Exploring seafarers' emotional responses to emergencies: An empirical study using a shiphandling simulator

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Abstract

Seafarers are required to make quick decisions to avoid accidents in case of emergencies. However, officers with anxiety generally have a high probability of making wrong decisions that threaten safety and security during the voyage. With the help of a shiphandling simulator, this study aims to investigate the emotional changes of seafarers under simulated scenarios of emergencies. The State-Trait Anxiety Inventory (S-TAI) scale and electrocardiograph (ECG) signal are adopted to evaluate the emotions of the participant seafarers. To classify the anxiety state of the participants, a support vector machine-based method is applied to establish an anxiety recognition model. Classification results reveal that this proposed model can effectively identify different emotions of participants based on ECG features (cross-validation accuracy: 86.0%; test accuracy: 92.3%). The experimental results show that poor visibility could cause the greatest impact on the anxiety of seafarers. In addition, navigational officers and marine pilots react differently in case of emergencies. Seafarers tend to experience more anxiety when dealing with emergency situations, while marine pilots experience more anxiety during multi-ship encounter periods. Consequently, the findings of this study aid to effectively identify the scenarios that cause anxiety emotion of different professional seafarers, providing the corresponding reference for the training of seafarers. This could help prevent catastrophic accidents that pose a threat to oceans and coasts caused by human error.

Keywords: Marine safety; Shiphandling simulator; Emergency response; Emotional response; ECG

1. Introduction

Around 80%-90% of global trade is facilitated through marine transportation, which plays an important role in international logistics. Although the marine transportation mode is considered to be a safe transportation mode, there are still some maritime accidents causing serious casualties, economic losses, and environmental pollution around the world (Hetherington et al., 2006). For instance, there were a total of 304 deaths resulting from the vessel SEWOL ferry sinking accident in 2014. In 2021, the vessel Ever Given ran aground and paralyzed the Suez Canal, which disrupted an estimated $9 billion of global trade daily (NBC, 2021). Among these accidents, human error is considered a significant factor affecting maritime accident consequences (Wang et al., 2021; Wróbel, 2021; Lan et al., 2022a, b).

With the improvement of navigation technology, accidents caused by technical faults

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have decreased significantly. However, human errors remain the leading cause of most accidents in the maritime industry (Fan et al., 2020). Previous studies showed that approximately 75-96% of marine accidents result from human and organizational factors (Rothblum, 2000). Specifically, 89-96% of collisions, 75% of fire/explosions, 84-88% of tanker accidents, and 79% of tugboat grounding accidents are caused by human errors (Dhillon, 2007). Tzannatos (2010) reported that 75.8% of human errors in maritime accidents occurred onboard, of which about 80.4% were attributed to the errors and violations of seafarers. A seafarer needs to issue navigation instructions, while other crews make corresponding operations according to the instructions. Once the seafarer makes an improper instruction, it will affect normal navigation and even cause an accident (Yang et al., 2023). Therefore, the primary premise of ensuring navigation safety is that seafarers are able to make correct decisions.

Emotion is an essential factor influencing seafarers' (i.e., navigational officers and marine pilots) decisions. When seafarers experience negative emotions during watch-keeping periods, it may affect their performance and decision-making (Fan et al., 2018). Overconfident or unconfident seafarers are more likely to exhibit risk-taking behavior (Wang et al., 2020). Furthermore, these special emotions affect their driving behavior patterns. For example, sadness can reduce the driver's perception of environmental information (Lafont et al., 2022), while anxiety can significantly influence the performance of seafarers (Tichon et al., 2014; Cui et al., 2022). Moreover, anxiety and anger can lead to negative and dangerous driving patterns (Roidl et al., 2014; Guo et al., 2021). Importantly, strong negative emotions are typically experienced by seafarers during emergency situations. Seafarers are required to take prompt action when encountering an imminent threat, which might lead to excessive psychological consequences for them (Schager, 2008; Kim, 2021). Therefore, negative emotions during emergencies may lead to a short-term reduction in driver capacity and an increased risk of maritime accidents (Simon and Corbett, 1996; Kim, 2021). Moreover, the work environment also affects the seafarers' emotions (Chung et al., 2017), especially in different professions of seafarers. For instance, the report by Zhang et al. (2005) revealed that navigational officers have poor mental health and emotional stability due to their monotonous life and relatively arduous work. Tait et al. (2021) reported that the irregular pilotage work of marine pilots can affect their work performance and safety in the long term. Thus, it is necessary to explore the difference between navigational officers and marine pilots.

This study aims to explore the emotions of seafarers in emergencies with the help of a shiphandling simulator. The contribution of this study is three-fold. First, with the ECG signal as an input, this study proposes an anxiety recognition model based on a machine learning method. Second, this study explores the effects of various emergency scenarios on seafarers. Third, the differences between navigational officers and marine pilots in encountering emergency situations are investigated. The significance of this study is to provide an emotion monitoring method for seafarers and to provide corresponding suggestions to train qualified seafarers according to the reaction of seafarers in emergencies.

The structure of this study is organized as follows: the literature review of the relevant studies is provided in Section 2. Section 3 shows the experimental data, experimental procedures, and corresponding methods. Section 4 describes the emotion assessment results and model recognition results. In Section 5, the analysis results present the emotions of participants during different emergency situations, as well as the emotional reactions of seafarers and marine pilots when facing emergencies. The last section concludes with a summary of the main conclusion and contributions of the study.

2. Literature review

Human errors could cause negative impacts on maritime safety, which is one of the most important causes of ship accidents. To reduce maritime accidents, it is essential to implement helpful measures to control and prevent the occurrence of human errors. Several studies have quantified the relationships between human errors and external factors such as environmental factors, accident factors, and ship factors (Weng et al., 2020; Li et al., 2021; Cao et al., 2023; Wang et al., 2023). However, the abnormal behavioral performance of the seafarer onboard is the root cause of these human errors. As such, one of the keys to reducing human errors is the identification of the factors that affect the performance of seafarers during the voyage (Fan et al., 2020, 2023). To evaluate these factors, subjective measures (e.g., subjective questionnaire) and objective physiological measures (e.g., electrocardiograph (ECG), electroencephalogram (EEG), galvanic skin response (GSR), electromyography (EMG), and eye movement) are generally used, as they can reflect human's actual performance (Guo et al., 2021; Vanderhaegen et al., 2022; Fan and Yang, 2023). Recently, an increasing number of researchers have focused on the unsafe states (i.e., physiological and psychological states) of seafarers during a voyage. Previous relevant studies have generally evaluated these states through three categories of indicators: (1) workload; (2) concentration; and (3) emotion.

The workload is an essential factor that affects the risk perception of seafarers. A full understanding of the workload during the voyage is one of the keys to reducing human error. For instance, Nilsson et al. (2009) utilized the NASA Task Load Index (NASA TLX) and expert scoring method to evaluate the workload and performance of seafarers operating various maritime equipment. The results showed that workload significantly influenced the performance of seafarers. Liu and Sourina (2014) used an ECG device to monitor officers' workload and pressure in a bridge simulator. Wulvik et al. (2020) employed the NASA TLX to explore the mental states (i.e., workload and stress) of seafarers under different scenarios. Orlandi et al. (2018) explored the effects of shiphandling manoeuvers on the seafarer's mental workload and physiological reactions. A high workload can lead to the difficulty of crew members in fully utilizing work resources, thereby affecting navigation safety (Wan et al., 2023). In addition, various scenarios can have a significant impact on the affective state of seafarers (Dybvik et al., 2018).

Regarding the concentration of seafarers during the voyage, numerous researchers assessed the situational awareness (SA) of these officers during the operating periods, as it is a crucial factor affecting driver performance. For instance, Saus et al. (2010)

used the Situational Awareness Rating Scale (SARS) to examine how experience, perceived realism, and SA affects the perceived effectiveness of navigation training based on simulator technology. Similarly, Jiang et al. (2021) evaluated the SA of pilots during the pilotage using eye movement features. The results showed that pilots' ability to maintain a high level of SA during the voyage is less reliant on navigational instruments and more on their cognitive skills and decision-making processes. Fan et al. (2021) explored the difference in SA abilities among maritime operations with different seafaring experiences. The experienced maritime operations exhibited stronger SA and higher decision-making abilities.

In addition, the emotions of seafarers during the voyage represent a crucial factor that influences their operational performance. Fan et al. (2018) explored the effects of seafarers' emotions on their performance in the ship bridge using the EEG and Self-Assessment Manikin (SAM) scale rating. The results of the study demonstrated a significant association between seafarers' emotions and their performance. In another study, Liu et al. (2020) proposed an EEG-based psychophysiological evaluation system to assess the mental states of seafarers using maritime virtual training simulators for training. Notably, anxiety is a significant emotion that affects driving behavior and risk, as evidenced by studies conducted by Shahar (2009) and Lim et al. (2022) using the State-Trait Anxiety Inventory (S-TAI). These studies found that drivers with high anxiety levels have a higher risk of making driving-related errors.

In summary, the existing studies show that the factors such as workload, concentration, and emotion can significantly affect the performance of seafarers. Therefore, it is critical to explore and quantify the influence magnitude of these factors to effectively reduce maritime accidents resulting from human errors. It is worth noting that the performance of seafarers is subject to higher requirements in emergencies during the voyage (Kim et al., 2021). Specifically, seafarers are required to promptly identify potential dangers and operate ships accurately during emergency situations. However, due to the difference in the professions of various seafarers (i.e., navigational officers and marine pilots), different response strategies should be chosen based on their professional characteristics and background knowledge. For instance, compared to officers, marine pilots are more familiar with the port waters environment, and the working hours of marine pilots are irregular (Mansson et al., 2017; Oldenburg et al., 2021). While research on the driving state of seafarers or marine pilots during sailing periods has been conducted, there are few studies investigating the emotional variations of these two professional seafarers in response to emergency situations. Hence, another novelty of this study is to explore the emotions of seafarers in emergencies and to analyze the differences in emotional reactions between seafarers and pilots by using the shiphandling simulator.

3. Material and method

3.1 Participants

Twenty-eight participants including 12 navigational officers and 16 marine pilots aged between 26 to 49 years (Mean=33.07; SD=4.69) with 3-17 years of navigation experience (Mean=8.71; SD=3.24) are recruited from different companies and ports.

The demographic characteristics of the participants are presented in Table 1. It should be noted that these participants have a richer experience of emergency response than inexperienced seafarers.

All the participants are recruited from the professional-level examination training period. To pass the examination successfully, these subjects should naturally have good health and rest, and any serious health conditions before the examination will stop their participation. Thus, the good physical condition of participants during this experiment period aided to ensure that their normal emotional state and the ECG signals were not affected. In addition, each voluntary subject is informed that they could quit the experiment at any time, if and when any concerns.

3.2 Apparatus

3.2.1 Shiphandling simulator

The experiment relies on the shiphandling simulator of Shanghai Maritime University, China. The shiphandling simulator is a simulated maneuvering device used for seafarers' steering training and practical operation examination, which can simulate the all-weather navigation environment and all kinds of ship accidents. As shown in Fig. 1, the shiphandling simulator is equipped with a range of navigation instruments to assist the ship's operator in controlling the ship, including marine radar, control display system, and Electronic Chart Display and Information System (ECDIS). Seafarers need to gain a higher level of qualification certificate through training and examination using the shiphandling simulators.

3.2.2 ECG acquisition equipment

The ECG signals of the participants are collected using PhysioLAB wireless physiological instrumentation, which is a physiological data recording system launched by the German company Egroneers. The PhysioLab machine is lightweight with little interference to participants, enabling steady signal collection even during intense exercise situations. The activity during the voyage is highly required of the seafarers who need to keep looking for navigation situations, so the device can be effectively used to obtain data.

3.3 Experimental Scenarios

These simulator experiments were carried out from 15th to 16th June, and 15th to 17th November 2021, respectivley. The route of navigation task in the experiment is mainly from the Waigaoqiao Port to the Yangshan Port, and all route environments are consistent with the actual environment. This route is chosen because it presents one of the most important waters with complex traffic in the world. The objective of this study is to gain further insights into the emotions of seafarers in emergencies so that a number of scenarios have been added during the sailing. Compared with other waterways, the high-risk navigational environment associated with this waterway makes it well-suited for assessing the emergency and emotional response of seafarers. The scenarios include fog navigation, night navigation, multi-ship encounter, the main engine being out of control, the whole ship losing power, radar malfunction, man overboard, and other emergency incidents that may occur during a realistic voyage, as shown in Table 2. Fig.2 shows the partially emergency situations that are stored in the simulator. Seafarers are responding to these scenarios that occurred randomly during the voyage.

3.4 Experimental situation

Fig. 3 shows the experimental situation of the shiphandling simulator. Each experiment is carried out by three seafarers, who acted as the captain, chief mate, and helmsman, with the captain wearing ECG devices to perform the task in the experimental scenarios. The captain makes decisions in emergencies during the voyage, and the chief mate and helmsman are responsible for assisting the seafarer to complete navigation operations. Each experiment recorded the physiological signals of the participant who acted in a captain's role. The captains bear the important responsibility of ensuring safe navigation and are more prone to human error (Kim, 2021).

3.5 Experimental procedure

Fig. 4(a) shows the experimental procedure. Initially, when arriving at the shiphandling simulator, the participants are introduced to the experiment regarding the navigation instrument and experiment task by an instructor. Next, all participants are required to familiarize themselves with the operation in the simulator. Then, the participants are wearing the ECG electrodes in preparation for the formal experiment. Subsequently, they performed the formal simulated sailing task for at least 50 minutes. The sailing task includes a complete voyage, as shown in Fig. 4(b). The crew first needs to control the ship leaving the port, then may encounter 2-3 emergencies while sailing in the channel, and finally safely dock. During the voyage, all participants are required to keep a lookout for the surrounding vessel and the environment to avoid maritime accidents occurring. In order to maintain a realistic sailing environment, there are no questionnaires and no extra interruptions during the voyage. Meanwhile, a camera is set up to record the whole experiment process to ensure the time of emergencies in the experiment record is accurate. It is noteworthy that the participants are required to fill out an emotional state questionnaire before and after the experiment, which is introduced in the next subsection. To obtain reliable emergency response characteristics of seafarers, each participant in this study only experiences one experiment to eliminate unfavourable factors such as seafarer fatigue and familiarity with the experimental scenarios that could potentially cause data errors.

3.6 Experimental methods

3.6.1 S-TAI scale

The emotional states of the seafarers are calibrated by the S-TAI scale, which is the definitive instrument for measuring anxiety (Spielberger, 1989). The S-TAI scale is utilized to measure anxiety by assessing someone’s state anxiety and trait anxiety. This is a Likert scale with 40 questions for state anxiety and trait anxiety, as shown in Annex I. It is essential to clarify that there is a clear difference between state anxiety and trait anxiety. Specifically, state anxiety refers to temporary emotions such as nervousness and worries when a person perceives a threat. Trait anxiety is a more general and longstanding quality, which is presented with stress and worry that people experience daily. In general, the participant's S-AI score is lower than their T-AI score in the normal state, otherwise in an anxious state (Wang et al. 1999). Therefore, the S-TAI scale is used to calibrate anxiety and normal emotion in this study. The S-AI score is used to reflect the subjective feelings of participants in emergencies during the simulated sailing scene, while the T-AI score is used to reflect the individual anxiety tendencies of the seafarers.

3.6.2 Feature extraction of ECG data

Heart Rate Variability (HRV) enables us to evaluate emotional differences by reflecting the autonomic nervous system's response to environmental factors in the body. Generally, the ECG signal is relatively stable when the seafarers are sailing normally. However, the external stimulus will lead to fluctuations in the ECG signal when they encounter emergencies. Therefore, the HRV measures extracted from ECG can well reflect the differences in the emotional states of seafarers under various emergencies.

The raw ECG data collected from seafarers usually requires preprocessing before its full use in this study. This is due to the fact that any seafarer on movement when acquiring the ECG data, could produce noise in the signal/data (Fig. 5(a)) and affect the recognition of physiological characteristics. In general, the following two steps are implemented to preprocess the ECG signal in Python. First, the ECG signal needs to be denoising. The wavelet transform is a method widely used in signal processing, which can reach the approximate optimal in terms of minimum mean square error. In this study, Daubechies wavelets db8 are used to reduce noise in the original ECG data. Fig. 5(b) shows the ECG signal after denoising. Second, an R peak is detected from the denoised ECG signal, as shown in Fig. 5(c). These R peaks are used to create inter-beat interval (IBI) (units: ms) time series to obtain other HRV measures, such as heartbeat (HB) (units: bpm), the standard deviation of normal to normal (NN) intervals (SDNN) (units: bpm), the standard deviation of the successive differences (SDSD) (units: bpm), the root mean square of successive differences between normal heartbeats (RMSSD) (units: bpm), coefficient of variation (CV) (units: unitless), coefficient of variation of continuous difference (CVCD) (units: unitless) and other time-domain measures. The HRV measures of the frequency domain can be obtained by fast Fourier transform (FFT) in Python, such as low-frequency power (LF: 0.04-0.15Hz), high-frequency power (HF: 0.15-0.40Hz), very low-frequency power (VLF: 0.0033-0.04Hz), LF/HF, normalized low-frequency power (LFnorm) (units: unitless), and normalized low-frequency power (HFnorm) (units: unitless). The formulas for calculating these HRV measures are shown in Equations (1)-(9):

$$IBI=\frac{1}{N}\sum_{i=1}^{N}RR_i \tag{1}$$

$$HB=\frac{60}{IBI} \tag{2}$$

$$SDNN=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(RR_i-IBI\right)^2} \tag{3}$$

$$SDSD = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[\left(RR_i - RR_{i+1}\right) - \left(IBI - RR_{i+1}\right)\right]^2} \tag{4}$$

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}\left(RR_{i+1} - RR_i\right)^2} \tag{5}$$

where N represents the number of inter-beat intervals; RR_i represents the i th inter-beat intervals.

$$CV = \frac{SDNN}{IBI} \tag{6}$$

$$CVCD = \frac{RMSSD}{IBI} \tag{7}$$

$$HFnorm = \frac{HF}{TP - VLF} \times 100 \tag{8}$$

$$LFnorm = \frac{LF}{TP - VLF} \times 100 \tag{9}$$

where TP represents total power.

In addition, the values of HRV measures were found to vary significantly not only among participants but also among the different HRV measures (Tjolleng et al., 2017). In order to obtain values of a common scale, the HRV measures of each participant are standardized using Equation (10):

$$x_i^* = \frac{x_i - \mu}{\sigma} \tag{10}$$

where x_i is the i th of the HRV measures; μ is the mean of x; σ is the standard deviation of data x.

These measures are often used to reflect the changes in the human state (Zhao, et al., 2012). For example, the officer's fatigue level increases with the decrease in HB and LF, the attention increased with an increase in HF, and the anger level increased with an increase in HB (Ramírez et al., 2015; Yan et al., 2018).

3.6.3 Support vector machine model

Support vector machine (SVM) is a supervised learning model that offers several advantages in solving small samples, nonlinear and high-dimensional data. It realizes the classification of samples by finding a hyperplane with the largest boundary for the learning samples. Currently, this method has been commonly applied to state recognition in the field of transportation. For instance, Liao et al. (2016) provided a method for detecting driver cognitive distraction at the stop-controlled intersection and speed-limited highway by the SVM model. Chen et al. (2019) applied the SVM model to distinguish the driver's alert and fatigue state, which helps to alert the driver while being sleepy or even fatigued. Zahabi et al. (2021) combined driver behavior and eye-tracking measurements to classify drivers' driving states based on the SVM model.

In this study, due to the limitations of the experimental condition, the quantity of physiological data collected from the seafarers is limited, and there are many physiological parameters obtained from calculating this data. The SVM model can solve the problem of a small sample and high-dimensional data. Therefore, this study uses the SVM model to discriminate the seafarers' emotional condition. Previous research points out that the RBF (Radical Basis Function) as the kernel function to construct the SVM model can recognize emotion. The mathematical expression of the SVM model is shown below:

$$K(x,y) = exp(-\gamma |x-y|^2) \tag{11}$$

where x and y represent the sample or vector in this model; γ shows the hyperparameters of this SVM model.

4. Results

4.1 Emotional assessment using subjective data

Through the experiment, 18 valid questionnaires from 28 participants were collected to reflect the seafarers' emotions, while the other 10 questionnaires became invalid due to non-response or incomplete answers. Fig. 6 shows the S-TAI score of seafarers and the norm. The S-TAI of the norm is obtained from testing a large number population of Chinese individuals, as reported by Zheng et al. (1993), which represents the common anxiety characteristics presented for the Chinese population (Wang et al., 1999). It can be found that the T-AI scores of seafarers (Mean=41.06, SD=9.83) and the norm (Mean=41.11, SD=7.74) are similar, which largely indicate that the trait anxiety of the seafarer is consistent with that of the norm ($t(17)=-0.023$, $p=0.982$). In general, the S-AI score of the seafarers is higher than the T-AI, indicating that the seafarers show their anxiety state when they encounter emergency situations. While the norm's S-TAI score shows that the S-AI score is much lower than the T-AI score under normal emotion. It is present that the questionnaire is effective in calibrating seafarers' emotions in emergency situations.

4.2 Emotional assessment using ECG data

4.2.1 Feature analysis

The ECG device recorded the signals of 28 participants at a sample rate of 1000 Hz. Considering the validity of the questionnaire, the ECG data from 18 participants are used to extract emotional characteristics. The recorded ECG data are segmented into 30-second intervals for the feature analysis, which can effectively reflect the changes in the physiological state of seafarers during the ultra-short periods (Wu et al., 2020). Based on the questionnaire calibration and feature extraction, the ECG features of seafarers are obtained in 41 emergency scenarios.

Fig. 7 shows that the differences in HRV measures are plotted for the normal and anxiety condition, with Fig. 7(a) - (g) representing time domain measures and Fig. 7(h) - (j) representing frequency domain measures. HB of the time domain parameter increased from normal to anxiety state, whereas IBI declined. Meanwhile, the HFnorm of the frequency domain parameter shows a declining trend from normal to anxiety condition. The remaining parameters, including SDNN, SDSD, RMSSD, CV, CVCD, LFnorm, and LF/HF show an insignificant change in emotion. In this study, one-way ANOVA is used to quantify the differences among the parameters. To verify the validity of the current sample size used in one-way ANOVA, the G-power software is used to calculate statistical power in this study. Specifically, α error prob is set to 0.10 in this study, and the effect size *f* is obtained by calculating the mean and variance in HRV measures. Based on the post hoc analysis, the power of this dataset is greater than 0.80, which can be considered valid in this study. Furthermore, the prerequisite for using one-way ANOVA is that the sample needs to follow a normal distribution. In this study, the statistical software SPSS (26.0) is used to conduct normal distribution tests. According to the results of the Kolmogorov-Smirnov test, the HRV features of HB, IBI, LF/HF, LFnorm, and HFnorm follow the null hypothesis ($p>0.05$), indicating that these features are considered to be normally distributed. As shown in Table 3, the results of one-way ANOVA suggest that there are significant statistical differences in the HRV features of HB, IBI and HFnorm under different emotions ($p<0.10$). Therefore, these three HRV features are utilized to characterize the emotional variations of seafarers.

4.2.2 Results of the Seafarers' emotion recognition model

The HB, IBI, and HFnorm of extracting HRV features are utilized as the input for the SVM classification model. Overall, 18 participants consisting of 41×3 matrix of emotion description, and 41×1 matrix of emotion labels are compiled. In this study, 70% of the samples are used to train the classification model and 30% are used to verify the model's accuracy.

The penalty parameter C and hyperparameters γ should be obtained to establish the SVM classification model. To improve the generality of this model, the GridSearch with Cross-Validation (GridSearchCV) model is used to find the optimal hyperparameters C and γ. When using cross-validation for model selection, it is possible to select the model with the best generality (i.e., the performance of the model when using other data) from multiple models (Schaffer, 1993). Fig. 8 shows that the SVM model results are selected by GridSearchCV, in which the optimal penalty parameter C is 19.2 and hyperparameters γ is 1.2. The result shows that the classification accuracy of the best classification model is 86.0%. The validation samples are used to validate the model; the test result is given in Fig. 9. Label 1 represents the seafarer's anxiety and label 0 describes the seafarer's normal emotion. The result shows that 12 of the 13 test samples are correctly identified, including all samples with anxiety emotions, resulting in an emotion classification accuracy of 92.3%.

In addition, other classification methods have been selected to compare the results and validate the reliability of the SVM model. The traditional methods of a binomial logistic regression model and another machine learning methods (i.e. the random forest method) are applied in this study to compare with the SVM model. However, these methods showed a worse recognition performance than the SVM model, in which the accuracy of the binomial logistic regression model is 85.4% and the random forest method is 84.6%. Therefore, it is evident that it is rational to use the SVM classification model for identifying the emotional state of seafarers.

5. Discussions

5.1 Emotions of seafarers under different emergencies

The anxiety experienced by seafarers during emergency situations can increase the risk of human error and result in traffic accidents. Previous studies (Nieuwenhuys et al., 2017) have shown that human performance on different levels of operational control i.e., attention and physical) and perceptual-motor behavior (i.e., situational awareness and decision-making) can be affected by anxiety. Therefore, it is necessary to explore the emotions of the seafarer in various emergencies.

In this study, the emergency situations encountered by seafarers are divided into three categories, including poor visibility, multi-ship encounter, and emergency incident. Poor visibility means the scenarios of fog navigation and night navigation. Ship encounter represents scenarios such as ship encoutners, ship overtaking, and ship crossing. The emergency incident refers to such scenarios as the main engine being out of control, the whole ship losing power, radar malfunctioning, or man overboard.

Fig. 10 displays the emotion identified by seafarers during different emergency situations. The results indicate that the frequency of anxiety is higher than that of normal emotion when the seafarers encountered an emergency situation. Especially in poor visibility scenarios, participants tended to experience a higher frequency of anxiety. As a result, seafarers will have a higher observation frequency (Jiang et al., 2021). It is found that even with the assistance of marine radar and EDCIS, the seafarer will still have more anxiety about the navigation environment that cannot be directly observed. In addition, Li et al. (2021) pointed out that restricted visibility has the highest likelihood of causing human errors. This may be explained by the fact that more human errors are caused by the anxiety of seafarers. Furthermore, the frequency of anxiety in emergency incidents is 62.5%, which is slightly below the scenario of poor visibility. When seafarers encounter the scenario of ship encounters, it is noteworthy that the frequency of anxiety in ship encounters is 56.25%, which is the lowest among the three types of emergencies. This shows that the seafarers can effectively avoid dangerous encounters because they keep a high attention lookout in the simulation.

5.2 Emotional differences between the navigational officer and marine pilot

Previous studies have shown that seafarers' occupation onboard a ship affects their perception of collision risk (Kim, 2021). Therefore, this study exploratory investigated the differences between marine pilots and navigational officers in encountering emergencies. Marine pilots can be defined as experts who guide ships entering and leaving the port waters, with extensive geographic and maritime experience. Navigational officers are professionals who work on the bridge and are responsible for watchkeeping. They have been working at sea for a long time, which has given them extensive sailing experience to ensure navigation safety. As shown in Table 1, this study selected navigational officers and marine pilots with similar demographic characteristics. Namely, this study can effectively compare the emotional reactions between navigational officers and marine pilots in emergencies.

5.2.1 Assessment of emotional difference using subjective data

The scores of the navigational officers on the S-TAI scale are significantly higher than those of the marine pilots according to the t-test ($p<0.01$). As a result, it is important to consider the differences in response to emergencies between the two professions. Fig. 11 presents the specific S-TAI scores of navigational officers, marine pilots, and the norm. For T-AI scores, the scores of navigational officers are higher than the norm, indicating that their daily stress and anxiety levels are higher than those of ordinary occupations. The probable reason is that the work environment of navigational officers is narrow and has long-time working cycles, which easily causes psychological problems. It is noteworthy that the T-AI scores of the marine pilots are significantly lower compared to the norm. This indicates that marine pilots have less work pressure than normal people in the general population. This is probably due to the fact that marine pilots often work in coastal ports with a high income and more time to live on land. For S-AI scores, the navigational officers and marine pilots scored higher than their T-AI scores, indicating that they are anxious when they encounter emergencies. Furthermore, the difference between the marine pilots' S-AI and T-AI scores is greater than that of navigational officers, which indicates that marine pilots are more anxious than navigational officers when they are in emergency situations and are more likely to have accidents.

5.2.2 Assessment of emotional differences using ECG data

As shown in Fig. 12, ECG data are used to identify the emotions of navigation officers and marine pilots in emergency situations. Fig. 12(a) presents that the frequency of an anxiety state in ship encounter situations is 50% for the navigational officers and 66.67% for the marine pilots, respectively. The results show that the anxiety frequency of the marine pilot is higher during multi-ship encounters, which is due to the fact that they work in dangerous or congested waterways such as high-density of ship traffic environments, leading to a greater sensitivity to the potential risks involved. When the marine pilot's psychological load is too high, it may lead to unfavorable results (Orlandi et al., 2018). However, it can be seen from Fig. 12(b) that navigational officers have a higher anxiety frequency when confronted with emergency incidents, while marine pilots tend to be in a normal emotional state. A possible reason is that marine pilots are familiar with response measures to emergency incidents in the waterway, allowing them to effectively avoid accidents. As shown in Fig. 12(c), the frequency of anxiety in dealing with poor visibility is high for both navigational officers and marine pilots, which exceeds 60%. It is found that poor visibility has a great impact on navigational officers and marine pilots. Among them, the frequency of anxiety for marine pilots is higher than that for navigational officers. This indicates that marine pilots probably rely more on their families in the navigational environment in port waters, where poor visibility may easily lead to misjudgment and traffic accidents. Similarly, previous studies have shown that marine pilots' psychology during the voyage in different waters is significantly different (Murai et al., 2004).

5.3 The relationships between the emotions of seafarers and the decision-making

To further assess the influence on navigation safety by seafarer emotions, the distance closest point approach (DCPA) and emotional changes are used to analyse the relationship between emotions and emergency decision-making. The DCPA is one of the commonly used evaluation indicators in ship collision avoidance, which present the urgency and risk level of ship collision avoidance (Wang et al., 2023). In the real-world decision-making process of seafarers in a ship bridge, they need to make timely decisions based on the DCPA to avoid collisions with other ships. In this study, due to the severe loss of samples' sailing trajectory data in the simulation experiment, only subject 6 with complete trajectory data is selected to disclose this relationship. Therefore, the result of this study only represents the emotions and decisions of subject 6.

Fig. 13 shows the DCPA and emotions of subject 6 during the 1-minute period before and after experiencing different emergency situations. When seafarers come cross multi-ship encounters and poor visibility emergency situations, their anxiety may lead to a wrong decision, hence a decrease in DCPA and an increase in collision risk, as illustrated in Figs. 13(a)-(c). It should be noted that the DCPA increased with the second anxiety emotion that appears within a short period. This may indicate that the seafarers have realized their decision-making errors during the second anxiety period, which can help correct their mistakes. In addition, it can be seen from Fig. 13(d) that the DCPA briefly decreases and then increases during anxiety in emergency incidents. In general, the anxiety of seafarers that arises during the initial encounter with emergency situations will possibly lead to incorrect decision-making. Therefore, identifying the anxiety of seafarers during emergency situations can help reduce navigation risks.

6. Conclusions

The emotions of seafarers could affect sailing safety significiently. Seafarers need to make appropriate decisions during emergencies to avoid accidents. In order to explore the emotional changes of seafarers when encountering emergencies, this study carried out a navigation simulation experiment to obtain primary data from seafarers, including subjective questionnaire data (i.e., S-TAI scale) and ECG physiological data. An anxiety recognition model was developed based on the SVM classification method using HRV indicators of HB, IBI, and HFnorm, achieving an accuracy of 92.3%. The results reveal that poor visibility has the highest probability of causing anxiety to seafarers, while multi-ship encounter has the lowest probability. In addition, although there are navigation facilities (e.g., marine radar, ECDIS) on board, the seafarers are more frequently exposed to anxiety in the sailing environment that cannot be directly observed.

The results also show that navigational officers and marine pilots have significantly different emotions in emergencies. The trait anxiety of navigational officers is significantly greater than that of marine pilots, while the trait anxiety of marine pilots is lower than the norm. Furthermore, marine pilots are more frequently involved in anxiety when dealing with ship encounters under poor visibility, while navigational officers more frequently show anxiety when encountering emergency incidents. Overall, this study assists maritime managers/authorities in understanding the difference in the emotional response of navigational officers under different emergency scenarios and different professions, providing a reference for the optimal allocation of training resources for navigational officers to reduce the occurrence of human error in the future.

However, this study has several limitations that could be further addressed in future. Firstly, this study only investigated the relationship between different emergencies and the emotions of seafarers. It is also interesting to further discuss the emotional differences in dealing with emergencies among different seafarers (e.g., officers with different ages and experiences). It will further help improve navigation safety and the associated training with a more specific targeted audience. Secondly, this study collected feedback data from 28 participants. Although it has revealed a better critical mass compared to the previous relevant studies in the area, more participants help improve the generality of the findings and promote the experiments of subsequent studies. Thirdly, more ship sailing trajectory data and seafarers' decision-making data could be collected to comprehensively evaluate the relationship between seafarers' emotions and decision-making in future research.

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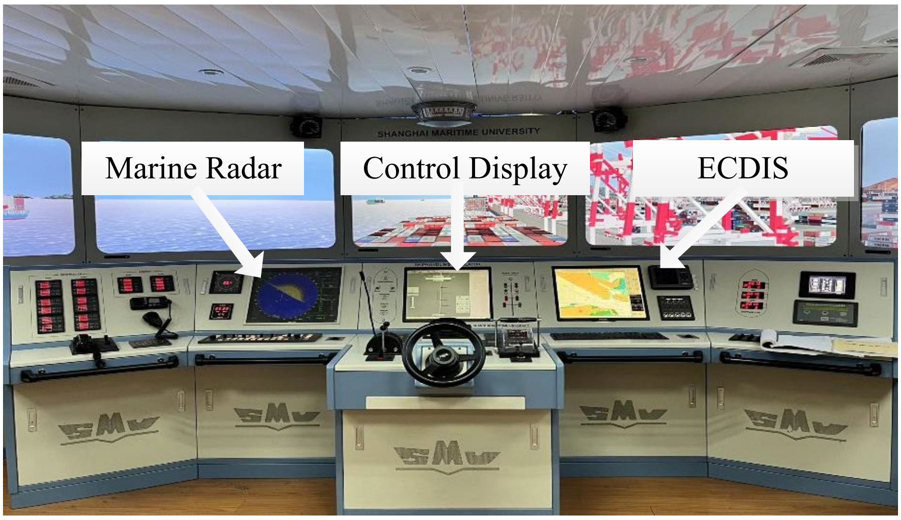


Fig. 1 Shiphandling simulator

(a) Poor visibility (b) Multi-ships encounter (c) People falling overboard

Fig. 2 Experiment scenarios

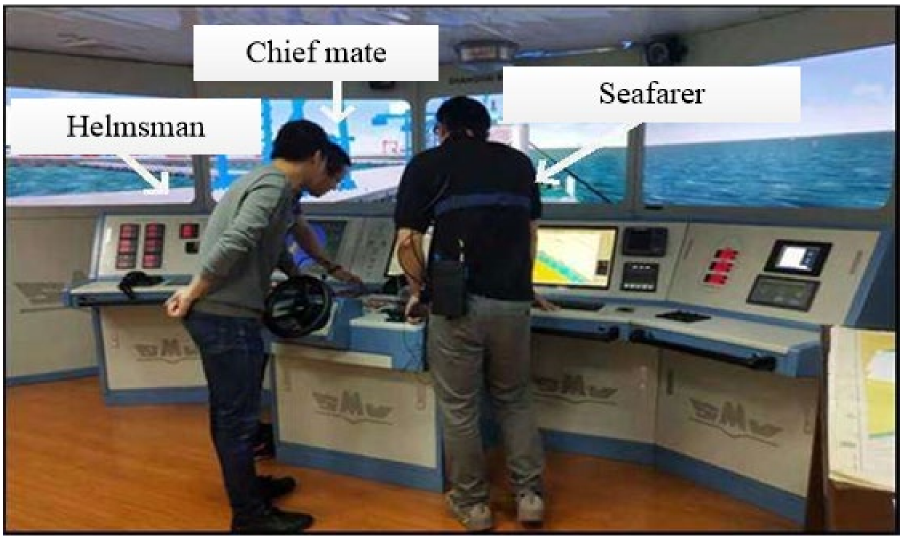
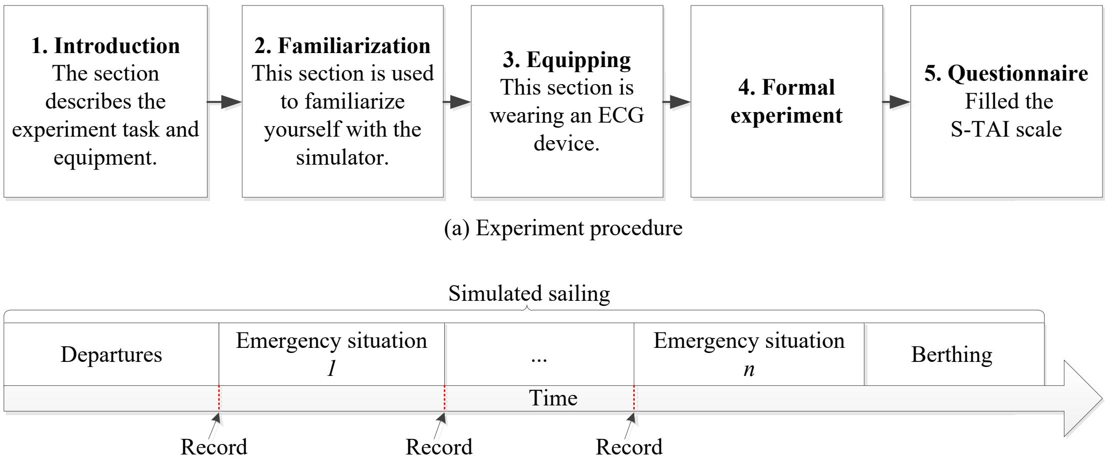
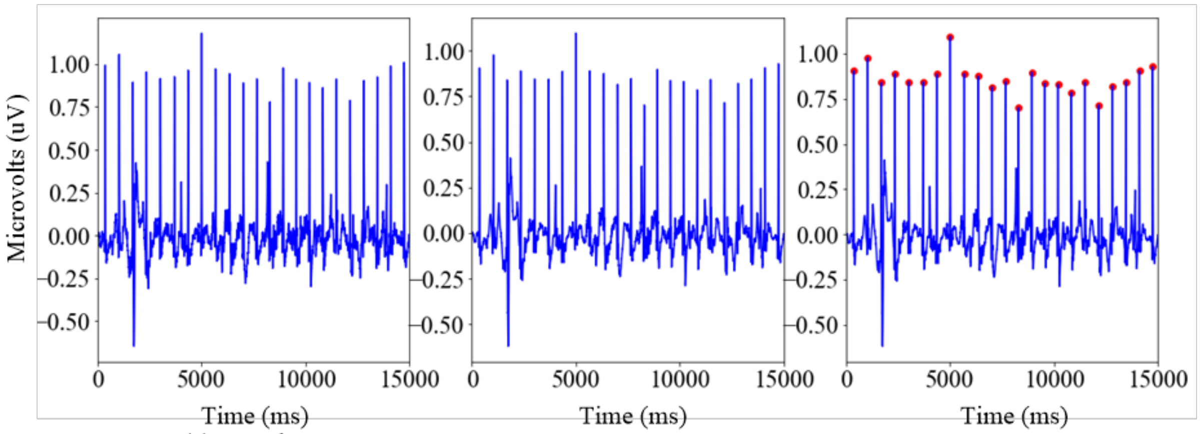


Fig. 3 The experimental situations of shiphandling simulator



(b) The process of formal experiment

Fig. 4 The overall process of the experiment



(a) Raw data (b) Data denoised by wavelet (c) Detected R peaks in signal

Fig. 5 ECG signal preprocessing

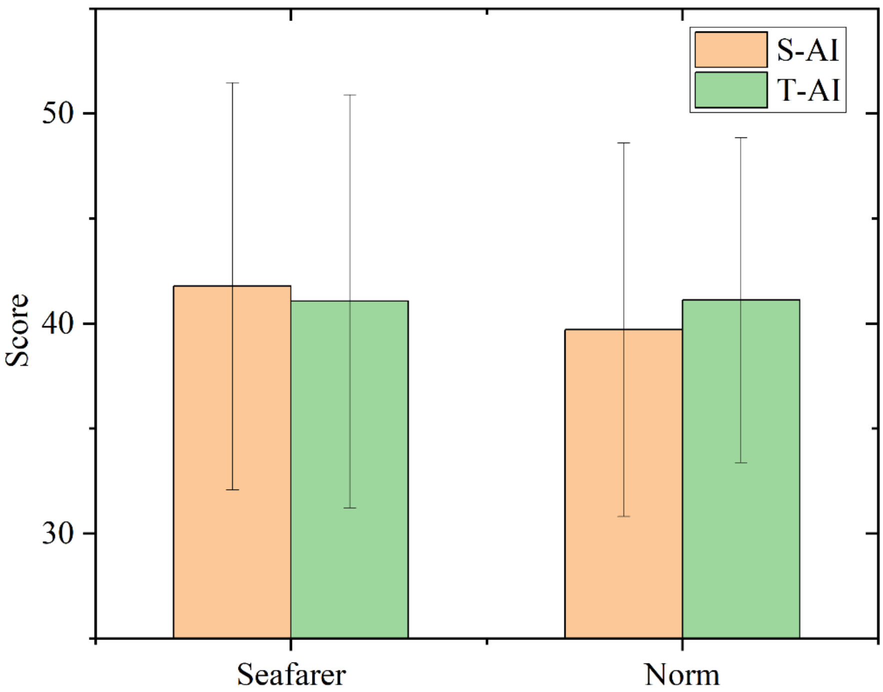


Fig. 6 S-TAI score of seafarer and norm

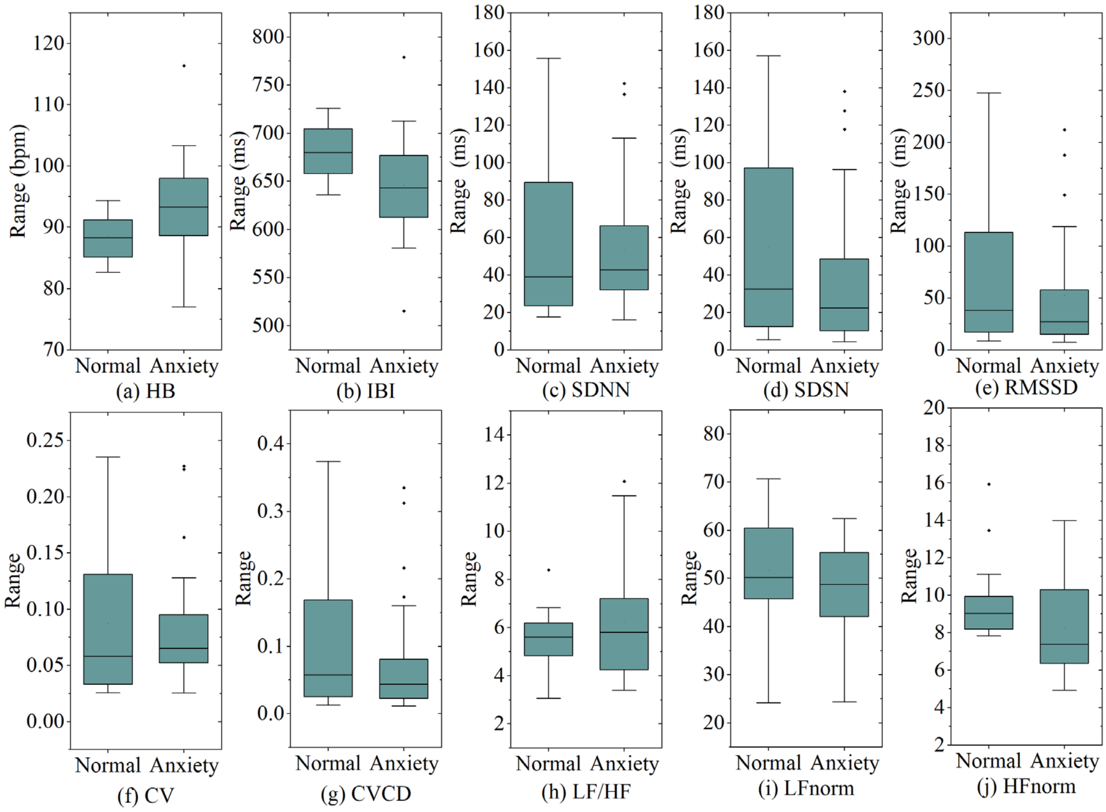


Fig. 7 Differences of HRV measures between normal and anxiety states

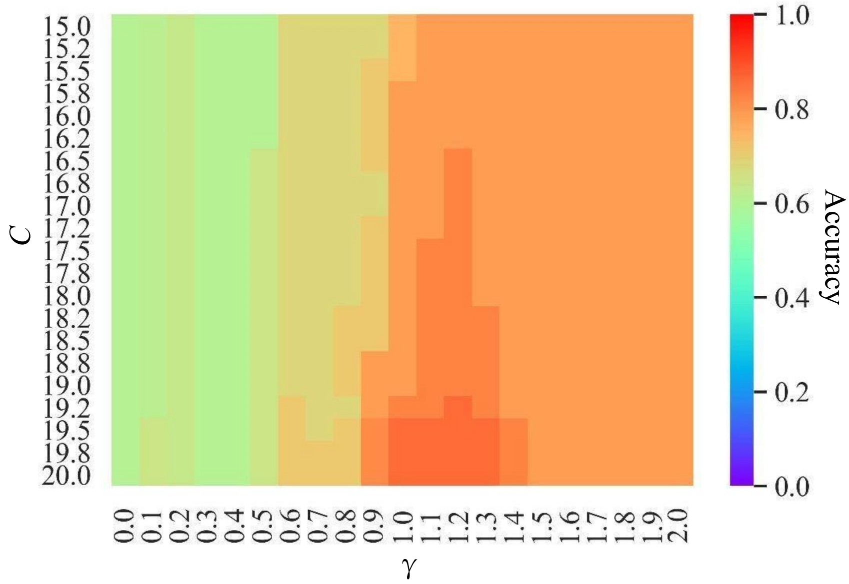


Fig. 8 SVM parameter results selected by GridSearchCV

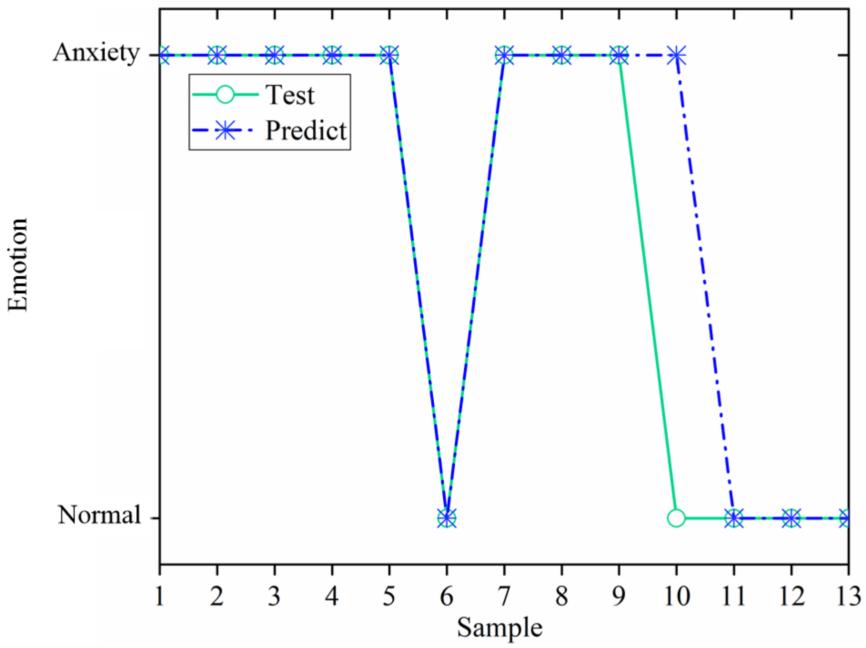


Fig. 9 Emotion identification result of the SVM model

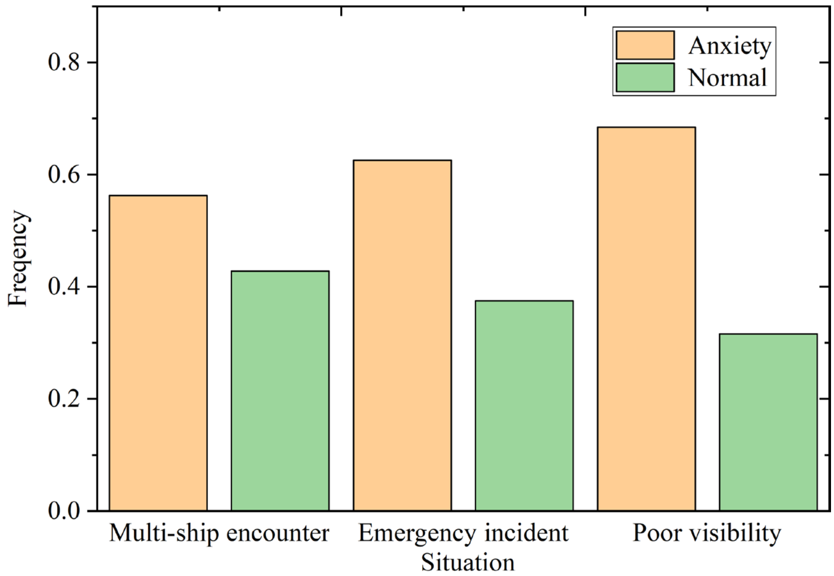


Fig. 10 Emotion identified by seafarers during different emergencies

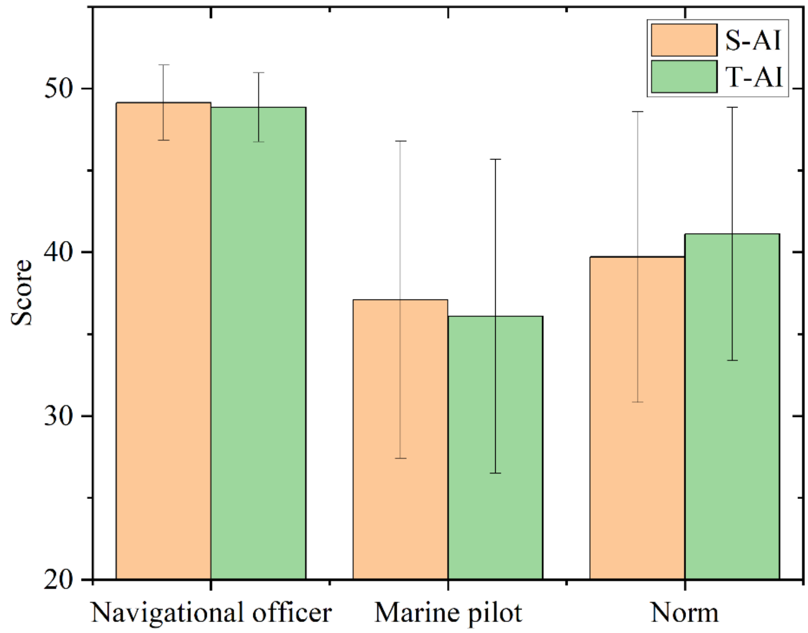
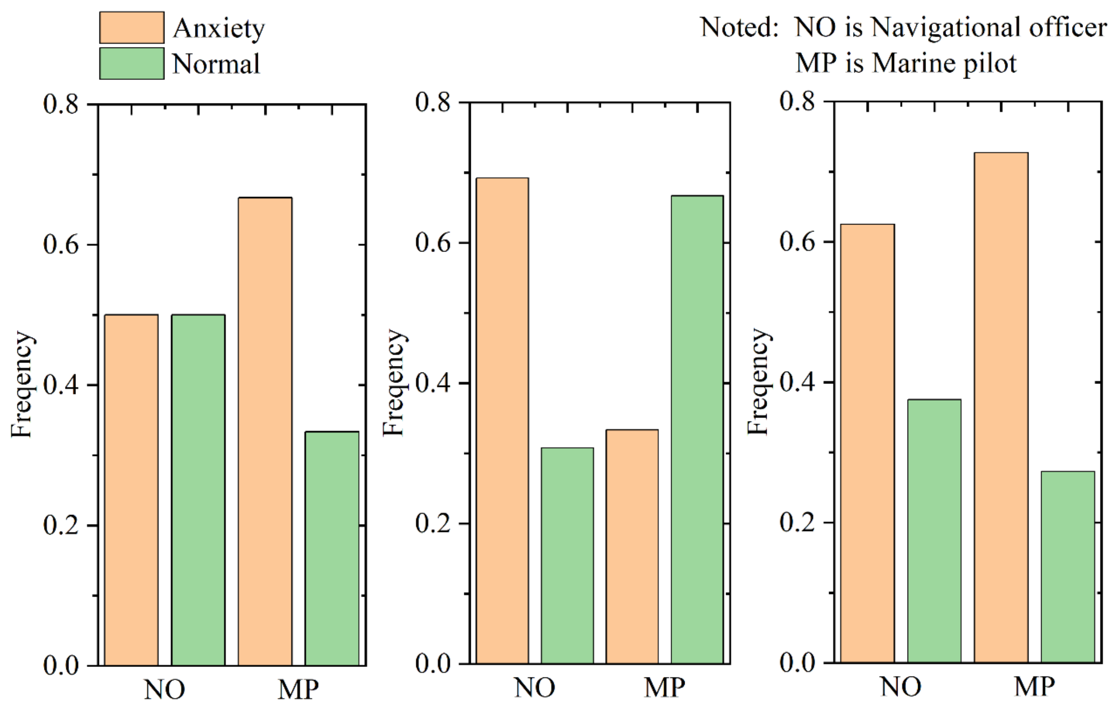


Fig. 11 The S-TAI scores of the seafarer, marine pilot, and norm



(a) Multi-ship encounter (b) Emergency incident (c) Poor visibility

Fig. 12 Emotions of the seafarer and marine pilot in emergencies

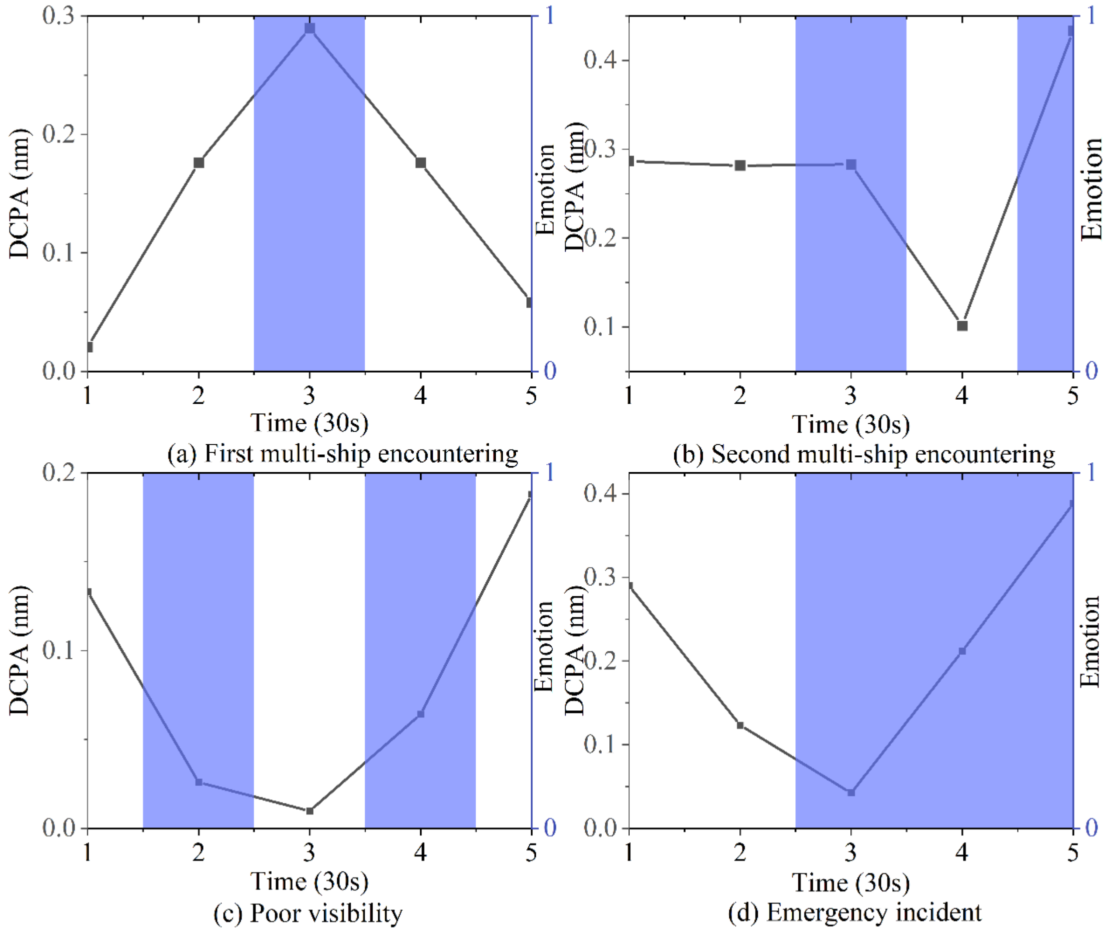


Fig. 13 The DCPA and emotions of subject 6 during the 1-minute period before and after experiencing various emergency situations (where emotion 1 represents anxiety and emotion 0 represents normal state)

Table 1 Demographic characteristics of participants

Profession	Number	Age			Experience		
		Mean	SD	Range	Mean	SD	Range
All seafarer	28	33.07	4.69	27-49	8.71	3.24	3-17
Navigational officer	12	34.83	5.62	27-49	9.58	2.81	7-15
Marine pilot	16	31.75	3.47	26-39	8.06	3.47	3-17

Table 2 The emergency scenarios in the experiment

Type of emergency situation	Emergency scenarios
Poor visibility	Fog navigation
	Night navigation
Multi-ship encounter	Overtaking situation
	Head-on situation
	Cross situation
Emergency incident	The main engine is out of control
	The whole ship losing power
	Radar malfunction
	Man overboard

Table 3 One-way ANOVA of HRV measures

HRV measures	F-value	*p*-value
HB	5.662	0.022**
IBI	5.350	0.026**
LF/HF	1.281	0.265
LFnorm	1.459	0.234
HFnorm	3.288	0.077*

*Significance at the 90% level of confidence.

** Significance at the 95% level of confidence.

Annex I

State-Trait Anxiety Inventory

Read each statement and select the appropriate response to indicate how you feel right now, that is, at this very moment. There are no right or wrong answers. Do not spend too much time on any one statement but give the answer which seems to describe your present feelings best.

1	2	3	4
Not at all	A little	Somewhat	Very Much So

S-Anxiety scale

1	I feel calm	1	2	3	4
2	I feel secure	1	2	3	4
3	I feel tense	1	2	3	4
4	I feel strained	1	2	3	4
5	I feel at ease	1	2	3	4
6	I feel upset	1	2	3	4
7	I am presently worrying over possible misfortunes	1	2	3	4
8	I feel satisfied	1	2	3	4
9	I feel frightened	1	2	3	4
10	I feel uncomfortable	1	2	3	4
11	I feel self confident	1	2	3	4
12	I feel nervous	1	2	3	4
13	I feel jittery	1	2	3	4
14	I feel indecisive	1	2	3	4
15	I am relaxed	1	2	3	4
16	I feel content	1	2	3	4
17	I am worried	1	2	3	4
18	I feel confused	1	2	3	4
19	I feel steady	1	2	3	4
20	I feel pleasant	1	2	3	4

T-Anxiety scale

21	I feel pleasant	1	2	3	4
22	I feel nervous and restless	1	2	3	4
23	I feel satisfied with myself	1	2	3	4
24	I wish I could be as happy as others seem to be 1	1	2	3	4
25	I feel like a failure	1	2	3	4
26	I feel rested	1	2	3	4
27	I am “calm, cool, and collected”	1	2	3	4
28	I feel that difficulties are piling up so that I cannot overcome them	1	2	3	4
29	I worry too much over something that really doesn’t matter	1	2	3	4
30	I am happy	1	2	3	4
31	I have disturbing thoughts	1	2	3	4
32	I lack self-confidence	1	2	3	4
33	I feel secure	1	2	3	4
34	I make decisions easily	1	2	3	4
35	I feel inadequate	1	2	3	4
36	I am content	1	2	3	4
37	Some unimportant thought runs through my mind and bothers me	1	2	3	4
38	I take disappointments so keenly that I can’t put them out of my mind	1	2	3	4
39	I am a steady person	1	2	3	4
40	I get in a state of tension or turmoil as I think over my recent concerns and interests	1	2	3	4