Fan, S, Fairclough, S, Khalique, A, Bury, A and Yang, Z

Towards advanced decision-making support for shipping safety: A functional connectivity analysis

Transportation Research Part E 193 (2025) 103861

Contents lists available at ScienceDirect

Transportation Research Part E

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

Towards advanced decision-making support for shipping safety: A functional connectivity analysis

Shiqi Fan [a,b], Stephen Fairclough [d], Abdul Khalique [c], Alan Bury [c], Zaili Yang [c,*]

[a] School of Transportation and Logistics Engineering, Wuhan University of Technology, China
[b] State Key Laboratory of Maritime Technology and Safety, Wuhan University of Technology, China
[c] Liverpool Logistics, Offshore and Marine (LOOM) Research Institute, Liverpool John Moores University, Liverpool, UK
[d] School of Psychology, Liverpool John Moores University, Liverpool, UK

ARTICLE INFO

Keywords:
Transportation engineering
Maritime transport
Human factors
Decision making
Human performance
functional Near-Infrared Spectroscopy

ABSTRACT

Decision making (DM) is essential and proven to be a natural and inherent part of the success of transport systems, particularly given the fast growth of autonomous systems in transport. It is critical but remains challenging to understand and predict DM performance in transport, because operators' mental states have not been effectively considered in complex DM processes such as ship anti-collision operations. This paper proposes an advanced decision support methodology that pioneers the incorporation of objective neurophysiological and subjective data to analyse functional connectivity in the brain and predict DM performance in ship navigation. Experiments were conducted using a functional Near-Infrared Spectroscopy (fNIRS) technology to explore the functional connectivity of two groups (low workload and high workload) and predict their DM performance in a ship collision avoidance situation. It brings brain science into transport engineering and the results generate new contributions to the existing knowledge, including (1) the establishment of a methodology to detect different workload levels in safety–critical transport systems using psychophysiological measurement; (2) analysis of brain's functional connectivity of different groups of decision makers (e.g., seafarers) with high and low workload tasks; (3) an advanced methodology to assess human reliability in complex scenarios and predict operational behaviours; (4) pioneering a human-centred approach to predict DM performance and demonstrate its feasibility in shipping. From a practical perspective, stakeholders can utilise the findings of this study to rationally evaluate human performance in transport system operations, aiding in operator qualification and certification processes. Furthermore, it is critical for adaptive automation regarding DM support in safety–critical systems.

1. Introduction

Decision making (DM) methods have been widely applied in safety–critical systems, such as transport and smart cities, to provide risk-informed support for challenging scenarios (Li et al., 2021, Chakraborty et al., 2024). The decision support systems and tools make a significant contribution to reducing risk levels and increasing efficiency in real-life transport applications. According to the annual statistical report, maritime transport consists of more than 80 % of world trade by volume (UNCTAD, 2020), and its success ensures the lifeline of global trade and the economy. However, shipping is a high-risk endeavour, with failure leading to potentially catastrophic

* Corresponding author.
E-mail address: z.yang@ljmu.ac.uk (Z. Yang).

https://doi.org/10.1016/j.tre.2024.103861
Received 3 July 2023; Received in revised form 8 November 2024; Accepted 8 November 2024
Available online 17 November 2024
1366-5545/

outcomes, as evidenced by previous maritime accidents. In March 2021, the Ever Given, one of the world's largest container ships, became grounded on the shores of the Suez Canal, leading to an estimated daily trade loss of around £7bn and incoming loss of up to £10.9 m (Michaelson and Safi, 2021). On September the 26th, 2002, an overloaded ferry (operating at nearly four times its design load) capsized off the coast of The Gambia, resulting in an estimated death toll of 1,864 (BBC, 2002).

Watchkeeping assigns seafarers to specific roles to navigate a ship at sea, with particular attention being given to avoiding collision and stranding (Branch et al., 2004). During their periods of duty, the Officer of the Watch (OOW) in taking charge of the bridge team and maintaining total responsibility on behalf of the ship's Master for safe navigation, is a critical aspect of ensuring maritime safety (Fan et al., 2018). Generally, the mental workload of OOWs increases with task complexity in a certain range. An Inappropriate mental workload could exceed OOW's capability and introduce human errors that lead to the occurrence of accidents. Obviously, the DM process of seafarers is critical for safe navigation, particularly in situations such as ship collision avoidance and emergency operations (Fan et al., 2021, Fan and Yang, 2023). However, the maritime sector is currently experiencing a paradigm shift from traditional manned ships to mixed traffic involving Maritime Autonomous Surface Ships (MASS). There are a limited number of studies on human DM in shipping, revealing an urgent need for new solutions. To ensure the safe navigation of ships now and in the future, this paper aims to propose an advanced DM method that focuses on the mental states of OOWs and supports prediction in DM performance.

DM in collision avoidance has long been considered a critical competency for deck officers in the maritime sector. However, with the development of MASS, previously established criteria and standards for evaluating seafarer competency are no longer fully applicable. Without appropriate modification, they cannot meet the demands of advanced automatic systems and interfaces in new maritime shipping scenarios. Specifically, in the past, the traditional method of assessing seafarers' DM performance has largely relied on professional judgement in past centuries. However, future hybrid navigation scenarios will involve traditional ships, remote-controlled ships, and autonomous vessels, resulting in complex encounters that call for new theoretical solutions in DM to ensure safe navigation.

Several challenges arise in this context. Firstly, since there is a lack of practical experience in remote-controlled or MASS shipping, it is difficult for training institutions to evaluate operators' behaviours and DM in such scenarios. Second, it is practically unrealistic to carry out accident data-based evaluations of seafarer DM to obtain insights for navigation safety, as there is no historical accident data or only scarce actual trajectory data under MASS hybrid scenarios. Third, in addition to gaining knowledge from navigating traditional vessels, seafarers must also familiarise themselves with MASS characteristics and adapt to different stresses and emergency scenarios that may arise, distinguishing them from those encountered on traditional ships. Therefore, a proactive and advanced approach is needed to evaluate DM performance with specific and measurable attributes.

Neuroimaging technology has made it possible to capture changes in human cognitive states and incorporate these data into decision support systems. Neuroimaging technologies, such as electroencephalography (EEG) (Hou et al., 2015, Fan et al., 2018), functional Near-infrared Spectroscopy (fNIRS) (Fan et al., 2021, Fan and Yang, 2023, Fan et al., 2023, Li et al., 2021), and functional Magnetic Resonance Imaging (fMRI) (Xu et al., 2020, Browne and Walden, 2021) have been used to study human performance. Additionally, bio-signals such as electrocardiography (ECG) (Chen et al., 2021) and eye movements (Argyle et al., 2020) can be utilised to conduct physiological monitoring in operational situations. EEG has the advantages of high temporal fidelity but poor spatial resolution, while fMRI forces participants to lie inside a scanner and is impractical for real-world behaviour. The fNIRS offers the advantage of higher spatial resolution compared to EEG, and unlike fMRI, fNIRS data can be collected without restricting the position and movement of the participant. However, the temporal resolution of neurovascular signals is inferior to EEG. Neurophysiological data can be analysed in a number of different ways, and functional connectivity refers to statistical dependence between time series of neurophysiological activity and oxygenated blood levels in spatially separated brain regions (Babaeeghazvini et al., 2021, Mohanty et al., 2020). Under a traditional similarity calculation such as Pearson's correlation, the relationship between two distinct brain regions can be assessed with respect to the degree to which they are functionally connected, i.e., co-activated in response to same event or activity.

To address the above challenges and complement human performance measurement, this paper proposes an advanced DM method to 1) objectively predict human performance in ship navigation and 2) evaluate DM process by incorporating both subjective and neurophysiological measurements. The combination of data to analyse functional connectivity can provide a more accurate solution to better aid DM. The results of this study will contribute to generating an objective and reliable tool to assess DM performance in real-time across various levels of tasks that require a decision to be made. Meanwhile, this method will pioneer a realistic approach concerning data acquisition and analysis for evaluating human reliability and machine states in critical scenarios such as ship encounters and predicting operational behaviours. Based on the findings of this study, requirements for operator DM competency in new scenarios can be assessed using data-driven human factor analysis. Autonomous systems can be designed and optimised in comparison to original systems through the evaluation of operators' DM performance given human–machine interfaces. Moreover, it will add significant value to the provision of maritime training and the seafarer certification process.

This paper is organised as follows: Section 2 reviews the state-of-the-art decision support methodologies from system-centred and human-centred perspectives. Section 3 describes the newly proposed methodology including both the experimental method and analysis approaches. Section 4 illustrates the results and Section 5 presents discussions, followed by a conclusion in Section 6.

2. Literature review

2.1. System-centred decision support methodology within human factors

Decision support methodologies have been developed with increasing demands for automated systems, with no exception for transport systems of different autonomy levels (Caballero et al., 2023, Li et al., 2024). Human factors have been significantly considered in the development of decision support systems because they are closely associated with procedures and environments. Adequate decision support is needed for increasing automation and demand change in logistics (Brau et al., 2024, Cedillo-Campos et al., 2024), road (Khosravi et al., 2022, Seet et al., 2022, Bai et al., 2024), rail (Zhou et al., 2021), aviation (Li et al., 2021) and maritime (Hogenboom et al., 2021, Zheng and Jiang, 2024) transports.

Decision support methodologies primarily focus on two parts: system-centred decisions and human-centred decisions. In terms of system-centred decisions, there are algorithms and models providing decision support for system prediction, performance management, automation, and logistics (Moktadir and Ren, 2024, Sonar et al., 2024). For instance, the dynamic features of train delay are predicted using random vector functional-link networks (RVFLNs) (Zhou et al., 2021). This method is for railway schedules to provide DM support for dispatchers. Similarly, the Multiple Criteria Decision Making/Aid methods (MCDM/A) are concerned with road performance with multidimensional risks, which aggregates the information on accidents' temporal behaviour in road networks (Martins and Garcez, 2021). In this way, a better allocation of traffic accident prevention resources which are limited and scarce can be prioritised. Similarly, a new MCDM model was generated defining relations between the ideal and anti-ideal alternatives (RADERIA) to rank alternatives for human resources in a transport company (Jakovljevic et al., 2021). Greenlee et al. (2022) conduct an empirical approach to develop and select aid activation methods for system-centred decision support design. In addition, forecasting methods have been proposed to assist DM, management, and maintenance. Tseremoglou et al. (2022) propose a data-driven algorithm to solve packing problems and predict shipment dimensions with uncertainty, which assists in both forecasting and optimising decision support. The freight forecasting method is developed for freight operation planning in short and long term periods using time series models and reinforcement learning methods (Hassan et al., 2020). The results show reduced forecast error margin in container shipment cases and effective freight demand prediction, which realises improved long-term forecasts.

In maritime transport and aviation, classical methods such as the cognitive reliability error analysis method (CREAM) (Pei et al., 2024), Success Likelihood Index Method (SLIM) (Kayisoglu et al., 2022), and Bayesian network (Zhou et al., 2023), are utilised to calculate the probability of human-related factors, serving the decision-making model in accidents. Hogenboom et al. (2021) integrate ship movement dynamics and response time to address the importance of time in maritime operations, which better controls the DM process when considering the risk of collision. To reduce the maintenance cost, Xu et al. (2021) utilise mixed integer programming and heuristic methods to allocate catenary maintenance tasks with predictive maintenance (PdM) policy, which reduces costs by 25 %. In production and logistics systems, measured human performance contributes feedback to the design level, which incorporates human factors into systems from a long-term design and a short-term operation (Vijayakumar et al., 2022). In addition, negative emotion and inappropriate behaviours of drivers in last-mile delivery affect customers' repurchase intentions (Masorgo et al., 2023).

System-centred decisions have concentrated on relationships between automation and human factors. Increased automation may result in "out-of-the-loop" problems induced by reduced human effectiveness, such as deterioration in situational awareness (SA) and mind wandering (Dehais et al., 2020). It addresses the significant role of human operators in automation. Therefore, adaptive automation, focusing on the allocation of control functions to accommodate changes in the physical environment and the human role, has been explored in the field of aviation and highway driving (Sheridan, 2011, Kaber et al., 2001). In addition, dynamic function allocation which solves the "out-of-the-loop" problems by adjusting the levels of human/machine control over system functions in a gas power plant uses a Bayesian network to determine trigger mechanisms and allocation strategies (Atashfeshan et al., 2021). It has improved human SA by around 30 %, which could be applied for automated system design as DM support. To improve the scalability of high-level autonomous vehicles, a decision-making framework was designed from driver intelligence, environment reasoning, and decision algorithm aspects, which can be applied in different scenarios (Wang et al., 2023). In the case of ship collision avoidance, a methodology based on genetic algorithms and fuzzy logic has been proposed to develop a decision support system for ship operators to take actions in encounter situations, which was validated in a ship's bridge simulator and an autonomous surface vessel (Fiskin et al., 2021). This illustrates the cooperation between human operators and automation in shipping. Moreover, smartphones have become real-time sensors to help detect driver behaviours and support driver monitoring using multi-layer perceptron, support vector machine, and convolutional neural network (Khosravi et al., 2022). From these perspectives, system-centred decision support studies show critical and strong connections between humans and systems.

Previous studies on system-centred decision support methodology focusing on machine performance, fail to consider human performance interactions. Although automation development introduces a new trend in intelligent DM for machines to operate safely and reliably, the human–machine interface reveals new challenges for cognitive behaviours and processes (Kessler et al., 2024). It is unreliable to judge whether system automation is good in DM tasks compared to traditional systems if there is no rational and precise measurement for the traditional human-centred DM process. Therefore, this study proposes a novel approach to quantify the DM process of maritime OOWs to support DM performance in human–machine systems.

2.2. Psychophysiological and neurophysiological measurements in human-centred decision support systems

Qualitative and quantitative methods have been used for human and machine analysis in the context of human-centred decision support systems. The SAfety FRactal ANalysis (SAFRAN) method, as a qualitative approach, is proposed to specify the human and organisational factors category and represent their variability in system performance (Accou and Carpinelli, 2022). Some quantitative measurements are also applied for cognitive DM. Integrating mouse-tracking and EEG signals can reveal the features of binary choices and temporal dynamics of DM and hesitation (Chen et al., 2022). To ensure effective supply chain decision-making, the compliance level of operators on the standard operating procedures from the postal service industry was investigated, showing that direct contributing factors were workload, fatigue, and work experience (Eskandarzadeh et al., 2023). An experiment by Xu et al. (2020) to measure brain activity associated with online DM shows significantly higher neural activity for high-reputation seller indicators in brain regions related to emotions in the prefrontal cortex. It has also been shown that investment decision-making can be improved by using brain information (Shimokawa et al., 2012); the neural correlates between emotional and cognitive responses and the degree of information recall can be studied using event-related EEG (Riaz et al., 2018).

Information behaviour is found to be closely associated with DM using information technology. Anderson et al. (2016) use eye tracking to study the neurophysiological manifestation of habituation which contributes to ineffective warnings. The results illustrate an increase of habituation with repeated security warnings, and suggest a polymorphic warning that repeatedly changes its appearance to effectively reduce habituation. Browne and Walden (2021) study the process of information searching and stopping decisions through brain activation networks and find that the patterns of stopping decisions are different from those of searching.

Moreover, some critical and timely decisions need to be made in highly complex work environments, such as aviation. It reveals age and expertise differences in DM performance of pilots. It is found that older pilots are more likely than younger pilots to make a decision to land with inadequate visibility, and faster processing speed contributes to higher landing decision false alarm rate (Kennedy et al., 2010). Pilots with fewer skills need more DM time on landing or go-around compared to experienced pilots (Kale et al., 2023). In addition, age-related cognitive assessment is a reliable predictor of flight DM performance, with the beneficial effects of flight experience (Causse et al., 2011). Hence, this shows the critical role of psychophysical technologies in DM measurements.

DM process studies have applied psychophysical technologies in real-world operations regarding safety–critical systems. Causse et al. (2013) use fMRI to investigate the effects of emotion on pilot decision-making. It shows that financial incentive contributes to risky behaviours, and plan continuation error (PCE) behaviours for pilots are affected by emotion during DM. Zhang et al. (2020) utilise EEG, eye movement, and ECG, to assess mental workload in maritime teams using random forests algorithm, where the low levels of Mean Absolute Percent Error prove accurate mental workload assessment results. Noise exposure from nighttime flight traffic influences airport residents' sleep quality measured by EEG, suggesting that a night-flight ban is the most effective way to improve this situation (Elmenhorst et al., 2024). A combination of self-report, fNIRS, and eye tracking, is utilised to study drives' gaze behaviour, working memory, and their relationship with driving performance (Broadbent et al., 2023). Also, ECG, electromyography (EMG), pulse, blood pressure, reaction time, and vital capacity (VC) have been used in miner fatigue identification, revealing that ECG-FD and EMG are the best indicators of fatigue (Chen et al., 2021). In terms of weather forecasting, an eye tracking system is used to measure eye movement and information usage for assessing SA (Argyle et al., 2020). The analysis reveals a relationship between SA and eye tracking which supports the use of eye movement to measure the DM process for weather forecasters.

Moreover, automation design in real-world operations shows an increasing need to facilitate decision support systems, which will significantly benefit automation design and operational procedures. For instance, the effects of three levels of automation and various traffic levels on eye movements, SA and mental workload for air traffic controllers are studied (Wang et al., 2021). The results show enhanced SA but reduced mental workload with the use of automation, revealing the impact of automation on the behaviours and DM process in air traffic management. The artificial intelligence (AI) integration has been investigated with different kinds of disruptions in supply chain management, revealing the need for cross-disciplinary study and sociotechnical perspectives (Hendriksen, 2023). Also, trust in Autonomous Vehicles (AV) can be evaluated through brain activity using frontal alpha EEG as a neural correlate (Seet et al., 2022). Evidence shows that a disrupted right frontal functional clustering is associated with enhanced approach motivation (i.e., desire to re-engage) during Full Automation Driving malfunctions, where the brain area supports executive cognition, i.e., DM. In other words, trust is deteriorated by the inability of human drivers to be on-the-loop for adjustment on malfunctions or violations, rather than by automation malfunctions (Seet et al., 2022). In addition, safety–critical systems often require both automation and human input, such as air traffic control (ATC), which still values human intelligence in the DM process. To design intelligent and adaptive ATC systems, human factors and human performance are measured using fNIRS and subjective data for a human-centred DM approach to adjust decision support systems to human factors (Li et al., 2021).

Regarding navigational safety, the mental states of seafarers and their DM performance have not been well addressed in advanced DM processes of ship navigation. This may result from most system designs and risk assessments concentrating on historical data but omitting human-centred demands which are difficult to evaluate through existing quantitative methods. It leads to failures in incorporating the human element into system evaluation. Meanwhile, there are limited studies on advanced DM evaluation for navigation in terms of effective human performance measurements. To address these research gaps, a human-centred DM method for navigational safety systems using fNIRS has been put forward in this paper.

2.3. New contributions

Towards advanced decision support for the maritime sector, this study proposes a novel methodology to pioneer the incorporation of psychological and subjective data to analyse the functional connectivity of operators' brains and predict DM performance in ship navigation. Although the methodology is applied to shipping safety, due to its generality, it can be tailored and used in other transport sectors. More specifically, the theoretical contributions to the literature include:

(1) The establishment of a methodology to detect different workload levels in safety–critical operations using psychophysiological measurement.

(2) Analysis of brain's functional connectivity of different groups of decision makers (e.g., watchkeepers) during high and low workload tasks.

(3) An advanced methodology to assess human reliability in complex scenarios and predict operational behaviours.

(4) A pioneering human-centred approach to predicting DM performance and demonstrating its feasibility in shipping using fNIRS.

Moreover, the insights advance practices in maritime operations and training for generating a reliable tool to assess human performance in real-time given tasks of various levels of decisions in maritime transport. Maritime training and education institutions can use the findings of this study for ongoing training and to evaluate DM performance improvement for individuals across different proficiency levels. In this way, seafarer competencies can be complemented and improved. In addition, the findings quantify the cognitive states of OOWs and analyse their DM performance across diverse scenarios to evaluate the adaptiveness of MASS automation levels in a smart manner.

3. Methods and materials

3.1. Participants

Ten professional watchkeeping officers (mean = 35.1 years, SD = 15.6 years) were recruited from the local branch of the Nautical Institute and Liverpool John Moores University, United Kingdom. All participants were males and had experience working at sea as qualified officers. The exclusion criteria for the participants were head injury conditions, high blood pressure, suffering from anxiety or receiving medication for anxiety. These were implemented as they may influence the signal quality of fNIRS (Fan et al., 2021, Fan et al., 2023).

3.2. Experimental design

An experiment was employed to assess the association among fNIRS, workload, and DM for ship collision avoidance during watchkeeping. The independent variable was the workload level within each scenario, which was presented in two conditions (low and high). The dependent variables comprised measurements taken by fNIRS and participants' DM evaluation carried out by expert assessors.

The fNIRS measurements were dependent upon the assignment of scenarios. Two participants were assigned for each test to work as a group with two scenarios (low and high) in a ship bridge simulator, where the order of two scenarios was randomised. The low workload scenario started with a port crossing ship event, followed by a starboard crossing ship event, as shown in Fig. 1. For both of

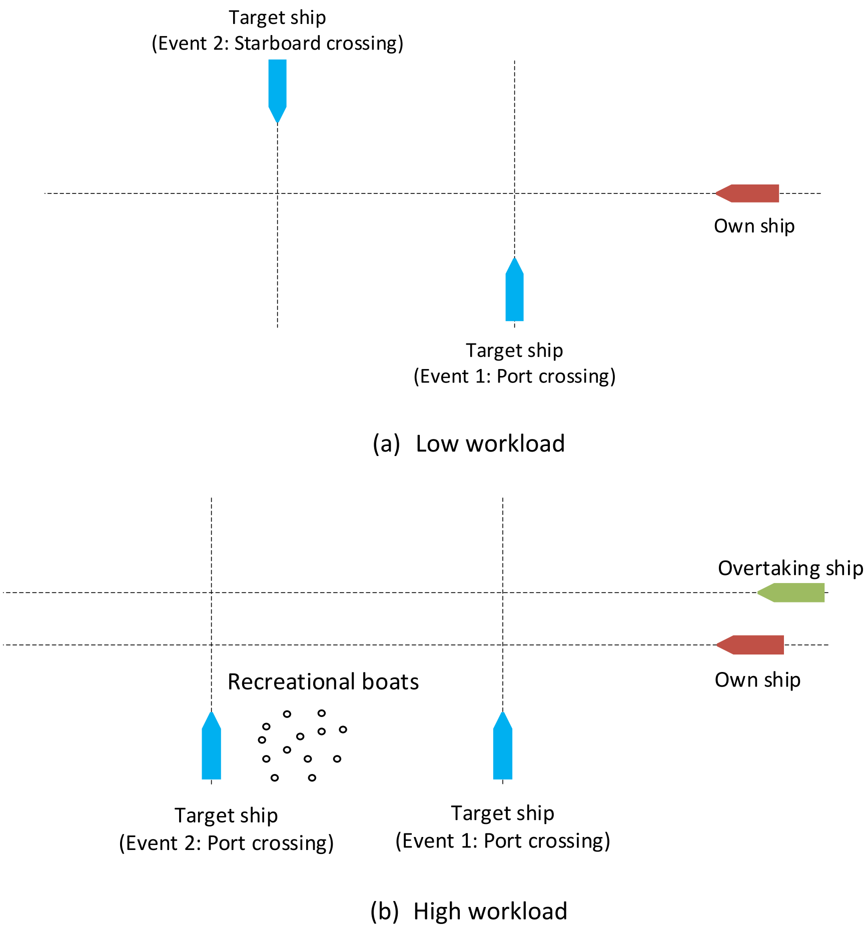

Fig. 1. Ship encountering scenarios for different workloads.

these occurrences, the ships followed the collision avoidance regulations as required (IMO, 1972). In comparison, the high workload scenario started with a port crossing ship that adhered to the regulations, followed by a second port crossing ship that did not give way (the regulation requires that the port crossing ship is the give-way vessel). In addition, there was an overtaking vessel on the starboard quarter of the watchkeeper's own ship (removing the option to alter course to starboard), together with several small recreational boats masking the approach of the port crossing ships on the radar, as shown in Fig. 1. The detailed environmental parameters and settings can be found in Table 1, created by experienced Master Mariner and Chief Mate using a Wartsila bridge simulator.

The two scenarios were distinguished by different workload levels. The high workload scenario was generated with reduced visibility, reduced radar range, complex traffic (i.e., an overtaking vessel and recreational boats), and involvement of a port crossing ship that didn't give way. Both scenarios required participants to follow the route set out on the chart and keep safe from navigational dangers. The test was terminated either when there was nothing the own ship could do to avoid collision (as judged by the instructor) or when 30 min had passed.

After signing consents and donning fNIRS equipment, the scenarios commenced. Each scenario took an average of 25 ~ 30 min, followed by participants filling out a workload survey. Finally, after completing both scenarios, a debrief was given. The order of presentation of low and high workloads was counterbalanced across the five groups of participants. Each scenario in tests was divided into 5 average periods, with event 1 occurring in the first period and event 2 occurring in the third period, as seen in Table 2. The expected actions in each period varied between the different scenarios. For the low workload scenario, participants were expected to spot a port crossing ship in r1, observe the port crossing ship to safely pass, spot a starboard crossing ship and realise the responsibility to give way in r3, observe the starboard crossing ship and take actions to avoid collision when appropriate. In contrast, for the high workload scenario, participants were supposed to spot a port crossing ship in r1, observe the port crossing ship until it has passed safely in r2, spot another port crossing ship in r3, monitor the port crossing ship and realise she did not give way in r4, and monitor the situation in r5.

3.3. *Subjective mental workload and behavioural measures*

Participants' mental workload was measured using a Team Workload Questionnaire (TWLQ), and their behavioural data were recorded using an observer-rated measurement. The TWLQ consisted of two parts, representing individual workload and team workload respectively. The first part was derived from the NASA Task Load Index (TLX) consisting of a questionnaire constructed around six elements: mental demand, physical demand, temporal demand, performance, effort, and frustration (Hart and Staveland, 1988). This has previously been applied in the maritime sector to measure corresponding workloads (Fan et al., 2021, Fan et al., 2023, Fan and Yang, 2023). The second part was proposed by Sellers et al. (2014) and Zhang et al. (2020) for team workload assessment in bridge teamwork, including communication activity, coordination activity, time management between individuals and teams, team monitoring, team performance, support from team members, and team frustration.

The observer-rated measurement was a decision-making/anticipation assessment constructed upon a 5-point scale: 5 = best practice, 4 = good, 3 = acceptable, 2 = needs improvement, 1 = unacceptable, referring to the Nautical Institute's guideline (Gale, 2016). Two experts with decades of navigational experience were invited to rank and comment upon the participant's DM performance in each scenario.

3.4. *fNIRS Apparatus*

The study used the NIRSport 2 fNIRS device for neurovascular and mental state measurements of participants. Optical density data were collected (10.2 Hz) with 8 sources and 8 detectors. Deoxygenated and oxygenated haemoglobin were detected at wavelengths of 760 nm and 850 nm. The fNIRS system has a wireless connection to a laptop. These features enable the neurophysiological measurement of participants in a ship's bridge simulator without restricting their movement and interaction with each other.

The study was designed with a montage consisting of 20 standard channels and 8 short-distance channels. Typically, standard channels capture both cerebral and extracerebral activities, while short-distance channels capture extracerebral signals. However, only cerebral activities are useful for the analysis. Therefore, using both standard and short-distance channels enables the calculation of participants' cerebral activities, eliminating the effect of extracerebral activity to improve signal quality (Brigadoi and Cooper, 2015). It is comprised of 8 sources and 7 detectors (the eighth detector is sacrificed for 8 short channels), as shown in Fig. 2, covering Brodmann's areas 8, 9, 10, and 46. The montage was divided into three regions of interest (ROIs) representing left, middle, and right, as shown in Table 3, for connectivity analysis.

Table 1
Experimental parameters and settings in the ship's bridge simulator.

Scenario	Visibility (Nautical miles)	Radar range (Nautical miles)	Traffic	Events
Low workload	10	6; 12	No other ship	Event 1: Port crossing ship Event 2: Starboard crossing ship
High workload	5	6; 6	Overtaking ship Recreational boats	Event 1: Port crossing ship Event 2: Port crossing ship that doesn't give way

Table 2
Expected events and duties in each task period for the two groups.

Group	Low workload	High workload
Task period r1	Event1, Monitor	Event1, Monitor
Task period r2	Monitor	Monitor
Task period r3	Event2, Action selection	Event2, Monitor
Task period r4	Monitor	Action selection
Task period r5	Monitor	Monitor

3.5. Data pre-processing

The raw fNIRS data were pre-processed using Satori software with the following steps. The modified Beer–Lambert law was used to calculate oxygenated haemoglobin (HbO) and deoxygenated haemoglobin (Hbb) changes.

i. Remove discontinuities: channel rejection with scalp coupling index (SCI) less than 0.75.
ii. Spike removal with a threshold of 3.5.
iii. Motion correction: Temporal Derivative Distribution Repair (TDDR).
iv. Short-channel regression with a general linear model (GLM).
v. Noise removal: temporal filtering with cut-off frequencies 0.01 Hz and 0.04 Hz (removing physiological signals such as heartbeat (1–1.5 Hz), respiration (0.2–0.5 Hz) and low-frequency blood pressure fluctuations (Mayer waves, 0.1 Hz)).
vi. Correlation-based signal improvement (CBSI).
vii. Z normalisation

The HbO and Hbb data were subjected to a correlation-based transformation, and the HbO and Hbb were negatively correlated after CBSI (Cui et al., 2010). Subsequently, the normalised data from 20 HbO channels were imported into MATLAB for further analysis.

3.6. Functional connectivity analysis and graph theory

Step 1: calculate partial correlation coefficients

The functional connectivity analysis was derived from Racz et al. (2017) using graph theory. This study modified the connectivity analysis by calculating partial correlation coefficients rather than Pearson correlation values between each available channel (Akın, 2017, Fan et al., 2021). For each participant, a matrix of partial correlation coefficients was calculated for 20 standard channels across five periods (r1, r2, r3, r4, r5).

Step 2: generate binary functional connection network through thresholding

Thresholding was applied to each matrix to construct an appropriate binary functional connection network. Firstly, any values below zero were removed to keep only positive associations. Then several levels (from 0.1 to 0.6 proportional threshold) were selected to observe the constructed network. After comparisons, it was found that the binary functional connection network showed a significant difference in functional connectivity parameters with 0.1442 as a criterion level. Therefore, it was selected to remove weak correlation while retaining critical features in the network. In this way, the original matrices were converted into binary adjacency

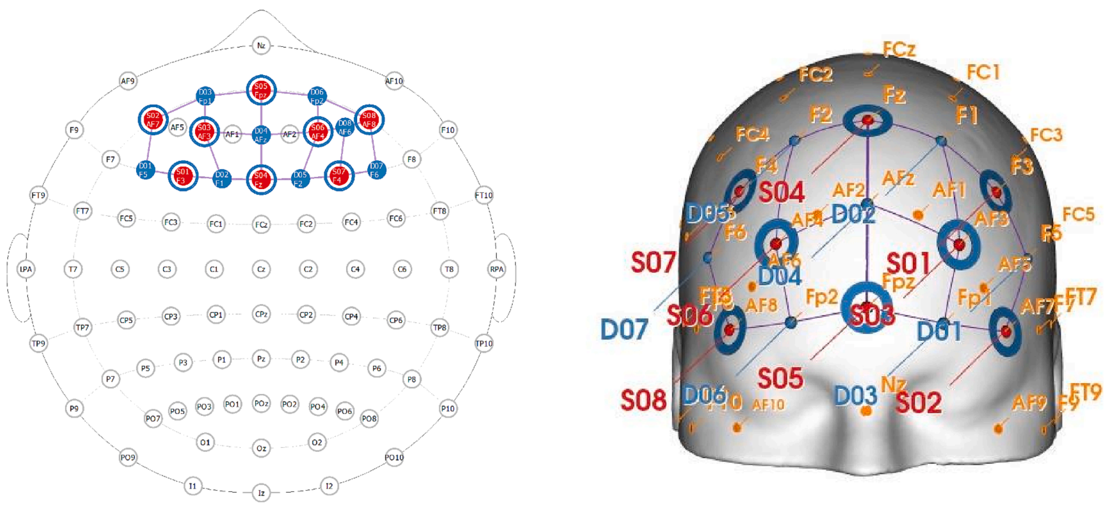

Fig. 2. Montage design with short distance channels consisting of 8 sources and 7 detectors.

Table 3
20 standard channels in three ROIs.

Left ROI	Middle ROI	Right ROI
Channel 1 S1D1	Channel 2 S1D2	Channel 15 S6D5
Channel 3 S2D1	Channel 7 S3D4	Channel 16 S6D6
Channel 4 S2D3	Channel 8 S4D2	Channel 18 S7D7
Channel 5 S3D2	Channel 9 S4D4	Channel 19 S8D6
Channel 6 S3D3	Channel 10 S4D5	Channel 20 S8D7
	Channel 11 S5D3	
	Channel 12 S5D4	
	Channel 13 S5D6	
	Channel 14 S6D4	
	Channel 17 S7D5	

matrices after thresholding, which were prepared for graph-theoretic analysis in the next step.

Step 3: calculate functional connection network parameters

To explore the features of a functional connectivity network, the connection density (D) and local clustering coefficient (C) were calculated based on the binary matrices for each participant per period (Racz et al., 2017). The D represented the proportion of the existing channel connections to all possible channel connections, while the C measured the proportion of neighbours to a node which are also neighbours of one other. These two parameters were calculated per participant for each period of the trial.

4. Results

4.1. Subjective mental workload

Each of the ten participants completed two trials, generating a total of 20 pieces of data. The experimental study comprised two groups: one with 10 participants assigned to the low workload condition and the same 10 participants assigned to the high workload condition. The sequence of workload conditions was randomised. TWLQ data were analysed via the repeated measures MANOVA model. The analysis revealed that the differences between low workload and high workload groups were not statistically significant in terms of the combined dependent variables ($p > 0.05$). However, the univariate test showed a main effect of workload in terms of mental demand [$F(1,9) = 7.875$, $p = 0.021$], which showed higher mental and perceptual activity in the high workload scenario. It was also apparent that temporal demand (time pressure) was greater in the high workload scenario [$F(1,9) = 21.246$, $p = 0.001$]. In addition, levels of effort were higher for participants in the high workload scenario [$F(1,9) = 6.667$, $p = 0.030$]. Communication and coordination activities were higher in the high workload scenario [$F(1,9) = 5.651$, $p = 0.041$; $F(1,9) = 10.756$, $p = 0.010$], as shown in Table 4.

4.2. fNIRS data average

The fNIRS data were grouped into three ROI corresponding to the left, central, and right areas of the brain's prefrontal cortex. Pre-processed fNIRS data for each ROI were analysed via a repeated measures ANOVA model. The HbO analysis from the left ROI failed to indicate any significant main effects of workload or task period. However, it revealed a significant interaction between workload x task period [$F(4,6) = 7.192$, $p < 0.018$, $\eta p2 = 0.87$]. Paired-samples t tests revealed that the average HbO at the left ROI was significantly higher for the participants in the low workload group during r3 [$t(9) = 2.992$, $p = 0.015$] and r5 [$t(9) = 5.840$, $p < 0.001$], but significantly lower during r4 [$t(9) = -3.658$, $p = 0.005$] compared to the high workload group. Only for the low workload group, the

Table 4
Statistical significance of TWLQ (N = 10).

Part	Criterion	F	Significance
Individual	Physical demand	3.768	0.084
	Mental demand	7.875	0.021
	Temporal demand	21.246	0.001
	Individual performance	1.210	0.300
	Effort	6.667	0.030
	Frustration	4.765	0.057
Team	Communication activity	5.651	0.041
	Coordination activity	10.756	0.010
	Time management between team and individual	3.768	0.084
	Monitor team	0.590	0.462
	Team performance	0.244	0.147
	Support difficulty	0.000	1.000
	Team frustration	0.310	0.591

HbO at left ROI was significantly lower at r4 compared to r3 ($p < 0.05$) and significantly higher at r5 compared to r2 and r4 ($p < 0.05$). as shown in Fig. 3.

The HbO analysis from the middle ROI indicated significant interaction between workload x task period after Greenhouse-Geisser corrections [$F(2.044,18.396) = 6.155$, $p = 0.009$, $\eta p2 = 0.406$]. Paired-samples t tests were conducted to analyse the significant interaction effects on the middle ROI. It was found that average HbO was significantly higher for participants in the high workload group during r1 [$t(9) = -3.040$, $p = 0.014$] and r4 [$t(9) = -2.850$, $p = 0.019$] periods; while it was significantly lower during r3 [$t(9) = 2.669$, $p = 0.026$] and r5 [$t(9) = 3.042$, $p = 0.014$] periods compared to the low workload group. For the low workload group, the HbO at the middle ROI was significantly lower at r4 compared to r3 ($p < 0.05$) and significantly higher at r5 compared to r4 ($p < 0.05$), as shown in Fig. 4.

The analysis of HbO data from the right ROI failed to indicate any significant main effects of workload or task period.

4.3. Functional connectivity

The functional connectivity of watchkeepers was calculated using Graph Theory. Then repeated measures were conducted on the parameter D. This model revealed a significant main effect for workload [$F(1,9) = 13.393$, $p = 0.005$, $\eta p2 = 0.598$], but no significant effects for task period or any interaction. The participants in the low workload group showed a higher connectivity density than those in the high workload group, indicating an average higher density of brain activities for the low workload group. The effect is illustrated in Fig. 5.

Similarly, repeated measures ANOVA was conducted on the parameter C. This model showed no significant main effects for workload, task period, or interaction between workload and task period in the model.

4.4. Prediction of decision making

Based on the results from the above section, connectivity density (D) with a significant main effect for workload was used to predict DM performance. A regression model was created, with DM performance value as a dependent variable and D as an independent variable.

The Pearson (23.68) and Deviance (22.85) statistics test proved that the model was fit ($p > 0.05$). Chi-square statistic (Chi-square value = 25.47, $p = 0.04$) assesses the model's fitness. It proved a significant relationship between the DM performance and D in the regression model. Moreover, the prediction accuracy of the regression was 75 %. The Pseudo R-Square measures were Cox and Snell (0.72), Nagelkerke (0.79) and McFadden (0.53). It illustrated that the model accounted for 52.7 % to 79.1 % of the variance and represents decent-sized effects. The Likelihood Ratio Test proved that the predictor variables such as D in r1 ($p = 0.01$) and r5 ($p < 0.001$) of the participants were significant, meaning that connectivity densities in r1 and r5 periods contributed significantly to the final model.

Regarding parameter estimates among the "needs improvement" participants (as identified in Section 3.3), D in r2 and r4 had a significant impact on DM of participants. The "needs improvement" participants were more likely to have better DM compared to "acceptable" participants due to an increase in r2 ($b = 813.799$, Wald = 68.503, $p < 0.001$). The "needs improvement" participants were less likely to have better DM compared to "acceptable" participants due to an increase in r4 ($b = -187.331$, Wald = 36.613, $p < 0.001$).

Among the "good" participants, D of r2 and r4 periods had a significant impact on DM performance of participants. The "good" participants were more likely to have better DM compared to "acceptable" participants, due to an increase in r2 ($b = 776.737$, Wald = 54.298, $p < 0.001$). The "good" participants were less likely to have better DM compared to "acceptable" participants due to an increase in r4 ($b = -200.555$, Wald = 34.381, $p < 0.001$).

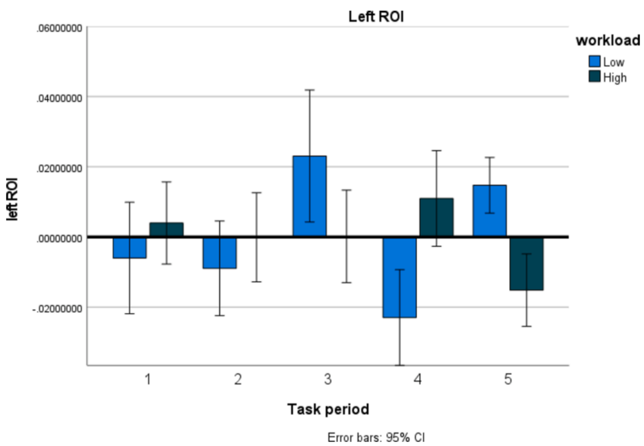

Fig. 3. The HbO analysis from the left ROI across 5 task periods.

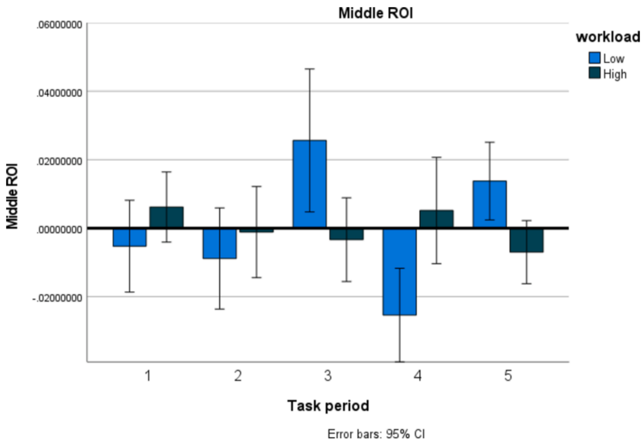

Fig. 4. The HbO analysis from the middle ROI across 5 task periods.

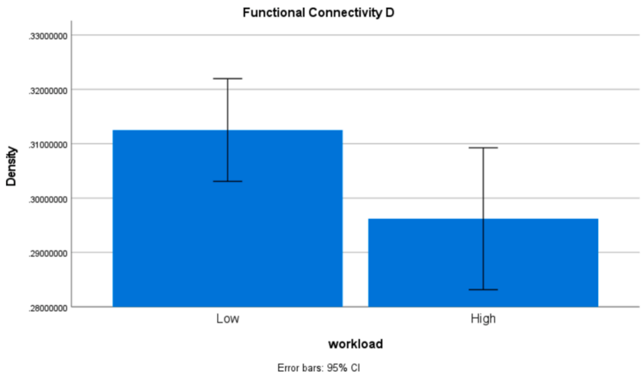

Fig. 5. Density in two workloads across all task periods.

5. Discussions

The test simulation was associated with watchkeeping tasks followed by decision-making processes. To be specific, the watchkeeping was a visual vigilance task where a participant must monitor the traffic around the own ship. Once the target vessel was spotted, the participant must observe and appraise the situation, then make a decision to avoid the collision. The scenarios were embedded with two kinds of ship encountering situations, i.e., port crossing ship and starboard crossing ship, where the regulation requires that the port crossing ship is the give-way vessel. In the study, the high workload scenario was distinguished from the low one in terms of reduced visibility, reduced radar range, complex traffic, and a port crossing ship that didn't give way. During periods r1 and r3, participants actively monitored the target vessel approaching and appraised the possibility of collision until they formulated and executed an action.

The analysis of subjective mental workload revealed increased mental activity and time pressure for individuals in the high workload group, due to increased traffic and complex collision avoidance scenarios. Collision avoidance tasks became more complicated in high workload situations. However, from the team perspective, only communication and coordination activities were found to be significantly higher in the high workload group. This finding resonates with a report emphasising communication or teamwork breakdowns contributed to numerous marine incidents (Canada, 1995). Similarly, optical measures demonstrated that frequent communication heightened the workload in human-agent teaming scenarios (Wright et al., 2022).

The above findings suggest considerable managerial advantages given the rising tide of automation and the trend towards reduced crew sizes aboard vessels in the era of MASS. The industry is undergoing a profound shift, offering a new pathway to redefine the roles and responsibilities of maritime operators. This redefinition depends on several factors, including operators' workplaces (whether onboard or ashore), the level of ship autonomy (ranging from human-in-the-loop to human-on-the-loop systems), and operators' roles (as monitor, supervisor, or decision maker). This transformation inherently fosters new interactions and collaborations. It requires enhanced communication between OOWs and captains, between seafarers onboard and shore-based crews, and even between remote control operators and other decision-makers. Communication emerges as a pivotal element in these novel scenarios, particularly given the high workloads involved. Therefore, maritime authorities can utilise these findings to bolster communication initiatives in the case of high workload requirements.

Moreover, maritime education and training institutions should emphasise communication competencies for seafarers within high-workload exercises. Within this context, more specific illustrative examples include when training cadets in shipping, their competencies for the tasks of a certain workload can be objectively measured. It aids to 1) inform the training institutes which tasks need better design on the man–machine interface, if and when the majority of trainees fail to conduct them and 2) improve the scientific assessment of their qualifications by introducing a more scientific and objective measure. Currently, transport operators' qualifications are certified mainly through subjective assessment by assessors, which could be biased, as evidenced by human errors introduced by certified operators who may be incompetent, contributing to transport accidents. Therefore, the findings of this study will significantly improve safety at sea first and other transport modes later by reducing introduced human errors due to operators' incompetence.

The analysis of average HbO for two groups across 5 task periods in the left and middle ROIs revealed statistically significant interactions: (a) higher HbO during r3 (event 2 happened) and r5 in the low workload group compared to the high workload one, and (b) higher HbO during r4 for the high workload group compared to the low workload group. The r4 in the high workload group and r3 in the low workload group represented the action selection with increased task difficulty. It corresponds with the findings in the literature, which observed a rise in HbO concentration within the dorsolateral prefrontal cortex under conditions of high task difficulty (Causse et al., 2024). Likewise, similar results were uncovered in the studies conducted by Zhang et al. (2021) and Li et al. (2020), suggesting activation of the dorsolateral prefrontal cortex during such decision-making phase.

In terms of functional connectivity analysis, a statistically significant difference was the lower D for the high workload group compared to the low workload group. This finding further indicated the reduced connection density in a high workload situation, aligning with prior research (Fan et al., 2021). It was noted that high workload was associated with reduced connection density of brain activity, which may imply more efficiency in high workload with more communication and coordination activities. Moreover, it should be noted that event 2 in the low workload group was a starboard crossing ship which required the own ship as the give-way vessel to take action; while in the high workload group event 2 was a port crossing ship which required the target ship as the give-way vessel to take action. Hence, this situation made the participants in the low workload group aware of taking collision avoidance action as the give-way vessel in r3 when event 2 occurred, while participants in the high workload group expected the target vessel to take action in r3 period and realised the vessel did not obey the regulation to give way in r4 period. That is to say, the increase of HbO in r3 for the low workload group was owing to the spot of starboard crossing ship, where the regulation required the own ship as the give-way vessel to take action. It showed that past experience contributed to the guidance of action selection, as evidenced by Koechlin et al. (2003). During r4, the increase of HbO for the high workload group indicated the participants realised the port crossing ship did not give way and the own ship had to unexpectedly (and at short notice) take action to avoid the collision. During r5, the decrease of HbO for the high workload group may result from the mental overload for avoiding collisions with a port crossing ship, an overtaking vessel, and recreational boats simultaneously. They had nothing to do with the complex situation after the action taken at r4, waiting for the ship collision avoidance results (success or failure) to happen. Therefore, it implies the potential for maritime training institutes to utilise seafarers' brain connectivity parameters for calibrating workload levels across diverse navigational scenarios. This approach can enable the customisation of competency training guidelines to better accommodate the evolving landscape of navigation traffic scenarios, encompassing both conventional and autonomous vessels, therefore benefiting the adaptive automation for human–machine interfaces towards a smart manner.

Regarding regression analyses, it was to investigate the association between functional connectivity in the PFC and decision-making performance of OOWs during the task simulation. From the results in the regression model, the density can significantly distinguish the DM performance. To be specific, it was evident that calculations of OOW's connection density D from the port crossing situation (r1) and the end for scenario (r5) using fNIRS can predict their DM in collision avoidance.

These results provided great insights for OOW performance measurement and improvement. Regarding parameter estimates among the "needs improvement" participants, if the value of D in r2 for OOWs in the latter training increased, OOWs' DM performance in the previous "needs improvement" group was more likely to be improved, compared to the "acceptable" group. It made the evaluation of OOWs' DM progress possible, proving the greater progress in the previous "needs improvement" group compared to the "acceptable" group if there were same trends in r2. Similarly, if the value in r4 for OOWs in the latter training increased, OOW performance in the previous "acceptable" group was more likely to be improved in terms of DM, compared to the "needs improvement" group. It proved the greater progress of OOWs in the previous "acceptable" group compared to the "needs improvement" group if the D in r4 for both groups increased.

Regarding the "good" participants, if the value in r2 for OOWs in the latter training increased, their performance in the previous "good" group was more likely to be improved in terms of DM, compared to the "acceptable" group. It implied the greater progress of DM performance in the previous "good" group compared to the "acceptable" group with the same increase of D in r2. Similarly, if the value in r4 for OOWs in the latter training increased, their performance in the previous "acceptable" group was more likely to be improved in terms of DM, compared to the "good" group. It proved the greater progress of OOWs' DM performance in the previous "acceptable" group with same increased D value in r4.

Within the maritime industry, there is an STCW code outlining the competence of seafarers, as shown by standards such as STCW Code Table A-II/1 and STCW Code Table A–V/2 (STCW, 2011). While this code requires diverse criteria, it fails to explain how these standards are objectively evaluated, especially within the context of the application of emerging MASS technologies. Even with adequate training based on the STCW framework, deviations in tasks by seafarers could potentially lead to hazardous situations (Rajapakse and Emad, 2021). It primarily addresses limited outcomes-based or behaviour-focused knowledge required by seafarers, revealing discrepancies between regulatory guidelines and practical performance. Therefore, the findings of this study serve as an objective tool for assessing seafarer competence in real-time across tasks involving different levels of DM performance in maritime transport and further offer operators feedback on various scenarios and new machinery designs, thereby bolstering existing industrial practices. It is confident that the success of using the new findings in the maritime sector first will be spread to the other transport sectors given they are also undertaking the evolution brought by new autonomy and automation technologies, which requires a groundbreaking change of operators' roles in transport science.

In this manner, it reveals managerial implications for maritime training and education. Maritime training institutions benefit from the proposed methodology using fNIRS to conduct objective performance evaluations. It can assess OOW performance for individuals in ongoing training and evaluate DM performance improvement for individuals across different proficiency levels by comparing their own historical performance records. In other words, maritime training institutions can now provide grades of OOWs' performance during professional training, with the support of fNIRS measurements during DM tasks. In this way, neuropsychological indicators help the subjective evaluation of seafarers' DM performance. At the same time, their improvements during different training periods can also be quantified by comparing fNIRS data in historical records and peer performance at varying skill levels. It serves as a practical record and measurement tool to improve OOW performance at sea. Therefore, it offers an advanced DM method that adapts to mental states of OOWs and supports autonomy design, through observing feedback from operators' predictive response and DM performance.

6. Conclusion

This study proposed an advanced DM method to predict human performance in ship navigation, and evaluate seafarers' DM, which incorporated subjective and neurophysiological measurements. Prior to the experimental study, a comprehensive literature review in multidisciplinary fields was conducted to investigate the state of the art on decision-making in the transport sector, and then a new approach (of using psychological means) beyond the state of the art was proposed. Appropriate techniques (fNIRS techniques and NASA-TLX questionnaire) and simulator scenarios (ship navigation scenarios with two levels of workload) were used to set up protocol through within-participants design. The advantage of a within-participants design is fewer participants because each person yields more data, which fits the nature of a low number of seafarer professionals. Next, robust procedures were implemented to ensure the accuracy and reliability of data. The data was collected through the oxygen level in a human brain, which has been proven to be reliable to measure human performance in very few selective areas (e.g. medicine) but yet in the transport sector. Specifically, the montage of fNIRS containing 8 short-distance channels to extract the cerebral activities of participants, can effectively eliminate the effect of extracerebral activity and improve signal quality.

The findings of this work revealed increased mental activity, time pressure, and efforts for individuals in high workload situations, due to heavy traffic and related complex collision avoidance scenarios. It also showed that communication and coordination were critical indicators of teamwork distinguishing two levels of workloads. It was indicated by a significantly higher level of oxygenated haemoglobin for the low workload group in r3 period when the own ship was the give-way vessel and required to take collision avoidance action. In addition, the oxygenated haemoglobin level in r4 period was significantly higher for the high workload group because they expected the port crossing ship to give way in r3 but had to unexpectedly (and at short notice) take action to avoid collision in r4. Finally, the oxygenated haemoglobin level and D in r5 period were significantly lower for the high workload group because the situation exceeded the participant's ability to cope with collision avoidance (a port crossing ship, an overtaking ship, and multiple recreational boats simultaneously), causing cognitive overload. There was nothing they can do to deal with this situation. Overall, the high workload group showed lower connectivity density than the low workload group. They obtained more efficiency in terms of increased communication and coordination activities. Finally, a significant relationship between DM performance and functional connectivity was proved using a regression model. It indicated acceptable prediction results on DM performance of OOWs through a functional connectivity analysis. Therefore, it illustrated the beauty of using fNIRS technology to measure DM performance, and hence the feasibility of using it to formulate a human-centred decision support methodology for maritime safety.

To conclude, the study established a methodology to detect different workload levels using psychophysiological measurements in transport systems. Through the analysis of the functional connectivity of seafarers, human reliability and operational behaviours in critical scenarios for seafarers were assessed and predicted. The results contribute to generating an objective and reliable tool to assess human performance in real-time given tasks at various levels of decisions in maritime transport. This method also pioneers an advanced approach for data collection and functional connectivity analysis to evaluate human and machine reliabilities in critical scenarios and predict operational behaviours. The proposed human-centred approach to predict DM performance using fNIRS can therefore benefit the adaptive automation for highly automated human–machine interfaces towards a smart manner. Autonomous transport systems can benefit from the findings and, in particular, be designed and optimised based on improved feedback from human operators, given their predictive response and DM performance.

CRediT authorship contribution statement

Shiqi Fan: Writing – review & editing, Writing – original draft, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Stephen Fairclough:** Writing – review & editing, Methodology, Investigation, Formal analysis. **Abdul Khalique:** Writing – review & editing, Resources, Formal analysis. **Alan Bury:** Writing – review & editing, Resources, Investigation. **Zaili Yang:** Writing – review & editing, Resources, Project administration, Investigation, Conceptualization.

Declaration of competing interest

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

interests: Zaili Yang reports financial support was provided by European Research Council. Zaili Yang reports financial support was provided by European Commission Marie Sklodowska-Curie Actions.

Acknowledgements

This project has received funding from the European Research Council (ERC) (Grant Agreement No. 864724), MarRI-UK Core Project (Grant Agreement No. MarRI-UK_CORE_2024_02) and Marie Curie RISE ENHANCE (Grant Agreement No. 823904) under the European Union's Horizon 2020 research and innovation programme.

References

Accou, B., Carpinelli, F., 2022. Systematically investigating human and organisational factors in complex socio-technical systems by using the "SAfety FRactal ANalysis" method. Appl. Ergon. 100, 103662.

AKıN, A., 2017. Partial correlation-based functional connectivity analysis for functional near-infrared spectroscopy signals. J. Biomed. Opt. 22.

Anderson, B.B., Jenkins, J.L., Vance, A., Kirwan, C.B., Eargle, D., 2016. Your memory is working against you: How eye tracking and memory explain habituation to security warnings. Decis. Support Syst. 92, 3–13.

Argyle, E.M., Gourley, J.J., Kang, Z.H., Shehab, R.L., 2020. Investigating the relationship between eye movements and situation awareness in weather forecasting. Appl. Ergon. 85, 103071.

Atashfeshan, N., Saidi-Mehrabad, M., Razavi, H., 2021. A novel dynamic function allocation method in human-machine systems focusing on trigger mechanism and allocation strategy. Reliab. Eng. Syst. Saf. 207, 107337.

Babaeeghazvini, P., Rueda-Delgado, L.M., Gooijers, J., Swinnen, S.P., Daffertshofer, A., 2021. Brain structural and functional connectivity: A review of combined works of diffusion magnetic resonance imaging and electro-encephalography. Front. Hum. Neurosci. 15, 721206.

Bai, C.C., Jin, S., Jing, J., Yang, C.C., Yao, W.B., Rong, D.L., Alagbe, J.A., 2024. A multimodal data-driven approach for driving risk assessment. Transport Res E-Log 189.

BBC, N. 2002. Hundreds lost as Senegal ferry sinks. BBC News, 27 September 2002.

Branch, M. A. I., House, C. & Place, C. 2004. Bridge watchkeeping safety study. Department for Transportation, Marine Accident Investigation Branch, Southampton.

Brau, R.I., Sanders, N.R., Aloysius, J., Williams, D., 2024. Utilizing people, analytics, and AI for decision making in the digitalized retail supply chain. J. Bus. Logist. 45.

Brigadoi, S., Cooper, R.J., 2015. How short is short? Optimum source–detector distance for short-separation channels in functional near-infrared spectroscopy. Neurophotonics 2.

Broadbent, D.P., D'Innocenzo, G., Ellmers, T.J., Parsler, J., Szameitat, A.J., Bishop, D.T., 2023. Cognitive load, working memory capacity and driving performance: A preliminary fNIRS and eye tracking study. Transportation Research Part F-Traffic Psychology and Behaviour 92, 121–132.

Browne, G.J., Walden, E.A., 2021. Stopping information search: An fMRI investigation. Decis. Support Syst. 143, 113498.

Caballero, W.N., Insua, D.R., Banks, D., 2023. Decision support issues in automated driving systems. Int. Trans. Oper. Res. 30, 1216–1244.

CANADA, T. S. B. O. 1995. A Safety Study of the Operational Relationship Between Ship Master/watchkeeping Officers and Marine Pilots, [Hull, Quebec]: Transportation Safety Board of Canada.

Causse, M., Dehais, F., Arexis, M., Pastor, J., 2011. Cognitive aging and flight performances in general aviation pilots. Aging Neuropsychol. Cogn. 18, 544–561.

Causse, M., Dehais, F., Peran, P., Sabatini, U., Pastor, J., 2013. The effects of emotion on pilot decision-making: A neuroergonomic approach to aviation safety. Transportation Research Part C-Emerging Technologies 33, 272–281.

Causse, M., Mouratille, D., Rouillard, Y., el Yagoubi, R., Matton, N., Hidalgo-Muñoz, A., 2024. How a pilot's brain copes with stress and mental load? Insights from the executive control network. Behav. Brain Res. 456.

Cedillo-Campos, M.G., Martner-Peyrelongue, C.D., Herrera-Garcia, A., Garcia-Ortega, G., Jimenez-Sanchez, E., Covarrubias, D., 2024. Demand and supply shocks derived from COVID-19 on the freight transportation system in Mexico. Int. J. Logist. Manag.

Chakraborty, S., Kiefer, P., Raubal, M., 2024. The influence of uncertainty visualization on cognitive load in a safety- and time-critical decision-making task. Int. J. Geogr. Inf. Sci. 38, 1583–1610.

Chen, K., Wang, R., Huang, J., Gao, F., Yuan, Z., Qi, Y., Wu, H., 2022. A resource for assessing dynamic binary choices in the adult brain using EEG and mouse-tracking. Sci. Data 9, 416.

Chen, S.K., Xu, K.L., Yao, X.W., Zhu, S.Y., Zhang, B.H., Zhou, H.D., Guo, X., Zhao, B.F., 2021. Psychophysiological data-driven multi-feature information fusion and recognition of miner fatigue in high-altitude and cold areas. Comput. Biol. Med. 133.

Cui, X., Bray, S., Reiss, A.L., 2010. Functional near infrared spectroscopy (NIRS) signal improvement based on negative correlation between oxygenated and deoxygenated hemoglobin dynamics. Neuroimage 49, 3039–3046.

Dehais, F., Lafont, A., Roy, R., Fairclough, S., 2020. A neuroergonomics approach to mental workload, engagement and human performance. Front. Neurosci. 14, 268.

Elmenhorst, E.-M., Mueller, U., Quehl, J., Basner, M., McGuire, S., Schmitt, S., Plath, G., Jordan, J., Aeschbach, D., 2024. Night-flight ban preserves sleep in airport residents. Transp. Res. Part D: Transp. Environ. 126, 104027.

Eskandarzadeh, S., Fahimnia, B., Hoberg, K., 2023. Adherence to standard operating procedures for improving data quality: An empirical analysis in the postal service industry. Transport Res E-Log 176.

Fan, S., Yang, Z., 2023. Towards objective human performance measurement for maritime safety: A new psychophysiological data-driven machine learning method. Reliab. Eng. Syst. Saf. 109103.

Fan, S., Zhang, J., Blanco-Davis, E., Yang, Z., Wang, J., Yan, X., 2018. Effects of seafarers' emotion on human performance using bridge simulation. Ocean Eng. 170, 111–119.

Fan, S., Blanco-Davis, E., Zhang, J., Bury, A., Warren, J., Yang, Z., Yan, X., Wang, J., Fairclough, S., 2021. The Role of the Prefrontal Cortex and Functional Connectivity during Maritime Operations: An fNIRS study. Brain and Behavior 11.

Fan, S., Blanco-Davis, E., Fairclough, S., Zhang, J., Yan, X., Wang, J., Yang, Z., 2023. Incorporation of seafarer psychological factors into maritime safety assessment. Ocean Coast. Manag. 237, 106515.

Fiskin, R., Atik, O., Kisi, H., Nasibov, E., Johansen, T.A., 2021. Fuzzy domain and meta-heuristic algorithm-based collision avoidance control for ships: Experimental validation in virtual and real environment. Ocean Eng. 220.

GALE, H. 2016. Navigation Assessments: A Guide to Best Practice, The Nautical Institute.

Greenlee, E.T., Funke, G.J., Hess, L.J., Vidulich, M.A., 2022. Optimizing aid activation in adaptive and non-adaptive aiding systems: A framework for design and validation. Appl. Ergon. 101.

Hart, S.G., Staveland, L.E., 1988. Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. Advances in psychology. Elsevier.

Hassan, L.A.H., Mahmassani, H.S., Chen, Y., 2020. Reinforcement learning framework for freight demand forecasting to support operational planning decisions. Transportation Research Part e: Logistics and Transportation Review 137, 101926.

Hendriksen, c., 2023. Artificial intelligence for supply chain management: Disruptive innovation or innovative disruption? J. Supply Chain Manag. 59, 65–76.

Hogenboom, S., Parhizkar, T., Vinnem, J.E., 2021. Temporal decision-making factors in risk analyses of dynamic positioning operations. Reliab. Eng. Syst. Saf. 207.

Hou, X., Liu, Y., Sourina, O., Muellerwittig, W.C., 2015. EEG-based Emotion, Mental Workload and Stress Visual Monitoring. International Conference on Cyberworlds 153–160.

Imo, 1972. Convention on the international regulations for preventing collisions at sea. Equasis, The world merchant fleet in, p. 2015.
Jakovljevic, V., Zizovic, M., Pamucar, D., Stevic, Z., Albijanic, M., 2021. Evaluation of Human Resources in Transportation Companies Using Multi-Criteria Model for Ranking Alternatives by Defining Relations between Ideal and Anti-Ideal Alternative (RADERIA). Mathematics 9.
Kaber, D.B., Riley, J.M., Tan, K.-W., Endsley, M.R., 2001. On the design of adaptive automation for complex systems. Int. J. Cogn. Ergon. 5, 37–57.
Kale, U., Alharasees, O., Rohacs, J., Rohacs, D., 2023. Aviation operators (pilots, ATCOs) decision-making process. Aircr. Eng. Aerosp. Technol. 95, 442–451.
Kayisoglu, G., Gunes, B., Besikci, E.B., 2022. SLIM based methodology for human error probability calculation of bunker spills in maritime operations. Reliab. Eng. Syst. Saf. 217.
Kennedy, Q., Taylor, J.L., Reade, G., Yesavage, J.A., 2010. Age and Expertise Effects in Aviation Decision Making and Flight Control in a Flight Simulator. Aviat. Space Environ. Med. 81, 489–497.
Kessler, M., Rosca, E., Arlinghaus, J., 2024. Risk management behaviour in digital factories: the influence of technology and task uncertainty on managerial risk responses. Supply Chain Management-an International Journal 29, 297–314.
Khosravi, E., Hemmatyar, A.M.A., Siavoshani, M.J., Moshiri, B., 2022. Safe Deep Driving Behavior Detection (S3D). IEEE Access 10, 113827–113838.
Koechlin, E., Ody, C., Kouneiher, F., 2003. The architecture of cognitive control in the human prefrontal cortex. Science 302, 1181–1185.
Li, X., Liu, K.W., Tseng, H.E., Girard, A., Kolmanovsky, I., 2024. Decision-Making for Autonomous Vehicles With Interaction-Aware Behavioral Prediction and Social-Attention Neural Network. Ieee Transactions on Control Systems. Technology.
Li, Q.B.A., Ng, K.K.H., Fan, Z.J., Yuan, X., Liu, H.S., Bu, L.G., 2021. A human-centred approach based on functional near-infrared spectroscopy for adaptive decision-making in the air traffic control environment: A case study. Adv. Eng. Inf. 49, 101325.
Li, L., Wang, H., Luo, H., Zhang, X., Zhang, R., Li, X., 2020. Interpersonal neural synchronization during cooperative behavior of basketball players: a fNIRS-based hyperscanning study. Front. Hum. Neurosci. 14, 169.
Martins, M.A., Garcez, T.V., 2021. A multidimensional and multi-period analysis of safety on roads. Accid. Anal. Prev. 162, 106401.
Masorgo, N., Mir, S., Hofer, A.R., 2023. You're driving me crazy! How emotions elicited by negative driver behaviors impact customer outcomes in last mile delivery. J. Bus. Logist. 44, 666–692.
Michaelson, R., Safi, M., 2021. Who pays for Suez blockage? Ever Given grounding could spark years of litigation [Online]. Available. https://www.theguardian.com/business/2021/mar/30/years-of-litigation-could-lie-ahead-as-insurers-eye-cost-of-ever-given-grounding.
Mohanty, R., Sethares, W.A., Nair, V.A., Prabhakaran, V., 2020. Rethinking measures of functional connectivity via feature extraction. Sci. Rep. 10, 1298.
Moktadir, M.A., Ren, J.Z., 2024. Towards green logistics: An innovative decision support model for zero-emission transportation modes development. Transport Res E-Log 189.
Pei, H.N., Gong, H., Bai, Z.H., Ma, Y.J., Xu, M.Z., Li, G.Y., 2024. A human factor reliability analysis method for maritime transport based on an improved CREAM model and group decision-making. Ocean Eng. 293.
Racz, F.S., Mukli, P., Nagy, Z., Eke, A., 2017. Increased prefrontal cortex connectivity during cognitive challenge assessed by fNIRS imaging. Biomed. Opt. Express 8, 3842–3855.
Rajapakse, A., Emad, G.R., 2021. Underlying factors which cause task deviation leading to dangerous situations at sea. Mar. Policy 130, 104548.
Riaz, A., Gregor, S., Dewan, S., Xu, Q., 2018. The interplay between emotion, cognition and information recall from websites with relevant and irrelevant images: A Neuro-IS study. Decis. Support Syst. 111, 113–123.
Seet, M., Harvy, J., Bose, R., Dragomir, A., Bezerianos, A., Thakor, N., 2022. Differential Impact of Autonomous Vehicle Malfunctions on Human Trust. IEEE Trans. Intell. Transp. Syst. 23, 548–557.
Sellers, J., Helton, W.S., Näswall, K., Funke, G.J., Knott, B.A., 2014. In: Development of the Team Workload Questionnaire (TWLQ). Sage Publications Sage CA:, Los Angeles, CA, pp. 989–993.
Sheridan, t. b., 2011. Adaptive automation, level of automation, allocation authority, supervisory control, and adaptive control: Distinctions and modes of adaptation. IEEE Transactions on Systems, Man, and Cybernetics-Part a: Systems and Humans 41, 662–667.
Shimokawa, T., Kinoshita, K., Miyagawa, K., Misawa, T., 2012. A brain information-aided intelligent investment system. Decis. Support Syst. 54, 336–344.
Sonar, H., Sharma, I., Ghag, N., Raje, B., 2024. Harvesting sustainability: assessing Industry 4.0 in agri-food supply chains. Int. J. Logist. Manag..
Stcw, i., 2011. International Convention on Standards of Training, Certification and Watchkeeping for Seafarers,(STCW) 1978, as amended in 1995/2010. International Maritime Organisation, London, UK.
Tseremoglou, I., Bombelli, A., Santos, B.F., 2022. A combined forecasting and packing model for air cargo loading: A risk-averse framework. Transportation Research Part e: Logistics and Transportation Review 158, 102579.
Unctad, 2020. Review of maritime transport 2020. United Nations Conference on Trade and Development.
Vijayakumar, V., Sgarbossa, F., Neumann, W.P., Sobhani, A., 2022. Framework for incorporating human factors into production and logistics systems. Int. J. Prod. Res. 60, 402–419.
Wang, Y.J., Hu, R.J., Lin, S.Y., Schultz, M., Delahaye, D., 2021. The Impact of Automation on Air Traffic Controller's Behaviors. Aerospace 8, 260.
Wang, Y.N., Jiang, J.K., Li, S.Y., Li, R.C., Xu, S.B., Wang, J.Q., Li, K.Q., 2023. Decision-Making Driven by Driver Intelligence and Environment Reasoning for High-Level Autonomous Vehicles: A Survey. IEEE Trans. Intell. Transp. Syst. 24, 10362–10381.
Wright, J.L., Lakhmani, S.G., Chen, J.Y.C., 2022. Bidirectional Communications in Human-Agent Teaming: The Effects of Communication Style and Feedback. International Journal of Human-Computer Interaction 38, 1972–1985.
Xu, Q., Gregor, S., Shen, Q., Ma, Q., Zhang, W., Riaz, A., 2020. The power of emotions in online decision making: A study of seller reputation using fMRI. Decis. Support Syst. 131, 113247.
Xu, R.-H., Lai, Y.-C., Huang, K.-L., 2021. Decision support models for annual catenary maintenance task identification and assignment. Transportation Research Part e: Logistics and Transportation Review 152, 102402.
Zhang, M., Jia, H., Wang, G., 2021. Interbrain Synchrony of Team Collaborative Decision-Making: An fNIRS Hyperscanning Study. Front. Hum. Neurosci. 15, 702959.
ZHANG, Y., ZHANG, Y., CUI, X., LI, Z. & LIU, Y. Assessment of mental workload using physiological measures with random forests in maritime teamwork. Engineering Psychology and Cognitive Ergonomics. Mental Workload, Human Physiology, and Human Energy: 17th International Conference, EPCE 2020, Held as Part of the 22nd HCI International Conference, HCII 2020, Copenhagen, Denmark, July 19–24, 2020, Proceedings, Part I 22, 2020. Springer, 100-110.
Zheng, S.Y., Jiang, C.M., 2024. Consortium blockchain in Shipping: Impacts on industry and social welfare. Transportation Research Part a-Policy and Practice 183.
Zhou, P., Chen, L.F., Dal, X.W., Li, B.X., Chai, T.Y., 2021. Intelligent Prediction of Train Delay Changes and Propagation Using RVFLNs With Improved Transfer Learning and Ensemble Learning. IEEE Trans. Intell. Transp. Syst. 22, 7432–7444.
Zhou, Z.P., Yu, X.H., Zhu, Z.Y., Zhou, D.Q., Qi, H.A., 2023. Development and application of a Bayesian network-based model for systematically reducing safety risks in the commercial air transportation system. Saf. Sci. 157.