statistical results of RIFs related to human factors in relevant studies, along with an index of the literature sorted by year of publication. Among these, human-driven RIFs including situation awareness, condition of operator(s), experience and training, and competence of operator(s) are frequently mentioned. It is widely accepted that human factors of MASS primarily arise from humans themselves, Remote Operation Center (ROC), design, and team and management issues (Fan et al., 2020).

From a pure human perspective, although the operators' tasks may differ for MASS with different Degrees of Autonomy (DoAs), their responsibility to ensure the ship's safety remains constant. Therefore, condition of operator(s), competence of operator(s), situation awareness, experience and training, automation-induced trust issues, communication, and other human-driven RIFs continue to be significant in terms of the impact on MASS safety. Wróbel et al. (2021a) utilized a Human Factors Analysis and Classification System-Maritime Accidents (HFACS-MA) framework to examine the human factors of remotely controlled MASS, relying on expert opinions. The study revealed that failure to correct known problems and condition of operators were potentially critical factors affecting the safety of MASS. Yoshida et al. (2021) further emphasized the impact of condition of operator(s), indicating that conflicts between navigation safety and efficiency, physical situation, lack of human–machine communication, impersonal movement, and visibility constraints can lead to excessive mental workload for operators. Consequently, these factors have a detrimental effect on condition of operator(s), potentially posing safety hazards for MASS. Currently, there is limited literature regarding how condition of operator(s) affects navigating safety. Nonetheless, extensive research in

Table 3
The RIFs related to human factors considered in the selected literature.

No.	References	H_1	H_2	H_3	H_4	H_5	H_6	H_7	H_8	H_9	H_{10}	H_{11}	H_{12}	H_{13}	H_{14}
1	Wahlstrom et al. (2015)	✓	✓		✓		✓				✓	✓		✓	
2	Ahvenjarvi (2016)	✓				✓		✓		✓					
3	Thieme and Utne (2017)	✓		✓											
4	Wróbel et al. (2017)	✓	✓		✓			✓	✓		✓		✓	✓	
5	Utne et al. (2017)					✓									
6	Thieme et al. (2018)	✓	✓	✓	✓	✓	✓					✓			✓
7	Wróbel et al. (2018a)	✓	✓	✓	✓	✓	✓	✓	✓						
8	Porathe et al. (2018)		✓							✓	✓				
9	Ramos et al. (2018)						✓	✓							
10	Man et al. (2018)	✓							✓	✓					
11	Banda et al. (2018)			✓					✓						
12	Ramos et al. (2019)	✓		✓	✓										
13	Zhang et al. (2019)	✓									✓				
14	Li et al. (2019)				✓										
15	Mallam et al. (2020)			✓	✓					✓					
16	Fan et al. (2020)	✓	✓	✓	✓		✓	✓		✓	✓				
17	Zhang et al. (2020)	✓	✓		✓	✓				✓	✓				
18	Goerlandt (2020)	✓		✓		✓	✓			✓					
19	Yoshida et al. (2020)	✓			✓								✓		
20	Chae et al. (2020)	✓	✓		✓						✓				
21	Wu et al. (2020)							✓							
22	Zhou et al. (2020)	✓				✓	✓								
23	Ramos et al. (2020a)	✓				✓	✓								
24	Chaal et al. (2020)							✓	✓						
25	Zhou et al. (2021)	✓					✓								
26	Chang et al. (2021)					✓		✓							
27	Yoshida et al. (2021)		✓												
28	Wróbel et al. (2021a)		✓			✓		✓	✓						
29	Storkersen (2021)	✓	✓			✓	✓						✓		
30	Dittmann et al. (2021)								✓						
31	Liu et al. (2022b)		✓	✓			✓					✓			
32	Zhang et al. (2022b)	✓	✓	✓	✓				✓						
33	Zhang et al. (2022a)	✓	✓	✓				✓				✓			✓
34	Luo et al. (2022)		✓	✓								✓		✓	
35	Lynch et al. (2022)	✓		✓		✓									
36	Fan et al. (2022)		✓	✓				✓	✓	✓			✓		
37	Veitch and Alsos (2022)	✓		✓	✓	✓			✓	✓					

the fields of aviation, unmanned vehicles, driverless trains, and remotely piloted vehicles has delved into condition of operator(s), encompassing aspects such as situational awareness, fatigue, emotion, concentration, and work intensity (Fonseca et al., 2022; Neubauer et al., 2011; Saffarian et al., 2012; Useche et al., 2017). Although not obviously applicable, these findings hold relevance for research on condition of operators in the context of MASS. Additionally, it has been suggested that remote operators should possess a broader knowledge base as well as superior learning abilities in comparison to traditional ship operators (Mallam et al., 2020; Thieme and Utne, 2017), imposing heightened requirement on the competence and training of remote operators. Yoshida et al. (2020) expanded upon the existing human behaviour model and constructed a Goal-Based Gap Analysis (GBGA) model to assess the operators' competence. A regulatory framework for remote operators has been developed based on the existing regulatory provisions of STCW, combined with the distinct characteristics of remote operators. Li et al. (2019) examined the operational differences between MASS and traditional ships, presenting a fuzzy comprehensive evaluation method for evaluating the competence of operators.

In the applications of remotely controlled ship with seafarers on board (DoA2) and remotely controlled ship without seafarers on board (DoA3) MASS, the personnel responsible for monitoring and ship operations on ships are moved ashore in part or full in the form of ROC and remote operation technologies. However, humans retain their roles as real-time supervisors and emergency decision-makers for the ships. Wrobel et al. (2016) pointed that the impact of human errors also hinges on the ship system designer's capacity to identify and anticipate potential accident scenarios caused by human error. In the context of remote operations, the HMI system serves as a vital component of DoA2 and DoA3 MASS, bridging the connection between the two unknown forms of human-human and human-machine interactions. It functions as an intermediary for human involvement. Therefore, the HMI system plays a critical role in human factors research. Man et al. (2018) demonstrated that the bridge design of traditional ships cannot be directly applied for MASS. Accordingly, they recommended the redesign of ROC to align with the specific characteristics of MASS and remote operators. The design of HMI system will significantly affect the operators' performance, and a subpar design can lead to unpredictable and severe consequences. Liu et al. (2022b) quantified human errors in HMI, revealing that condition of operator(s), such as stress, task complexity, training, environmental factors, communication, and fatigue, significantly contribute to human error.

Autonomous systems are pre-programmed computer systems with a certain degree of autonomous decision-making capability. However, they are limited in their ability to cope with abnormal and unexpected situations. The pre-programmed software cannot anticipate scenarios beyond those considered in the software system's design, such as hardware failures, multiple sensor failures, and communication device failures. The onboard crew and remote operators of DoA2 and DoA3 MASS serve as the last line of defense to ensure the ship's safety. In the event of system failure or unforeseen circumstances, they undertake necessary actions and make appropriate decisions to avoid accidents or mitigate the severity of accident consequences. The significance of human involvement in the operational loop becomes even more apparent. In order to ensure the effectiveness of human as "the last line of defense" (Ramos et al., 2019), it is essential to design the HMI, ROC, and emergency operations processes. This encompasses, considering the tasks to be performed by remote operators, the prerequisites for successful task execution, and the potential errors that may arise during task execution. The prerequisite for that is to ensure the smooth execution of remote operator's core tasks, encompassing the transition between operating modes such as active continuous monitoring, passive takeovers, and backup to autonomous system. In the event of a node failure while ROC is overseeing multiple ships, the resulting malfunctions may affect not only the failed ship but also other ships under its control or other ships in the domain. In this case, personnel such as designers, operators, and maritime supervisors are required to perform appropriate hazard mitigation functions (Kari et al., 2018). Zhang et al. (2020) demonstrated that the probability of human error by remote operators of DoA3 MASS during emergency processes is greater than that of traditional ships. This aligns with the findings of Ramos et al. (2018), who identified three human error events that could potentially result in accidents during the navigation phase of MASS. These events encompassed that failure to respond to alarms promptly, inability to handle the ship remotely, and failure to take over the ship promptly when necessary. The operations examined in these studies primarily involved emergency situations. However, it is important to recognize that human error is a consequence of events or incidents. Identifying human error and human error scenarios is not the end of the risk analysis process.

In the limited studies that refer to management factors, Goerlandt (2020) conducted an exploration and prediction of the risk characteristics of different levels of MASS based on International Risk Governance Council Risk Governance Framework (IRGC-RGF). These characteristics served as a basis for elaborating stakeholder responsibilities and developing risk governance strategies from a macro perspective. However, management factors encompass not only the maritime supervision of one or multiple MASS in service but also the management and staffing of ROC's bridge resources. From a human error prevention perspective, an effective safety management system plays a crucial role in minimizing the occurrence of human errors. Banda et al. (2018) developed a safety management strategy for the conceptual design phase of MASS, addressing challenges that need resolution before the operation. Through a literature review, Storkersen (2021) investigated safety management in future remote control ship operations. The study highlighted that safety management practices effective on traditional ships can enhance the safety of remotely controlled ships. However, it also noted that these practices might contribute to an increase in operator workload, and traditional safety management methods may lead to personnel imbalance. Therefore, remote control and HMI are not the only factors leading to information overload and increased workload for operators. Burdensome workflows can also contribute to increased personnel workload, resulting in human error scenarios. It is worth noting that, at this stage, the relevant studies related to management factors primarily concentrate on formulating risk management strategies and providing safety control measures for the conceptual design phase of MASS from a macro perspective. In contrast, human resource management aspects of MASS operation have not received sufficient attention from academics, particularly in term of the safety management of personnel associated with ROC.

3.2. *Ship-related factors*

It is necessary to establish a clear definition of the MASS system before analysing risks related to ship systems (Mai et al., 2019). As a complex system, ship systems, subsystems, and interactions among them are more intensive, multiple, and interconnected. However, the software and hardware facilities of MASS lack specific forms and uniform design standards, making it uncertain whether the risk analysis method used for traditional ships can be applied to MASS. Further research is necessary to determine the applicability of such methods.

Table 4 presents the statistical results of RIFs related to ship-related factors identified in the selected literatures. Reliability of hardware is the most emphasized RIF. As a large-volume transport vehicle, MASS will suffer from unacceptable potential consequences of accidents resulting from failures in the propulsion system, power system, and other hardware systems (Zhang et al., 2022a). The consequences of such failures have the potential to encompass vast areas of the ocean, multiple maritime routes, and coastal regions, with lasting, possibly permanent, adverse effects on the marine environment. Moreover, increased remediation costs for corrective maintenance for MASS at sea lead to higher temporal expense in restoring operational capabilities

Table 4
The RIFs related to ship-related factors considered in the selected literature.

No.	References	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8
1	Wróbel et al. (2017)	✓	✓			✓			
2	Thieme et al. (2018)	✓	✓	✓	✓		✓		
3	Wróbel et al. (2018b)	✓	✓	✓	✓			✓	
4	Wróbel et al. (2018a)	✓	✓	✓	✓		✓		
5	Banda et al. (2019)	✓	✓	✓			✓		
6	Zhang et al. (2019)	✓	✓			✓		✓	✓
7	Felski and Zwolak (2020)	✓				✓			
8	Fan et al. (2020)	✓	✓	✓	✓	✓			
9	Utne et al. (2020)	✓						✓	
10	Wu et al. (2020)	✓		✓					
11	Zhou et al. (2020)	✓	✓	✓			✓		
12	Ventikos et al. (2020)	✓	✓	✓	✓		✓		
13	Dittmann et al. (2021)	✓		✓	✓				
14	Eriksen et al. (2021)	✓	✓					✓	
15	Chae et al. (2020)	✓	✓	✓		✓	✓	✓	
16	Chang et al. (2021)	✓		✓					
17	Bolbot et al. (2021)	✓	✓	✓	✓				
18	Zhang et al. (2022b)	✓	✓						✓
19	Chou et al. (2022)	✓							
20	Zhang et al. (2022a)	✓							✓
21	Tusher et al. (2022)	✓		✓					
22	Luo et al. (2022)	✓	✓			✓			✓
23	Fan et al. (2022)	✓				✓			

(Eriksen et al., 2021). The upper limit of the severity of such consequences is further exacerbated by the loss of maneuverability of MASS at sea. The design of ship systems for large-scale MASS operation necessitates ensuring the hardware system's utmost reliability, especially in exceptional and unexpected situations. Redundancy stands out as one of the effective ways to mitigate such hardware system failures in the design phase (Fan et al., 2020). In addition, software system is the core of a ship system, and the design of the ship system also needs to ensure the correctness, completeness, and adherence to standards of the software program code. Software system failures primarily stem from defects in the software design and development phases, potentially persisting throughout the product's life cycle. Thus, a thorough understanding of highly autonomous systems and a systematic hazard analysis before the design of MASS will contribute to the development of risk management strategies and the establishment of redundancies to mitigate such unidentified risks. Eriksen et al. (2021) examined the applicability of the Reliability Centered Maintenance (RCM) method to MASS and revealed that not only hardware design affects the mechanical reliability of MASS, but also the maintenance of ship plays an equally crucial role. However, due to the current lack of experimental data on software and hardware failures of MASS, there are fewer risk analyses related to software and hardware reliability. It is recommended to conduct trials on actual ships under real traffic conditions to obtain precise simulation data, supporting risk analysis and aiding in the development of effective risk strategies (Felski and Zwolak, 2020).

In the existing research literature, ship-related RIFs, encompassing loading, tonnage and age, structure, and maneuverability, are commonly identified from the risk analysis of MASS in specific navigation scenarios, such as inland waterways (Zhang et al., 2019), navigation scenarios (Luo et al., 2022), and different operational modes (OMs) (Fan et al., 2022). Moreover, RIFs related to cargo management are mainly identified from previous literature and accident reports.

Compared to the studies on human factors, ship-related one lacks available data, making associated risks more challenging to quantify. This type of analysis contains more uncertainties due to the unknown nature of MASS systems and the inherent unpredictability in their interconnections. Consequently, current ship-related factors studies aim to provide valuable insights during the conceptual design phase of MASS while minimizing the costs associated with trial and error in the future.

3.3. Environmental factors

Table 5 presents both the frequency of extracted RIFs related to environmental factors in the selected literatures and an index of the literature sorted by year of publication. The physical environment, encompassing natural environment, traffic environment, and work environment, constantly undergoes changes with time and space, directly or indirectly affecting the safety of ship navigation. Among these factors, natural environment and traffic environment are the most frequently appeared environmental factors in the field. For traditional ships, humans and ships form sets with stable reliability in complex navigational environments (Xue et al., 2019). The physical environment negatively impacts the safety of ship navigation mainly by interfering with the decision-making of human and reducing the ship's maneuverability. With an increasing DoA, the physical environment also interferes with collision avoidance decisions, navigation planning, and other autonomous system functions (Zaccone and Martelli, 2020). The journey towards full autonomy for MASS is a lengthy process. For the foreseeable future, onboard crew, remote operators, or a combination of both will remain responsible for the ship's operation. They will be required to take over in response to unforeseen events that exceed the capabilities of the autonomous system. The transfer of risk manifestations caused by the reduction or transfer of personnel is a gradual process. Consequently, the navigational risks caused by physical environment disturbance will manifest through factors such as the decision and perception performance of autonomous system, the decision of operators, the reliability of hardware and software, and redundancy, depending on the DoA. These complex traffic situations, which may surpass the performance limits of autonomous systems, can result in accidents. For instance, there are multiple ships or obstacles in the MASS domain (Ramos et al., 2018), navigation in inland waters may be influenced by factors such as berthing conditions and interference (Zhang et al., 2019). Failure paths related to the physical environment will not be confined to following

Table 5
The RIFs related to environmental factors considered in the selected literature.

No.	References	E_1	E_2	E_3	E_4	E_5	E_6
1	Wahlstrom et al. (2015)						✓
2	Wróbel et al. (2017)	✓	✓	✓			
3	Hoyhtya et al. (2017)	✓	✓	✓	✓	✓	
4	Wróbel et al. (2018b)	✓		✓		✓	
5	Wróbel et al. (2018a)	✓	✓	✓	✓		
6	Thieme et al. (2018)	✓	✓	✓			
7	Ramos et al. (2018)		✓				
8	Man et al. (2018)			✓			✓
9	Shipunov et al. (2019)			✓	✓	✓	
10	Banda et al. (2019)	✓					
11	Zhang et al. (2019)	✓	✓	✓	✓	✓	
12	Fan et al. (2020)	✓	✓	✓		✓	✓
13	Utne et al. (2020)	✓	✓				
14	Wu et al. (2020)	✓					
15	Zhou et al. (2020)				✓	✓	
16	Ventikos et al. (2020)				✓	✓	
17	Bolbot et al. (2020)				✓		
18	Felski and Zwolak (2020)			✓	✓		
19	Yoshida et al. (2020)			✓			✓
20	Yoshida et al. (2021)			✓			✓
21	Wróbel et al. (2021a)	✓	✓				
22	Zhou et al. (2021)				✓	✓	
23	Chang et al. (2021)	✓	✓				
24	Bolbot et al. (2021)				✓	✓	
25	Guo et al. (2021)	✓	✓				
26	Zhang et al. (2022b)	✓	✓				
27	Chou et al. (2022)	✓				✓	
28	Johansen and Utne (2022)	✓	✓				
29	Zhang et al. (2022a)	✓	✓				
30	Luo et al. (2022)	✓	✓	✓			
31	Veitch and Alsos (2022)		✓	✓			
32	Lynch et al. (2022)	✓					✓
33	Fan et al. (2022)	✓			✓		

specific situations. ROC cannot fully replicate the actual console environment. As physical limitations deprive the “implicit experience” of physical perception, leading to decision faults caused by a lack of sense and confidence (Lynch et al., 2022; Wahlstrom et al., 2015; Yoshida et al., 2021). These faults can also be attributed to decision-making delays and a decline in situational awareness due to the work environment, such as HMI design (Man et al., 2018), and loss of control due to network connectivity failures caused by changes in the geographical conditions, such as nearshore, port area, deep sea, and Arctic (Hoyhtya et al., 2017).

The security and cyber environment during the navigation stage of MASS are likewise hotspots in current research on environmental factors. For traditional ships, the security environment, considered a physical realm, encompasses issues such as pirate attacks, political instability in certain regions, and other threats. In the era of information technology, the frequency of cyber-attacks is on the rise. When considering network risk sources, the security of data exchange channels becomes the primary concern in the network security system of MASS (Hassani et al., 2017). This type of risk can be classified as “external” or “internal”, referring to security issues in cyber environment and the safety issues in technology factor.

The “external” security issues in the cyber environment are typically non-intentional and malicious cyber-attacks. Since the system of MASS is under continuously monitoring and can be directly controlled by ROC at any time, the onboard system has the function of receiving operational commands unconditionally. As a result, pirates or terrorists may be more inclined to exploit high-value, low-cost cyber-attacks to get control over ships. Data exchange channels that are prone to serious consequences, such as ship control systems, functional and inter-system interfaces, and data flows, are the vulnerabilities of the system against cyber-attacks (Felski and Zwolak, 2020). Studies have demonstrated that sensor-based systems, automated docking systems, global navigation satellite systems (GNSS), and automatic identification system (AIS) may have exploitable cyber vulnerabilities (Shipunov et al., 2019), making them potential targets for cyber intrusions. Some researchers have also proposed that ROC is the most likely target in a cyber-attack, followed by the collision avoidance and situational awareness systems of MASS (Bolbot et al., 2020). Cyber-attacks from “external” sources have multiple and unknown intrusion paths, with sources not limited to individuals or organizations such as pirates, criminals, and business competitors. These attacks may have various unknown purposes and motivations, making them challenging to detect and prevent.

The competence of operators, or their extent in controlling ship capabilities, may also contribute to cybersecurity vulnerabilities. For instance, operators’ unfamiliarity with the simulated console could lead to failure in detecting cyber intrusions, operators’ lack of information technology skills could result in a failure to defend against cyber intrusions, and operators’ inexperience could lead to situations where the ship cannot be extricated. Nevertheless, several studies have identified it as a less important aspect of cyber environment (Shipunov et al., 2019; Tam and Jones, 2018). These researchers have pointed out that intruders may take forms not restricted to cyber-attacks to take control of the ship. Since MASS can be unmanned or have very few crew members on board, external intruders might resort to physical attacks, such as forced boarding and multi-ship sieges, to disrupt the ship’s systems and take control over the ship to exert pressure on relevant governments or ship owners. On the other hand, according to Simola and Poyhonen (2022), factors such as personnel from “inside” the system, operational flows, and related technologies are key factors that lead to vulnerabilities in the cyber environment. However, the common perspective of these studies is that it is not enough to detect network vulnerabilities and cyber-attacks only through passively monitoring the flow of information across the screen. Active and continuous cyber situational awareness techniques are necessary and applications of new technologies such as blockchains to increase the trustworthiness between the entities in the MASS networks are insightful (Wang et al., 2022). Consequently, MASS’s network and system-related security technologies must possess sufficient capacity to address these issues. This is the reason why technology factors are chosen as the fourth category of risk factors in this study, in addition to human, ship-related, and environmental factors in the classification criteria.

The current view of researchers on the legal environment stems mainly from the legislative gaps in cargo transportation, onshore infrastructure, insurance, and collision avoidance (Fan et al., 2020; Man et al., 2018; Shipunov et al., 2019; Thieme et al., 2018; Wróbel et al., 2017), etc., which contribute to the design and regulation of relevant pre-operational preparations. Further elaboration on the legal environment is omitted, as the actual operation of MASS must be based on a comprehensive set of laws and regulations.

3.4. Technology factors

Currently, the shipping industry is in the transitional phase between the design and operation of MASS. Research related to human, ship-related, and environmental factors focuses on investigating “known unknowns”, as most of the hazardous scenarios faced by MASS in the studies mentioned above are predictable. Nevertheless, the precise definition of the MASS system remains unknown. At this stage, the butterfly effect is the most appropriate description for fault propagation, where a minor failure can trigger a series of chain reactions. Therefore, hazard identification and risk analysis related to technology factors need to incorporate such dimensions of uncertainty, ambiguity, and knowledge into the assessment metrics (Porathe et al., 2018). This includes identifying known hazards that can be mitigated by applying new technologies, assessing potential unknown hazards arising from the applications of new technologies, and predicting the acceptable level of unknown hazards in situations exceeding redundancy.

Table 6 describes both the frequency of extracted RIFs related to technology factors in the selected literatures and an index of the literature sorted by year of publication. Among the most frequently considered technology factors are RIFs related to autonomous systems, such as autonomous perception technology, decision-making technology, ship-control technology, and monitoring technology. More specifically, autonomous perception technology, decision-making technology, and ship-control technology form the foundation of MASS system, especially the collision avoidance technology in decision-making technology (Chae et al., 2020). The systems of MASS are highly integrated, software-intensive, and susceptible to environmental influences. The autonomous perception system collects information on the physical environment surrounding the ship, the ship’s condition, cyber environment information, traffic flow information, etc., through sensors. The decision-making system analyses the above information, assists the ship itself or ROC in decision-making, and controls the movement of the ship through the ship-control system. Existing studies on how technology affects ship safety have predominantly focused on functional failures caused by software and hardware malfunctions. However, the deeper propagation and potential risk factors of these failures have not been extensively examined.

In addition to this, even extremely advanced technologies may have unforeseen failures that cannot be resolved. Such failures might only become apparent under certain conditions during actual operation, necessitating more costly remedial measures for mitigation (Banda et al., 2019). Most relevant studies suggest incorporating redundancy or enhancing the reliability of software and hardware in the design phase to mitigate this hazard (Eriksen et al., 2021; Martelli et al., 2021; Wróbel et al., 2018a). Complex systems like autonomous systems, software algorithms, and data interaction systems require more redundancy compared to mechanical systems such as ship-control and power systems. The stability of information and communication technologies and cybersecurity are also hotspots in current studies on technological factors. As a complex safety-critical cyber-physical system (CPS), MASS exhibits the following characteristics: highly dynamic and unstable

Table 6
The RIFs related to technology factors considered in the selected literature.

No.	References	T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8	T_9	T_{10}	T_{11}	T_{12}
1	Hoyhtya et al. (2017)			✓						✓	✓		
2	Utne et al. (2017)	✓				✓						✓	
3	Thieme et al. (2018)	✓	✓		✓	✓			✓				
4	Porathe et al. (2018)						✓	✓	✓				
5	Tam and Jones (2018)			✓						✓			
6	Wróbel et al. (2018b)	✓	✓		✓	✓	✓					✓	
7	Wróbel et al. (2018a)	✓	✓		✓	✓		✓			✓		
8	Shipunov et al. (2019)	✓		✓									
9	Vander Maelen et al. (2019)	✓				✓	✓		✓				
10	Banda et al. (2019)	✓			✓								✓
11	Zhang et al. (2019)		✓	✓	✓					✓			
12	Fan et al. (2020)		✓	✓	✓					✓			
13	Utne et al. (2020)	✓				✓	✓		✓				
14	Chae et al. (2020)	✓		✓		✓							
15	Bolbot et al. (2020)			✓			✓						
16	Felski and Zwolak (2020)		✓	✓	✓		✓					✓	✓
17	Goerlandt (2020)		✓										
18	Wu et al. (2020)	✓	✓			✓							
19	Zhou et al. (2020)	✓	✓	✓	✓								
20	Ventikos et al. (2020)	✓			✓		✓		✓			✓	
21	Ramos et al. (2020a)	✓	✓			✓					✓		
22	Chaal et al. (2020)	✓				✓		✓					
23	Zhou et al. (2021)	✓	✓	✓				✓			✓		
24	Chang et al. (2021)	✓	✓	✓		✓	✓						
25	Fan et al. (2021)	✓	✓	✓	✓								
26	Bolbot et al. (2021)	✓		✓	✓			✓					
27	Guo et al. (2021)	✓		✓									
28	Dittmann et al. (2021)		✓	✓						✓			
29	Martelli et al. (2021)	✓	✓			✓			✓				
30	Zhang et al. (2022b)	✓	✓										
31	Simola and Poyhonen (2022)	✓	✓	✓							✓		
32	Chou et al. (2022)	✓	✓										
33	Wang et al. (2022)	✓											
34	Johansen and Utne (2022)	✓				✓		✓					✓
35	Zhang et al. (2022a)	✓	✓		✓	✓							
36	Tusher et al. (2022)			✓	✓								
37	Luo et al. (2022)	✓	✓								✓		
38	Veitch and Alsos (2022)	✓						✓					
39	Fan et al. (2022)	✓		✓	✓					✓			✓

connections, high mobility, and massive bi-directional data exchange. Compared to traditional ships, the operation and decision-making of MASS heavily rely on information exchange between ships and ROC, ships and nearby ships, and ships and shore-based support, making these exchanges vulnerable to cyber-attacks with unpredictable consequences, encompassing human casualties, environmental pollution, and economic damage (Gu et al., 2021). Furthermore, the frequent human-system and system-system interactions, as well as the data exchange of various control, communication, and perception systems, contribute to an increasing number of non-reciprocal data exchange interfaces. Ensuring the availability, reliability, and integrity of exchanged data is especially important. The most widely used method for cybersecurity risk analysis is the Maritime Cyber Risk Assessment (MaCRA) model (Tam and Jones, 2019). Shipunov et al. (2019); Tam and Jones (2018) extended the MaCRA model and generated cyber risk lists of MASS based on historical cyber-attack data of traditional ships in their investigations of Advanced Autonomous Waterborne Applications (AAWA), Mayflower Autonomous Ship (MAS), and YARA unmanned ship projects, respectively. This pattern has influenced subsequent research on cyber risk analysis. Bolbot et al. (2020) utilized historical literature and existing vulnerability databases as data sources to develop the CYber-Risk Assessment for Marine Systems (CYRA-MS) based on Cyber Preliminary Hazard Analysis (CPHA). They identified and ranked scenarios where inland MASS navigation and propulsion control systems may be subject to cyber-attacks. The management and system design suggestions for specific scenarios were presented, namely: adding firewalls at interfaces between controlling systems, increasing communication redundancy between controlling systems, installing intrusion detection systems and eliminating external network links. Tusher et al. (2022) utilized a multi-criteria decision making (MCDM) framework to analyse the ability of MASS devices and systems to resist cyber intrusions. The results indicated that navigation systems are the most vulnerable to cyber intrusions, followed by ROC, while propulsion control system is the least vulnerable. Besides trust management within the network poses another risk within the system. Wang et al. (2022) stated that lacking identity authentication, message authentication, and trust censorship are the major reasons for data loss and spoofing. In response, an architectural framework for assessing trustworthiness in communication loops was developed based on blockchain technology.

The operation of MASS poses greater challenges than initially anticipated. It relies not only on various systems onboard but also on complete shore-based supervision facilities. However, few studies currently focus on the impact of shore-based equipment on the safety of MASS navigation. At the same time, ships with DoA encounter situations that will be increasingly common in the future. As a result, the shift in operation modes and the inclusion of autonomous systems also pose challenges to the regulation of various stakeholders. The development of more advanced vessel traffic management technologies is necessitated to address these situations.

4. Systematic risk analysis of MASS

The previous section classified and summarized RIFs in the selected literatures, analysing RIFs in the design, construction, regulation, and operation phases of MASS from a microscopic perspective. However, examining hazards and factors at the micro level can hardly capture the overall safety impact resulting from a single risk or a combination of risks at the causal level.

Systematic risk analysis of MASS takes a holistic approach, considering the entire system and utilizing a systematic methodology to assess associated risks. These studies aim to establish a comprehensive, precise, and systematic risk analysis process. Specifically, the analysis process should be applicable to most MASS systems (comprehensiveness), provide detailed insights into the nature of identified risks and confirm the level of risk (precision), and follow a structured, systematic flow (systematicity). As depicted in Figs. 1 and 23 papers related to systematic risk analysis of MASS are extracted from the final database through manual paper-by-paper analysis. This section will thoroughly discuss these papers from the perspective of data sources and risk analysis methods.

4.1. Data sources for systematic risk analysis of MASS

In order to gain a clear understanding of the data sources required for systematic risk analysis of MASS, a statistical analysis is conducted on the data sources utilized in these papers. The statistical results are presented in Fig. 5. Literature and expert opinions have consistently served as the primary data sources for systematic risk analysis of MASS. In addition, experimental data has never been utilized before 2022. Overall, there is a significant increase in publications utilizing historical data and expert opinions as data inputs in recent years.

Table 7 presents the statistical results of data sources utilized in systematic risk analysis studies. The statistical results show that out of 23 papers, 10 papers utilized historical data of traditional ships as input, including marine accident investigation reports and regional ship accident statistics, etc. Only Wu et al. (2020) utilized historical data as a single data input. Wróbel et al. (2017) utilized historical data and literature as inputs. Additionally, the remaining 8 papers utilized a dataset combining expert opinions as inputs.

Out of 23 papers, 15 papers sourced information from previous literature, with only 2 papers (Wróbel et al., 2020; Ventikos et al., 2020) utilizing literature as a single data source. They utilized the safety control structure developed by Wróbel et al. (2018b) as the basis of their studies. The remaining 13 papers utilized a dataset combining expert opinions or historical data as inputs. Notably, subjective expert opinions are the most frequently utilized input data, supported by 19 papers.

Furthermore, 4 papers utilized a combination of three data sources to construct a dataset. Zhang et al. (2022a) utilized historical data for qualitative analysis of ship systems that were still in the conceptual

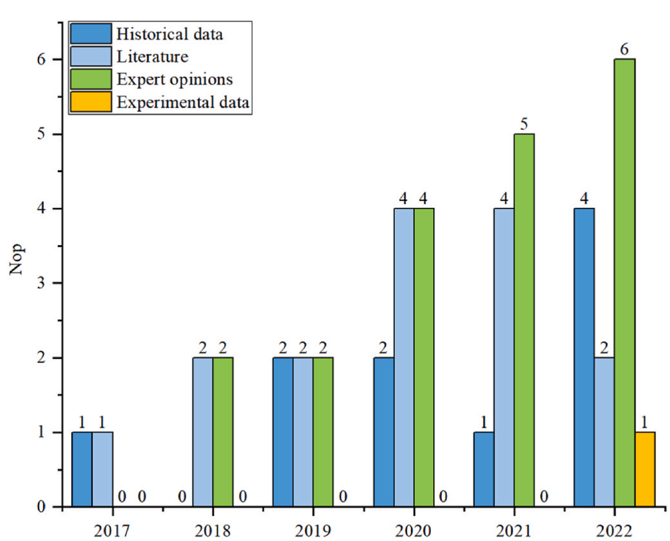

Fig. 5. Trends in data sources for systematic risk analysis of MASS by year of publication.

design stage, such as ship mechanical systems, and experimental data for quantitative analysis of the systems that were already in the experimental stage, such as autonomous navigation systems. In addition, expert opinions were utilized for the prioritization of indicators and hazard scenarios, and for the setting of node weights in the model. Zhang et al. (2019) combined historical data, literature review results, and expert opinions to determine the prior probabilities of a Bayesian network (BN) and establish a risk indicator framework. Banda et al. (2019) utilized marine accident statistics to identify common accident scenarios for autonomous ferries in a case study. Expert opinions from different industry fields and historical literatures are utilized to propose safety management strategies. Chaal et al. (2020) utilized existing literatures on MASS and its systems, currently available information from the maritime field, and the empirical knowledge of active seafarers to construct a hierarchical control structure framework applicable to MASS.

4.2. Methodology of systematic risk analysis of MASS

In this section, 23 papers are classified based on the primary risk analysis methods used. Since 17 of these papers utilized two or more risk analysis methods, the total count exceeds 23. Table 8 presents the classification results, including the names of risk analysis methods, brief descriptions, and a list of literatures utilizing these methods. As seen from Table 8, STPA is the most frequent risk analysis method among the existing studies related to systematic risk analysis of MASS. There are 8 papers utilizing STPA for qualitative risk analysis of MASS, followed by BN, Delphi method, and literature review. Both the Delphi method and brainstorming can support qualitative and quantitative risk analysis of MASS, but the analysis process often involve subjectivity. Besides, Failure Modes and Effects Analysis (FMEA), Hybrid Causal Logic (HCL) methodology, and Hierarchical Holographic Modelling-Risk Filtering, Ranking, and Management (HHM-RFRM) frameworks have also been used for both qualitative and quantitative risk analysis of MASS.

In order to track the distribution of academic enthusiasm for the major existing risk analysis methods and their introduction timeline to the field, a statistical analysis is conducted based on year of publication of these publications. As depicted in Fig. 6, STPA is the first risk analysis method applied to this field and still maintains a high level of academic interest as of the search data. BN gained increasing attention from researchers in this field after 2020. Similarly, FMEA, an established risk analysis method emerging in this field, has drawn attention from the academic community after 2021.

Fig. 7 depicts the combined use of risk analysis methods in the selected literatures. Among these methods, BN, STPA, Delphi, and literature review are most frequently utilized in combination with other risk analysis methods. While STPA is the most common method utilized for risk analysis of MASS, many studies solely utilized it for qualitative analyses. However, Chaal et al. (2022) employed STPA in combination with BN and utilized the results of STPA as input to BN, achieving Supervisory Risk Control (SRC) through online risk models. It is worth noting that methods like HCL and H-SIA incorporate multiple risk analysis methods, such as ESD, FTA, CoTA, BBN, and others. In conjunction with Tables 8, it becomes apparent that using a combination of qualitative and quantitative analysis methods is the predominant approach in this field.

4.3. Evaluation in risk analysis of MASS

The analysis of the methodology in the selected literature indicates that these methods represent different understandings of the risk analysis of MASS. Chen et al. (2021) classified risk analysis methods into three stages: qualitative analysis, semi-quantitative analysis, and quantitative analysis. Building upon this classification scheme, this study classifies the existing studies on systematic risk analysis of MASS into the following three stages.

Table 7
The statistical results of systematic risk analysis dataset by year of publication.

NO.	Reference	Year of publication	Historical data	Literatures	Expert opinions	Experimental data
1	Wróbel et al. (2017)	2017	✓	✓		
2	Wróbel et al. (2018b)	2018		✓	✓	
3	Wróbel et al. (2018a)	2018		✓	✓	
4	Zhang et al. (2019)	2019	✓	✓	✓	
5	Banda et al. (2019)	2019	✓	✓	✓	
6	Fan et al. (2020)	2020		✓	✓	
7	Wu et al. (2020)	2020	✓			
8	Wróbel et al. (2020)	2020		✓		
9	Chaal et al. (2020)	2020	✓	✓	✓	
10	Ventikos et al. (2020)	2020		✓		
11	Ramos et al. (2020b)	2020			✓	
12	Ramos et al. (2020a)	2020			✓	
13	Chang et al. (2021)	2021		✓	✓	
14	Zhou et al. (2021)	2021		✓	✓	
15	Fan et al. (2021)	2021	✓		✓	
16	Bolbot et al. (2021)	2021		✓	✓	
17	Guo et al. (2021)	2021		✓	✓	
18	Zhang et al. (2022b)	2022		✓	✓	
19	Chou et al. (2022)	2022	✓		✓	
20	Zhang et al. (2022a)	2022	✓		✓	✓
21	Chaal et al. (2022)	2022	✓		✓	
22	Luo et al. (2022)	2022		✓	✓	
23	Fan et al. (2022)	2022	✓		✓	

1) Qualitative analysis conducted through hazard identification that may exhibit some degree of subjective bias.
2) Qualitative analysis conducted through risk analysis methods.
3) Quantitative analysis conducted through the combination of hazard identification or risk analysis methods with risk assessment models.

These three stages are identified after the search. It should be noted that these stages are not mutually exclusive, as some studies may fall into more than one category. The classification here aims to cluster literatures with similar characteristics, providing a more straightforward overview of the various academic perspectives on systematic risk analysis of MASS.

4.3.1. *Qualitative analysis with focus on hazard identification*

The initial task of risk analysis is to determine the specific vital components included in the system, influencing new risks and potential consequences associated with the operation of MASS (Aven, 2016). Six out of seven studies that utilized either the Delphi method or literature review identified and prioritized hazards, establishing risk index systems.

As one of the pioneering studies in the final database to include a complete MASS risk index system, Wróbel et al. (2017) performed a quantitative hypothesis analysis based on existing accident reports of traditional ship to identify factors leading to MASS accidents and create a risk list. The study identified 21 causal factors, which were further refined and classified into five levels: external factors, organizational influences, unsafe supervision, preconditions, and unsafe acts. Similarly, based on accident reports and expert opinions, Wrobel et al. (2016) established a BBN structure, identified potential RIFs and events that may lead to accidents, and causal propagation relationships between them. Luo et al. (2022) constructed a risk assessment index framework for the navigation of smart ships by complementing and eliminating common risk factors of traditional ships through the Delphi method and brainstorming. Chou et al. (2022) combined experts' subjective evaluations of large MASS and objective accident data of large traditional merchant ships to assess the risk level of MASS accidents in terms of accident probability and damage. The study revealed that mechanical malfunction accidents pose the highest risk when sailing on the high seas, while collision accidents pose the highest risk when entering and departing from ports. Although the factors in the resulting risk index framework have a strong causal relationship with the occurrence of accidents, these studies lack the analysis of the causal relationship with factors at higher levels. Establishing causal relationships between different layers is crucial in transitioning from a flat risk list to a dimensional framework of risk indexes, helping designers recognize the source paths of potential risk factors in the initial design phase.

The primary challenge faced by most researchers in conducting ground-breaking qualitative risk analysis of MASS is the lack of available data. To overcome this, researchers initially utilized historical data of traditional ships combined with expert opinions to construct a risk list or framework applicable to MASS. Alternatively, some studies solely relied on expert opinions to modify and broaden the risk list of traditional ships. Although the Delphi method and literature review are convenient ways to understand the composition of MASS, relying solely on subjective data sources will lead to limitations and unpredictable incompleteness when conducting risk analysis on "unknown unknowns". This could ultimately lead to doubtful credibility of the risk list or framework.

4.3.2. *Qualitative analysis with focus on risk analysis*

In addition to qualitative analysis, which examines the causal relationship of RIFs, hazard analysis is another commonly utilized risk analysis method in the field. It helps identify hazardous actions or scenarios in a MASS system and provide risk control measures.

Several studies (Chae et al., 2020; Stringfellow et al., 2010; Zhou et al., 2020) have pointed out that increased system complexity results in the failure paths that are densely interleaved. Traditional hazard analysis methods, such as Hazard and Operability (HAZOP), FMEA, and FTA, are not directly applicable for the safety assessment of MASS. As the hazard analysis method that has received the most attention in systematic risk analysis of MASS, STPA was initially introduced by researchers (Wróbel et al., 2018a, 2018b). It has been applied to the risk analysis of autonomous merchant ships and remotely controlled merchant ships. Through adopting the top-down strategy, a safety control structure was constructed to describe the potential interactions between systems. A list of hazards that MASS may encounter and the likelihood that unsafe control actions may lead to hazards were provided. Ventikos et al. (2020); Wróbel et al. (2020) provided an in-depth analysis of the safety control structure developed in the study of Wróbel et al. (2018a). Wróbel et al. (2020) utilized STPA to obtain safety control actions corresponding to the safety control structure and provided a literature review of safety control actions that interacted in the structure. They summarized the existing research results and highlighted relatively scarce research directions, particularly concerning DoA3 MASS. The results revealed that most of the existing studies focus on the technical

Table 8
The statistical result of the risk analysis method in relative studies.

Methods	Description	Qualitative analysis	Quantitative analysis	Reference	Nop
STPA	STPA has gained popularity as a hazard analysis method in recent years and is widely utilized for hazard identification during the early development stages of complex systems. It adopts a top-down approach based on established system interaction structures and hazard lists to proactively identify unsafe control behaviours in the interaction processes among complex system components. STPA is an efficient approach for risk analysis of complex systems when available data is insufficient.	✓		(Banda et al., 2019; Chaal et al., 2020, 2022; Ventikos et al., 2020; Wróbel et al., 2018a, 2018b, 2020; Zhou et al., 2021)	8
BN	BN is an effective tool for uncertainty knowledge representation and inference. Both BN and STPA do not rely on a large amount of historical data (Veitch and Alsos, 2022). BN has rarely been utilized as a stand-alone method in the risk analysis of MASS. It is usually combined with other risk analysis methods and applied in the quantitative analysis process.		✓	(Chaal et al., 2022; Chang et al., 2021; Guo et al., 2021; Wu et al., 2020; Zhang et al., 2019, 2022a)	6
Delphi method	Delphi method draws on the knowledge and experience of domain experts to provide a structured and systematic understanding of rare, unimaginable, and unexperienced issues in the form of questionnaires. In related studies on risk analysis of MASS, the Delphi method is commonly used in the process of hazard identification and indicators prioritization.	✓	✓	(Bolbot et al., 2021; Chou et al., 2022; Fan et al., 2020, 2022; Luo et al., 2022; Zhang et al., 2019)	6
Literature review	Literature review is a retrospective analysis of previous research, a comprehensive analysis of avoidable information, and extracts available information in the field or similar fields.	✓		(Bolbot et al., 2021; Fan et al., 2020; Luo et al., 2022; Wróbel et al., 2020; Zhang et al., 2019)	5
FMEA	FMEA is a bottom-up risk analysis method widely applied in offshore safety and reliability analysis. FMEA evaluates a single potential failure mode in terms of Occurrence (O), Severity (S), and Detection (D) of potential failures in the system.	✓	✓	(Chang et al., 2021; Fan et al., 2021, 2022)	3
Brain-storming	Brain-storming is an innovative discussion method designed to get participants to develop more creative ideas. In related studies on risk analysis of MASS, brain-storming is often applied in the process of developing a risk system or risk list for MASS.	✓	✓	(Chaal et al., 2020; Guo et al., 2021; Luo et al., 2022; Zhou et al., 2021)	4
24 model	The 24 model, derived from Heinrich's Accident Causation Theory and the Swiss Cheese Theory, is based on behavioural safety theory and identifies the causes of accidents at both the organizational and individual levels. In related studies, the 24 model has been applied to analyse the direct and external causes of a given accident.	✓		(Fan et al., 2021, 2022)	2
H-SIA	The method Human-System Interaction in Autonomy (H-SIA) consists of two main methods, namely, Event Sequence Diagram (ESD) and Concurrent Task Analysis (CoTA). H-SIA considers MASS as a whole and analyses failure events in specific MASS scenarios, which are used to develop risk management measures.	✓		(Ramos et al., 2020a, 2020b)	2
HCL	HCL combines ESD, Fault Tree Analysis (FTA), and Bayesian Belief Network (BBN) to provide a comprehensive risk analysis of MASS. The framework of HCL is a three-layer model with ESD at the top layer, FTA in the middle layer, and BBN at the bottom layer.	✓	✓	(Wu et al., 2020; Zhang et al., 2022a)	2
HFACS	The Human Factors Analysis and Classification System (HFACS) method was derived from Reason's Swiss Cheese model and focuses on the classification of four levels of active failures and potential conditions, such as unsafe acts, preconditions for unsafe acts, unsafe supervision, and organizational influences (Chen et al., 2013).	✓		Wróbel et al. (2017)	1
HHM-RFRM	In related studies, HHM is used for identifying risk factors, and RFRM is used for screening and assessing risk factors.	✓	✓	Zhang et al. (2022b)	1
Hierarchical analysis	In related studies, Hierarchical Analysis (HA) is applied to predict navigational risk. The researchers have established a hierarchical structure containing the entire navigational risk for MASS, the category of marine accidents, the probability of an accident, and the damage and loss in one marine accident.	✓		Chou et al. (2022)	1

aspects of the operation and design of MASS. Few studies provided detailed analysis of communication and data transmission, while organizational and social factors are difficult to analyse in-depth due to the uncertainty of autonomous ships. Ventikos et al. (2020) further refined the classification criteria of DoA based on the IMO guidelines and identified the potential RIFs of different DoAs of MASS through STPA. The analytical results of STPA were classified according to the mitigable potential of risk, resulting in a list of mitigation measures for MASS with different DoAs. The results indicated that with an increase in DoA, there was a corresponding increase of the mitigation measures that may reduce risk. Zhou et al. (2021) improved STPA from a safety and security perspective and proposed a novel STPA-based methodology that synthesizes safety and security (STPA-SynSS). This approach aimed to identify a higher number of unsafe/unsecure control actions (UCA) and loss scenarios, generating more targeted hazard control strategies. Bolbot et al. (2021) developed a hybrid, semi-structured risk assessment process for the initial design phase of MASS, integrating safety, security, and cybersecurity concerns. This process identified and ranked hazardous scenarios while proposing risk control measures.

While most of the studies utilized STPA to analyse the failure events of interactions in systems, there are also some studies that used the results as guiding recommendations for the design and management of MASS. Utne et al. (2020) utilized STPA to identify real-time dynamic risks during the voyage of MASS. The results were utilized as the basis for BBN modelling to provide decision support for real-time ship operations. They proposed a theoretical framework for developing a ship

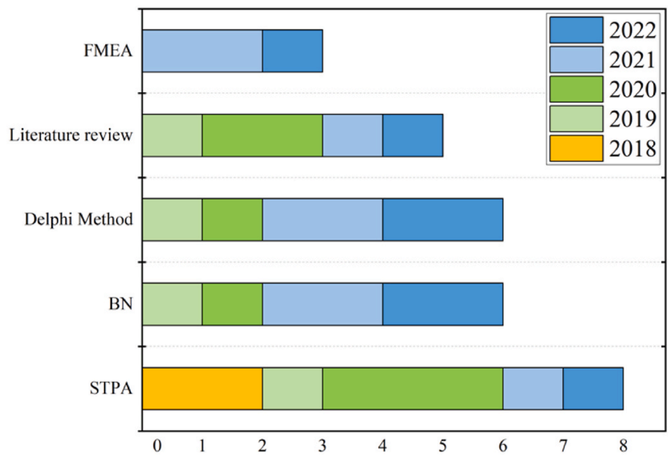

Fig. 6. Trend of Top 5 Risk Analysis Methods by year of publication.

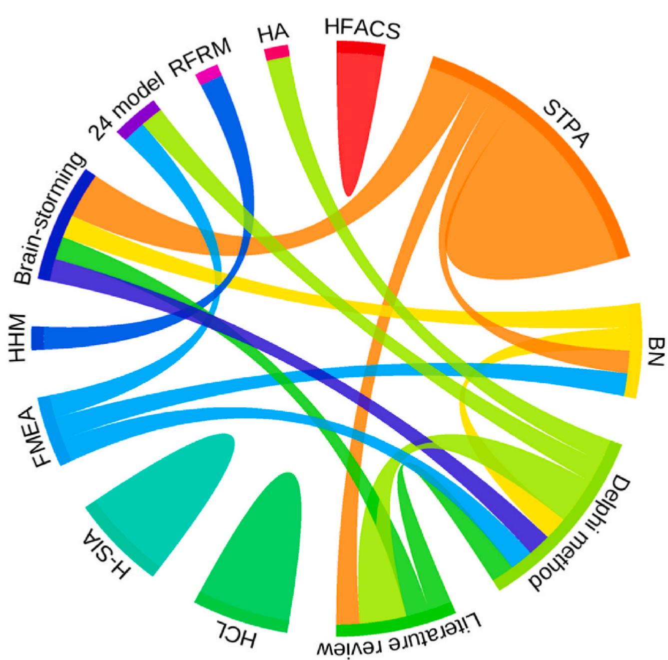

Fig. 7. Combined use chart for risk analysis methods.

control system towards supervisory risk control, which addressed the inability of STPA to quantify risk in the process of risk analysis. Johansen and Utne (2022) further improved this framework by incorporating the quantified results as input to a supervisory risk controller (SRC), thereby implementing a ship control system integrated with an online risk model. Nonetheless, such hazard analysis methods focusing on real-time effects, such as traffic and weather conditions around the ship, are not directly applicable to the systematic risk analysis of MASS.

4.3.3. Quantitative analysis with focus on modelling

Most of the studies mentioned above primarily focus on identifying RIFs and establishing risk index frameworks for MASS, with the ultimate goal of providing risk control recommendations. However, these studies are primarily qualitative, focusing mainly on hazard identification rather than risk quantification. This section summarises the analysis of all quantitative risk analysis of MASS.

Firstly, some studies have investigated whether the risk models of traditional ships can be directly applied to the risk analysis of MASS. Thieme et al. (2018) conducted a review of existing collision and grounding risk models of traditional ship. They found that these models typically utilize accident analysis data, expert opinions, or a combination of both as inputs. However, the scarcity of accident data and historical data for MASS makes it difficult to use these inputs for the risk model of MASS. Additionally, the risk models of traditional ships and some of the risk models that have already been implemented on MASS lack the analysis of subjective hazard actions and ship-shore and ship-ship communication. In many cases, these models assume no communication between ship-shore and ship-ship to simplify the analysis. Precisely these reasons make it infeasible to apply traditional ship risk models directly to MASS. However, some of these risk models and frameworks developed for traditional ships can serve as a foundation for developing risk models for MASS.

Subsequently, researchers had utilized a combination of multiple methods to quantitatively analyse the risk of MASS, including the Delphi method, literature review, and BN. BN is a commonly utilized risk model in existing studies, as presented in Table 8. Based on an existing ship collision model, Guo et al. (2021) utilized BBN to quantify the navigational risk of an autonomous ferry in a collision scenario. They explored changes in collision risk compared to traditional ferries, examined the form of change in accident type, and the shift in accident rates. Wu et al. (2020) demonstrated complete HCL modelling for MASS safety by extending the collision scenario for traditional ships. The experimental results proved that the introduction of MASS will reduce the risk of ship collision. However, this doesn't imply that RIFs show a subtraction trend, like disappearing from the risk list. It is possible that new RIFs that have not appeared in traditional ship collision scenarios may emerge. Zhang et al. (2019) identified the RIFs of traditional ships through a literature review. They constructed a navigation safety assessing model for unmanned ships in inland waters utilizing expert opinions and a fuzzy BN. Chang et al. (2021) established the MASS operational risk index framework through a literature review and expert questionnaire. They further assessed MASS operational risks by combining FMEA, Evidence-based Reasoning (ER), and Rule-based Bayesian Network (RBN). The results of MASS operational risk prioritization were obtained, namely "interaction with manned vessels and detection of objects", "cyber-attacks", "human error", and "equipment failure".

The above studies aim to analyse risks across all DoAs of MASS. Considering the differences in the composition and priority of the risk for different DoAs of MASS, the Operational Modes (OMs) of MASS determines its DoA. On the one hand, changes of the OMs result in changes among different DoAs, and new risks arise in association with such changes. As the autonomy level of the system changes dynamically, the responsibilities of humans in the "loop" also change, as highlighted by Ramos et al. (2020a). They conducted a risk analysis of complex systems from a holistic perspective, focusing on qualitative risk analysis between different system interactions. Following the HCL modelling approach, the Fault Tree (FT) was integrated into the improved H-SIA method to obtain the failure path of MASS. Ramos et al. (2020b) proposed an H-SIA approach for collision scenarios using ESD and CoTA. Additionally, Fan et al. (2021) established a generic four-step risk-informed framework applicable to the three OMs of MASS, applicable to manual control, remote control, and autonomous control. In the study, the 24 model was utilized to identify failures, and the risk priority number (RPN) concept in FMEA and expert scoring was utilized to define and quantify risks with the MASS model-bank allision as the input source. Then, Fan et al. (2022) also improved this framework by extending the fault identification scope of the 24 model for a decision-transparent traceability process. On the other hand, researchers have quantified the risk of MASS with different DoAs in different navigation phases. The four-layer risk index framework established by Fan et al. (2020) was applicable to four operational phases of DoA3 MASS, including voyage planning, berthing and unberthing, port approaching, and departing. Zhang et al. (2022b) utilized HHM to identify the main risk scenarios for DoA3 and fully autonomous ship (DoA4) MASS navigation phases, namely sailing plan decision, berthing and unberthing, port entrance and departure, and open water navigation. The RFRM model was utilized to prioritize RIFs, and the seven most crucial RIFs were identified, namely traffic flow, navigation environment understanding, ship-shore interaction capabilities, ship target identification capabilities, reliability of communication, professional skills, and situational judgment. Zhang et al. (2022a) conducted a qualitative and quantitative assessment of the overall risk of DoA3 MASS utilizing HCL, which was a combination of various risk analysis methods. Among them, ESD was utilized to establish a hazard scenario framework for MASS; FT was utilized to analyse non-human related mechanical events in hazard scenarios; BBN was utilized to analyse human factors-related events with strong uncertainty.

5. Discussion

5.1. The main findings of this study

The first five sub-sections below present the main findings in terms of hazard identification, and the last two present the main findings in terms of research methodology.

5.1.1. Unveiling statistical insights of publications

The systematic analysis of the literature indicates a growing academic interest in hazard identification and risk analysis of MASS since 2017, with two notable increases in 2018 and 2020. The journals with the most publications in this field are RESS, SS, and OE. RESS has continued to publish highly relevant literatures in this field from 2017 to 2022 and is currently on an upward trend. Among the active institutions in this field are NTNU, Aalto, and WUT, while the countries with the highest number of publications are Norway, Finland, China, Poland, and the UK. This distribution aligns with the geographic distribution feature that most autonomous shipping projects are concentrated in the EU, Norway, China, and Japan (Liu et al., 2022a).

5.1.2. Evolving perspectives on human factors

From the perspective of research content, the impact of human as a part of the "loop" on MASS safety is the main focus of RIFs research. Most existing literature has examined RIFs originating from humans themselves, including situation awareness, condition of operator(s), experience and training, competence of operator(s), automation-induced trust issue, information overload, and communication. However, it is generally accepted that there has been a shift in the experts' view of human factors (Chang et al., 2021), i.e., human factors have transitioned from human-oriented RIFs to design-induced defects. This shift becomes more significant as the DoA increases. Although the impact of pure human RIFs on safety is undeniable, as the DoA increases, they may not be the most critical factor in the operations of MASS. Instead, timely prevention and correction of hardware or software development defects can significantly aid in reducing the costs of correcting such errors during actual operation. Nonetheless, relevant studies for such RIFs are deficient in the existing literatures. Another emerging RIF is humanitarianism, as expert opinions shift. Only 3 papers mentioned this, with Luo et al. (2022) categorizing it as a social-environmental factor and Wahlstrom et al. (2015) identifying humanitarianism from the military field without specifying its classification.

This study further identifies maritime supervision, bridge resource management, and manning are the management-related RIFs. Maritime supervision is particularly noteworthy, appearing in 10 studies related to management factors, underscoring its importance. In contrast to the RIFs related to management factors listed in Table 2, emergency management mechanisms were not identified in the literatures, with only one similar RIF identified, which is system emergency mechanisms. Describing the emergency management mechanism as the uncertain form of MASS is a challenging task. Though its importance is recognized, the definition of emergency and the specific content of management still remain unclear, leading academic research demands more on ship software, hardware systems, and autonomous technology (Wróbel et al., 2020).

5.1.3. Ship-related factors: reliability takes center stage

Reliability of hardware is examined in all ship-related studies, with more than half of the literatures also examining maintainability of hardware and reliability of software and algorithms. As a result, reliability and maintainability of software and hardware are considered the most significant RIFs in ship-related factors. It is worth noting that MASS necessitates testing and validation before actual operation to minimize unforeseen potential risks and ensure the stability of software and hardware. However, current research on the risks associated with testing and validation of ship software and hardware systems is insufficient. Furthermore, there is limited research on RIFs related to reliability and maintenance of software and algorithms, compared to those related to ship hardware. Contemporary researchers tend to overlook the impact of software failures on safety, possibly due to the reliance on historical data, which often omits ship software and algorithm-related aspects.

5.1.4. Bridging gaps in environmental and ship-related studies

Only 4 studies mentioned ship conditions, and all of them conducted systematic risk analyses of MASS. Despite incorporating more advanced systems and technologies, MASS shares physical properties with traditional ships. Consequently, the physical properties of MASS do not change significantly compared to traditional ships, as well as similarities in physical environment, management factors, and other risk factors. However, the failure paths of accidents stemming from ship conditions remain unknown, possibly explaining the scarcity of research related to the risk analysis of ship conditions at this stage.

For the same reason, research on the risk analysis of environmental factors remains inadequate. Most studies examined two or more RIFs related to environmental factors, 9 studies examined three or more RIFs, and only 3 studies examined five or more RIFs. Among these RIFs, natural environment and traffic environment were mostly examined in the form of textual narratives, with limited quantitative assessment of their influence on ship safety. The current quantitative analysis of environmental factors primarily focuses on the impact of remote operators' work environment.

5.1.5. Navigating the technological landscape

The highest number of relevant studies examining technology factors is 39. Among these, 20 studies examined four or more RIFs related to technology factors. However, the distribution of RIFs related to technology factors in these studies is relatively scattered. Associated with the discussion of technology factors in the previous section, it can be deduced that the research directions of technology factors in the final database are also relatively scattered. Notably, autonomous perception technology, reliability of ICT, decision-making technology, and ship-control technology tend to appear in groups, representing the foundation of MASS navigation. Ensuring cybersecurity in the data transmission system and providing sufficient redundancy are crucial for the proper operation of the fundamental functions of MASS. While 18 and 14 studies examine these two RIFs, respectively, none quantified the specific amount of redundancy required.

5.1.6. Data source credibility challenges

From the perspective of research methodology, the risk analysis of MASS faces the challenge concerning the credibility of data sources. Five studies relied solely on historical data or expert opinions as their input source, and all of these studies were published before 2020. Conducting a comprehensive and systematic quantitative analysis of MASS safety utilizing just one data source proves difficult. However, the form of the dataset could help mitigate this limitation. According to Table 7, datasets incorporating expert opinions have become the prevailing trend in this field since 2020. Out of 19 studies that utilized expert opinions as input, 17 also integrated other objective data into the analysis.

Furthermore, there were no publications on WOS Core Collection applying experimental data to hazard identification and risk analysis of MASS before 2022. However, along with the disclosure of MASS real-ship trials data or part of the technical experimental data, some researchers have applied such data to the risk analysis of MASS (Zhang et al., 2022a).

5.1.7. General practice for quantitative risk analysis of MASS

The findings reveal that literature review, ESD, and the 24 model are the primary hazard identification methods. For systematic risk analysis of MASS, the most frequently utilized risk analysis methods are STPA and HFACS. While STPA, lacking a quantitative risk analysis process, typically relies on existing control structures and hazard lists. In-depth analysis shows that 12 studies conducted quantitative risk analysis of MASS, utilizing methods such as BN, FT, FMEA, Delphi method, and brain-storming as the primary risk quantification methods. Among these methods, BN stands out as the most frequently utilized modelling method, utilized in 6 studies. In summary, combining the above hazard identification methods and risk quantification methods is a common practice in quantitative risk analysis of MASS. However, from the perspective of research content, only five studies have developed complete risk models, and most of them lack a detailed analysis of technology factors.

5.2. The research directions of risk analysis of MASS

5.2.1. Shifting focus and emerging challenges

Firstly, due to the current scarcity of available data, academic attention still focuses on human-driven RIFs in the context of MASS. However, experts' revised views on human factors and the progress of real-ship trials have led to a shift in attention towards the manning of ROC, management of operators, training of operators, and procedures of operating in future human factors research. Secondly, for autonomous onboard systems, even though software errors can be rectified in the form of system upgrades, addressing hardware defects is challenging during actual operation. Therefore, it is crucial to prevent development defects in the design phase, and conducting thorough testing and verification of systems can effectively address such potential risks. However, research in this field is currently lacking. As autonomous technology advances and real-ship trials keep improving, studies on software reliability and maintenance will obtain available data for risk analysis. Thirdly, security and cybersecurity are critical issues that require attention before operation. A great range of attack instruments, both traditional and emerging, in information technology, such as boarding, hijacking, and network intrusions, may occur collectively. Network intrusions to ROC may cause multiple ships to lose control simultaneously. Real-ship trials should focus on scenarios where traditional and emerging intrusions could occur in different combined forms to obtain comprehensive data. Fourthly, autonomous technologies form the foundation for MASS operation, but the RIFs related to these technologies often lack a specific form and are challenging to quantify. Consequently, redundancy is one of the critical technology factors that necessitate in-depth analysis at the design stage. Quantifying redundancy poses a pressing challenge that requires urgent resolution.

In general, the aforementioned studies related to these RIFs represent a step-by-step exploration of the specific form of MASS in current academia, with the common goal of facilitating the introduction of MASS. Meanwhile, these studies serve as the basis for developing well-established safety management systems for maritime administrations.

5.2.2. Advancements in methodology for risk analysis of MASS

The qualitative analysis process is no longer adequate for meeting the demands of risk analysis in the initial design phase of complex systems due to its subjective nature. Moreover, relying on single data sources, such as historical data with inapplicability and expert opinions with subjectivity, lacks wide applicability to support the quantitative analysis of RIFs. Researchers currently tend to use combined datasets and combined risk analysis methods. Additionally, the study identified a total of 12 studies on quantitative risk analysis of MASS, with 10 of them published between 2021 and 2022. Quantitative risk analysis of MASS is a major research direction in this field for the future as if MASS risk cannot be assessed quantitatively, the established safety management system does not motivate industrial professionals for its implementation. This is potentially due to their effects being invisible in a state-of-the-art risk assessment (Yang et al., 2014). Currently, BN stands as the most common method for building models in quantitative risk analysis of MASS.

5.2.3. Unresolved challenges and opportunities on research methodology

There remain several unresolved issues. On the one hand, both STPA and BN share the advantage of being accommodative to both subjective and objective data, making them suitable for risk analysis scenarios with limited available historical data for MASS. However, the combination of STPA with risk models for quantitative analysis is rarely observed in quantitative risk studies. This could be attributed to several reasons: STPA relies on a well-established systematic interaction framework and hazard list while lacking a systematic approach to identifying hazards and establishing such a framework during the analysis process (Bolbot et al., 2021).

On the other hand, data with subjectivity and inapplicability continue to serve as primary sources of input datasets, often leading to biased analysis outcomes. One solution being explored to address this issue is the use of datasets that include real-life ship trial data. Consequently, future risk analyses of MASS are expected to rely on outputs derived from real-ship trials. Moreover, statistical results indicate that the distribution of countries or regions of authorship is similar to the distribution of autonomous shipping projects. Researchers from these countries or regions at the forefront of MASS development may be one step ahead in adopting real-ship trial data for risk quantification analysis of MASS.

5.2.4. Quest for acceptable criteria

The acceptable criteria in quantitative risk analysis are currently lacking. On the one hand, establishing acceptable criteria for risk can enhance the scientific and applicability of quantitative risk analysis. Reasonable acceptable criteria for risk are fundamental to risk quantification analysis, which, in turn, serves as the crucial foundation for proposing risk control measures. Divergences in the inter-individual understanding of risk lead to differences in individual standards of risk acceptability. Therefore, developing reasonable acceptability criteria for risk is a prerequisite to proposing practical risk control measures. In this context, Fan et al. (2022) provided a new perspective on this issue, selecting the operation mode with the lowest risk and uncertainty by comparing the quantitative risk under different operation modes. On the other hand, acceptable risk levels are intrinsically linked to the capacity of risk control measures. The available resources for controlling risks are often limited in practical risk management. Fischhoff (1981) contended that the issue of acceptable risk is inherently a decision-making problem, where the selection of acceptable risk is contingent on the outcome of decision-making rather than the inherent level of risk present. Currently, a limited amount of information is available regarding the acceptable risk criteria for MASS. Rødseth and Burmeister (2015) defined an acceptable risk level for MASS as being no higher than that from a traditional ship. However, this definition is not a general standard that can be used for MASS risk management. At this point, risk matrix serves as a more suitable representation of acceptable risk standards. Fan et al. (2024) proposed a framework for designing risk matrices based on fuzzy Analytic Hierarchy Process (AHP). The proposed framework comprehensively considers the uncertainty in MASS risk analysis, filling the existing gap in the creation process of MASS risk matrices.

5.3. Biases and limitations

This research is subject to certain limitations. Firstly, there is a degree of subjectivity involved in the search process. Although the literature selected from the WOS core collection encompasses representative studies in the field of hazard identification and risk analysis of MASS, the chosen keywords may not be exhaustive in retrieving all relevant literatures due to the diversity and richness of linguistic expressions. Furthermore, manual screening is utilized to exclude low-relevance literatures, which inevitably brings a degree of subjectivity. Future studies can improve the quality of literature retrieval, screening, and classification by expanding the search database and adopting diverse keyword collocation or bibliometric methods.

Secondly, to ensure the validity and forward-looking nature of the established risk list, this study manually refines the RIFs and takes a relatively macroscopic approach. Uncertainty is one of the key concepts in risk analysis (Aven, 2016) and has been present throughout the process of MASS hazard identification and risk analysis. The study adopts a manual, paper-by-paper reading approach to extract RIFs that may impact the safety of MASS from narrative text, study objects, and diagrams in the selected literatures, from which a risk list is constructed. However, this process is subjective and may result in some omissions. To address this, future studies could incorporate text mining techniques to extract RIFs from the selected literature. Additionally, most studies tend to rely on the experience and knowledge of domain experts and front-line crew members for hazard identification. Since real-ship trials for MASS are currently in a small-scale experimental stage, experience in real-ship trials and MASS is relatively limited and not sufficiently comprehensive. Therefore, the data sources for extracting RIFs in this study also entail a certain degree of subjectivity and uncertainty. In general, the risk list presented in this study is not a comprehensive catalog of risks. It attempts to explain the potential “unknown unknowns” and “known unknowns” that may arise in the design, operation, and regulation of MASS.

6. Conclusions

This study presents a comprehensive review and summary of hazard identification and risk analysis of maritime autonomous surface ships based on 62 selected literatures spanning from 2015 to 2022. Key metrics in terms of journal, year of publication, countries or regions of authorship, and institution are provided, revealing a discernible increase in academic interest since 2017, with significant peaks in 2018 and 2020. Journals such as Reliability Engineering & System Safety, Safety Science, and Ocean Engineering have emerged as key contributors to this evolving discourse.

The risk influential factors are classified into human factors, ship-related factors, environmental factors, and technology factors. Both the prominent factors and the relatively overlooked factors in the existing literature on hazard identification and risk analysis of maritime autonomous surface ships are explored to reveal a growing academic interest, geographic trends, and shifts in focus. The study highlights a shift in focus within human factors research, transitioning from traditional human-oriented risk influential factors to a heightened awareness of design-induced defects. Humanitarianism emerged as a novel consideration in the safety context of maritime autonomous surface ships. Maritime supervision, bridge resource management, and manning are identified as crucial management-related risk influential factors, underlining their significance in ensuring the safe operation of maritime autonomous surface ships. While the study identifies technology factors as a significant research area, the lack of a specific form for risk influential factors in this domain and the challenge of quantifying redundancy are emphasized. Autonomous perception technology, reliability of Information and Communication Technologies, decision-making technology, and ship-control technology are identified as foundational elements requiring focused analysis.

Statistical analysis of systematic risk analysis studies focused on data sources and methodologies, revealing a positive trend in incorporating real-ship trials data, enhancing analysis credibility. Firstly, the transition of utilized datasets from reliance on historical data and expert opinions to that incorporating expert opinions since 2020 signifies a positive shift in research methodology. Secondly, with the first application of experimental data in 2022, the utilization of experimental data has proven crucial in overcoming the challenges associated with subjective and historical data sets. Finally, quantitative risk analysis, particularly through methods like Bayesian Network, has emerged as a major focus for future research.

The future developments in this field have been proposed in association with the statistical results, including human-driven risk influential factors and manning, addressing hardware defects, security and cybersecurity, redundancy in technology factors, and quantitative risk analysis. Attention on human factors research reflects evolving expert views, stressing the critical importance of preventing hardware defects through testing and verification of systems in the design phase. In-depth analysis of redundancy in technology factors is identified as a pressing challenge that requires urgent resolution to ensure the stability and proper operation of maritime autonomous surface ships. The study advocates for an increased focus on quantitative risk analysis, emphasizing the necessity of assessing risk quantitatively to motivate the implementation of safety management systems.

CRediT authorship contribution statement

Juncheng Tao: Writing – original draft, Validation, Methodology, Conceptualization. **Zhengjiang Liu:** Validation, Funding acquisition, Conceptualization. **Xinjian Wang:** Writing – original draft, Validation, Methodology, Conceptualization. **Yuhao Cao:** Writing – review & editing, Validation, Conceptualization. **Mingyang Zhang:** Writing – review & editing, Validation, Conceptualization. **Sean Loughney:** Validation, Writing – review & editing. **Jin Wang:** Writing – review & editing, Validation, Methodology. **Zaili Yang:** Writing – review & editing, Validation, Funding acquisition, Formal analysis.

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.

Data availability

Data will be made available on request.

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