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Letting losses be lessons: Human-machine cooperation in maritime transport

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A B S T R A C T

Navigation safety has been a critical guarantee of global shipping, and it becomes more challenging given the increasing employment of advanced technologies and novel ship design in the era of Maritime Autonomous Surface Ships (MASS). The human-centred risk analysis of human-machine cooperation is scarce in general and emerging in maritime transport in specific. This paper aims to develop a new approach enabling the analysis of significant risk influencing factors (RIFs) in human-machine cooperation through an in-depth investigation of the occurred mistakes and violations in the cooperative operations of seafarers and machines in maritime transport. Its novelties consist of (1) a novel approach to analysing and quantifying the connectivity between humans and machines in safety-critical operations, (2) new integration of the frequency and impact of RIFs in the human-machine cooperation model, and (3) ultilisation of graph theory to generate a network to analyse critical human-machine RIFs and their interactions with the system. The connectivity analysis of RIFs is conducted through a weighted undirected network, showing the features of RIF connectivity accommodating the closed-loop system. The proposed novel approach, which combines the frequency and impact features to identify critical RIFs and analyses graphical features, will aid to realise the human-centred risk analysis for MASS. The findings make contributions for ship designers to rationalise the clustering design of function-based automation and training organisations to improve seafarer skills by rationally considering the identified risk-based human-machine cooperation features, and providing new competence schemes that can fit the demands of MASS in future.

1. Introduction

By January 2023, the global fleet comprised 105,493 vessels weighing 100 gross tons or more, and international trade volume reached 12,027 million tons in 2022, highlighting its crucial role in global transportation [63]. Navigation safety has been a significant guarantee of global shipping, however, the introduction of advanced technologies and novel ship design in the era of Maritime Autonomous Surface Ships (MASS) demands new studies on human's role in navigation safety. Although there are several aspects associated with navigation safety, including humans, vessels, environment, and organisation, the interactions between humans and machines are among the most prominent due to the increasingly popular evaluation of human-machine interface (HMI) and human-machine cooperation [24, 36,42]. Their dynamic interaction process in a system is often tested using simulation, and the causal relationship is investigated through risk analysis models [36,43]. So far, current state-of-the-art methods have failed to demonstrate quantified risk levels of entire systems in terms of dynamic changes among system elements and human competencies. It is therefore essential to understand, analyse and quantify the hidden intercommunication mechanism between humans and machines. The connectivity patterns among risk factors in human-machine systems have yet to be harnessed and the principle of utilising identified features to enhance system performance from a human-centred perspective remains unclear, wanting a new solution to be found. Within this context, this study aims to identify and analyse critical risk influencing factors (RIFs) in human-machine systems, through the development of a new framework of risk-based human-machine cooperation feature configuration, to realise function-based seafarer competency training and to pioneer human-centred design for human-autonomy systems in maritime operations.

The shipping industry has faced a transformation from working on

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conventional ships to navigation with contemporary ships with high levels of automation, digitalisation, and decarbonisation, where human-machine cooperation can be seen in various autonomous assistance systems. To be specific, the MASS innovation has been assessed using the Technology Adoption model, proving the significance of human capital and its necessity to be considered in relevant studies and future policy [28]. To maintain safe operations, the focus has to be given to the process of humans manipulating machines, e.g., cooperation between humans and machines. Furthermore, emerging of the MASS featured with different autonomy levels of ships, has attracted industrial concerns about safe and reliable operations during various types of interactions between human operators and automation sub-systems [18]. Therefore, understanding the cooperation between humans and machines is pivotal for ensuring safe navigation for contemporary vessels. Previous studies on HMI mainly investigate the effects of system design and interfaces on human performance, contributing to function design and validation from a machinery perspective [8]. However, the input and output of machine systems connecting with human competencies have not been addressed. Specifically, the human-centred analysis of significant RIFs in human-machine cooperation is scarce. Thus, proposing a systematic analysis framework of human-machine systems from a human perspective will reveal risk features of the system and the interaction among RIFs, providing insights into maritime training and ship design. Therefore, this paper investigates the significant RIFs in human-machine cooperation, mainly represented by mistakes and violations in the cooperative operations of seafarers and machines in maritime transportation.

The human-machine cooperation can be investigated through two aspects, one is the machine-centred analysis of a system to achieve expected functions from a micro perspective, which can be validated through simulation and experiment; the other is the human-centred aspect to model the human-machine interactions from a systematic perspective. This study mainly focuses on the latter aspect by proposing a novel approach to investigating risk-based RIF connectivity among deficiencies in human-machine systems. Consequently, seafarer competencies in maritime systems are analysed to address RIFs and their associations with machine sub-systems through a historical accident-driven approach.

This study pioneers a novel approach to analysing connectivity between humans and machines considering their frequency and impact features in safety-critical operations. Through a graph-based approach, a weighted undirected network model is developed to identify critical human-machine RIFs consisting of human competencies and machinery elements with specific functions. A weighted undirected network is employed because it allows for weighted evaluations between seafarer competencies that do not reveal single directional influence. Then, accidents occurring in restricted waters are selected from a global perspective to generate the database, serving as a case study to demonstrate how frequently an RIF happens and the extent to which each RIF impacts accidents. The choice of restricted waters lies in the higher level of human involvement in the accidents [24]. Highlighted RIFs with diverse graph theoretical features in human-machine cooperation are identified and analysed as a benchmark, revealing implications in terms of future ship automation and seafarer training in the investigated waters and beyond towards regions of other risk features.

The rest of the paper is structured as follows. The literature review of human factors in maritime safety and their interdependency analysis model is conducted in Section 2. Next, Section 3 proposes the methodology of human-machine cooperation analysis involving human competencies and machine sub-systems. Section 4 examines the proposed approach by analysing accident data from restricted waters from a global perspective, followed by implications. Finally, Section 5 concludes the paper.

2. Literature review

2.1. Human factors in maritime transport

Human factors in maritime transport have been investigated to identify critical RIFs and their association with maritime operations through various approaches and models. Typically, a data-driven Bayesian network (BN) was utilised to model the interdependency among the RIFs and causational analysis in terms of different maritime accident types [23]. This methodology was also applied to analyse port hazardous cargo accidents, revealing predominant safety issues, inadequate supervision, intellectual issues, and violations [39]. Targeting specific waterways, such as Three Gorges Reservoir, investigations were conducted to analyse grounding accidents using the BN [37]. To evaluate the performance of a seafarer prior to his designation, the BN enabled to quantify their performance reduction resulting from insufficient recuperative rest [55].

Moreover, BN was integrated with other methods to offer rational strategies for maritime management and accident prevention. To be specific, the BN and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) were utilised with statistical methods to select the best-fit strategies for maritime accident prevention [15,27]. To improve the robustness of the data-driven BN, the least absolute shrinkage and selection operator (LASSO) algorithm was integrated to optimise the feature selection process [26]. Taking advantage of the classification capability of the Technique for Retrospective and Predictive Analysis of Cognitive Errors (TRACEr) [30], it was combined with the BN to assess human errors in collision risks with a focus on human-centred design [60]. The utilisation of a Functional Resonance Analysis Method (FRAM) and Dynamic Bayesian Network (DBN) enabled ship pilotage operation analysis, identifying inadequate human look-out as the most influential factor [32]. Furthermore, the BN can be integrated with the Human Factor Analysis and Classification System (HFACS) to facilitate qualitative and quantitative modelling in maritime transport and analyse the potential errors and violations of seafarers [64]. The study on the effects of human fatigue on maritime groundings revealed that vessel certifications, manning resources, and quality control were critical factors related to fatigue management aspects [3]. Additionally, other data-driven methods have been utilised to analyse important human factors in maritime accidents, for instance, Random Forests (RF) and Multiclass Support Vector Machines with Boolean Kernels (MSVM-BK) [19]. A graphical network model was introduced to represent imprecise probabilistic inference in ship collision accidents, demonstrating the important role of human and organisational factors (HOFs), and that the relative bearing, TCPA, and presence of other ships, influenced the ship collision probability [17].

In the context of a comprehensive systematic framework, the HFACS has been important and popular in maritime accident investigations [14]. It provides a hierarchical relationship among unsafe acts, pre-conditions, unsafe supervision, and organizational influences, which explains the occurrence of accidents at different levels [10]. In addition, it demonstrates descriptive information on errors and violations when operators manipulate devices and equipment, explaining the process of human-machine interaction in maritime transport. When the HFACS was used with BN, the risk factors including human-machine cooperation affecting allision accidents can be analysed during port manoeuvres [9]. Integrated with the Analytical Network Process (ANP), it provided advantages of weighing accident causes to cargo ships [4]. Combined with the Success Likelihood Index Method (SLIM), the HFACS was used to calculate seafarers' errors in maritime pilot transfer operations [7]. In terms of different types of vessels, such as passenger vessels, the framework was modified with analytical methods to analyse HOFs [68]. In addition, another systematic approach, i.e., the Systems Theoretic Process Analysis (STPA), was applied to analyse hazards in inland passenger ship operations, which delivered the identified Unsafe Control Actions (UCA) in a ship bridge and highlighted the human factor as the most contributory one [62].

To reduce human errors, several approaches have been utilised in maritime operations to calculate human error probability (HEP). The Cognitive Reliability and Error Analysis Method (CREAM) model was widely used to quantify human reliability analysis [6]. It can be integrated with Event Tree Analysis (ETA) - Fault Tree Analysis (FTA) to conduct qualitative and quantitative analyses of human-related and non-human-related events [53]. Through the use of Evidential Reasoning (ER) and Decision Making Trial and Evaluation Laboratory (DEMATEL), the CREAM enabled the calculation of HEP so as to provide suggestions to reduce human errors [66]. Moreover, the Success Likelihood Index Method (SLIM) was extended with fuzzy logic for the Ballast Water Treatment (BWT) system in the ship to calculate HEP [5]. Integrating with FTA, the SLIM was used to investigate container loss risks, showing that safety culture, experience, and fatigue were highly influential factors affecting crew performance [21]. Because human factors are primary causes of marine oil spill pollution [16], the SLIM can be used to calculate the HEP of bunkering operations, and the results helped prevent ship-based oil spills [38].

Several critical human factors and relevant scenarios are highlighted in maritime transportation. The situational awareness (SA) errors in collisions were identified using Endsley's model and analysed to represent associations with contributing factors for duty officers, identifying significant collision causes including inadequate operation planning, inadequate bridge design, insufficient training, communication failures, and distracting elements [58]. The identification of SA information requirements of navigators could also be achieved through an interview using Goal-Directed Task Analysis (GDTA) [59]. Regarding fatigue factors in the maritime field, it was evident that fatigue was a critical human factor [26] and positively correlated with mental workload, especially in the night shift among Vessel Traffic Services (VTS) [47,48].

Recently, the significance of human-centred research in MASS has arisen [29,41]. A navigational risk framework consisting of human, ship, environment, and technology aspects was proposed for remotely controlled crewless ships, which assisted in the design process and operational planning of remote-control centres [22]. The grey and fuzzy theories were utilised to investigate the decision-making prioritisation for autonomous ship manoeuvring [67]. Also, a neurophysiological approach has been adopted to analyse and validate maritime safety systems [25]. For instance, the electroencephalographic (EEG) was utilised to validate the Human Risk-Informed Design (HURID) framework, showing a statistically significant lower mental workload and stress, and higher attention while performing critical shipboard tasks with the HURID [56]. The psychology questionnaire was utilised to analyse the personality and aggression levels of seafarers, proving the resilient personality among master mariners and 33% of the students with overcontrolling personalities [44]. A notable correlation was discovered between crew burnout and job satisfaction levels and fatigue [20].

However, current research on calculating the HEP overlooked the impact of RIFs, leaving a significant research gap in RIF assessment in maritime transport. Without considering the impact of each RIF, it is impossible to clarify risk levels of maritime transport given some RIFs with a low frequency in overall accidents but a high impact (i.e., repeated occurrence) in a single accident.

2.2. Human-machine cooperation in the maritime field

Given new technologies in the era of MASS, there are some studies on human-machine cooperation in the maritime field. Instead of merely replacing human work, the evolving human-in-the-loop configurations necessitated the creation of new roles and the redefinition of existing expertise to assess maritime operations and meet systematic requirements and changes [31,52]. To develop the dynamic analysis for the HMI function design, the Information, Decision, and Action in Crew Context (IDAC) model was combined with the simulation system to avoid human errors in the interaction [34].

Classical models and approaches to human factor studies for conventional ships can be used for human-machine cooperation. Technique for Human Error Rate Prediction (THERP) and BN model were utilised to calculate HEP focusing on human-autonomy collaboration, which provided suggestions for the Shore Control Centre (SCC) construction and operator training [70]. The Success Likelihood Index Method (SLIM) was combined with an interval type-2 fuzzy sets (IT2FSs) approach to predicting operational errors based on the human-machine interface (HMI) in autonomous ships, where the IT2FSs tackled the decision-making uncertainty and SLIM handled HMI errors [43]. The SLIM was also integrated with STPA to calculate the HEP in HMI, proving the importance of human performance in the interaction among humans, machines, and software [2]. The risk appetite-oriented collision avoidance decision-making system (RA-CADMS) was proposed utilising human-machine interaction principles to facilitate automatic ship collision avoidance for MASS under remote control [65]. Moreover, the framework of an HMI-oriented Collision Avoidance System (HMI--CAS) was developed to enable automatic collision avoidance and share the decision-making with human operators to take control when necessary, which was validated through simulation [36]. An ETA method was used to evaluate the seafarer's performance in the human-machine relationship, showing that additional alarms prevented further deterioration in fault recognition [13].

Considering complex interactions among humans, machines, and software, the Systems Theoretic Accident Model and Process (STAMP) model was used to analyse ship allision accidents in narrow waters, identifying violations of safety constraints at control structures [12]. It addressed the features of system-based, dynamic, and complex situations, but did not demonstrate the connection degree of the identified causes. Aiming at complex human-machine technical systems, the STPA and Markov chain (MC) methods were used to simulate interactions and reveal the characteristics of risks during ship navigation [40]. The results showed the significant role of external environmental disturbances in terms of randomness and complexity. However, the issue of how the disturbance dynamically interacts with other elements in the human-machine system has not been revealed. With regards to the SA evaluation, the head-down time of navigators was measured to illustrate the human and machine interaction and effects of augmented reality (AR), which showed the use of AR significantly reduced head-down time and occurrences but did not improve mean SA [35]. To illustrate SA requirements for human supervisors in collision avoidance, a goal-directed task analysis was conducted to find increased cognitive activities in human autonomy tasks and the significance of transparency for a safe and effective system [46]. Another instance of human-machine collaboration was evident in cyber-physical systems (CPSs) through safety and security analysis, which incorporated information technologies into control frameworks and modified interactions between automation and human operators [33].

Although human-machine cooperation in the maritime field is still in its infancy, other sectors with higher levels of automation, such as the road sector, witness more quantitative approaches to human factor investigation and help define specific metrics [51]. In order to design automated vehicles, automation-related accidents in transport modes (aviation, maritime, and rail) were investigated using the AcciMap technique and network metrics [54]. Similarly, human-machine cooperation in the maritime field can learn lessons from others. To evaluate the seafarer competencies and their interactions with machines, a dynamic model in shipping was developed referring to Crew Resource Management (CRM) and the International Convention on Standards of Training, Certification and Watchkeeping for Seafarers (STCW), to qualitatively analyse seafarer competencies in a closed-loop mode [24].

Previous studies on HMI evaluation and systematic risk analysis of human-machine cooperation neither address the association between seafarer competencies and machine systems, nor quantify the effects of such RIFs on system safety. Therefore, it is urgent to deploy a novel approach to uncovering the interaction among systematic RIFs in human-machine cooperation. This study pioneers a graphical methodology to reveal the RIF connectivity of seafarer competencies in human-machine systems through a human-centred risk analysis.

2.3. New contributions

This study proposes a new methodology to analyse human-machine cooperation in maritime transport from a human-centred perspective, utilising graph theory to address critical RIFs through a data-driven approach. Although targeting maritime transport systems, the new framework is generic in nature and hence can be adopted to analyse HMI and human-machine cooperation of other systems involving automation and autonomy. More specifically, its novelties and contributions consist of:

- Proposing a novel approach to analysing connectivity between humans and machines in safety-critical operations through historical accident data.
- Pioneering the integration of the frequency and impact of seafarer competencies in the human-machine cooperation model.
- Utilising graph theory to generate a network to analyse critical human-machine Risk Influential Factors (RIFs) and their interactions with the system.
- Generating insights into enhancing human-machine cooperation in terms of Maritime Autonomous Surface Ships (MASS).

The study reveals the significance of RIFs in dynamic human-machine cooperation and their graphical features in maritime transport. The proposed novel approach that combines, for the first time, the frequency and impact features of seafarer competencies to identify critical RIFs and evaluate their graphical implications will pioneer the human-centred risk analysis in connectivity analysis between humans and machines in the maritime field. It can help ship designers rationalise the clustering design of module-based automation with optimised displays and seafarer training organisations to enhance seafarer competencies in human-machine cooperation tasks, providing insights into future development of MASS.

3. A graph-based approach for human-machine cooperation analysis

To analyse the risk level of the human-machine system, a graph-based approach is utilised, as illustrated in Fig. 1. First, the RIFs from seafarer competencies and other elements in systems are identified through the STCW code and literature review. Subsequently, a human-machine cooperation model is constructed using a closed-loop structure. Then, the graph-based approach is proposed to generate a connectivity matrix, followed by the creation of a weighted undirected network. At last, network features are calculated using graph theory to illustrate the risk level of human-machine cooperation.

3.1. Seafarer competency identification

To investigate human-machine cooperation in maritime operations, one needs to analyse two main components in the process, i.e., humans and machines. By reviewing international codes and literature, the human-related components were represented by seafarer competencies involving human and organisational factors. They were identified based on the competence requirement outlined for officers in STCW Code Table A-II/1, and for crisis management for senior officers as detailed in STCW Code Table A–V/2. The STCW Code Tables are mandatory, representing the minimum standards of competence requirement for seafarers, which are used in maritime professional training. Referring to CRM in aviation [45] and Bridge Resource Management (BRM) in the maritime sector [61], seafarer competencies within the human-machine system are outlined in Table 1. The phases of input, process, output, and

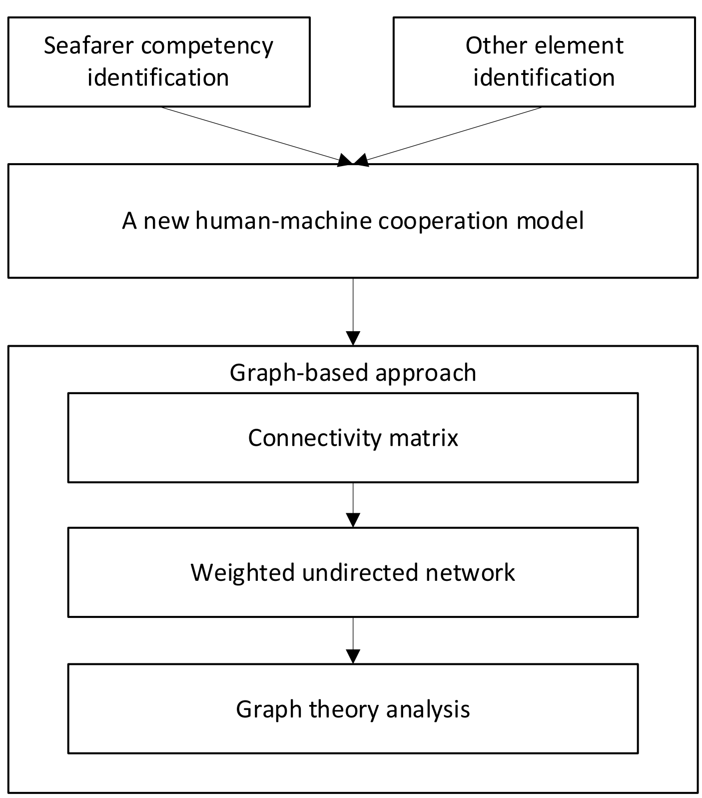

Fig. 1. The methodology of human-machine cooperation analysis.

Table 1
Seafarers' competencies in the human-machine system [24].

Phase	Abbreviation	Competency	Description
Input	KNO (1)	Knowledge	A good knowledge of equipment/device, having qualified skills and precautionary thought, illustrating the capacity to deal with route work and emergency cases.
	CC (2)	Cognitive capacity	Appropriate cognitive states and mental workloads, being influenced by "inattention", "inadequate procedures", "observation missed", and "communication failure".
	INF (3)	Information	Reliable and accurate information obtained and updated from the nautical chart, publications, radar, ECDIS, Automatic Radar Plotting Aid (ARPA), weather and meteorological data.
	TD (4)	Task demand	The difference between the reference signal and the machine sub-system.
Process	SA (5)	Situational awareness	Effective understanding of anything that could impact the security, safety, economy, or environment in maritime domain, in order to increase effectiveness in the planning and conduct of operations.
	TWL (6)	Teamwork and leadership	Effective support and proper supervision, not working isolated with various hazards.
	COM (7)	Communication	Effective communication, being influenced by cultural issues, language barriers, educational qualifications, and training.
	DM (8)	Decision making	Utilising information, knowledge, situational awareness, teamwork and communication to make rational decisions, usually with adequate supervision and support from the team.
Output	EQM (13)	Equipment correctly used	Correctly positioning or detecting alarm systems, navigational indicators (e.g., working lights), and correctly using information from the equipment.
	SO (14)	Manoeuvres	Appropriately selecting steering modes, correctly utilising manoeuvre signals, operating actions under regulations and rules; not exceeding the safe operating limits of ship propulsion and power systems.
	SC (15)	Amend/ maintain ship course	The ability to amend and maintain a ship's course and speed under adequate information, sufficient knowledge, and correction of errors in equipment or system.
	PO (16)	Procedure operations	Being in accordance with contingency plans, handling of dangerous cargoes, cargo inspections, cargo operations, and pollution prevention actions to safeguard the environment, personnel, and the ship.
Reference signal	PP (9)	Passage plan	Appropriate plan for the passage, being absent or unapproved revision leads to maritime accidents.
	RM (10)	Comply with regulations and management	Complying with regulations and management involving organisational factors, such as codes, endorsements, regulations, procedures, instructions, operation manuals, and requirements.

reference signal are created from human elements, representing groups of seafarer competencies. The competencies occurring at the beginning of actions and interacting with machine sub-system are grouped as the input phase of human elements; the competencies including interactions with individuals and teams are classified as the process phase; the competencies with action executions and interacting with machine sub-system are the output phase. In addition, the reference signal means considered references within the input phase for human sub-systems. The details of grouping relevant seafarer competencies in the dynamic system are documented in a previous study [24].

3.2. Human-machine cooperation system

To establish a comprehensive human-machine system, there are other non-human elements associated with machines and the environment, as described in Table 2 [24]. The machine sub-system is created from ship conditions and their related equipment; the disturbance is the element influencing both human and machine sub-systems, which consists of a comprehensive human-machine cooperation system.

The above human-machine model, consists of machine sub-system, reference signal, disturbance, and human elements including input, process, and output phases. The disturbance influences both human elements and machine sub-systems; the output of machine and reference signal point to the input phase of human elements; the output phase of human interacts with the input of machine. Therefore, the logic of these elements is shown in Fig. 2.

Taking advantage of the closed-loop model, the proposed framework enables the clarification of RIFs' frequency and impact on human-machine cooperation. Specifically, the human-machine system functions are adaptive to an evolving process of existing issues in safety-critical operation, represented by the discrete occurrence of RIFs referring to the timeline. For example, some RIFs, such as communication (COM), appeared more than once in a single maritime accident, resulting from the event of "INF – COM – machine sub-system – KNO – COM – SO" in the closed-loop system. In this case, previous studies counting the occurrence of COM only once in the accident analysis model, do not demonstrate the true impact of COM (higher than the others) regarding its repeated occurrence in a single accident. Therefore, the proposed model addresses the multiple occurrences of an RIF and quantifies the impact through the closed-loop system. Both the frequency (e.g., whether the RIF occurs in an accident) and impact (e.g., how many times

Table 2
Other elements in the human-machine cooperation [24].

Element	Description
Machine sub-system (12)	Vessel conditions, devices, and ergonomic impacts; increasing complexity regarding ship automation.
Disturbance (11)	Environmental and geographical factors.

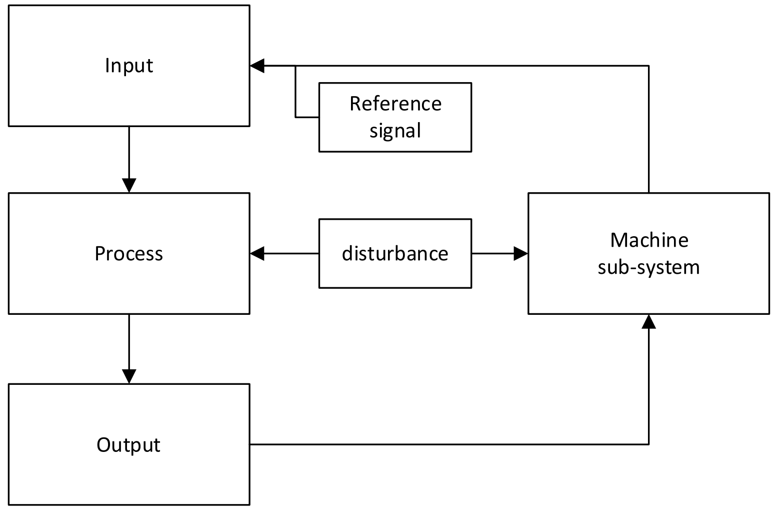

Fig. 2. Human-machine cooperation model.

the RIF happens in an accident) of RIFs are clarified in this study, to demonstrate risk interactions between humans and machine systems. In this process, every accident needs to be thoroughly analysed to understand its evolution from the initial event to the final consequence, and to quantify the number of occurrences of each identified RIF in order to accurately reflect their true impact.

3.3. Graph-based approach for RIFs

To analyse RIF connectivity in the human-machine model, this study proposes a graph-based approach to identify critical RIFs and assess their features in the system. Compared to other methods to analyse causal relationships of RIFs, such as DEMATEL [1], the proposed graph-based approach can explore network properties and examine the connectivity of RIFs in overall topology through a symmetric matrix, for instance, the identification of clustered RIF groups. The interconnectivity among each RIF is explained through a weighted undirected network, where the "weighted" denotes the magnitude of RIF connectivity and the "undirected" accommodates the competency relationships in the closed-loop system. In this way, a graph theoretical model is generated to illustrate human-machine cooperation within safety-critical operations. There are four steps to conduct the analysis:

1) Database reflecting frequency and impact

The raw dataset is derived from historical maritime accident reports, identifying RIFs and their occurrences in human-machine cooperation process. Diverging from conventional factor identification methods, these RIFs are quantified based on their frequency and impact, forming a dataset for subsequent analysis. The frequency of an RIF is represented by its occurrence ratio across all accidents, while its impact is disclosed by the number of occurrences within a single accident. For example, in a dataset of 4 nodes [INF, COM, Machine, KNO, SO], the COM is counted as 2 and the others as 1 in one accident with the occurrence of "INF – COM – machine sub-system – KNO – COM – SO", formulating [INF, COM, Machine, KNO, SO]=[1, 2, 1, 1] as one row of accident records. It is noteworthy that two events may occur simultaneously, which does not influence the structure of an undirected network. As a baseline for the analysis, all accident types are included in the counting of frequency and impact to provide findings for the investigated database. However, the proposed approach may generate different implications with other database inputs.

2) Connectivity matrix

Taking the frequency and impact concepts of each RIF into account, a connectivity matrix of RIFs within human-machine systems is formulated using a partial correlation method. To be specific, every cell in the matrix is represented by a partial correlation value of the corresponding row and column, calculated using 64 data pieces, each corresponding to a line with node counts from Step 1. To investigate the relationship between two RIFs, correlation coefficients will obtain misleading results when another RIF is numerically related to both RIFs. It can be avoided by using partial correlation, which explains the degree of association between two RIFs, removing the influence of other RIFs. In this matrix, each row and column correspond to a specific RIF, with the cell value indicating the partial correlation between the two RIFs situated in the respective row and column.

3) Weighted undirected network

A network representation of the human-machine system comprises a set of nodes, interconnected by links between pairs of nodes. In this network, the nodes represent identified RIFs in the model, while links represent effective connections between pairs of RIFs. In order to construct an undirected network, the connectivity matrix needs 1) to be symmetric, which is consistent with the original connectivity matrix features; 2) all values equalling 1 or <0 are replaced with 0 [57], as shown in Fig. 3. The weights of links in the network vary depending on the values in the matrix cells. Then, a weighted undirected network is constructed, with the rows/columns representing nodes and the entries in the matrix representing links in the network. An undirected network accommodates nodes with non-hierarchical characteristics, where the influence of two factors does not always follow a single homogenous direction. Therefore, it best fits the nature of relationships being explored for seafarer competencies.

4) Graph theory calculation on degree, strength, clustering, and betweenness centrality

To capture the characteristics of the weighted undirected network, the integration of graph theory with partial correlation analysis is utilised to identify critical RIFs. In this network, the nodes denote RIFs, and the weighted links signify the correlation strength between every pair of RIFs. To investigate critical RIFs in human-machine cooperation, both degree and strength are calculated. Clustering is used to explore dense activities within a small group of RIFs and their connections to machine sub-systems. Betweenness centrality is analysed to identify nodes with the shortest paths in the network, illustrating human-machine

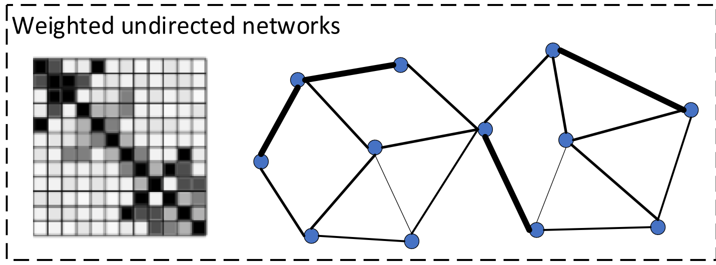

Fig. 3. Weighted undirected network.

cooperation patterns in maritime safety.

Regarding diverse features in the network, the results are calculated using converted matrices, such as the normalisation matrix and weighted connection-lengths matrix. Below is a 4 × 4 matrix example featuring nodes A, B, C, and D, illustrating the calculation of degree, strength, clustering, and betweenness centrality [11,50]. This showcases connectivity features of the proposed methodology.

Example

	A	B	C	D
A	0	0.2	0.1	0.8
B	0.2	0	0.3	0.2
C	0.1	0.3	0	0.1
D	0.8	0.2	0.1	0

a. Degree: Node degree refers to the count of links connected to a node. In weighted networks, calculations do not take into account connection weights.

$$Degree\ (i) = \sum\nolimits_{j\neq i} a_{ij}$$

Where a_{ij} equals 1 if there is a link between nodes i and j, 0 otherwise. In the provided example, all nodes A-D have the same degree value, which is 3. Normally, a node with the highest degree signifies that the corresponding RIF has the most connections with other RIFs, suggesting its centrality in human-machine cooperation. Such a node is expected to play a busy role in facilitating interactions between humans and machines.

b. Strength: Node strength is the aggregate of weights associated with links connected to the node.

$$Strength\ (i) = \sum_{j=1}^{n} w_{ij}$$

Where w_{ij} is the strength or weight of the edge linking nodes i and j. In the example provided, the strength values for nodes A-D are 1.1, 0.7, 0.5, and 1.1, respectively. In the proposed model, the nodes A and D with the highest strength indicate their greatest weight within the system and prominence in association with other connected nodes.

c. Clustering: The clustering coefficient represents the proportion of triangles surrounding a node and is equivalent to the fraction of a node's neighbours that share a connection with each other.

$$Clustering\ (i) = \frac{1}{k_i(k_i-1)}\sum_{j,k} a_{ij}a_{jk}a_{ki}$$

Where k_i is the total weighted degree of node i; the clustering equals 0 when k_i is 0 or 1. Before conducting the clustering calculation, the example matrix is normalised as follows:

$$\begin{bmatrix} 0 & 0.25 & 0.125 & 1 \\ 0.25 & 0 & 0.375 & 0.25 \\ 0.125 & 0.375 & 0 & 0.125 \\ 1 & 0.25 & 0.125 & 0 \end{bmatrix}$$

Following the normalisation, the clustering values of nodes A-D are calculated as 0.291, 0.284, 0.235, and 0.291, respectively. The nodes A and D with the highest clustering coefficient indicate dense activities among RIFs and play a critical local role in the interaction functions.

d. Betweenness centrality: Node betweenness centrality indicates the proportion of all shortest paths in the network that traverse through a specific node.

$$Betweenness\ centrality\ (i) = \sum_{s\neq v\neq t}\frac{\sigma_{st}(v)}{\sigma_{st}}$$

Where σ_{st} is the total number of shortest paths from node s to node t, and $\sigma_{st}(v)$ is the number of those paths that pass through v. Utilising the provided example, non-zero elements in the matrix are identified, followed by the reciprocal. Then the matrix is transformed into a weighted connection-lengths matrix.

$$\begin{bmatrix} 0 & 5 & 10 & 1.25 \\ 5 & 0 & 3.33 & 5 \\ 10 & 3.33 & 0 & 10 \\ 1.25 & 5 & 10 & 0 \end{bmatrix}$$

The betweenness centrality values for nodes A - D are 0, 4, 0, and 0, referring to calculation in Rubinov and Sporns [57]. This indicates that the majority of the shortest paths in the network traverse through node B, highlighting its pivotal role in facilitating connections within the network. Indeed, nodes with higher betweenness centrality values play a crucial role in numerous shortest paths within the network. This indicates that the corresponding RIF serves as a key element for important information transfer along these shortest paths, ultimately influencing the efficiency of system functions.

To summarise, the aforementioned features illustrate the human-machine cooperation analysis using graph-based approaches, as shown in Table 3. Aiming at human-machine cooperation, RIFs are identified and influential patterns among seafarer competencies and machine subsystems are specified, sufficing to serve the aim of this study.

Table 3
Features in graph theory and their purposes.

Feature	Purpose
Degree	Central RIFs with the most connections
Strength	Prominent RIFs, taking into account weights (correlation values)
Clustering	RIFs' dense activities in a cluster
Betweenness centrality	RIF efficiency and impact pattern in human-machine cooperation

4. Experimental results with a case of human-machine cooperation in restricted waters

4.1. Dataset

To examine the proposed methodology, this study compiled the database sourced from historical maritime accident reports. The dataset consists of two features: 1) the frequency, indicating whether the RIF contributed to the accident; 2) the impact, representing the number of occurrences of the RIF in an accident. Considering both in the proposed dynamic model, the accident data was obtained between January 2012 to December 2017 from the Marine Accident Investigation Branch (MAIB) and the Transportation Safety Board of Canada (TSB), and between January 2005 to April 2021 from the Global Integrated Shipping Information System (GISIS), in restricted waters. In total, there were 64 report records in restricted waters as cases to illustrate deficiencies in both human and machine sub-systems, showcasing the frequency and impact of RIF occurrences in the area. The 64 are reported to a level from which all the detailed impacts between RIFs can be detected and quantified. It means that any other cases lacking such specific information are excluded from the raw input data. Among the database, accident types of restricted waters include collision, grounding, contact, foundering, striking, fire, and capsize.

4.2. Connectivity matrix for human-machine systems

This study extracted RIFs and calculated correlation values in human and machine sub-systems, generating a connectivity matrix to illustrate their cooperation process in maritime transport. In the closed-loop system of maritime accidents, both human-related and non-human-related RIFs played crucial roles. Human-related RIFs were explained by seafarer competencies, while non-human-related RIFs stem from machinery deficiencies and environmental factors contributing to accidents. To be noted, the focus of this model was not on specific machinery deficiencies, but rather on understanding the interaction process between human elements (such as seafarer competencies) and machines. Following this approach, the connectivity matrix for human-machine systems was constructed, incorporating RIFs along with corresponding partial correlation values. In this matrix, each value denotes the partial correlation between the RIF in the respective row and column. It represented the degree of association between two RIFs in the model, with the influence of a set of controlling RIFs taken into account and removed.

Before generating the weighted undirected network, values representing partial correlation in the connectivity matrix were converted into positive values. By removing all negative values and self-connections, the matrix was exactly symmetric (by correcting for round-off error), as shown in Fig. 4. The row and column numbers from 1 to 16 represent RIFs KNO, CC, INF, TD, SA, TWL, COM, DM, PP, RM, Disturbance, Machine sub-system, EQM, SO, SC, and PO.

Moreover, certain values between rows and columns in Fig. 4 revealed a high correlation. They were CC (2) and EQM (13) (r (48) =0.466, $n = 64$, $p < 0.001$), TD (4) and SA (5) (r (48) =0.427, $n = 64$, $p =$ 0.002), COM (7) and SO (14) (r (48) =0.489, $n = 64$, $p < 0.001$), DM (8) and Disturbance (11) (r (48) =0.468, $n = 64$, $p < 0.001$). That is to say, there was a significant relationship between inappropriate use of equipment (13) and cognitive capacity (2); improper task demand (4) had a significant association with affected situational awareness (5); ineffective communication (7) was significantly related to manoeuvring issues (14); and violated decision making (8) had a significant connection with disturbances (11) in the system. From these perspectives, the connections between each pair of RIFs were demonstrated through the matrix.

4.3. Weighted undirected network

The weighted undirected network was constructed based on the connectivity matrix, incorporating the identified RIFs and their links. To calculate the graph features, the original connectivity matrix was converted into different forms. To begin with, the degree and strength were computed using the original matrix in Section 4.2. Subsequently, the clustering was calculated after matrix normalisation, where

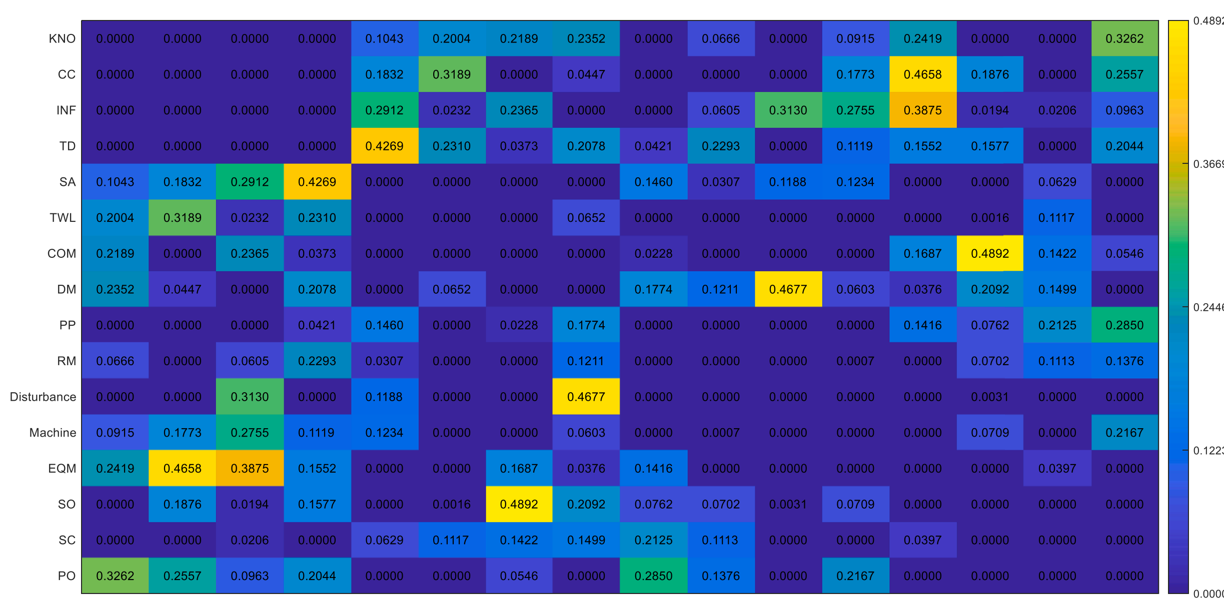

Fig. 4. Connectivity matrix after correction.

normalisation rescaled all weight measurements to the range from 0 to 1, as shown in Fig. 5. To calculate the betweenness centrality, weights in the network were transformed into lengths to produce a weighted connection-lengths matrix, as shown in Fig. 6. In a weighted connection network, higher weights naturally signify shorter lengths. Therefore, in this context, the connection-lengths matrix is defined as the inverse of the connection-weights matrix.

4.4. Graph-based analysis results

To create a benchmark for the graph-based analysis, all accident records were used to construct the weighted undirected network. The analysis utilised network features to illustrate the effect of RIFs on human-machine cooperation, aligning with the frequency and impact of RIF occurrences. This study utilised the database with each RIF's occurrences in all accident types, formulating the whole network with 16 nodes. The connectivity matrix was obtained by calculating partial correlations between each two RIFs. Then the weighted undirected network was established according to steps in Section 3.3. At last, the degree, strength, clustering, and betweenness centrality vectors consisting of 16 nodes were calculated for the proposed network and the significance of RIFs and their connections with other RIFs were revealed. The results showed that the RIF with the highest value in a specific feature provided implications for seafarer competency training and human-autonomy design. The details of network features are shown in Table 4.

4.4.1. Degree

From Table 4 and Fig. 4, the DM had the most connections (11) with other RIFs, demonstrating its central role in facilitating human-machine cooperation. To be specific, decision making was a critical competency associated with multiple risk factors in maritime accidents, including the disturbance from environment (disturbance), knowledge of crews (KNO), task demand (TD), and manoeuvres of vessels (SO). Among these elements, the only significant connection in the model was observed with the disturbance ($p < 0.001$). In addition, it demonstrated connections, albeit not strong ones, with the machine sub-system. That is to say, the role of seafarer decision making appeared to be surrounded by other competencies and machine sub-systems. Enhancing seafarer training in decision making could involve improving competencies, such as professional knowledge and manoeuvring skills. Moreover, proficient practice in safe navigation, considering diverse external disturbances and machinery deficiencies, would likely enhance the decision-making capabilities of seafarers in human-machine cooperation.

Besides, the RIF with the least degree value was the disturbance, showing its fewer connections with other RIFs. There were only four RIFs connected with disturbance, involving INF, SA, DM, and SO. Among them, INF ($p = 0.027$) and DM ($p < 0.001$) showed significant correlations. Given the impact of disturbances on both human and machine sub-systems, such two RIFs, i.e., information and decision making, emerge as crucial factors for competency training and ensuring the reliability of machine systems.

4.4.2. Strength

Task demand had the strongest weight and stood out prominently with certain elements in human-machine cooperation. Specifically, task demand was significantly associated with SA ($p = 0.002$), and relatively close to TWL, DM, RM, and PO, as shown in Table 5. The task demand denotes the difference between the reference signal and the machine sub-system. When the reference signal failed to be reliable or accurate in representing the state of machine sub-systems, task demand inevitably increased to accommodate the complexity of the situation, thus becoming the input of the human sub-system. Evidently, the SA emerged as a critical RIF associated with such a process. Hence, the assessment of task demand for seafarers must take into account the SA, particularly concerning the challenges introduced by higher automation in advanced ships. Although task demand did not have the highest number of connections, it illustrated close links to SA issues and was prominent in terms of seafarer training and ship automation.

4.4.3. Clustering

In the light of clustering, the machine sub-system showed the highest clustering coefficient, demonstrating dense activities within a cluster. This cluster consisted of KNO, CC, INF, TD, SA, and PO with the machine sub-system as a centre. Among them, the partial correlation between machines with INF was significant ($p = 0.053$), proving a strong causal relationship that machinery deficiencies may deteriorate the information transformation for seafarers. From a clustering perspective, the machine sub-system was engaged in dense activity with the input phase of the human sub-system, i.e., KNO, CC, INF, and TD. The improvement

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	0.0000	0.0000	0.0000	0.0000	0.2132	0.4097	0.4474	0.4808	0.0000	0.1362	0.0000	0.1871	0.4944	0.0000	0.0000	0.6669
2	0.0000	0.0000	0.0000	0.0000	0.3745	0.6518	0.0000	0.0914	0.0000	0.0000	0.0000	0.3624	0.9521	0.3834	0.0000	0.5228
3	0.0000	0.0000	0.0000	0.0000	0.5954	0.0475	0.4835	0.0000	0.0000	0.1237	0.6399	0.5631	0.7922	0.0396	0.0422	0.1969
4	0.0000	0.0000	0.0000	0.0000	0.8727	0.4722	0.0761	0.4248	0.0861	0.4687	0.0000	0.2286	0.3172	0.3224	0.0000	0.4179
5	0.2132	0.3745	0.5954	0.8727	0.0000	0.0000	0.0000	0.0000	0.2984	0.0627	0.2428	0.2523	0.0000	0.0000	0.1286	0.0000
6	0.4097	0.6518	0.0475	0.4722	0.0000	0.0000	0.0000	0.1333	0.0000	0.0000	0.0000	0.0000	0.0000	0.0033	0.2284	0.0000
7	0.4474	0.0000	0.4835	0.0761	0.0000	0.0000	0.0000	0.0000	0.0466	0.0000	0.0000	0.0000	0.3448	1.0000	0.2907	0.1116
8	0.4808	0.0914	0.0000	0.4248	0.0000	0.1333	0.0000	0.0000	0.3626	0.2476	0.9561	0.1232	0.0769	0.4277	0.3065	0.0000
9	0.0000	0.0000	0.0000	0.0861	0.2984	0.0000	0.0466	0.3626	0.0000	0.0000	0.0000	0.0000	0.2894	0.1557	0.4345	0.5826
10	0.1362	0.0000	0.1237	0.4687	0.0627	0.0000	0.0000	0.2476	0.0000	0.0000	0.0000	0.0014	0.0000	0.1434	0.2275	0.2812
11	0.0000	0.0000	0.6399	0.0000	0.2428	0.0000	0.0000	0.9561	0.0000	0.0000	0.0000	0.0000	0.0000	0.0064	0.0000	0.0000
12	0.1871	0.3624	0.5631	0.2286	0.2523	0.0000	0.0000	0.1232	0.0000	0.0014	0.0000	0.0000	0.0000	0.1450	0.0000	0.4431
13	0.4944	0.9521	0.7922	0.3172	0.0000	0.0000	0.3448	0.0769	0.2894	0.0000	0.0000	0.0000	0.0000	0.0000	0.0812	0.0000
14	0.0000	0.3834	0.0396	0.3224	0.0000	0.0033	1.0000	0.4277	0.1557	0.1434	0.0064	0.1450	0.0000	0.0000	0.0000	0.0000
15	0.0000	0.0000	0.0422	0.0000	0.1286	0.2284	0.2907	0.3065	0.4345	0.2275	0.0000	0.0000	0.0812	0.0000	0.0000	0.0000
16	0.6669	0.5228	0.1969	0.4179	0.0000	0.0000	0.1116	0.0000	0.5826	0.2812	0.0000	0.4431	0.0000	0.0000	0.0000	0.0000

Fig. 5. Matrix normalisation for clustering calculation.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	0.0000	0.0000	0.0000	0.0000	9.5896	4.9898	4.5689	4.2519	0.0000	15.0146	0.0000	10.9276	4.1346	0.0000	0.0000	3.0652
2	0.0000	0.0000	0.0000	0.0000	5.4591	3.1363	0.0000	22.3559	0.0000	0.0000	0.0000	5.6414	2.1470	5.3316	0.0000	3.9102
3	0.0000	0.0000	0.0000	0.0000	3.4336	43.0737	4.2282	0.0000	0.0000	16.5216	3.1945	3.6303	2.5806	51.5623	48.4520	10.3796
4	0.0000	0.0000	0.0000	0.0000	2.3424	4.3294	26.8449	4.8121	23.7564	4.3617	0.0000	8.9405	6.4441	6.3408	0.0000	4.8914
5	9.5896	5.4591	3.4336	2.3424	0.0000	0.0000	0.0000	0.0000	6.8503	32.5786	8.4189	8.1018	0.0000	0.0000	15.8942	0.0000
6	4.9898	3.1363	43.0737	4.3294	0.0000	0.0000	0.0000	15.3393	0.0000	0.0000	0.0000	0.0000	0.0000	612.7076	8.9509	0.0000
7	4.5689	0.0000	4.2282	26.8449	0.0000	0.0000	0.0000	0.0000	43.8827	0.0000	0.0000	0.0000	5.9284	2.0442	7.0314	18.3194
8	4.2519	22.3559	0.0000	4.8121	0.0000	15.3393	0.0000	0.0000	5.6379	8.2570	2.1381	16.5939	26.5710	4.7794	6.6702	0.0000
9	0.0000	0.0000	0.0000	23.7564	6.8503	0.0000	43.8827	5.6379	0.0000	0.0000	0.0000	0.0000	7.0626	13.1253	4.7052	3.5086
10	15.0146	0.0000	16.5216	4.3617	32.5786	0.0000	0.0000	8.2570	0.0000	0.0000	0.0000	1418.6409	0.0000	14.2533	8.9871	7.2696
11	0.0000	0.0000	3.1945	0.0000	8.4189	0.0000	0.0000	2.1381	0.0000	0.0000	0.0000	0.0000	0.0000	320.3999	0.0000	0.0000
12	10.9276	5.6414	3.6303	8.9405	8.1018	0.0000	0.0000	16.5939	0.0000	1418.6409	0.0000	0.0000	0.0000	14.0978	0.0000	4.6138
13	4.1346	2.1470	2.5806	6.4441	0.0000	0.0000	5.9284	26.5710	7.0626	0.0000	0.0000	0.0000	0.0000	0.0000	25.1686	0.0000
14	0.0000	5.3316	51.5623	6.3408	0.0000	612.7076	2.0442	4.7794	13.1253	14.2533	320.3999	14.0978	0.0000	0.0000	0.0000	0.0000
15	0.0000	0.0000	48.4520	0.0000	15.8942	8.9509	7.0314	6.6702	4.7052	8.9871	0.0000	0.0000	25.1686	0.0000	0.0000	0.0000
16	3.0652	3.9102	10.3796	4.8914	0.0000	0.0000	18.3194	0.0000	3.5086	7.2696	0.0000	4.6138	0.0000	0.0000	0.0000	0.0000

Fig. 6. Weighted connection-lengths matrix for betweenness centrality calculation.

Table 4
Calculation of network features in human-machine cooperation model.

Number	RIFs	Degree	Strength	Clustering	Betweenness centrality
1	KNO	8	1.485	0.101	10
2	CC	7	1.633	0.092	20
3	INF	10	1.724	0.080	30
4	TD	10	1.804	0.120	22
5	SA	9	1.487	0.089	4
6	TWL	7	0.952	0.063	4
7	COM	8	1.370	0.126	10
8	DM	11	1.776	0.103	20
9	PP	8	1.104	0.116	8
10	RM	9	0.828	0.096	0
11	Disturbance	4	0.903	0.107	8
12	Machine	9	1.128	0.128	2
13	EQM	8	1.638	0.109	16
14	SO	10	1.285	0.084	8
15	SC	8	0.851	0.092	0
16	PO	8	1.577	0.127	26

Table 5
Partial correlations between task demand and other RIFs.

RIF	Partial correlation with task demand	Significance
5 SA	0.4269	0.002
6 TWL	0.2310	0.107
8 DM	0.2078	0.148
10 RM	0.2293	0.109
16 PO	0.2044	0.154

in such competencies will accommodate the evolution of machine sub-systems. These competencies should be enhanced and prioritised in the training program, particularly in the investigated scenario. As machine sub-systems are replaced by high autonomy systems, the clustering of competencies must be redefined to meet the demands of ship autonomy. The competency training of seafarers can be reshaped based on the clustering results, aligning competencies grouped within a cluster with the functions of machines.

On the one hand, it implies the possibility of enhancing human performance at the input phase by improving machine sub-systems, aligning with the MASS design clues. To be specific, the results showed that the KNO, CC, INF, TD, and SA were clustered around the machine sub-systems. If the novel ship design aims at new functions to improve such RIFs, it will significantly improve the deficiencies in HMI and enhance human performance. For instance, the development of autonomous technologies and manoeuvring assistance systems augmenting reality will benefit information reliability and enhance the SA of seafarers, as so to improve human-machine cooperation. Moreover, the practice of shaping seafarer competencies aiming at cognitive capacity, can be achieved through different scenarios setting with machine functions. The high autonomy of certain machine sub-systems may relieve the cognitive burden on humans when dealing with information. However, to what extent the autonomy influences seafarers' cognitive workload is still unclear, and can be further explored using the clustering result of this study.

4.4.4. *Betweenness centrality*

The INF had the highest betweenness centrality values and played a significant role in terms of efficiency through numerous shortest paths within the network. That is to say, the INF transferred along the shortest paths and influenced the efficiency of the human-machine system. This suggests that accurate and reliable information in maritime operations is crucial for ensuring safe navigation and fostering efficient human-machine cooperation.

The INF was significantly correlated with the disturbance ($p = 0.027$), machine sub-systems ($p = 0.053$), TD ($p = 0.005$), and EQM ($p = 0.005$). Although the information was human-related RIF, both seafarer competencies and machine sub-systems relied on its high betweenness centrality features. Enhanced information processing and maintenance enabled appropriate individual and teamwork tasks, resulting in more reliable interactions with RIFs from a systematic perspective. Therefore, reliable information regarding vessels, environment, and human responses should be integrated to serve the whole human-machine system. It should be noted that automation technologies aiming to simplify the process of human operations cannot scarify the accuracy and clear information, otherwise these technologies could induce systematic failures and even catastrophes in extreme cases. For example, after two Boeing 737 MAX crashes in 2018–2019, it was found that the Manoeuvring Characteristics Augmentation System (MCAS) automatically controlling pitch based on airflow sensors, malfunctioned, causing the nose to dip without the pilots knowing of the system's existence

[49]. Additionally, the increased Artificial Intelligence (AI) interaction was argued to introduce higher mental workload among seafarers, subsequently undermining their performance [69]. Similarly, the procedure operation competency had a relatively high betweenness centrality value, proving its high efficiency in improving system safety by handling contingency plans and cargo operations.

4.5. Comparisons between the benchmark and the collision accident

To generate more accident-type insights, this section describes the experiment results on collision accidents in restricted waters. By doing so, it can also reveal a comparative result between the above general findings and the specific ones against specific accident types, while it also helps illustrate how the generic methodology can be used in different settings for new insights into managerial implications. This yielded insights into tailored strategies for seafarer training in various risk scenarios. To specify, the most common accident types in the investigated database were collisions (32) and groundings (11); however, only collisions were analysed in this section using the graph-based approach, as the node number in the network should be less than the record number in the connectivity matrix calculation.

To perform the graph-based analysis for collisions, 32 accident records from the raw database were selected to create a connectivity matrix. This matrix was then utilised to construct a weighted undirected network, and subsequently, the degree, strength, clustering, and betweenness centrality of each node in the network were calculated. The results of the calculation on collisions are shown in Table 6.

From Table 6, it was evidence that 1) Degree: procedure operation (PO) had the most connections with other RIFs, implying its central role in developing collision avoidance strategies; 2) Strength: cognitive capacity (CC) had the strongest weight for qualified seafarers to manipulate multiple tasks and machines in collision accidents; 3) Clustering: passage plan (PP) revealed dense activities in the human-machine system, especially closely with decision making (DM) and equipment use (EQM) in collision avoidance; 4) Betweenness centrality: procedure operation (PO) demonstrated high efficiency in ensuring system safety by managing contingency plans and cargo operations, a trait that was also relatively prominent in the benchmark analysis.

Compared with benchmark findings from all accident types, this analysis identified different critical RIFs in association with connectivity features (degree, strength, clustering, and betweenness centrality), implying their diverse influential effects on human-machine cooperation in collision scenarios. Therefore, it is applicable to provide bespoke seafarer training to enhance skills in facing with risks of collisions or other accident types. The proposed methodology shows promising applications in maritime transport, offering insights into seafarer training tailored to various scenarios and tasks involving human-machine cooperation.

Table 6
Network features for collisions.

Number	RIFs	Degree	Strength	Clustering	Betweenness centrality
1	KNO	7	2.300	0.013	12
2	CC	7	2.988	0.026	24
3	INF	7	2.337	0.024	12
4	TD	8	1.034	0.089	2
5	SA	8	1.771	0.064	18
6	TWL	9	2.067	0.029	2
7	COM	7	2.853	0.020	22
8	DM	9	2.505	0.049	18
9	PP	6	1.010	0.128	0
10	RM	6	0.887	0.074	0
11	Disturbance	7	1.735	0.043	10
12	Machine	8	2.144	0.078	8
13	EQM	8	2.469	0.024	12
14	SO	8	2.550	0.047	12
15	SC	9	2.923	0.069	12
16	PO	10	2.443	0.069	26

4.6. Implications

The main implications of the study benefit both the current fleets and future ship automation. Evidently, the proposed model quantifies the significance of RIFs in human and machine sub-systems, highlighting their features and closely connected competencies within the network. These connections and mechanisms of highlighted competencies pave the way for addressing deficiencies in HMI through the lessons learned from historical accidents. Therefore, the results provide suggestions and recommendations for HMI in future ship designs and shape trends in ship automation development, along with the associated dynamic interactions with seafarer competencies.

To begin with, seafarer competencies should be redefined in light of advanced machine automation. The findings provide that seafarers' DM competency should be trained, taking into account factors from humans (knowledge of crews), environment (external disturbance), task (task demand), and ships (ship manoeuvres). Previous research on ship decision-making, which primarily focuses on ship trajectories and environmental variables, may not be sufficient to address human competencies comprehensively. In order to collaborate and interface effectively with advanced autonomy technologies, the decision-making requirements for operators in remote control centres of MASS are urgently required to be reshaped aligning with MASS features and relevant RIFs. The proposed methodology emphasises the necessity of DM competency training in association with environmental disturbance and adaptive ship autonomy. It provides insights for maritime education and training institutions to redefine and evaluate the DM competency of seafarers properly given advanced technologies. Utilising the proposed methodology to generate findings with other databases, it is possible to suggest DM competency training in different accident types or diverse waterways. In addition, task demand, representing the variance between the reference signal and the machine sub-system, has been shown to be closely linked with SA. The maritime SA serving as a critical factor to keep safe navigation for conventional ships, is also dominant in MASS workplaces such as remote control centres. Advanced ships require operators to establish and sustain appropriate SA during navigation given task demands under remote working mode, especially in restricted waters. It suggests maritime authorities enhance SA through rationale task demand allocation, i.e., keeping machine functional indicators consistent with reference signals and minimising time delays in their transmission.

Moreover, the development of machine sub-systems should prioritise human-centred concepts to mitigate inherent flaws introduced by human operations and enhance systematic efficiency in line with seafarer competencies. In the light of machine automation technologies, knowledge, cognitive capacity, information, task demand, and SA are clustered around the machine sub-systems. That means the next generation of advanced autonomous ships must take these competencies of operators into account for ship design and construction. From a systematic perspective, ship automation should convey reliable information, keep rational task demands, and sustain the SA of humans but not beyond their knowledge and cognitive capacity. Ship designers must prioritise machine functions that enhance the previously mentioned competencies. Otherwise, the designed machine sub-system will be susceptible to human errors and lack resilience within the overall system in restricted waters. Furthermore, the information serving with high betweenness centrality influences the efficiency of human-machine cooperation. In restricted waters, timely information is crucial for maintaining efficient interactions between humans and machines, especially in adaptive and complex navigational environments. Both conventional ships and autonomous ships require reliable and sufficient information to sense internal and external situations. Maritime authorities can utilise these findings to evaluate and manage navigational risks by assessing the quality of information exchange in restricted waters. This proactive approach helps prevent maritime accidents and enhances risk management. Aiming for safe navigation of MASS, the maritime industry also benefits from these results to promote autonomous ships in restricted waters first, which can then spread to a wider range of applications in open seas. In other words, the advancement of ship autonomy must be grounded in the enhancement of information reliability, serving the most efficient effects on safe navigation systems.

5. Conclusion

This paper develops a novel approach to analysing the connectivity between humans and machines in safety-critical operations, pioneering the integration of frequency and impact of RIFs within a mathematical model. It combines graph theory and statistical methods to generate systematic features that reflect significant human-machine RIFs through various matrices for the weighted undirected network. The results indicate that decision making exhibits the highest degree, task demand demonstrates the highest strength, the machine sub-system displays the highest clustering, and information possesses the highest betweenness centrality, all of which are critical RIFs in the human-machine cooperation model. In addition, a comparison study is conducted to provide discussions on seafarer competency training and human-machine cooperation across various scenarios. These findings reveal their interactions aligning with graph theoretical features and generate implications for seafarer competency training and novel ship design.

Although there is existing research on risk analysis and modelling of maritime accidents, where significant risk factors are identified and their interdependencies with safety are uncovered through machine learning and data mining approaches using various data resources [38], the basis of these findings is restricted to the frequency of RIFs occurring in maritime accidents. Traditionally an RIF is only and maximumly counted once in every accident, and it could not truly reflect its impact, as it is evident that one factor could have a higher impact degree in one accident if it repeatedly occurs in the chain of accident occurrence. Obviously, repeated factors will matter more than those of one presence. Therefore, only considering the frequency of RIFs is not scientifically rigorous for maritime risk analysis targeting process assessment among human and machine interactions. This study fulfils the research gap by extracting the frequency and impact of RIFs from historical accident data into a graph-based model to examine dynamic human-machine cooperation.

However, the study has a limitation on the network construction. Although the proposed undirected network outweighs the directed one in terms of non-hierarchical relationships among RIFs, it is possible to develop a directed network for comparison with this benchmark if ample data with time series are collected. This study only addresses the human-centred model so future work can be done with extended machine categories when the relevant data is feasible. In conclusion, this study pioneers a novel approach by combining the frequency and impact of RIFs to analyse the connectivity between human and machine cooperation. The generated network identifies critical RIFs and the function-based features, generating implications for enhancing human-machine cooperation for future ships.

CRediT authorship contribution statement

Shiqi Fan: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Kun Shi:** Writing – review & editing, Validation, Investigation. **Jinxian Weng:** Writing – review & editing, Investigation. **Zaili Yang:** Writing – review & editing, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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Data availability

Data will be made available on request.

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