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Research paper

An investigation of the effect of workload on ship engine room operators using *fNIRS*

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ABSTRACT

This is an investigation into the Performance Shaping Factors (PSFs) associated with ship engine room operators. This study looks at the effect of workload. There is a large portion of human error associated with marine incidents. Human error may be considered as a result of additional supplementary tasks on top of an accustomed workload. The aim of this study is to evaluate the effect of workload on human performance. To achieve this, a TRANSAS simulator series 5000 was used to replicate a real scenario with the addition of workload as a PSF. Each participant engaged in a fault detection and correction task. 20 participants were used for the workload study; all 20 were trained for 3 h to use the engine room software interface. The participants then completed a 30-min ballasting task. During this interaction, 50% of the participants underwent a simulated scenario where the workload was increased. The other 50% were given a standard task. Functional near-infrared spectroscopy (fNIRS) was used to measure the participant's activation levels, more specifically from the dorsolateral prefrontal cortex (DLPFC) region of the cerebrum. The results showed an increase in activation of the DLPFC during each phase of the task, this trend was magnified by the addition of increased workload. The results are discussed with respect to human performance during varying workload. From the results of this study, a human classification performance model was developed. This model can be used by the maritime industry to better evaluate and understand human error causation.

1. Introduction

This research is an investigation into the effect of Performance Shaping Factors (PSFs) on ship engine room operators. More specifically, this study looks at workload as a PSF. To carry out such a study, it is necessary to first describe error causation, ship engine room neuroergonomics, and the background of current Human Reliability Analysis HRA techniques.

1.1. Error causation

There are multiple hypotheses concerning the cause of human error within a ship engine room. Engine room operators are all trained to different levels (Bielic et al., 2017). Generally speaking, experienced operators complete tasks more efficiently (Xu et al., 2009), and experienced operators can cope better with workplace factors (for example, a higher workload) compared to inexperienced operators (Baker et al., 2018). For clarity, interviews with experts in the marine sector, conducted by the researchers, defined experience with relation to the time working in a particular position (1 or 10 years at sea for example). However, the experts did acknowledge that some experienced operators are susceptible to 'cutting corners' which can lead to error, but on average, it was said that experienced operators still outperform inexperienced operators. Marine accident databases, from organisations such as the National Transport Safety Board (NTSB), European Maritime Safety Agency (EMSA), UK, Australian, Hong Kong, Canadian and US governments, were analysed to show accidents caused due to human error within the engine room only. The accident reports were then analysed to see if there were any specific duties where human error occurred more frequently, and if PSFs were reported as a contributing factor towards the human error. Reoccurring issues reported from the statistical analysis were: distraction 11%, multitasking 20%, fatigue

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10%, engine room temperature 16%, noise and vibration 6%, and time pressure 16% (European Maritime Safety Agency, 2017) (Australian Government, 2017) (GOV, 2017) (Government of Canada, 2018) (National Transport Safety Board (NTSB), 2017) (The Government of Hong Kong, 2017). The tasks that showed to be the most consistent with human error from the aforementioned accident databases referenced above, was ballasting, oil transfer, machine maintenance, fuel system and seawater treatment systems.

1.1.1. Human error

To provide a more balanced perspective on human error, there are two main definitions considered in this research. The first is 'sharp end' human error, which corresponds to an active error. For example, a blunt end error is interpreted as a personal error (an engineer opens the wrong valve) (Bye and Aalberg, 2018). The second is referred to as a 'blunt end' human error. This error type is classed as a latent error. For example, an error due to workplace factors (fatigue due to excessive working hours) (Akyuz et al., 2018).

1.1.2. Neuroimaging

Neuroimaging is a modern and novel tool for the investigation of human performance (Jahanshahloo et al., 2006). Neuroimaging is used to evaluate operators' functional state (OFS) whilst performing tasks (experimental or daily duties) (Li et al., 2014). Neuroimaging can be used to look at specific areas of the cerebrum that correspond to various human executive functions, for example hand-eye coordination and working memory (Xi et al., 2017). It does this by either directly or indirectly imaging the cerebral structure, function, or physiology (Pomorstvo, 2006). Neuroimaging has been used in previous studies in the maritime sector, more specifically for bridge operations, as a HRA technique to evaluate human error (Australian Government, 2017) (Aghajani et al., 2017). One of the neuroimaging techniques used is called functional near-infrared spectroscopy (fNIRS).

1.1.3. Neuro-ergonomics

The branch of neuro-ergonomics considered in this study focuses on human limitations and capabilities, both physical and cognitive (Fuster M, 2015). Understanding human limitations allows engineers to develop technologies and work environments so that they are safer, more efficient, and designed with the human operator in mind (Koenigsberg and Fong, 2007).

The main theory behind neuro-ergonomics is that human factors research and practice consider the results and theories rooted in neuroscience (Lim et al., 2018). Modern neuroimaging techniques have the potential to estimate maritime operational errors and measure covert changes in neurophysiology, which may not be apparent in the measurement of performance (Parasuraman et al., 2011a, b) (Somon et al., 2017). Due to the increasing growth of neuroscience, theories of human performance are extended or constrained when considering the results of modern neuroscience (Chua and Causse, 2016). Neuro-ergonomics has a potential application for research intending to improve work efficiency, without compromising the unseen wellbeing and mental workload of seafarers within the engine room (Koenigsberg and Fong, 2007).

The neuroimaging hardware used in this project is fNIRS, which is a non-invasive, user-friendly neuroimaging technique (Gautier et al., 2016). FNIRS, with the use of classification performance modelling, coupled with AI, machine learning algorithms and interlinked brain-computer interface (BCI) techniques, allows us to provide a means for decoding brain activity (Pomorstvo, 2006). Integration of the above method advances the science of human performance (Kojima et al., 2004), and exploits a potential for addressing questions concerning brain function within a ship engine room environment (Parasuraman and Mustapha, 1996).

The human factors psychologist, Hancock conducted a behaviourist analysis of Neuro-ergonomics as a concept. Hancock began his study by looking at neuro-ergonomics critically, with a view from radical behaviourism. He stated "*I am optimistic of punctate successes here, along this line of development in the near future. More understanding in this domain will also help us distinguish between simple, quantifiable processing capacities, and what the human brain actually achieves*" (Hancock, 2019). Hancock concluded his investigation by stating, "*neuro-ergonomic designs have proven to epitomize the marriage of pure science and application in the real-world. A greater level of insight into the symphonic productions of the neural orchestra could provide exceptional opportunities to advance human-technology interaction.*" Hancock also looked at the use of new techniques for providing neuro-ergonomic signals (Hancock, 2019).

A world leader in the field of neuro-ergonomics, Parasuraman (Hancock, 2019), argues for studying neuroscience in an applied context and developing models of human performance that are grounded in neuroscientific models (Parasuraman and Mustapha, 1996). He also addresses the fact that sustained attention would very likely result in mental fatigue (Koenigsberg and Fong, 2007). The engine room features BCIs that present complex and dynamic visual information such as monitoring ballast tank volume whilst figuring out flow rates on ballasting tasks (TRANSAS). Parasuraman's research looks into the effects of changing workplace and environmental factors on human performance and then uses neuroimaging and behavioural data to back up his theories (Koenigsberg and Fong, 2007).

1.2. Current human reliability analysis techniques

A few examples of commonly used HRA techniques are nuclear action reliability assessment (NARA) (Hasan et al., 2011), cognitive reliability and error analysis method (CREAM) (Hiteshk, 2017a) and a technique for human event analysis (ATHENA) (Heike et al., 2016). These techniques are all similar in approach as they work based on defining the study scope, defining the tasks, defining the PSFs and then calculating the human error probability (HEP) (Hasan et al., 2011). It is often too difficult to use these techniques in a human factors study, as fNIRS data has too many complexities to calculate an accurate HEP (for example, 1/1000 chance of human error cannot be determined as the HEP will differ between participants).

The next examples are HRA techniques that have been used in previous studies in conjunction with simulators. These techniques are: a probabilistic cognitive simulator (PROCOS) (Hlotova et al., 2014), information, decision and action in crew context (IDAC) (Hiteshk, 2017b) and a standardized plant analysis of a risk to human reliability analysis (SPAR-H) (Takashi et al., 2006). These aforementioned HRA models are simulation-based approaches that look at a scenario in normal working conditions before applying human factors techniques. They consider the interaction of the operator with other crew members and their decisions based on external factors. These techniques are appealing, however, they do not incorporate neuroimaging. More specifically, fNIRS. Furthermore, they use HEP to try to predict the root cause of the error which can be heavily scrutinised.

The addition of fNIRS coupled with human factors, AI, Machine learning and psychology techniques accentuates the research gap with current HRA techniques used in maritime engineering and technology. The majority of the current HRA techniques aim to provide a nominal HEP value (Heike et al., 2016). Due to the complexities of human performance against various human factors, it is not possible to obtain an accurate nominal HEP value (Mobility, 2017). This prevents the use of current maritime HRA techniques without major improvements.

1.3. Neuroimaging techniques used in the studies

Many academics such as Dehais et al. (Rabiul et al., 2018) and Vierdiere et al. (Organisation, 2019) have found human performance to be an interesting field of research. Such research has focused primarily on an analysis of various aircraft operations (Faisy et al., 2016), air traffic control duties (Somon et al., 2017) and the impact of new flight regulations affecting the safety of personnel (National Transport Safety Board (NTSB), 2017). These studies used fNIRS to gauge the mental workload of pilots at various stages of their tasks. Later, they modelled their findings using a performance classification model to deduce the pilot's ability and how each task influences the risk of human error.

Fan et al. (Australian Government, 2017) (Aghajani et al., 2017) have conducted human error studies using fNIRS and a ship simulator. These studies used fNIRS again, to gauge the mental workload of seafarers on the bridge whilst conducting standard ship operations. In these studies, tasks and conditions were manipulated to investigate the effect of various PSFs. The data was then evaluated using a connectivity matrix to analyse the relationship between functional connectivity and seafarer behaviour.

These investigations have been conducted on aircraft or solely on ship bridge operations with little consideration of engine room operations. However, it has been documented that engine room operations have a significant impact on the 80% of maritime accidents that result from human error (Thibault et al., 2018) as previously mentioned. Additionally, academics have explored maritime human error incidents with the limitations of expert opinion, resulting in speculative data (Kaushik, 2017). There are very few published papers investigating ship engine room operators using fNIRS technology. There are no maritime studies to date that have successfully modelled the relationship between seafarer performance and PSFs using fNIRS technology as Fan et al.'s (Fan et al., 2019) study only provides stressor-based inter-cerebral interaction without any human error or seafarer performance models. Also, Fan et al.'s (Fan et al., 2017) study used a connectivity matrix based solely on the dorsal lateral pre-frontal cortex (DLPFC) which does not consider the interaction between frontal, temporal, parietal and occipital regions. On top of this, the model used (Support Vector Machine) is heavily scrutinised when used in BCI-fNIRS studies due to the large datasets involved and the accuracy of the model (Hasan et al., 2011).

2. Methodology

This study describes the method used, how the data is extracted and how the data is analysed.

2.1. Identification of PSF

Section 1 detailed how the PSF workload was identified by consulting the following databases.

- Transportation Safety Board (TSB).
- The Marine Accident Investigation Branch (MAIB).
- The European Maritime Safety Agency (EMSA).
- The Nautical Institute (MARS).
- Various government databases, including; Australia, the United States of America, Hong Kong, China and the UK.

Also, a filtering system was used to narrow down the number of reports (between 2012 and 2018, engine room, human error) and to increase their relevance to this study. This system simply removed all accident reports before 2012 and looked at ones that specifically referred to human error within a ship engine room. This provided us with 217 reports in total.

2.2. Experimental design

After analysis of the 217 reports mentioned above, a PSF that showed to have a regular occurrence, a significant effect on human performance and thus, will be investigated for this part of the study is workload.

Previous studies (some of which are mentioned in Section 1) have used, with success, a workflow style task design (Thibault et al., 2018) (Verdiere et al., 2018) (Thibalut et al., 2015). This workflow style task design allows for the compartmentalisation of various sub-tasks and stages of a ship engineer's daily duties for ease of analysis. The workflow design in this study will follow a 5-stage workflow process listed below.

2.2.1. Baseline

For the first baseline, the participants would be expected to monitor the liquid cargo screen (LCS) whilst ballasting from pump number two as shown in Fig. 1 (ballasting from pump two was set up by the instructor before the task started). The LCS is split into 3 sections; the left is the ships ballast tanks (marked in white is the specific tank that is being filled in the test), The right hand side shows the specific tanks and their various specs, including, fill volume. The participants would have no active input for the monitoring stage to allow for a 5-min (300s) baseline to be taken.

2.2.2. Fault occurrence

This stage of the task took participants between 31 and 46 s to complete. For the fault occurrence stage of the workflow, pump number two will fail. The participant must.

a) Orientate to the alarm as shown in Fig. 2 below. The alarm is solely a visual alarm with no audio.
(b) navigate to the alarm summary screen (see Fig. 3) to record the details of the alarm.
(c) check the ship's log noting any previous faults or maintenance work.

2.2.3. Fault detection

During the fault detection stage, participants must localise the presence of a fault with ballast pump number one. This is achieved by.

(a) navigating back to the LCS screen to check the flow rate (Fig. 1)
(b) navigate to the ballast system screen to check the water line as shown in Fig. 4. Fig. 4 shows the vessels ballast system. The green bars within the tanks show the tanks volume and the water line that is being used is highlighted in green. The participant will be looking to see if there is or isn't an active water flow (the active flow is shown by the illuminated green piping line). If there is an active water flow then this indicates that there is no blockage or leak in the water line indicating that the problem is a fault with the ballast pump.
(c) access the cargo control room ballast pump screen (Fig. 5) to check the pump pressure gauge (as prompted by the alarm summary screen in Fig. 3).

2.2.4. Fault solution

The next stage of the workflow requires the participants to determine a solution to correct the fault. To correct this fault, participants must: (a) navigate to the cargo control room ballast pump screen (Fig. 4) and switch off pump number two, (b) access the ballast system mimic panel (Fig. 6), (c) open valves BA538F, BA547F and BA544F and close valves BA537F, BA546F and BA543F to re-route the water line to ballast pump number one.

(c) Access the screen for engine room three (ER3) to power on pump number 2 (the additional task of synchronisation to an additional power generator was performed by the instructor prior to starting the test due to the complexity and the amount of additional time that would be required).

(d) Navigate back to the cargo control room ballast pump screen (Fig. 5) to check that pump number 2 has power and switch the pump on.

(e) Re-access to the ballast system screen to check that there is a water flow through the new pump as shown in Fig. 7.

(f) Return to the LCS to identify the new flow rate as shown in Fig. 1 above.

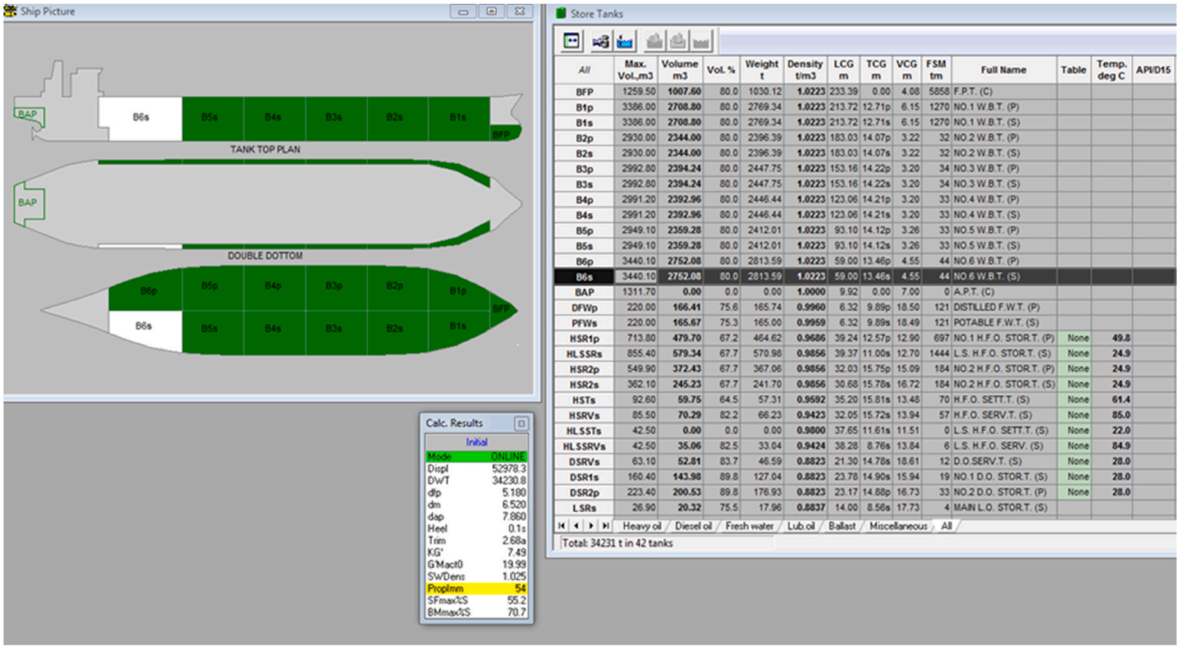

Fig. 1. The liquid cargo screen. Used for monitoring the ballast tank readings.

Fig. 2. The ship alarm icon flashing.

2.2.5. 2nd baseline

The last stage of the workflow requires the participants to continue to monitor the LCS until the tank has filled to the required volume set by the instructor before the task.

Due to the unpredictable and differing nature of human physiology from person to person. The first stage is used as a baseline reading of each participant. A fault with the ballasting pump occurs in stage 2. The participants must find the fault in stage 3. In stage 4 the participants must solve the problem to continue the ballasting process. Stage 5, like stage 1 is a second baseline. The second baseline is used to see if any residual activation exists post experiment, as this may lead to increased levels of activation for a following task.

10 of the 20 candidates participated in a study where they were given an increased workload (6 ballast tanks), the other 10 had a standard (1 Single ballast tank) test. The candidates in the 'increased workload' and 'standard test' groups consisted of an equal share of 10 fully trained individuals (All candidates were trained for 3 h; 2 h theoretical learning from a book, and a final hour doing a tutorial using the ballasting system specifically). This experiment replicated the stages mentioned in stage 1 to stage 5 as noted above. The difference was that the increased workload candidates, specifically, for the fault detection stage had to check more data obtaining to the additional tanks found on the LCS. Also, for the fault solution stage, the participants had to open and close additional valves, spend more time and thought when re-routing the water line, test each of the 6 tanks and test the ballast pump using the information found on the LCS (Fig. 1). This replicates what would be done in real operations (Hiteshk, 2017a). The LCS readouts consist of ballast tank volume percentage, flow rates, max tank volume and tank volumes in m^3.

2.3. Experiment participants

20 candidates were used for this study. All 20 had qualifications to the level of a BEng or higher in marine engineering. All participants had sea time and/or engine room experience. 12 were ex and current armed forces engineering officers and 8 engineering non-commissioned officers (NCOs). The average age of the workload group was 29 and the standard test group was 31. All 20 were male.

2.4. Data analysis strategy

The data analysis was conducted using the methods and software platforms listed below.

- Correction based signal improvement (CBSI).
- Statistical package for the social sciences (SPSS).
- ANOVA analysis.
- R-Studio.
- Linear Discriminant analysis (LDA).

The first method listed is CBSI. In theory, the oxygenated (oxy-hb) and deoxygenated haemoglobin (deoxy-hb) volume signals transmitted from the fNIRS hardware should have a negative correlation during neural activation (Aghajani et al., 2017) (when the oxy-hb volume increases, the deoxy-hb decreases). However, in practice, this is not always the case due to noise and motion artifacts. Therefore, we removed the

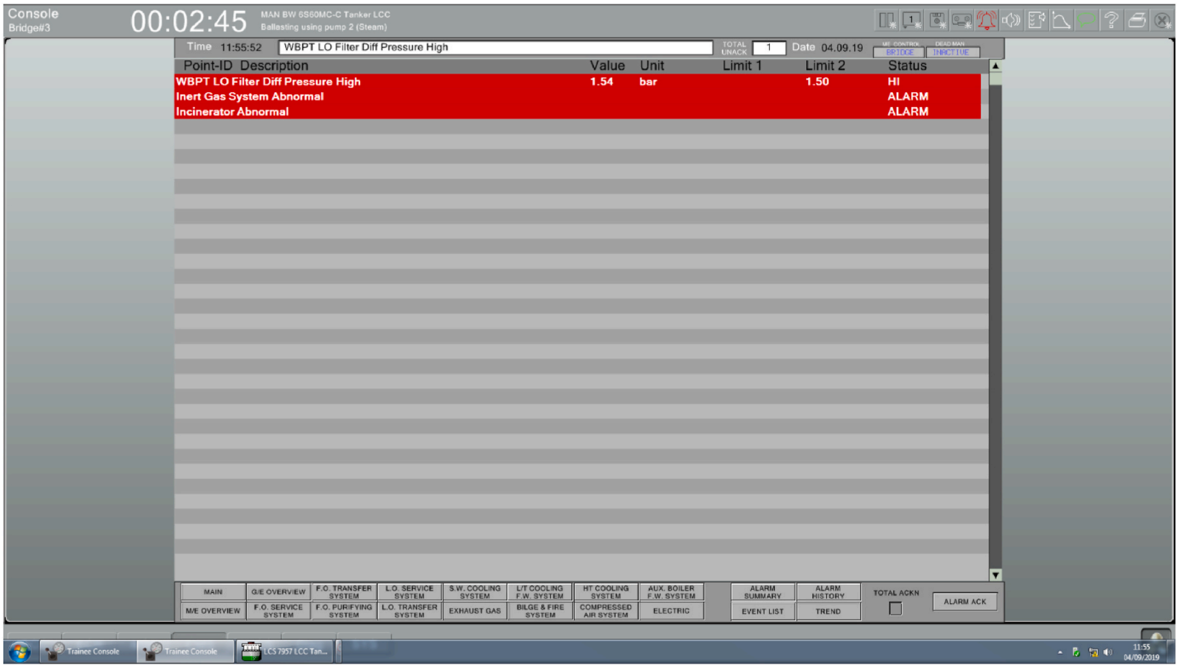

Fig. 3. The alarm summary screen.

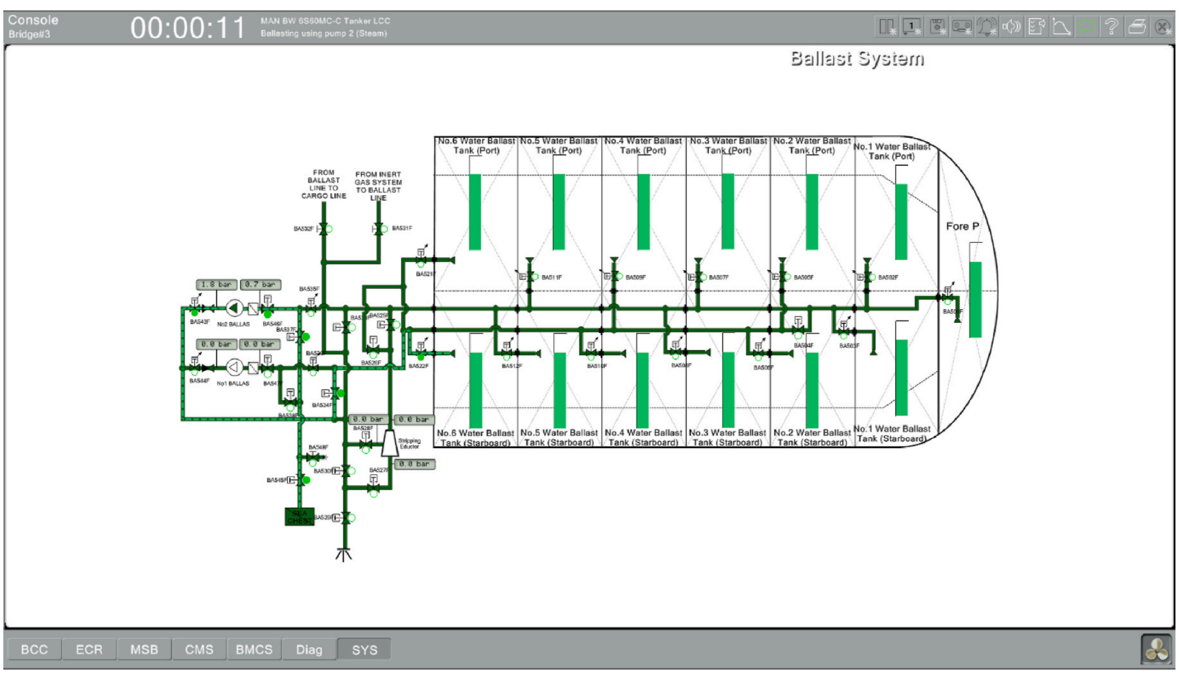

Fig. 4. The ballast system screen showing water flow through pump 2.

aforementioned noise and motion artifacts based on the theory that if the measured oxy-Hb and deoxy-Hb signals are not strongly negatively correlated, the signals likely contain substantial noise and motion artifacts (Ayaz et al., 2017).

SPSS is the software package that was used to undertake the ANOVA studies. The ANOVA studies will tell us the significant effects found between participants individually and between the 2 groups (standard and increased workload).

R-studio is a software platform used to implement the mechatronic code needed for a machine learning based analysis. R-studio is the software platform that was used to format the raw fNIRS data (using CBSI) and implement an LDA.

The corresponding results from the above techniques and software packages are given and discussed in Section 3.

3. Results & discussion

This section shows and discusses the results of the workload study. More specifically, this section shows the results from ANOVA (time and fNIRS data), the human error model (LDA using oxygenation features and a participant/group classifier) and discusses the findings.

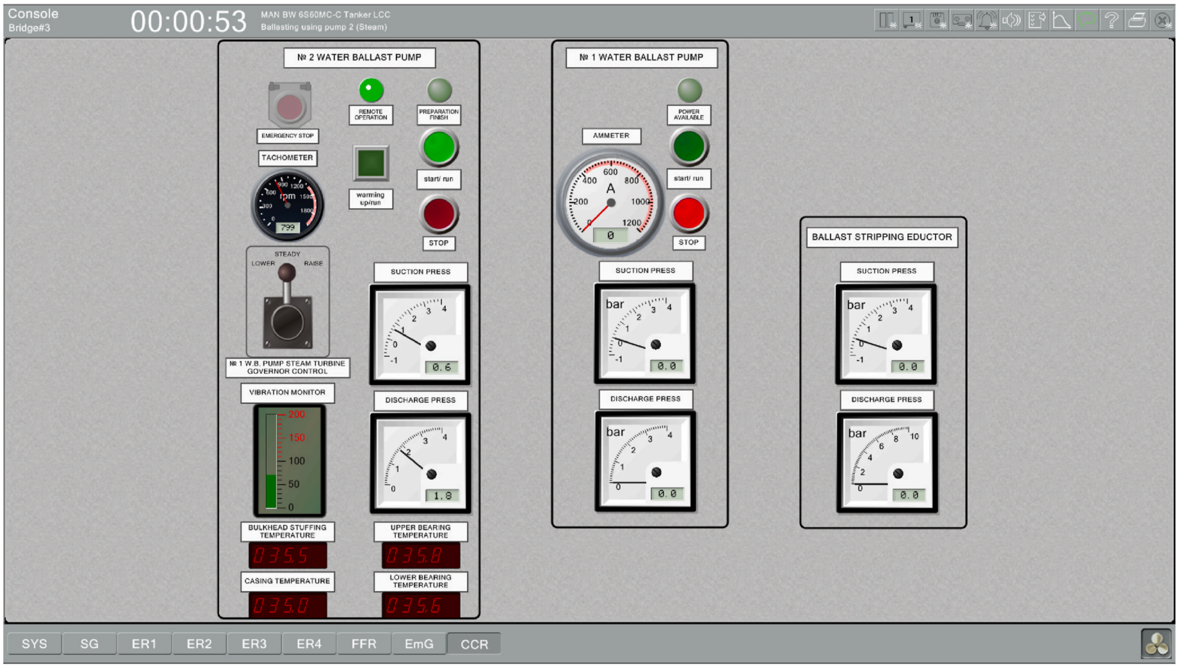

Fig. 5. The ballast water pump control panel.

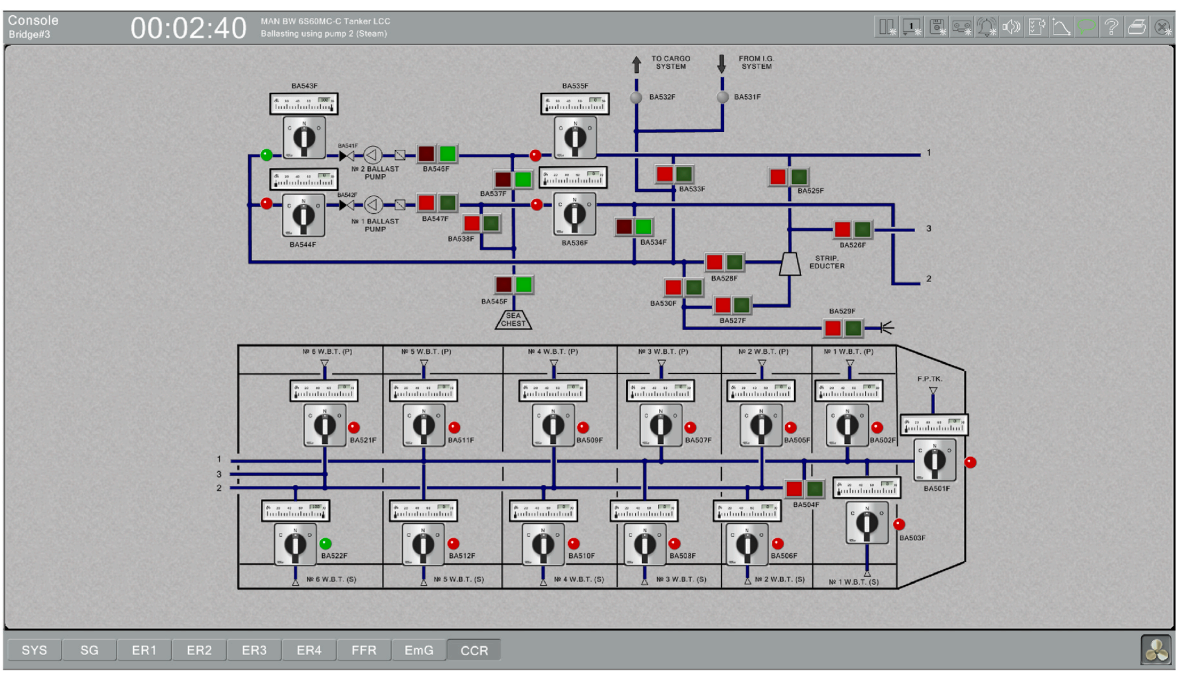

Fig. 6. The ballast system mimic panel.

3.1. ANOVA results

The data from the study was analysed via ANOVA procedures using SPSS v.26. Outliers were identified as any value that deviated more than 3 standard deviations from the cell mean and were omitted from ANOVA testing. The ANOVA outputs are as follows: F = variation between sample means/variation within the samples. The higher the F-value in an ANOVA, the higher the variation between sample means relative to the variation within the samples. P (the p value or probability value) tells us how likely it is that our data could have occurred under the null hypothesis. It does this by calculating the likelihood of our test statistics, which is the number calculated by a statistical test using our data. The p value tells us how often we would expect to see a test statistic as extreme or more extreme than the one calculated by our statistical test if the null hypothesis of our test was true. The p value gets smaller as the test statistic calculated from your data gets further away from the range of test statistics predicted by the null hypothesis. η^2 is a measure of effect size that is commonly used in our ANOVA model. It measures the proportion of variance associated with each main effect and interaction effect.

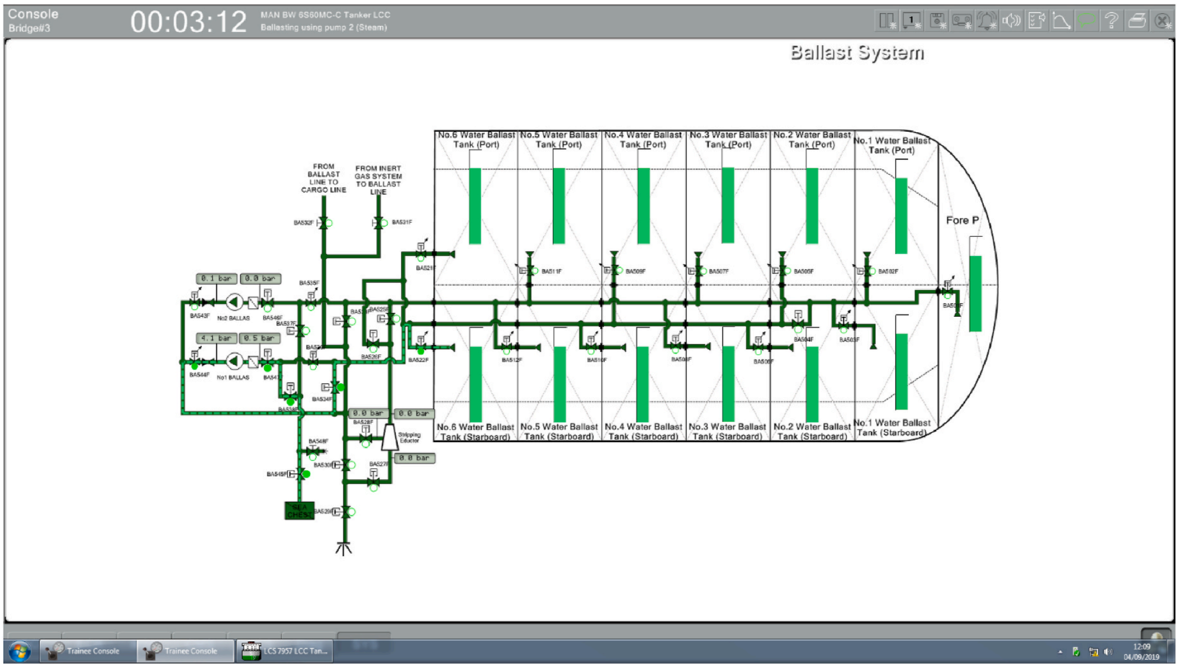

Fig. 7. The ballast system showing water flow through pump 1.

3.1.1. Significance found with respect to time

The time taken to complete each phase of the workflow was subjected to a 2 (standard/high workload) × 2 (fault detection/fault solution) ANOVA. The fault occurrence workflow phase was not used, as preliminary analysis showed that the data provided was not as relevant due to the similarity in the task. This model revealed significant main effects for workload [$F(1,18) = 301.40$, $p < 0.01$, $\eta^2 = 0.94$] with the increased workload group showing an increased time taken ($M =$ 269.8s, s.e. = 2.61) compared to that of the standard test group ($M =$ 210.30s, s.e. = 2.43). There was also a significant main effect found for the workflow phase [$F(1,18) = 9808.98$, $p < 0.01$, $\eta^2 = 0.99$], which was unsurprising as the Fault Solution phase took significantly longer to complete ($M = 401.81$s, s.e. = 3.23) than the fault detection phase ($M =$ 78.32s, s.e. = 0.63). The ANOVA study also revealed a significant interaction between workflow phases [$F(1,18) = 356.19$, $p < 0.01$, $\eta^2 =$ 0.95]. Post-hoc t-tests revealed that the time to complete the fault

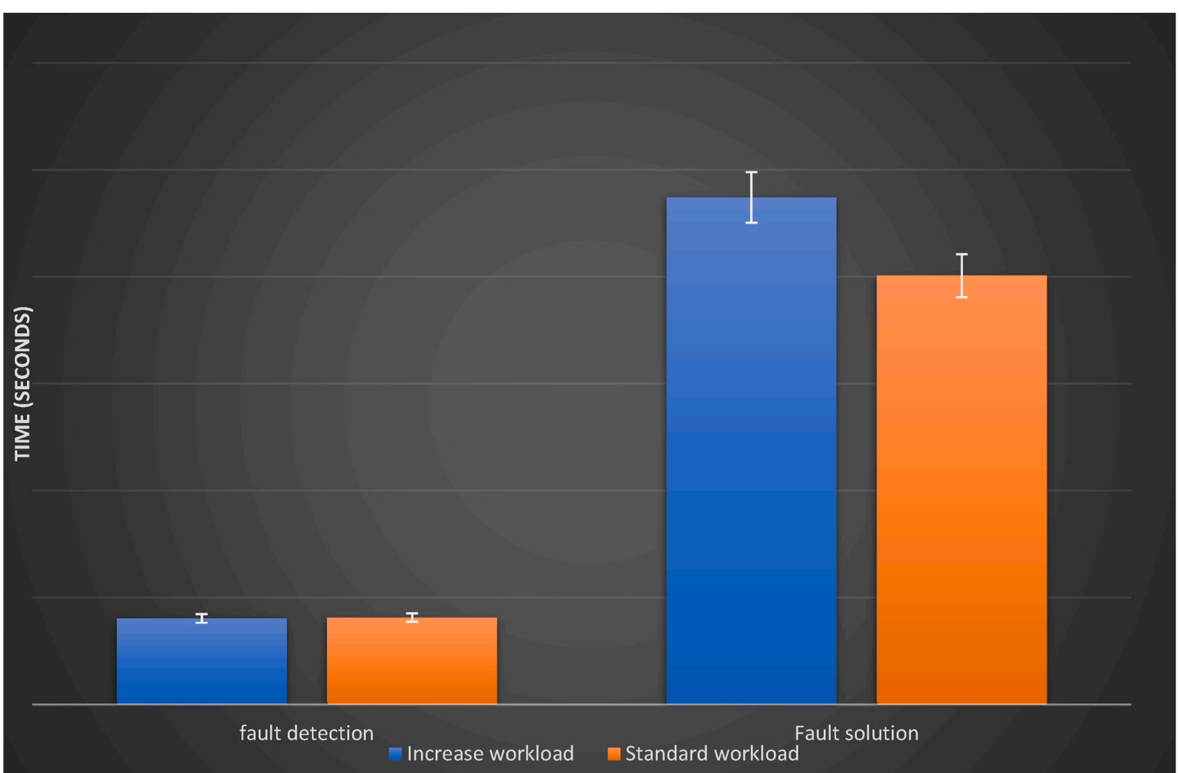

Fig. 8. Average times to complete each phase of the workflow for the standard test and increased workload groups (N = 20).

solution phase was significantly longer for the increased workload group when compared to the standard test group [$t(18) = -18.42$, $p < 0.01$]; however, there was no significant effect of increased workload on time during the fault detection phase, see Fig. 8.

3.1.2. Significance found with respect to oxygenation data

Average levels of oxy-hb were estimated using fNIRS for the fault detection and fault solution phases of the workflow. Data from all channels was averaged into three regions of interest (ROI) corresponding to the left, medial and right regions of the prefrontal cortex. All oxy-hb data was subsequently baselined using data gathered during the first phase of the workflow, this lasted for 300s, i.e., baselined oxy-hb = oxy-hb during the task phase minus the oxy-hb during the 300s baseline period, hence positive oxy-hb values indicate an increase above the baseline levels.

Activation of the prefrontal cortex during the fault detection phase was explored via a 2 (standard test/increased workload) × 3 (left, medial and right ROI) ANOVA. This analysis revealed no significant effect for workload [$F(1,18) = 2.02$, $p = .17$] or ROI [$F(1,18) = 1.05$, $p = .33$], and no significant interaction.

Activation of the pre-frontal cortex during the fault solution phase was explored via a 2 (standard/High workload) × 3 (left, medial and right ROI) ANOVA. This analysis revealed significant main effects for workload [$F(1,18) = 152.1$, $p < .1$, $\eta^2 = 0.894$] and ROI [$F(1,18) = 40.46$, $p < .01$, $\eta^2 = 0.692$]. The ANOVA also revealed a significant interaction between both factors [$F(1,18) = 82.19$, $p < .01$, $\eta^2 = 0.906$]. The main effect for workload indicated that mean HbO was significantly greater during the high workload condition ($M = 0.052$, s.e. $= 0.002$) compared to the low workload condition ($M = 0.009$, s.e. $= 0.002$). For ROI, the main effect revealed that mean HbO at medial ROI ($M = 0.006$, s.e. $= 0.002$) was significantly lower than either left lateral ROI ($M = 0.038$, s.e. $= 0.005$) or the right lateral ROI ($M = 0.047$, s.e. $= 0.002$) ($p < 0.01$) – see Fig. 9.

To explore the interaction, several post-hoc t-tests were performed. T-tests are specifically used to investigate the differences found between 2 means as opposed to ANOVA which investigates the differences between group means (Bu et al., 2016). These tests revealed that the mean HbO was significantly greater during high workload compared to low workload at the left lateral ROI [$t(18) = -6.53$, $p < 0.01$] and right lateral ROI [$t(18) = -15.54$, $p < 0.01$], but there was no significant effect of workload at medial ROI.

3.2. Discussion

3.2.1. Time

The significant effect found was as expected, as participants in the increased workload group had additional tasks to perform resulting in a longer time taken. The mean times for the increased workload group were higher in only the fault solution stage. This was due to the additional tasks being only in the fault solution stage of the workflow. However, it was predicted that participants would take longer for every stage of the workflow as additional checks are needed in stages 2, 3 & 4. These checks are all on the same simulator screen as the standard workload checks. This could result in similar mean times for the fault detection workflow stage.

Post-hoc t-tests showed significant differences between all workflow stages. This is expected as the t-tests solely compared the differences in time between workflow stages. There was a difference in time between all workflow stages due to the different activities contained within each stage. As predicted the size of the effects from t-tests showed that the largest effect is always between fault solution and other workflow phases. This is due to the largest mean time difference being for the fault solution stage of the increased workload group. The interesting outcome for time taken is the size of the difference in time between the increased workload group and a standard test group. The theory is that the longer a participant takes to deal with a problem or task, the higher the likelihood of error (Fan et al., 2017).

3.2.2. fNIRS data

A significant effect was found for increased workload when compared to standard test participants. This is to be expected as the increased workload participants had significantly more tasks with a greater level of difficulty. The fault solution stage is the workflow stage that contains the greatest difference in task volume in comparison to a standard test. This explains the significant effect found only in the fault solution workflow stage. Unpredicted, was the level of increase between a standard test and increased workload test participants for the fault solution stage of the workflow as shown in Fig. 8. This shows that the participants in the increased workload group were experiencing a much higher mental workload from the additional tasks. This shows consistencies with Verdiere et al. and Dehais et al.'s neuroimaging studies involving an increased workload element (Rabiul et al., 2018) (Hocke et al., 2018). Verdiere et al.'s investigation, like this study, found that participants undertaking a task with an increased workload (manual landing scenario) showed a significant effect when compared to that of a standard test (a landing scenario with autopilot engaged (Thibault et al., 2018)). Dehais et al.'s investigation used several air traffic control instructions in order to evaluate working memory whilst in flight using a simulator. Like this study, Dehais et al. (Thibalut et al., 2015), showed that increased workload resulted in an adverse effect on operator performance and in his case, flight safety.

The tasks in the increased workload group would closely resemble those done by a marine engineer in a 'real-world' situation (Isbilir et al., 2016).

Mauchly's test of sphericity is used to test whether the assumption of sphericity is met in a repeated measures ANOVA. Sphericity refers to the condition where the variances of the differences between all combinations of related groups are equal. If this assumption is violated, then the F-ratio becomes inflated, and the results of the repeated measures ANOVA become unreliable (Raichle and Mintun, 2006). Mauchly's test of sphericity showed a significant effect. Therefore, a test of within subjects effects was done, showing a large significant effect ($F = 152.1$, $t = 14$). This is to be expected as the individuals go from a mundane monitoring task to a complex seawater line re-routing task. When compared to other studies (Australian Government, 2017), (Hitoshi and Kazuki, 2009). The effect size found in this study is considerably greater. Fan et al.'s (Aghajani et al., 2017) investigation of increased workloads shows an effect size of 4.1 and Kojima et al.'s (Hong et al., 2015) investigation showed an effect size of 7. This could be expected as our investigation of increased workload involved five more ballast tanks when compared to a standard test. Fan et al. (2017) used additional verbal reporting as opposed to a practical approach to increasing workload, which could be said to be a less intense workload increase

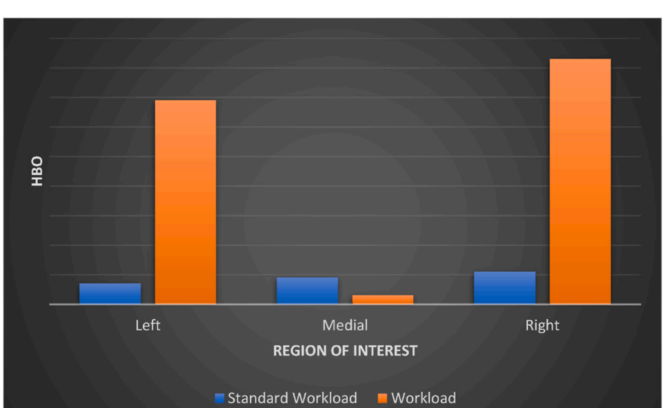

Fig. 9. Average HBO for each Region with respect to standard (blue) and high workload (red).

than in this study. Kojima et al. (2004) used a more similar approach to that in our study as they used additional train signalling, traffic and manoeuvring, hence explaining why their effect size is closer to ours. The issue with Kojima et al.'s study is that the operator's experience was not stated. Due to their effect size of 11 against ours (14), one can only predict that the difference may have been due to the operator's experience as the participants in this study had a limited training time (3 h) whereas the participants in Kojima et al.'s study could have had months or even years.

Post-hoc t-tests between the increased and standard workload groups, for all workflow stages combined, showed a significant effect for left lateral ROI1 [$t(18) = -6.53$, $p < 0.01$] and right lateral ROI3 [$t(18) = -15.54$, $p < 0.01$], but there was no significant effect of workload at medial ROI2. This is to be expected given the significance found in the fault solution workflow stage. The size of the effect would be greater if the comparison was made using the fault solution stage instead of the mean from all workflow stages. This is again due to the fault solution stage being the only stage with a significant increase in mental workload for the increased workload group. Also, a significant interaction was found between workload and workflow [$F(1,18) = 82.19$, $p < .01$, $\eta^2 = 0.906$]. This interaction is due to the fault solution stage of the workflow as detailed above.

3.2.3. Region of interest (ROI)

A significant effect was found for ROI. The left and right regions of the DLPFC were shown to have a much higher mean HbO when compared to the middle region [medial ROI2 (M = 0.006, s.e. = 0.002), left lateral ROI1 (M = 0.038, s.e. = 0.005), and right lateral ROI3 (M = 0.047, s.e. = 0.002) ($p < 0.01$). The reason for this is that the left region of the DLPFC controls working memory. More specifically, remembering goals and any instructions needed to accomplish those goals, speech, comprehension, arithmetic, writing and positive feelings. The right region controls creativity, planning, maintaining focus, spatial ability, artistic and music skills, and negative feelings [145] whereas the middle region is involved mainly in body regulation, attuned communication, emotional balance, empathy, self-awareness, and fear modulation (Giorgio and Stephen, 2002). Therefore, it is to be expected that the middle region would have a lower mean HbO. Interestingly the right region showed a higher mean HbO. This could be due to the participants being new to the simulator system and thus taking a pessimistic approach. This tells us that on average, participants are focusing on creativity and planning rather than working memory. This is consistent with the work done by Fairclough et al. 2020 (Faisy et al., 2016) where they also found the left and right side DLPFC to have the most significance when undertaking a task associated with executive functions, working memory, and selective attention.

Pairwise comparisons showed a significant effect on ROI. The most significance was found between left–middle and right–middle. This is to be expected when considering what has been previously mentioned above. Interestingly, for t-tests, the largest effect size was shown on the left against the middle region. This contradicts what is shown with respect to HbO volume, as the mean HBO was higher for the right region of the DLPFC as shown in Fig. 9. However, the t-tests make more theoretical sense, as our tasks involve a large amount of working memory, controlled by the left region of DLPFC.

A significant interaction was found for ROI with respect to workflow. This is predicted as the fault solution stage required a larger number of the right and left region DLPFC functions when compared to the middle region.

A significant effect was found for ROI combined with increased workload against ROI combined with standard workload [$F(1,18) = 64.09$, $p < .01$, $\eta^2 = 0.846$]. This is to be expected as the mean HbO was significantly higher for increased workload individually. One interesting finding is that for the standard workload group the right region of the DLPFC showed a higher mean HbO [right region M = 0.047, s.e 0.002, left region M = 0.038, s.e 0.005]. However, for the increased workload group, the left region of the DLPFC showed a significantly higher mean HbO [right region M = 0.028, s.e 0.002, left region M = 0.041, s.e 0.002]. The reason for this could be that the increased workload task involved managing 5 additional ballast tanks. This would require participants to remember the names, numbers and locations of the tanks being filled, the fill levels and the previous water line used. Another significant factor is that working memory is one of the main functions of the left region DLPFC.

3.3. Human error model

The data classification, pre-processing and feature extraction were conducted using software programs called Statistical Package for the Social Sciences (SPSS), R-studio and NIRx. These software packages were used to implement the relevant code for pre-processing raw data. To quantify the data provided by fNIRS, a modified version of the Beer-Lambert law is used (Bu et al., 2018) as the Beer-Lambert law alone can only be used on non-scattering data (Solovey et al., 2012). Therefore, it cannot be applied to biological tissue without modifying the law to allow for light scattering (Ayaz et al., 2017). This is done by the NIRx software (Aghajani et al., 2017). The data was then exported into R-studio. R-studio is used firstly to implement correlation-based signal improvement (CBSI). CBSI is a technique used to improve the fNIRS signal based on a negative correlation between oxygenated and deoxygenated haemoglobin dynamics. Improving signal quality and reducing noise, especially noise induced by head motion, is challenging, particularly for real time applications. In a study done on the properties of head motion induced noise, it was found that motion noise causes the measured oxygenated and deoxygenated haemoglobin signals, which are typically strongly negatively correlated, to become more positively correlated (Xu et al., 2009). Therefore, the CBSI method was developed to reduce noise based on the principle that the concentration changes of oxygenated and deoxygenated haemoglobin should be negatively correlated (Baker et al., 2018). This data was then exported to SPSS to implement an ANOVA analysis (the results of which are discussed in Section 3.3.1). Post ANOVA analysis, R-studio was re-used to predict classification performance percentages using linear discriminant analysis (LDA) as discussed below.

3.3.1. Results

The data used to conduct the LDA was taken from the fault solution workflow stage. This was done due to the fault solution stage having the most significance as outlined by the ANOVA results discussed in Section 3.1.

Fig. 10 depicts the classification performance of the increased workload participants for each of the 6 oxygenation features. The area under the Curve (85.15%) and Variance (83.96%) had the best performance compared to Kurtosis (79.02%), Slope (80%), Skewness (82.9%) and Average (80.1%).

All oxygenation features had a significantly higher classification performance than the chance value (56.09%). Additionally, the lowest classification performance is Kurtosis (79.2%), which is 23.11% above the chance value.

Table 1 shows the classification performance of the 6 oxygenation features (Average, Variance, Area under the curve [AUC], Skewness, Slope and Kurtosis) for each participant throughout the task. The classification performance results above in Table 1 tell us the influence of increased workload against those participating in a standard test. This is shown by the high levels of prediction accuracy. A significant effect is shown by prediction accuracies of over 70% for brain computer interface (BCI)-fNIRS studies (Thibault et al., 2018).

3.3.2. Discussion

Our subjective measures confirmed that a normal workplace environment is heavily contrasted to that of adverse workplace factors as workplace factors led to significantly higher average oxygenated

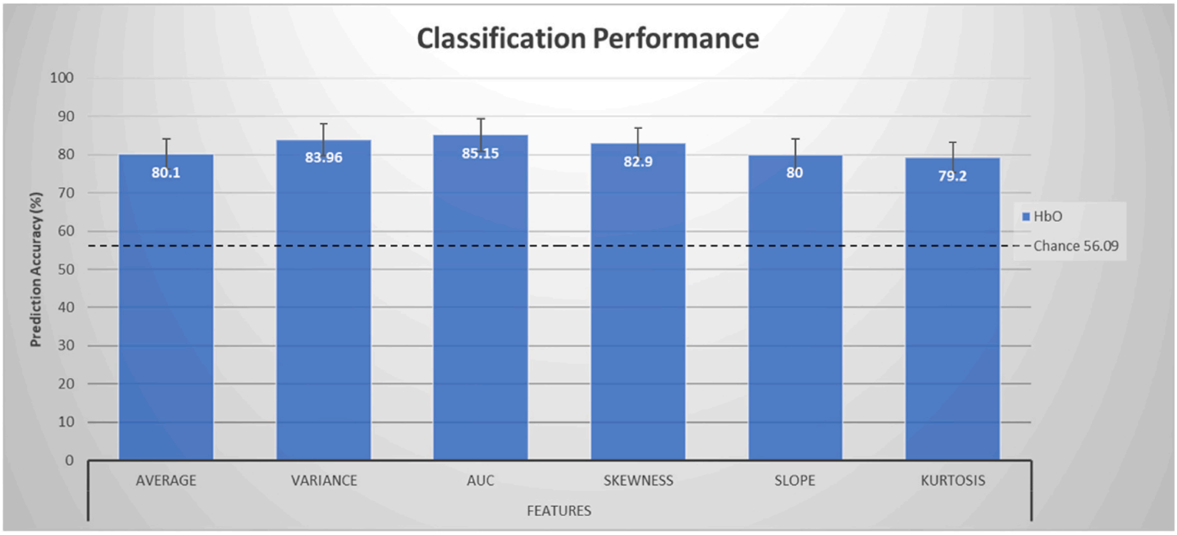

Fig. 10. Classification performance of Increased workload participants.

Table 1
Increased workload vs standard workload classification performance for each epoch with respect to feature type.

Participants	Average	Variance	AUC	Skewness	Slope	Kurtosis
1	81	85	84	83	81	79
2	80	84	86	82	80	79
3	80	85	87	83	81	79
4	81	84	85	84	80	80
5	80	84	87	83	80	80
6	82	83	84	82	82	79
7	82	84	86	84	81	80
8	80	85	83	84	82	81
9	80	85	87	83	80	81
10	79	84	85	85	81	80
11	80	85	86	83	82	79
12	78	83	87	82	82	80
13	80	85	86	83	81	79
14	82	86	85	85	80	80
15	81	83	85	82	80	81
16	81	83	85	82	81	80
17	81	84	87	82	80	79
18	80	82	86	83	81	80
19	82	83	88	84	81	81
20	80	84	84	83	80	79

haemoglobin levels when compared to a standard test.

The overall classification results confirmed that increased workload as a workplace factor could be discriminated in an engine room simulator. This is substantiated by previous neuro-ergonomics studies showing that fNIRS is well suited for operator mental state monitoring in ecological situations (Kojima et al., 2004) (Isbilir et al., 2016) (Hlotova et al., 2014) (Ying-Ming et al., 2009).

The best classification accuracy percentage obtained is 85.15%, taken from the AUC oxygenation feature. This result compares favourably with recent studies. For instance, Verdiere et al. (Hlotova et al., 2014) obtained a classification performance of 66.9% on 11 subjects using oxygenation features, connectivity features and chromophore concentration. Studies by Hong et al. (Paolo and Maria, 2009), Holper and Wolf, 2012 (Gul et al., 2017) and Naseer et al. 2016 (Yang et al., 2013) obtained a classification performance of 75.6% on 10 subjects, 81.3% on 12 subjects and 93% on 7 subjects respectively. These results compare similarly with ours. However, these studies did not consider continuous, but multiple set sub-tasks assessment of specific cognitive activity, contrarily to our engine room simulator task which involved different executive and attentional skills. Similar to our study Khan and Hong, 2015 (Chauvin et al., 2013) also showed that oxygenation features could yield a high accuracy (84.9%) using a driving simulator to monitor fatigue/drowsiness.

The comparison of oxygenation features classification performance revealed that AUC and Variance resulted in significantly higher classification accuracies. This is similar to the study conducted by Vierdiere et al. (Hlotova et al., 2014) where AUC was found to be the oxygenation feature with the most significance.

It is interesting to note that features present complementary advantages. All oxygenation features are an uncomplicated and low-cost computational measurement to effectuate. This is of considerable advantage as long as passive Brain-Computer Interfaces are concerned. Moreover, the oxygenation features computed in our study can consider both time and chromophore. Oxygenation features from fNIRS data have been used for some years to evaluate operator performance in the aerospace sector, but to date it has not been used in the maritime sector to evaluate engine room operators. Therefore, it is difficult to compare results from other maritime studies. Based on the comparisons to other studies above, undertaken using oxygenation features as a classifier, it can be said that our study had a successful outcome. Our study provides some novel methodological guidance for the implementation of fNIRS based BCI metrics in the maritime industry. This study may be the first to benchmark different fNIRS oxygenation metrics and to use them for classification purposes in ecological settings for the benefit of human error assessments. It paves the way forward toward operator mental state estimation in an ecological maritime environment although some challenges remain.

4. Conclusions

When compared to a standard test, from the ANOVA, increased workload participants showed higher levels of neurophysiological activation in the DLPFC. This resulted in a significant effect shown for increased workload participants with respect to the time taken to complete the workflow stages and HBO volume. A significant effect was also found for workflow with respect to the time taken to complete the tasks and HBO volume. The fault solution workflow phase induced the highest levels of activation and the longest times taken to complete the stage.

The left and right regions of the DLPFC showed the most significant effects when compared to the middle region. The middle region (channels 6–10) showed varying levels of sensitivity, anomalies and outliers which had to be omitted due to tolerance. Therefore, the middle region data was deemed invalid/less accurate.

The results from the human error model discussed above in 3.3 showed a BCI-fNIRS classification performance significantly above what is deemed the minimum allowable (70%) for all oxygenation features. Therefore, the contribution to existing knowledge is that increasing an operator's workload has a significant effect on overall performance. Moreover, the significant effect is high as per the results discussed above in 3.31. This would indicate that risk control options should be implemented to support operators who have to increase their workload in any situation.

This work allows for further research to be conducted in the same way to investigate other performance shaping factors in the maritime sector. Increased workload as a PSF could be compared to, for example, fatigue, distraction, or weather conditions in the workplace environment. This would allow us to know the higher risk PSFs in the workplace and to target these factors when looking to decrease the risk of human error.

CRediT authorship contribution statement

Steve Symes: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Eddie Blanco-Davis:** Writing – review & editing. **Steve Fairclough:** Writing – review & editing. **Zaili Yang:** Writing – review & editing. **Jin Wang:** Writing – review & editing. **Edward Shaw:** Writing – review & editing.

Declaration of competing interest

The authors declare the following personal relationships which may be considered as potential competing interests: Dr Steve Symes reports a relationship with Liverpool John Moores University School of Engineering that includes: employment. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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