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Raheleh Kari

Exploring EEG Based Stress in Remote Ship Operations as Foundation of Customized Training

Doctoral thesis

NTNU
Norwegian University of Science and Technology
Thesis for the Degree of Philosophiae Doctor
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Abstract

Remote operations have grown dramatically in popularity in recent years across countless industries thanks to technological advancements that enable human operators to monitor and control machines from distant locations. Remote operations are widely considered to be a tool that improves the performance and efficiency of ship operations. However, simply relocating humans from onboard a ship to a shore control center (SCC) and replacing existing ships with autonomous or unmanned ships does not prevent accidents or improve the efficiency of ship operations. Humans significantly affect performance, even with remote operations. This reality underscores the need for companies to employ new approaches to assessing human factors within remote ship operations. This thesis studies the human factors behind remote operations with a focus on those that impact performance and efficiency. This thesis proposes the novel smart training in remote operations (STiRO) methodology to predict the status of human factors, including mental workload and stress during remote operations, using machine learning (ML). The proposed methodology produces an interpretable ML model that accurately correlates the brain activity of human operators with the level of mental workload and stress that they perceive during remote ship operations. In this methodology, an electroencephalogram (EEG) device records the brain activity of human operators, which the ML model uses to predict human operators' levels of stress and mental workload. In fact, interpretable ML models allow observers to infer the human factors that contribute to mental workload and stress levels. In this way, training programs can utilize the STiRO methodology to identify human factors that influence operator performance and provide customized training programs based on individual differences. In effect, the STiRO methodology enables remote operations' stakeholders to replace traditional technical training with efficient, human-centered training and, in turn, to mitigate human factor issues during remote operations. In addition, SCC designers can utilize the STiRO methodology to identify human-human and human-machine interactions that transform into human factors issues while standardization organizations regulate SCC designs to mitigate human errors.

Preface

This doctoral thesis is submitted to the Department of Ocean Operations and Civil Engineering at the Norwegian University of Science and Technology (NTNU) to fulfill the requirements of the joint Doctor of Philosophy (PhD) degree in Nautical Operations. This doctoral thesis was conducted under the supervision of Professor Martin Steinert from the NTNU and the co-supervision of Professor Anne H. Gausdal from Kristiania University College and Dr. Runar Ostens and Professor Hans Petter Hildre from the NTNU. The research began in September 2017 and continued until November 2022; 25% of that time was dedicated to duties in the NTNU. During this period, 32.5 credits of academic courses were completed as part of the educational portion of this PhD.

Acknowledgments

I wish to express deep gratitude to those who have supported me throughout my PhD journey. First, I would like to thank my husband—the love of my life, Maghsoud Morshedi—for his unwavering love, support, and patience. He stood by me through all the good and bad days and always supported me. I would also like to thank my baby girl, Nora, who joined us during my PhD journey to give me extra strength and an infinite amount of love.

I would like also to thank Professor Martin Steinert for his considerable support and encouragement. His continuous support enabled me to overcome every problem I encountered, and it was essential to my completion of this PhD journey and this thesis. I must also thank Professor Anne H. Gausdal for her continuous support and encouragement during my PhD journey. She always had the time to listen to the academic challenges that I faced, and she always provided me with great support. I also wish to thank Dr. Runar Ostens for his support and assistance. Last but not least, I want to thank professor Hans Petter Hildre, head of the Department of Ocean Operations and Civil Engineering, for his support and help in guiding me on my PhD journey.

Thesis Structure

This thesis comprises two parts, with Part I detailing the research domain and contextual background and Part II presenting the scientific papers in which the results of this PhD thesis were published. In Part I, Chapter 1 serves as an introduction to the research domain and covers the research motivations and questions underlying the thesis. Chapter 2 presents the technical background of this thesis, categorizing it into five groups: remote ship operations, human factors in remote ship operations, mental workload and stress, electroencephalography (EEG), and machine learning. Chapter 3 investigates state-of-the-art and reviews the literature, categorizing it into three groups: human factors issues in remote ship operations, EEG human-centered experiments to assess the stress and workload of human operators, and maritime training strategies. Chapter 4 summarizes the contributions of this thesis based on the results published in scientific papers. Ultimately, Chapter 5 summarizes the contributions of this thesis in terms of how it addressed its own research questions and goals.

Part II comprises four scientific papers that showcase the achievements of this research. Each chapter presents the content of a single paper in a reformatted manner to ensure uniform presentation.

List of Publications

This PhD thesis incorporates the following papers labeled with letters A–D. Among these papers, one published in a proceeding, and two published in journals where the last one has been submitted for the review process. The author of this PhD thesis is the corresponding author of all the following papers. The list of papers are as follows:

Paper A
Raheleh Kari, Martin Ralf Steinert.
"*Human Factor Issues in Remote Ship Operations: Lesson Learned by Studying Different Domains*"
Published in Journal of Marine Science and Engineering. vol. 9 (4).

Paper B
Raheleh Kari, Martin Steinert, Henrique Murilo Gaspar.
"*EEG Application for Human-Centered Experiments in Remote Ship Operations*"
Published in CENTRIC 2019, The Twelfth International Conference on Advances in Human-oriented and Personalized Mechanisms, Technologies, and Services.

Paper C
Raheleh Kari, Anne Haugen Gausdal, Martin Steinert.
"*EEG Based Workload and Stress Assessment During Remote Ship Operations*"
Published in The International Journal on Marine Navigation and Safety of Sea Transportation.

Paper D
Raheleh Kari, Anne Haugen Gausdal, Martin Steinert, Runar Osten.
"*Predicting Stress in Maritime Remote Operations using Machine Learning*"
Under Review in Journal of Marine Science and Technology.

Contents

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List of Abbreviations

MASS	Maritime Surface Autonomous Ships
IMO	International Maritime Organization
MUNIN	Maritime Unmanned Navigation through Intelligence in Networks
IoT	Internet of Things
SCC	Shore Control Center
AAWA	Advanced Autonomous Waterborne Application
EEG	Electroencephalogram
STiRO	Smart Training in Remote Operations
ASM	Advanced Sensor Modules
ANS	Autonomous Navigation System
ASC	Autonomous Ship Controller
TCI	Technical Condition Index
VHF	Very High Frequency
GMDSS	Global Maritime Distress and Safety System
TLX	Task Load Index
ECG	Electrocardiogram
GSR	Galvanic Skin Response
RG	Relative Gamma Power
ML	Machine Learning
REPTree	Reduced-error Pruning Tree
MLP	Multilayer Perceptron
MET	Maritime Education and Training
MIST	Montreal Imaging Stress Task
FAA	Frontal Alpha Asymmetry
VR	Virtual Reality
AR	Augmented Reality

UAV	Unmanned Aerial Vehicles
FFT	Fast Fourier Transform
LNG	Liquefied Natural Gas
HFs	Human Factors
SA	Situation Awareness
OOW	Officer of Watch

PART I

1 Introduction

Automated systems and remote maritime operations are rapidly growing in popularity. Therefore, improving the performance of remote human operators is of significant interest to leaders in the maritime industry. More than 80% of accidents in the maritime industry can be attributed to human error [1]. Hence, maritime research is beginning to look at how to minimize human-driven problems and improve operational performance. At the same time, the concept of autonomous ships—more specifically, maritime surface autonomous ships (MASS)—has been introduced as a mean of improving maritime operational performance. Such new types of autonomous ships are thought to potentially be more safe than traditional manned ships [1, 2]. However, even with such ships, humans remain a key factor—albeit a distant one—behind their operational performance.

Based on the definition from the International Maritime Organization (IMO), MASS can operate with a degree of independence but can feature four different levels of autonomy [3]. A ship's level of autonomy dictates the roles and responsibilities of its human operators. Level-one autonomy refers to a ship with decision support and some automated processes. Level-two autonomy entails a remotely operated ship that still has a crew onboard. Level-three autonomy refers to a remotely operated ship without a crew onboard. Finally, level-four autonomy entails completely autonomous operation ship [4]. Today, on account of regulations and maritime laws, the reality of ship steering is typically restricted to remote operation, meaning that fully autonomous operations are highly uncommon [1].

1.1 Background and Motivation

In recent years, various national and international projects have been invested in autonomous and remotely operated ship operations. The Maritime Unmanned Navigation Through Intelligence in Networks (MUNIN) project, for example, has been a pioneer in the use of autonomous and remotely operated ships in Europe since 2012 [5]. In 2014, DNV GL and Rolls Royce introduced their visions on the future of autonomous and remote ship operations. Finally, in 2017, the first commercial contract to build an autonomous ship was signed between Yara and Kongsberg [6].

Today, technological advancements, such as sensor technologies and the Internet of things (IoT), have facilitated the proper implementation of autonomous and remote ship operations [7]. The challenge lies in finding an efficient, reliable, and cost-effective approach that leverages existing technologies to make these pursuits worthwhile [7]. Still, countless potential use cases, such as small unmanned ships that carry extra cargo, motivate leaders in the maritime industry to invest in this technology [2]. Autonomous and remote ship operations have the potential to improve both the performance and efficiency of ship operations [4] through the mitigation of human error [7]. However, several new types of risks and issues come alongside autonomous and remote ship operations [2, 7], largely on account of a lack of operational experience and knowledge [4].

The MUNIN project envisaged a fully autonomous ship through both on-ship elements (advanced sensor modules, autonomous navigation system, autonomous engine-monitoring and -control system) and off-ship elements (shore control center, control center operator, control center engineer, control center situation room) [5]. This design entails autonomous ship operations with human operators monitoring the ship operations from a shore control center (SCC) [8]. This design's operations can be categorized into five control modes: manned operations, autonomous executions, autonomous problem-solving protocols, remote operations, and fail-safe operations [9]. The first mode in that list refers to the fact that human operators at SCCs can intervene whenever a maritime operation is not in a desired state, meaning that they can take over control of the ship in specific situations [8]. In this way, ship operations can be situational based on the necessary level of autonomy amid current circumstances.

While autonomous ship operations are, by definition, performed independently, they still require remote human supervision, meaning that they will never be wholly autonomous [10]. Effectively, autonomous ship operations are those that follow predefined plans with no crew onboard, but this design does not completely eliminate human operators [10, 11]. An SCC must still continuously monitor and wield authority over the autonomous ship operations to ensure efficiency and, more importantly, safety [5]. SCC operators must maintain stringent monitoring efforts to ensure that remote ship operations do not deviate from pre-defined plans. If they detect deviation, they can issue high-level commands to autonomous systems [5].

Existing designs leave many unanswered questions regarding the impacts of human factors on autonomous and remote ship operations. In remote ship operations, human factors—especially human-machine interactions—play a substantial role [11]. Distributing operators in remote ship operations introduces different types of human factor issues associated with remote supervisory operations [12].

1.2 Research Questions

Incorporating automation technology into ship operations inevitably reduces the number of required crew members [13] from that on conventional ships. According to MASS, intervention by human operators increases alongside the first and third levels of autonomy [1]. However, the MUNIN and AAWA (Advanced Autonomous Waterborne Application) projects only focus on MASS's third level of autonomy [13]. In addition, Delft's ship-design laboratory has tested human-machine interactions during remote operations on an autonomous cargo ship in China. A common approach among existing autonomous and remote ship operation projects is to relocate human operators from the ship itself to an SCC [13, 14]. Therefore, improving human factors at SSCs [13–15] will significantly improve the performance of autonomous and remote ship operations.

During remote operations, SCC operators monitor ships' status and operational information, including their environmental situation, weather conditions, and position [14], to determine whether there is any need for intervention. In most existing SCC designs, human operators are expected to monitor up to six autonomous or remote ships [14, 16], though this number is typically capped at six [16]. Notably, however, few studies have investigated the optimal workload level for SSC operators or how workload levels can impact operators' decisions. This is worrisome, as the literature indicates that SCC operators' workload is a major factor impacting operators' behavior during remote operations [17]. Human operators' stress levels also constitute a key factor behind their behaviors, with high stress levels potentially leading to unsafe actions and excessive risk [18]. In stressful situations, operators have insufficient available resources to manage the situation effectively [18]. Evidently, mental workload and stress are significantly interrelated [19].

The lack of tailored training programs that consider operators' mental workload and stress levels is a major problem with the maritime industry's autonomous and remote ship operations. While a few human factor studies have sought to mitigate human error and unsafe behavior via training programs the maritime industry desperately needs certified mariners who are trained to follow international guidelines. In fact, international guidelines have been established specifically to prepare mariners and crew members to operate ships. However, the current approach is technical and ship-centered despite the maritime industry requires more human-centric skillsets [20]. In addition, the IMO defines maritime training as a solution to manage the impact of fatigue and stress among human operators. However, the introduction of new technologies in autonomous or remote ship operations does not necessarily mitigate human error in high-stress situations, when human operators are required to take control. Therefore, up-to-date training programs and guidelines are required to improve stress management among operators [21].

This thesis investigates the human factors that can impact the performance of human operators, which is why it identifies mental workload as a major factor. Therefore, this study considers the main research problem to be the identification of the adequate level of mental workload for SCC operators while monitoring remote ship operations. The main aim of this thesis is to employ objective approaches, such as electroencephalogram (EEG) and machine learning (ML), to assess workload and stress levels among human operators during remote ship operations. In this way, it explains the factors that training programs must consider to craft effective training programs and, in turn, mitigate human error. To do this, this thesis proposes the novel STiRO methodology to assess workload and stress levels among human operators using ML algorithms. The STiRO methodology's main advantage is its provision of an interpretable model that enables training programs to infer the human factors that contribute to individuals' high mental workload and stress levels. Some of its other advantages are as follows: (1) provides an objective method to assess human factors instead of time-consuming and costly traditional subjective methods, like questionnaires; 2) facilitates the study of human factors; 3) allows training programs to consider individuals' unique traits; 4) provides a generic method that can be used across many industries.

To achieve the objectives of this study, this thesis aims to answer the following research questions, starting with the general research question:

How can objective techniques including EEG and machine learning help to address human factor issues in remote ship operations?

This thesis divides the general question into more specific questions to facilitate more in-depth analysis. At the first step, human factors in remote operations and state-of-the-art are investigated to identify human factor issues (RQ1). Then, new technologies are studied to identify tools that can be utilized to assess human factors objectively (RQ2). After finding EEG as a reliable tool for human factor assessment, this thesis developed human centered-experiments to assess the mental workload and stress of human operators during remote ship operations (RQ3). Ultimately, this thesis proposes a novel STiRO methodology to promote human-centered training strategy by predicting the mental workload and stress of human operators using machine learning techniques (RQ4).

The first specific research question serves to investigate the state-of-the-art literature to identify human factor issues during remote operations across multiple domains. Therefore, the first question is formulated as follows:

Question 1: Which human factors affect remote operations?

This thesis analyzes existing remote operational approaches to identify human factors issues that impact remote operators' performance and efficiency across various domains (Goal 1/Paper A). The analysis identifies 13 human factor issues categorized as either human-human or human-machine interactions. However, self-reported questionnaires and interviews are the traditional approaches to assessing human factors across multiple industries. Therefore, the second question is formulated as follows:

Question 2: How can EEG be utilized to objectively assess human factors in remote ship operations?

This question serves to examine the use of new technologies, such as EEG, to objectively assess human factors. This thesis identifies EEG as a reliable tool to correlate brain activity to human factors, such as mental workload and stress. Therefore, it investigates how EEG should be utilized to assess human factors in remote ship operations (Goal2/Paper B). Naturally, the third question is formulated as follows:

Question 3: How can EEG be utilized to objectively assess workload and stress as the two main human factors in remote ship operations?

To address this question, this thesis performed a series of human-centered experiments to assess mental workload and stress levels among human operators during remote ship operations. The results indicate that the brain activity of human operators correlate with their mental workload and stress levels (Goal 3/Paper C). Thus, an efficient method is required to predict mental workload and stress levels during remote operations to be able to address human factors that impact human operators' performance and efficiency. Therefore, the fourth question is formulated as follows:

Question 4: How can ML techniques be used to predict human factors in remote ship operations and enable providing customized training to address human factor issues?

Table 1.1: An overview of the thesis.

Question 1	Which human factors affect remote operations?
Goal	Analyze state-of-the-art and identify human factor issues affecting remote operations.
Paper	Human Factor Issues in Remote Ship Operations: Lesson Learned by Studying Different Domains.
Method	A critical literature review was performed. Based on the research scope, more than 50 papers investigated in a non-structured method from different industries. And results were analyzed via inductive coding process.
Result	This part provided an overview of human factor issues which may affect the operators' behavior during remote operations. human factor issues are classified into 13 groups according to the type of the human interactions within the shore control centers.
Question 2	How can EEG be utilized to objectively assess human factors in remote ship operations?
Goal	Identify new technologies to study human factors objectively during remote ship operations.
Paper	EEG Application for Human- Cantered Experiments in Remote Ship Operations.
Method	This paper applied wayfaring model to develop human-centered experiments by utilizing EEG. This model provides a methodology for practical exploration. A critical literature review was done on EEG applications.
Result	The paper introduces the electroencephalography (EEG) EPOC Flex in order to objectively investigate human interactions. It provides an example case of a human-centered experiment to investigate operators' stress and mental workload. This paper focuses on the different levels of workload in SCCs as one of the main findings of the previous paper.
Question 3	How can EEG be utilized to objectively assess workload and stress as the two main human factors in remote ship operations?
Goal	Perform a series of human-centered experiments to assess the level of mental workload and stress of human operators during remote ship operations.
Paper	EEG Based Workload and Stress Assessment During Remote Ship Operations.

Method	Utilizing self-reported questionnaire and NASA TLX techniques to investigate mental workload and stress. Statistical analysis/ paired sample t-test/ correlation matrix were used to analyse the brain signals recorded by EEG.
Result	Results indicate that there is a significant change in stress when workload increases e.g, when ships are operating in harsh weather and when the number of ships to be monitored increased. The beta and gamma band powers of the EEG recordings were highly correlated with workload and stress levels during remote ship operations.
Question 4	How can ML techniques be used to predict human factors in remote ship operations and enable providing customized training to address human factor issues?
Goal	Propose a methodology to predict human factor issues such as high mental workload and stress using machine learning techniques and thus improve the performance and efficiency of human operators by providing customized training programs.
Paper	Predicting Stress in Maritime Remote Operations using Machine Learning.
Method	Six ML algorithms were trained with the EEG dataset to identify the best model for estimating the stress of remote operators. A self-reported questionnaire and NASA TLX techniques were utilized as well.
Result	This study proposed a novel methodology called Smart Training in Remote Operations (STiRO) to predict the level of stress in human operators which employs machine learning to identify the human factors that affect stress using brain signals.

Finally, this question investigates methods to predict human factor issues such as high mental workload and stress using machine learning techniques. Ultimately, this thesis proposes the STiRO methodology alongside an interpretable ML model for these predictions, which collectively allow for observers to infer the human factor issues that contribute to operators' high levels of mental workload and stress during remote ship operations (Goal 4/Paper D). In effect, maritime stakeholders can utilize the STiRO methodology to develop tailored training programs for remote operators that consider their individual capabilities and previous experiences.

As established, this thesis wields four main goals, listed below, aimed at answering its four research questions. While each research question is mapped to a goal and a research paper, all four of the research papers ultimately address the general question. Therefore, following research goals were formulated:

- **Goal 1:** Review the state-of-the-art literature and identify the human factor issues that impact remote operations.
- **Goal 2:** Identify new technologies with which to objectively study human factors during remote ship operations.
- **Goal 3:** Perform a series of human-centered experiments to assess mental workload and stress levels among human operators during remote ship operations.
- **Goal 4:** Propose a methodology to predict human factor issues such as high mental workload and stress using machine learning techniques and, in turn, improve the performance and efficiency of human operators by providing customized training programs.

Each paper corresponds to a research question and goal. Research Question 1 prompted Paper A to fulfill Goal 1. Research Question 2 initiated Paper B's verification of EEG as a reliable tool for human factor assessment (Goal 2). Research Question 3 led Paper C to perform a series of human-centered experiments to investigate the correlation between brain activity and mental workload and stress levels (Goal 3). Finally, Research Question 4 prompted Paper D to propose the STiRO methodology for predicting human factor issues such as stress using ML techniques and EEG data (Goal 4). The papers in Part II are ordered based on their contribution to the research questions and the goals of this thesis. Table 1.1 presents the research questions and their relationship to the aims of this thesis.

1.3 Structure of the Thesis

This thesis covers four research questions and four research papers to address each of its research goals. The final outcome of the PhD is addressed in the two most recent papers, as shown in Table 1.2.

Chapter 2 establishes a common background for readers by clearly defining remote ship operations, autonomous ships, the role of remote operators, SCCs, human factor issues, mental workload and stress, and EEG. Chapter 3 details the state-of-the-art application of EEG and ML in remote operations. Chapter 4 details the contributions of this thesis to the literature. Finally, Chapter 5 presents its main results and their implication for the maritime industry in addition to detailing the thesis's limitations and opportunities for further research.

Table 1.2: Research Papers.

Paper A	Human Factor Issues in Remote Ship Operations: Lesson Learned by Studying Different Domains
Authors	Raheleh Kari, Martin Steinert
Journal	Journal of Marine Science and Engineering. vol. 9 (4)/ NSD level 1
Status	Published
Paper B	EEG Application for Human-Centered Experiments in Remote Ship Operations
Authors	Raheleh Kari, Martin Steinert, Henrique Murilo Gaspar
Conference	CENTRIC 2019, The Twelfth International Conference on Advances in Human-oriented and Personalized Mechanisms, Technologies, and Services / NSD level 1 (Received the best paper award)
Status	Published
Paper C	EEG Based Workload and Stress Assessment During Remote Ship Operations
Authors	Raheleh Kari, Anne Haugen Gausdal, Martin Steinert
Journal	The International Journal on Marine Navigation and Safety of Sea Transportation / NSD level 1
Status	Published
Paper D	Predicting Stress in Maritime Remote Operations using Machine Learning
Authors	Raheleh Kari, Anne Haugen Gausdal, Martin Steinert, Runar Osten
Journal	Journal of Marine Science and Technology / NSD level 2
Status	Under review

2 Contextual background

This chapter establishes a common background required for contribution of the current thesis. The contextual background explains concepts that are associated to the contribution of this thesis.

2.1 Remote Ship Operation

The MUNIN project introduced the concept of unmanned dry bulk carriers in the European Union. This project defined an autonomous ship as one that is able to act independently with a pre-defined degree of freedom. SCCs monitor autonomous ships constantly [9]. These autonomous ships comprise modular controller and communication systems, including wireless monitoring and control, advanced decision-support systems, and remote and autonomous operations. On the other hand, unmanned ships are those with no crew onboard that do not need to operate autonomously, as they can be remotely operated by human operators at SCCs or other land-based stations [17, 22].

An autonomous ship can operate on the different categories of the autonomy. According to the MUNIN project, crew will be available onboard during sailings between berths and start point and end point of the sea voyage. In addition, they determined to have technical crew onboard for the maintenance and repairs of the onboard systems. However, MUNIN project attempted to decrease crew on the bridge who are available to solve a specific situation when the autonomous systems fail [9]. In fact, an autonomous ship uses new types of automated onboard systems while a human operator in shore control center will monitor status indicators and execute controlling functions when required [23]. The MUNIN project defines the following systems for operating autonomous ships:

- Advanced sensor modules (ASM): ASM systems perform monitoring tasks on ship elements, including traffic, environmental conditions, and obstacles around the ship. These systems are active during autonomous operations, though they can also be active during remote operations to assist the operator.
- Autonomous navigation system (ANS): These systems follow planned routes with pre-defined degrees of freedom. They can adjust their route autonomously depending on the situation (e.g., collision, harsh weather). These systems are active during autonomous operation. Initial ANS prototypes include two hazard-avoidance programs called foundering and collision.
- Autonomous engine and monitoring control system: These systems enhance engine efficiency through various capabilities, such as failure pre-detection.
- Shore-based control center (SCC): SCCs monitor and control autonomous and remotely operated ships [23].
- Remote maneuvering support system (RMSS): These systems assist human operators at SCCs. They enable shore-side operators to perform safe maneuvering operations. RMSSs consider ships' dynamic parameters (e.g., course, heading, position) when aiding human operators in designing steering sequences, monitoring, and remotely maneuvering the ship. They comprise electric chart modules to assist in the maneuvering process during remote operations. They also enable operators to "look ahead" and have a better sense of a ship's maneuvering characteristics.

During an autonomous ship's sea voyage, an onboard autonomous ship controller (ASC) system takes over control of the ship in cooperation with an SCC, which is

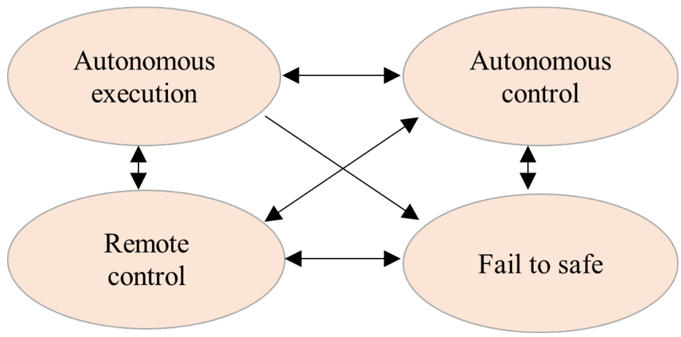

Figure 2.1: Operational modes of an Autonomous Ship Controller (ASC). Adopted from [9].

able to regain control if necessary [9]. The ASC comprises multiple sub-modes, including engine control, autonomous navigation, energy efficiency management, and engine condition modules [24].

In an ASC's autonomous execution mode, a ship follows its planned route and means of navigation (e.g., speed) while sensors monitor its environment and status. This mode independently handles low-risk situations, such as simple deviations from the planned route or reduced visibility. However, when more dire circumstances arise, human operators can override the ASC and take control of the ship from an SCC. An ASC can also enter fail-safe mode so that remote operators cannot regain full control [9]. As shown in Figure 2.2, based on these different ASC operation modes, SCCs operate in various modes of operation. Of course, an SCC requires certain systems to monitor and control remote ship operations [23]. Autonomous and unmanned ships already wield, by necessity, complex software systems to manage all possible situations. Thus, SCCs fundamentally serve as backup for autonomous operations, ensuring that autonomous ships can operate in a safe manner with minimum deviation from their pre-defined plans [23].

Generally, SCCs enter into remote monitoring mode when their main responsibility is to monitor ships' status indicators. In this mode, when all ship indicators are normal, no intervention is required [9]. Operators can use different performance parameters to track their ships' performance across multiple areas and determine whether intervention is necessary [25]. In addition, there are different types of ship status indicators, listed below, based on the Technical Condition Index's deconstruction of ship functions [9, 23]:

- Location: Presents the distance from the planned position with respect to speed, heading, and current position.

- Visibility: Presents the visibility status including infrared (IR)/Normal, clutter and radar range. Visibility indicators also comprises International Regulations for Preventing Collisions at Sea (COLREG) status indicators.
- Weather: Presents wind speed/direction, wave and swell height/length/direction.
- Collision: Presents the status, heading, and speed of targets in addition to their vectors to targets (traffic).
- Communication: Presents critical communication directed at ships via very high frequency (VHF) methods and the Global Maritime Distress and Safety System (GMDSS).
- Propulsion: Presents the status of propeller and steering systems.
- Safety: Presents scenarios for evacuation and extinguishing, especially in the context of fires.
- Machinery: Presents information on fuel, piping, auxiliaries, and engine status.
- Environment: Presents data on sea and air emissions as well as overall environmental performance.
- Stability: Presents the status of water ingress, void space, trim, heel, and draft.
- Hull equipment: Presents the status of various pieces of equipment, including ladders, towing equipment, the anchor, and the hull.

These status indicators impact ships' voyage plans, as they may impact safety risks. For example, weather conditions are not fully predictable, meaning that human operators at SCCs must regularly update voyage plans as weather projections continue to develop. If status indicators indicate abnormality, operators investigate the situation and update the ASC accordingly, as shown in Figure 2.2. Once the critical situation has passed, the operators return to monitoring mode [9].

When the ASC cannot manage non-navigational problems (e.g., problems with propulsion, the engine, or other systems), human operators enter intervention mode. If communication with a ship is completely lost, they enter fail-safe mode. In Figure 2.2, entering fail-safe mode represents a ship's recovery state [9].

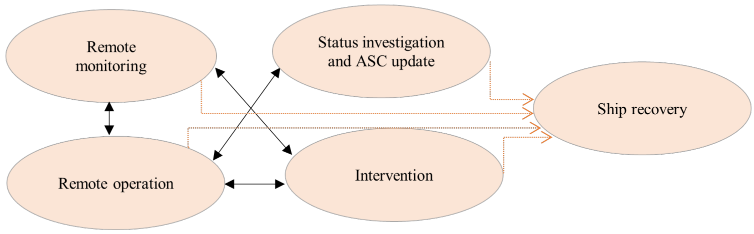

Figure 2.2: Operational modes of the shore control centers (SCCs) (adopted from [9].

2.2 Human Factors in Remote Ship Operations

Human operators play a key role at SCCs by monitoring and remotely operating ships. Incorporating humans in a system introduces human factor issues which may significantly affect performance and reliability of the system particularly during the monitoring and remote control of ship operations [17]. Human factors constitute a scientific discipline focused on improving system performance and human well-being. Human factor studies aim for a comprehensive understanding of the different categories of human interactions, including both interactions between humans and other humans (human-human interactions) and interactions between humans and other system components (human-machine interactions). In addition, human factor studies investigate theories, methods, data, and principles to improve system designs in a way that fulfills expectations [26].

Incorporating new technologies into autonomous and remote ship operations has many advantages, though these technologies increase the complexity of both human-human and human-machine interactions and introduce new types of human factor issues [17, 27]. One study shows that 80–90% of maritime accidents can be attributed to human error [8, 28]. This statistic applies also across multiple fields, including unmanned aerial vehicle (UAV) flight, crane operations, automated trains, and mining [17]. As already established, human operators' interactions are either human-human interactions or human-machine interactions. In human-machine interactions, SCC operators interact with the shore control systems; for instance human operators interact with RMSS to maneuver remote ships. Meantime, human operators cooperate with each other to perform certain tasks, e.g. cooperation between captain and operators or engineers and supervisors during monitoring and remote operations [5, 17]. Human operators interact with SCC systems [5, 8] in various forms:

1. In the monitoring mode, human operators monitor the status of autonomous and unmanned ships via indicators. If necessary, they can issue high-level commands to the ships. This role primarily entails human-machine interac-

tions.

2. Qualified engineers reside at SCCs to assist operators with technical and maintenance tasks. This role entails both human-human and human-machine interactions.

3. SCC “situation teams” comprise a captain and engineers who are responsible in the event of certain dire situations. They have the potential to wield full remote control over ships via the RMSS. During total remote operation, these teams also engage in both human-human and human-machine interactions.

Considering human-human and human-machine interactions, many studies have investigated the human factor issues during the remote operations in various industries. As this thesis focuses on mental workload and stress levels among human operators, the following sections detail background concepts pertaining to these human factors.

2.3 Mental Workload and Stress

The term workload in the context of the human factor can be defined as all tasks that are imposed to the operators and required subjective responses. When an operator perform a task, task load defines as perceived task’s objective demands where workload defines as perceived the subjective demand [28]. In another definition, mental workload defined as operator’s information capacity which is needed to fulfill the system demands [29, 30]. Alternatively, mental workload can be defined as the operator’s information capacity [29, 30]. This thesis focuses on the mental workload imposed on SCC operators during interactions. Considering mental workload, the MUNIN project developed a hypothesis that the successful implementation of human-machine interfaces enables one operator to effectively monitor up to six ships at a time

Mental workload levels vary, meaning that operators are not always encumbered to the same degree. In complex autonomous systems, human operators need an adequate level of knowledge about system functions, interaction procedures, different modes of operation, levels of autonomy, and information perceptions. All of these functions constitute secondary tasks and, along with primary tasks, increase the risk of high mental workload during complex remote ship operations. In fact, high mental workload levels increase the risk of human error and the risk of losing control over automated or remotely operated systems [31]. Other human factors, including stress, time pressure, and distractions, also affect the “human cost” of operations [31].

High mental workload levels during remote operations exist across multiple domains, including the remote operation of UAVs, cranes, mines, and metro systems [17]. In remote ship operations, SCC systems like the RMSS present information through multiple screens and simulators, resulting in information overload [11]. It is clear that SCC systems aim to establish situational awareness among human operators to enable them to make appropriate and timely decisions. In this way, human operators are overloaded with too much information, increasing their mental workload. Monitoring more than one ship at the same time is another source of information overload that increases mental workload and, in turn, the likelihood of human error [32].

Complex activities, such as operating a nuclear power plant and piloting an airplane, can impact the performance of human operators and exacerbate human error with severe consequences [33]. In human factor studies, four main methods have been used to assess human operators' mental workload [30, 34]:

1. Subjective assessments: Subjects assess their mental workload with regard to subjective criteria and rate their level of mental workload on a scale (e.g., NASA Task Load Index [TLX]).

2. Vehicle behavior measurement (performance-base): This method is mostly utilized in driving domains to evaluate drivers' mental workload. In this method, observers measure driving parameters, including speed, lane deviation, and gear changes.

3. Video-based measurement: In this method, observers investigate head and eye movements as well as facial expressions. This method is unreliable, especially in dark environments or with operators that wear glasses. In addition, operators can control their emotions, which hinders proper interpretations.

4. Physiological-based measurements: In this method, physiological signals are captured using tools like EEG, galvanic skin response (GSR), and electrocardiogram (ECG) to assess operators' levels of mental workload. This method provides many data points, contributing to its accuracy. This thesis uses EEG as a physiological method to investigate mental workload and stress among human operators during remote ship operations. This method is discussed further in Section 2.4.

Generally, stress is defined as a normal reaction of the body to prepare itself in the face of difficult situations to improve alertness, strength, and focus. Stress is categorized as either physical or mental. For example, when a driver is sleepy, they are exhibiting physical stress. In addition, stress can be categorized based on its impact as either eustress or distress. Eustress refers to a positive stress that helps operators to face challenging situations, while distress refers to a negative stress that increases mental workload [30]. In other words, distress entails perceived stress, demoralization, restlessness, and discomfort [35].

When human operators perceive insufficient resources and information, they experience a stressful situation, leading to a lower level of focus. In fact, human operators focus only on some parts of the task when experiencing a stressful situation and often take risky, unsafe decisions [18]. The literature also indicates that there is a strong link between stress and mental workload. This highlights the fact that human operators perceive a situation as stressful when performing complex activities with a high level of mental workload [19].

In a stressful situation, sympathetic system activities increase while parasympathetic activities decrease due to changes in the autonomic nervous system (ANS). The literature has used various physiological sensors (e.g., EEG, EKG, GSR) to detect and assess stress levels among human operators [30]. The literature also indicates that complex activities are associated with acute physiological stress, which can hamper decision-making, attention, and memory [33, 36]. In fact, stress can be caused by physical and cognitive factors, including financial strain, pressure at work, declining health, and relationship troubles.

Notably, stress can also be classified based on its duration as either acute or chronic. Immediate events can cause acute stress for a short period of time. During periods of acute stress, physiological and psychological defense mechanisms are activated; after a short period of time, individuals recover. Consistent events, however, can cause chronic stress, which is a long-term phenomenon. Daily events and circumstances can cause chronic stress, negatively impacting one's health (e.g., impairing their immune system or their metabolism) [37].

Medical studies have already verified that EEG equipment can be used to assess different types of stress in humans. In addition, human factor studies have effectively used EEG to assess human factors that impact performance across various domains. Hence, the next section details the basics of EEG, establishing the necessary background for using EEG in remote ship operations.

2.4 Electroencephalogram (EEG)

Identifying reliable physiological signatures of human operators is key to developing an adaptive system that reduces human error [33]. Hence, EEG can be used as a reliable measurement tool to identify the signatures of brain signals during demanding and stressful tasks. Generally, EEG has been used in clinical studies to investigate brain activity during vision, memory, emotion, perception, and recogni-

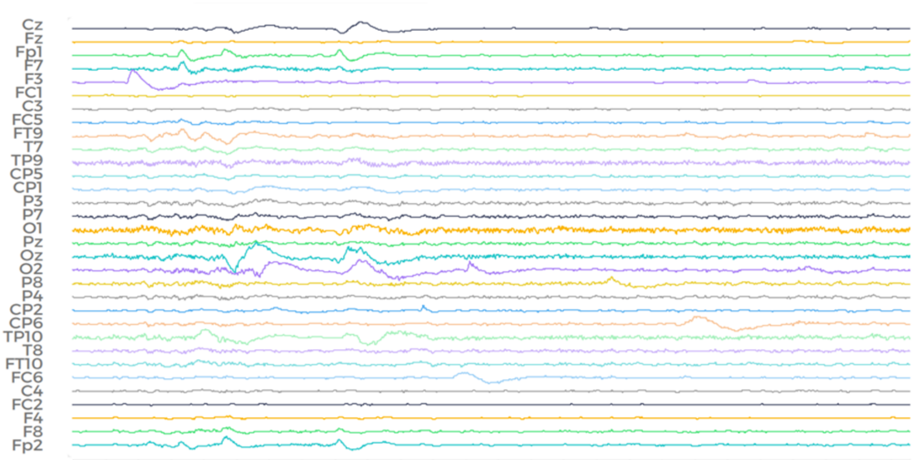

Figure 2.3: EEG data recording.

tion experiments. Since EEG captures electrical neuronal activities of brain, EEG data contains important information about the brain's operating state [38]. EEG sensors measure brain activities in frequency bands between one and 50 Hz. These bands are divided into delta, theta alpha, beta, and gamma band powers. In addition, band powers are presented in uV per Hz, resulting in many data points per second.

The literature indicates that brain activity in the prefrontal cortex plays a critical role in individuals' responses to stress [37, 39]. Particularly, a decline in the frontal alpha band power and a rise in the frontal beta band power indicates stress [39]. Figure 2.3 shows continuous EEG signals recorded via multiple sensors.

Alpha band power represents the 8–12 Hz frequency ranges [40]. Its amplitude increases during relaxed, fully awake situations in normal adults. Malik et al. [38] determined that alpha oscillation is more dominant in the parietal area when the eyes are closed. Alpha band power is active in the posterior cortical, frontal, and occipital areas of the brain [41, 42]. The literature indicates that alpha band power is positively correlated with mental and physical relaxation [42].

Beta band power represents the 12–25 Hz frequency ranges [42] and is more dominant in the frontal and central areas of the brain. The amplitude of beta band power increases during anxious thoughts, activeness, deep concentration, and problem-solving [38]. IMotions [42] reports that the amplitude of beta band power increases in the central cortex of the brain during physical movement, such as grasping and finger movement, and heightened focus. Other studies indicate that there is a positive association between individual stress levels and the amplitude of beta frequencies [43, 44]. In fact, the amplitude of beta band power increases during movement and cognitive processing [38, 45].

Theta band power represents the 4–8 Hz frequency ranges [38] and can be recorded from various brain regions, including the central parental, temporal, and prefrontal cortices [42]. The literature indicates that there is a positive correlation between the amplitude of theta band power and focus, mental workload, memory recall, and learning [38, 45–47]. Thus, in cases with demanding tasks and, thus, a higher mental workload, the amplitude of theta band power will increase throughout the brain [42].

Gamma band power represents the 25–50 Hz frequency ranges. High gamma amplitude in the temporal region of the brain is associated with memory processes. In addition, gamma waves are involved in working memory, long-term processes, and focus [38]. Minguillon et al. [37] used prefrontal relative gamma power to assess stress levels in healthy subjects. The results show that EEG prefrontal relative gamma waves and heart rate are positively linked to stress levels. Additionally, Ehrhardt et al. [39] found that gamma activities increase when subjects experience stressful situations.

This thesis uses EEG EPOC Flex to perform the human factor experiments. Emotive EPOC Flex includes 32 sensors connected to a wireless control box, which communicates with the EasyCap system. It records brain activity with a frequency of 128 Hz, producing 128 data points per second. This thesis utilizes the EPOC Flex Saline Kit, which comprises the classic saline felt sensors. Figure 2.4 depicts the 32 sensor channels EEG EPOC Flex. The EPOC Flex Saline Kit is preconfigured with a 56 cm cap size, allowing for quicker setup. Additionally, it is pre-configured with the following sensor locations: AFz (DRL), FCz (CMS), Fp1, Fp2,F7, F3, Fz, F4, F8, FT9, FC5, FC1, FC2, FC6, FT10, T7, C3, Cz, C4, T8, CP5, CP1, CP2, CP6, TP9, TP10, P7, P3, Pz, P4, P8, O1, Oz, O2 [48].

2.5 Machine Learning

EEG equipment generates a considerable amount of data with a frequency of 128 Hz. The amount of data point produced in one experiment is large enough to complicate the generating of accurate mathematical models using traditional approaches. Particularly, when dimensions of datasets increase, finding statistical or mathematical models becomes complex and time consuming [49]. Hence, the use of ML techniques is a more efficient approach to model EEG data.

Of course, the performance of ML models greatly depends on the characteristics of the provided training data, which can lead to overfitting or underfitting. The performance of an underfitted ML is worse than expected and predictions are not highly accurate [50]. In contrast, overfitted ML models learn a specific trend

Figure 2.4: 32 channel Emotive EEG EPOC flex.

that cannot be generalized to other data [51]. ML techniques are categorized into supervised learning, unsupervised learning [52], semi-supervised learning [53], transfer learning [54], and reinforcement learning [55].

Unsupervised learning techniques are generally used to model data without any help from humans [52]. They are the most suitable for detecting anomalies, such as unusual brain activities. When they cannot feasibly label all instances, semi-supervised learning techniques are used to allow for a combination of both labeled and unlabeled instances [53].

Supervised learning techniques require humans to label instances with known outcomes to produce a dataset with input and output pairs [50, 56]. This thesis employs supervised learning techniques to predict levels of stress among human operators during remote ship operations. Therefore, it produces a dataset comprising power bands of EEG sensors labeled with the level of stress of human operators in remote ship operations.

Supervised learning can be categorized into classification and regression techniques for predicting discrete classes and continuous numbers, respectively [50, 57]. Various metrics have been introduced to measure the performance of ML classification models, including accuracy, confusion matrix, precision, recall, and F1 score [58].

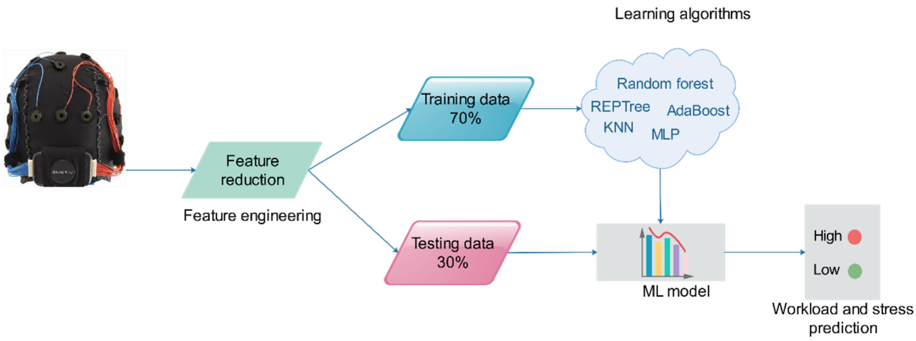

Figure 2.5: Machine learning process flow employed in this study.

The accuracy metric presents percentage of correct prediction when the dataset is balanced. The confusion matrix is a table presenting the predicted labels compared with actual labels in the dataset which enables the extracting true positives, false positives, true negatives and false positives. In regards to the confusion matrix, the precision metric provides the ratio of correct predictions to the total number of positive predictions, while the recall metric provides the ratio of predictions that the model correctly predicted as positives. Generally, the precision and recall metrics are employed to measure the performance of imbalanced datasets and they are calculated using the confusion matrix. The F1 score uses the harmonic mean of precision and recall to balance precision and recall as a single number [58].

Since the results of the STiRO methodology are presented via binary stress levels, predicting human operators' stress levels using EEG data falls within the scope of the classification problem. There are several ML classification algorithms that vary in accuracy. These algorithms can be categorized as decision trees, neural networks, lazy learners, or ensemble learning algorithms. To train ML algorithms, this thesis performed a series of experiments to produce a dataset that comprises the amplitude of band powers from EEG sensors labeled with binary stress levels. In addition, the EEG dataset requires pre-processing to eliminate unnecessary features, ensuring that the ML model will achieve the highest possible accuracy and precision. Therefore, feature engineering techniques are used to improve the efficiency of ML algorithms with an EEG dataset. A 70–30 % training-testing split is identified as the optimal split for training and testing ML algorithms with an EEG dataset. Figure 2.5 depicts the ML process flow in this study.

Classification Algorithms

Classification problems entail predicting the labels of new instances of data. Classification problems are categorized into binary, multi-class, and multi-label problems [59] groups. Binary classification is the simplest form, as it entails predictions between two states, such as low or high levels of stress. Multi-class classification involves predicting from multiple labels, and the complexity of prediction increases alongside the number of labels [50, 57]. Multi-label classification entails prediction from all possible labels that fit data; one notable example of this type is the identification of objects in images [59, 60]. As this study labels EEG datasets with either high or low levels of stress, it employs binary classification. Various ML algorithms, including decision trees, neural networks, lazy learners, and ensemble learning, are capable of producing a binary ML model.

Decision trees divide data recursively in each node until the data space is no longer dividable. In a decision tree, each node represents a feature in the dataset, while edges are labels for instances. The best attribute with which to divide the data space is selected for each individual node based on the piece of information that most effectively reduces the randomness of labels [61]. However, different decision algorithms utilize different approaches for selecting the best attribute in each node. This thesis employs the reduced-error pruning tree (REPTree) [62] and random forest [63] algorithms to predict stress levels among human operators during remote ship operations.

The REPTree algorithm is a fast and cost-efficient decision tree that uses information gain to choose the best attribute for each node and uses reduced-error pruning to reduce the size of the final tree [64]. The random forest algorithm combines multiple unpruned trees to produce a final decision tree through the use of information gain and Gini impurity techniques [63, 65].

Neural networks are developed based on the way that neurons operate in the human brain. Neurons are stimulated by their inputs to trigger output if the stimulation exceeds a certain threshold. There are various types of neural networks, including feedforward, convolutional, recurrent, modular, sequential, generative adversarial, and multilayer perceptron networks [49]. This study employs a multilayer perceptron (MLP) neural network algorithm with sigmoid output [18]. MLP algorithms perform best on problems that cannot be linearly separated. However, they are slow and require extensive training with large datasets.

Ensemble learning algorithms, including those that employ the bagging, stacking, and boosting techniques, use multiple learners to improve predictions. The bagging technique uses homogeneous weak learners to predict multiple outputs and then combine them. However, this technique uses homogeneous weak learners to predict outputs sequentially. On the other hand, the stacking technique uses heterogeneous weak learners to predict multiple outputs and then combine them [49, 57]. As Adaboost performs best with decision trees, this thesis employs the AdaBoost M1 technique [66] to improve the accuracy of the REPTree algorithm.

Lazy learners delay generalization and simply store training data until a prediction is requested. The KNN [67] algorithm is among the most famous lazy learners, using a distance function on a whole dataset to identify where the new prediction fits best. Lazy learners are particularly suitable for datasets with few features that experience significant changes between instances. Training the KNN algorithm with datasets that house multiple irrelevant features and scales may result in inaccurate findings.

This chapter offered some context on the concepts and techniques required to predict stress levels among human operators during remote ship operations. Leveraging the concepts and techniques presented here, this thesis performed a series of experiments to produce a dataset on brain-activity amplitudes measured by EEG sensors. Then, it trains various algorithms with the dataset to predict stress levels. The next chapter presents state-of-the-art research on human factors prominent in the maritime industry with a particular focus on studies that used ML to predict stress levels among human operators. In this way, this thesis can clarify its precise contribution to the literature.

3 From Technology-Centered Training to Human-Centered Training

Today, training products and processes that enhance knowledge about human resources play a critical role in the competitiveness of maritime actors, especially in Europe. Increasingly complex challenges in remote areas of the world's oceans require world-class crews and operators. Therefore, new training strategies are necessary to develop high-quality seafarers and operators. This opens the door to various new types of education, such as electronic learning, simulation, adaptive courses, and management development [68].

However, global maritime education and training (MET) programs need new strategies to address modern human factors. Thus, maritime training should employ human-centered strategies instead of traditional ship-centered/technical strategies. Therefore, this thesis reviewed the literature to analyze existing human-centered training approaches that could warrant consideration by MET programs. Doing so enables this thesis to achieve an understanding of the existing gaps and position the contributions of this study in the maritime domain. Hence, this thesis organizes the state-of-the-art literature into three focus categories: *(i)* human factor issues in remote ship operations; *(ii)* human-centered EEG experiments to assess mental workload and stress levels among human operators; *(iii)* maritime training strategies. The knowledge gained from this review aids in the development of an efficient training strategy for remote ship operations. In addition, it helps this thesis to identify existing gaps in the literature and, therefore, guide its contributions to the field.

3.1 Human Factor Issues in Remote Ship Operations

Wahlstrom et al. [69] presented an overview of the human factor issues behind unmanned ships and SCCs. They reviewed factors across various fields, including aviation, forestry, cars, subway systems, space operations, military operations, and cranes. They considered the following human factor issues during remote operations: information overload, boredom, lack of a sense of the ship, mishaps during handoffs, monitoring and control delays, and reorientation to new tasks.

Zhang et al. [70] discussed human factors that lead to errors during emergency situations. They discussed 16 human factors, including information overload, poor mental and physical situations, situational awareness defects, psychological differences, uncoordinated man-machine interactions, fatigue, and insufficient training. They asserted that insufficient training can lead to human error during remote ship operations.

Man et al. investigated the human factor issues within remote ship-monitoring processes [12]. They invited six participants to perform scenario-based simulation trials and ultimately found that decision-making latencies, limited interface usability, and a lack of ship sense are the main challenges faced during monitoring tasks. Their results highlighted the problematic gap between remote operators' capabilities and the modern responsibilities of SCCs despite the necessary decision-making strategies being those embraced by traditional navigational systems. In addition, they argued that technological developments are advanced but that organizational factors are relatively downplayed in remote ship operations; thus, they asserted that the maritime industry should look at SCCs as socio-technical systems

Veitch and Alsos [71] performed a systematic review of human-AI interaction research in the field of autonomous ships. They reviewed 42 papers on autonomous ships, human supervision, and control. Their results showed that human operators play an active role in the safety of autonomous ships in addition to their backup role. Furthermore, they argued that SCC operators require updated training programs. They identified human factor issues that may result in human error and, thus, require improved socio-technical systems that consider sense-making, trust, workload, and fatigue, among other factors. In addition, they highlighted the training requirements of MASS operators who work at SCCs. In fact, training programs and competency requirements for human operators in SCCs are considered to be a hindrance to the implementation of MASS projects. Furthermore, Thieme et al. [72] investigated factors that increase the probability of an accident in autonomous ship operations. They identified human factor issues, including operators' competence, experience, stress, fatigue, and inadequate training.

Wrobel et al. investigated the impact of human factors on the safety of remotely operated ships [55]. Their results showed that insufficient training leads to increased human error and unsafe situations. They asserted that proper training must be viewed as a key safety factor in the remote operation of ships, meaning that the lack of adequate training programs for remote operators increases the risk of accidents. In addition, they argued that ship-management companies are responsible for coordinating operators' activities via the provision of operational procedures, the management of onboard maintenance systems, and the organization of adequate modern training programs. They stated that chief engineers and master marines are likely the best candidates for the position of remote operator at SCCs so long as they received adequate training. Experienced and well-trained remote operators can make the most appropriate decisions across a wide variety of situations. Ahvenjarvi [73] argued that new types of training programs are necessary for seafarers, especially with regard to interactions between manned and unmanned ships.

3.2 EEG Human-Centered Experiments to Assess Human Operators' Stress and Mental Workload Levels

Minguillon et al. [37] invited six healthy participants to perform the Montreal Imaging Stress Task (MIST) followed by a relaxation period while their brain signals were recorded using EEG. Their findings showed that prefrontal relative gamma band power is highly correlated with individual stress. Peng et al. [73] studied the spectrum power and overall complexity of theta, alpha, and beta band powers during high- and moderate-stress situations via EEG in the prefrontal area (Fpz, Fp1, and Fp2 sensors). Their results indicated that participants with chronic stress (seven participants) had higher left prefrontal activity. Vanitha et al. [74] investigated the efficiency of EEG in detecting real-time stress. They recruited six students to solve mathematical questions within a specific time frame. They used the NASA-TLX technique to collect self-reported stress levels. Their results confirmed that EEG is a valuable tool with which to detect and assess individuals' stress levels.

Vanhollebeke et al. [75] conducted a systematic literature review on the topic of EEG to evaluate stress responses in individuals. The results indicated that alpha, beta, and frontal alpha asymmetry (FAA) band powers can be used to detect stress levels. Furthermore, they showed that alpha band power continuously decreases while beta band power increases during stressful situations. Perrin et al. [76] invited 24 healthy males to an experiment and assessed their stress and alertness levels using EEG during on-call situations. The results indicated that, with open eyes, beta band power declines during low-stress situations, while theta band power rises during high-stress situations. Alpha band power was fairly low amid low-stress situations compared to the control condition. However, alpha band power did not change significantly. Hafeez et al. [77] investigated the effect of time limitations on exam performance. They recruited 14 students to perform mental arithmetic tasks based on the MIST. Their EEG results indicated that theta, alpha, and beta EEG band powers are positively correlated with stress levels.

Iqbal et al. [78] invited six participants to perform eight tasks and evaluated their mental workload via EEG. They sought to assess the value of EEG in capturing the cognitive mental workload levels of human operators in chemical control rooms. Their results indicated that power spectral density in theta band power is highly associated with performance. Mohanavelu et al. [79] measured EEG frequencies among pilots during changes in their mental workload. In total, 14 pilots participated in the experiment to perform tasks with four different levels of workload. Their results showed that mental occupation increases beta band power, while wakefulness and relaxation boost alpha band power.

3.3 Maritime Training Strategies

The majority of maritime operations, such as loading, transporting, and unloading cargo, are considered to be low-stress tasks, though unanticipated accidents constitute complex exceptions. Notably, most technologies used in the maritime industry only serve to enhance tasks associated with low-stress situations. Therefore, human operators are still wholly responsible for handling complex situations (i.e., situations featuring an accident or the failure of automated systems. The IMO advocates for the use of training as a solution to decrease stress and fatigue among human crew members [21]. However, remote and autonomous operations require new training strategies to address new types of human factor issues.

Reviewing the literature makes it clear that the maritime industry has not kept up with rapid modernization in terms of education and training. Studies on SCCs and the operation of autonomous ships highlight the importance of emotional intelligence and social skills among seafarers during training programs [68].

Liu et al. [80] showed that accident rates have not declined significantly despite the maritime industry implementing many new advanced technologies. They asserted that human factor issues like high mental workload and stress levels still drive human error and, in turn, accidents. By assessing the stress and workload of trainees using EEG, they developed a method to improve the efficiency of maritime training programs. They utilized raw EEG data from four pilots to evaluate levels of mental workload and stress among seafarers during training tasks on virtual simulators. They argued that the result of a pilot's training program—pass, retrain, or fail—should be determined based on their experienced levels of stress and workload. In their experiment, two pilots received "fail," one pilot received "pass," and one pilot received "retrain" based on their simulator performance.

Aatif Shahab [81] proposed new metrics to quantify operators' learning outcomes based on mid-simulator eye-tracking data, assuming that operators focus on the specific human-machine variables that are directly associated with their current situation during training.

Various studies have introduced new technologies, including augmented reality (AR) and virtual reality (VR), to enhance maritime training. For example, Huizhen et al. [82] employed VR to train UAV operators. They collected the brain activity of 92 college students using EEG when participants performed UAV tasks in both real and virtual environments. They collected the relative power of the beta, alpha, theta, and delta frequency ranges and calculated absolute power using a fast Fourier transform. Additionally, they assessed mental workload during both monitoring and task-execution situations in real and virtual environments. Ultimately, their results showed that there are notable similarities in brain activity between real and virtual situations, meaning that VR can be used as an efficient training tool.

Liu et al. [83] assessed human factors like situational awareness, decision-making, and vigilance among operators during VR-based firefighting training. They developed a virtual training scenario for liquefied natural gas (LNG)-based firefighting to assess and train firefighters. Six trainees and two trainers participated in this experiment. Their results showed that the participants felt the same real-world emotions, including stress and fear, during VR training [83]. Chae et al. [84] highlighted the fact that maritime training programs require significant changes to reduce the number of ship accidents. They used VR training of a passenger ship abandonment to investigate and compare the results with those of conventional video training. The results indicated that participants in VR training achieved higher scores across all training items.

Reviewing the literature reveals that various human factor issues can be identified and addressed to mitigate human error. However, no study has yet to develop a methodology capable of identifying the root causes of these human factors issues and determining how the maritime industry should address them. Hence, this study proposes a STiRO methodology using EEG data on human factors and an interpretable ML model to predict the extent of human factor issues. Through these predictions, observers can infer the root causes of human factor issues and, accordingly, develop tailored training programs to address them and, in turn, boost the performance and efficiency of remote operators.

4 Exploring Human Factors in Remote Ship Operations

This thesis contributes to human factor research in the maritime industry by proposing a novel method for assessing workload and stress levels during remote ship operations. The proposed method applies ML techniques to EEG data in order to transform MET's prevailing strategies into more human-centered initiative. In the first step, this thesis investigated existing human factor studies that identified human factor issues in remote operations. In the second step, it identified existing challenges and potential gaps in remote ship operations and presented an appropriate framework. It then proposed a novel method with which to address human factor issues and potential gaps in remote ship operations through four scientific articles (three of these articles have already been published; the fourth is under review for publication). The author of this thesis is also the author of these four articles. This chapter summarizes the articles' contributions, with full manuscripts provided in Part II. The contributions of these articles are split into four sections—one for each paper.

4.1 Human Factor Issues Across Multiple Remote Domains

Remote ship operations have grown dramatically in recent years, revolutionizing the maritime industry. While this growth is expected to boost efficiency, it has already introduced a wide array of new operational problems, one of the most prominent being the relocation of crew positions from onboard ships to SCCs, resulting in new types of human factor issues [17]. At SCCs, human operators monitor and control autonomous ships with varying levels of autonomy from a distant location. They perform multiple unique functions, including remote monitoring, remote operation, and status investigation, though monitoring and supervision are their most important modes of operation [9].

The literature indicates that most maritime accidents have historically been caused by human error [8, 17, 28, 85]. However, the introduction of autonomous systems has not significantly reduced the number of accidents. This lack of decline is also evident in other autonomous fields, such as UAV flight [85]. Considering the critical role of human operators at SCCs, the main question surrounds what human factors impact the performance of remote operators. Remote operators interpret sensory information to determine whether it is necessary for them to intervene through an automated system, such as the RMSS. At each SCC, operators monitor automated ships and send high-level commands to them whenever necessary. In addition, SCC engineers cooperate with SCC operators on technical and maintenance tasks, while the SCC situation team takes full remote control of ships in certain dire situations. Thus, SCC operations entail both human-human and human-machine interactions that affect the performance of human operators [17].

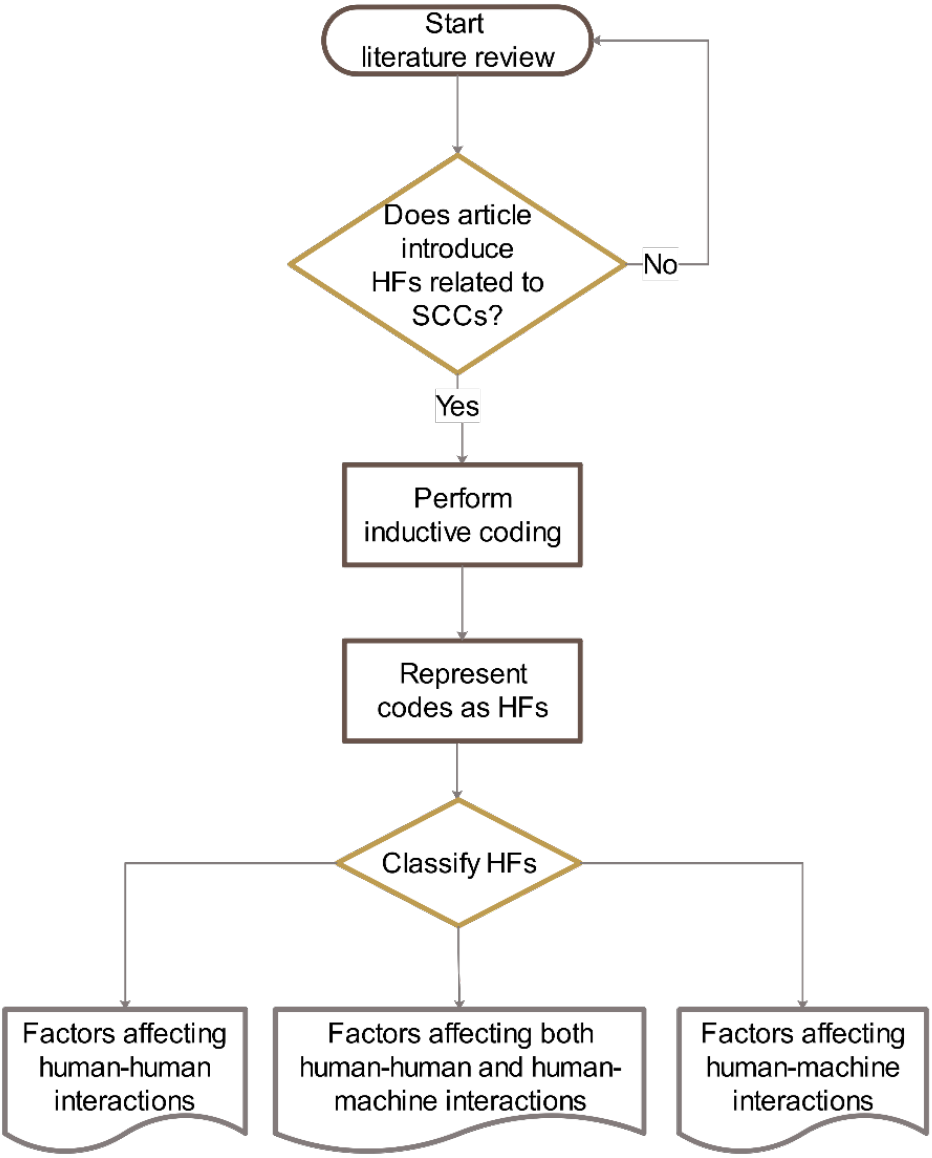

Figure 4.1: Literature review process [17]

Kari and Steinert [17] presents an overview of the human factor issues based on the human-machine and human-human interactions that can affect the performance of operators during remote ship operations. In the research of Kari and Steinert [17], different databases such as IEEE Xplore, Science Direct and Scopus were utlized to gather peer-reviewed research papers in the field of the remote operations in different domains including shipping industry, unmanned aircraft systems (UASs), Unmanned aerial vehicles (UAVs), self-driven trains, autonomous cars, remote mining and remote operated cranes. The results collected in a non-structured way based on the key word comprising shore control center, remote operations, human factors, autonomous vessels, ship operations and unmanned ships. For the first stage, more than 50 research papers were collected, and their abstract were reviewed by the corresponding author. In the second stage, 38 relevant research papers within the problem scope for further analysis [17].

Kari and Steinert [17] conducted their literature review using the inductive coding method, which serves to analyze various sources of information, including journals, documents, and interview transcripts, among others. During the coding process, they labelled a specific portion of the data with codes. They conducted coding analysis across two phases. In the first phase, they deeply reviewed the 38 papers and generated primary codes comprising a single phrase (e.g., cultural problem, situational awareness, decision-making). In the second phase, they revised the selected codes with greater precision to prevent any mistakes or overlap. Finally, they identified 13 groups of codes and presented them as classifications of human factors during remote operations, splitting them into two categories: human-human interactions and human-machine interactions [17]. This categorical split is what makes the study from Kari and Steinert [17] stand out in the literature. Their classification offers a greater understanding of the source of operators' human factor issues and, in turn, can be used to enhance MET strategies. In addition, their findings could aid in the development of efficient SCCs through improvements to human-machine interface design. Figure 4.1 depicts the process that Kari and Steinert used to identify the human factors that impact remote operations [17].

For collision avoidance and risk assessment of the autonomous ship operations, human-machine interactions and human errors should be investigated more thoroughly to mitigate sever consequences [2]. The classification presented by Kari and Steinert [17] constitutes a starting point for the analysis of human reliability in remote operations by distinguishing between human factors that impact the performance of human operators. Kari and Steinert [17] categorized the results of their literature review into the following 13 main human factors:

1. **Situation Awareness (SA):** A lack of consistent situational awareness is a human-machine interaction error that occurs across many domains. Maintaining SA (e.g., accurately perceiving the ship status) is an important challenge for SSC operators monitoring and supervising ships from a distant location.

2. **High mental workload:** SCC operators are faced with multiple types of information that they must balance to effectively manage a situation. As the

MUNIN project assumed that one SCC operator can be assigned to multiple (up to six) ships, multiple screens and simulators often result in high levels of mental workload among operators.

3. **Trust:** The main matter of contention when utilizing automated systems is how much trust should be given to automation. This level of trust determines the success of human-machine interactions.
4. **Boredom:** Looking at multiple screens filled with data alongside ergonomic factors at the SCC causes a high level of boredom.
5. **Fatigue:** Active and passive fatigue both arise during remote operations across multiple domains. This issue is associated with high mental workloads and the continuous monitoring of ship operations.
6. **Skill degradation:** This factor can be discussed from various angles. On the one hand, using automated systems for a long period of time can cause skill degradation. On the other hand, high levels of trust in automated systems can also result in skill degradation.
7. **Human-machine interfaces:** This factor refers to ergonomic dynamics at SCCs (e.g., the size and number of screens).
8. **Lack of direct sensory information:** Remote human operators rely on sensory information to make their decisions. Given the distance between the land-based control center and the ship, there is a lack of direct sensory information.
9. **Communication challenges:** This factor can be discussed from various angles, including poor communication links between ships and SCCs, lags in VHF communication, and misunderstandings.
10. **Decision making:** Decision-making processes at SCCs are impacted by various issues, including the level of SA, human-machine interfaces, and communication challenges. Thus, obstacles that hinder understanding lead to poor decisions during remote ship operations.
11. **Cultural and linguistic problems:** Organizational climate, culture, values, and policies at SCCs can all drive human error. Linguistic problems between SCC operators and onboard crews can also create a challenging dynamic.
12. **Teamwork:** SCC operators, engineers, and situation teams collaborate and interact with each other during remote ship operations. Hence, the quality of human-human interactions at SCCs impacts the effectiveness of teamwork and human operators.

Figure 4.2: Recording brain activities of participant in the experiment environment (adapted from [44], P.5)

Kari and Steinert [17] identify the human factor issues that drive human error in remote operations. In this way, they answered Research Question 1 by detailing the human factors that affect remote operations. However, these human factors must be investigated in the context of remote ship operations to identify their impact on the performance of human operators at SCCs. The next section details the study of Kari et al. [44] (Paper B), which entails human-centered experiments aimed at objectively assessing human factors using EEG.

4.2 EEG as a Tool to Investigate Human Factors in Remote Ship Operations

Kari and Steinert [17] identified various human factor issues that influence the performance of human operators at SCCs, including emotional and cognitive factors like fatigue, stress, and workload. A comprehensive understanding of these factors would facilitate the development of efficient MET programs. With respect to the requirements of remote ship operations, MET programs should emphasize human-centered training requirements instead of technical or ship-centered requirements. Thus, an effective method with which to assess human factors is critical to mitigating human error in remote ship operations. The literature indicates that EEG is an effective tool for assessing humans' cognitive characteristics and processes. Kari et al. [44] utilized EEG Emotive EPOC Flex to assess human factors, including stress and mental workload, among operators during remote ship operations.

In addition, MUNIN project assumed that one operator can be assigned to monitor more than one ship (up to six ships) [11, 12] in SCCs where the multitasking directly affect the mental workload of the operators. On the other hand, increasing the mental workload may cause high level of stress in operators. Human operators act as a backup system during the operations of autonomous ships such that human operators have to handle complex and stressful situations during remote ship operations [17, 44]. Therefore, it is important to have an understanding of situations that can increase human operators' mental workload and stress, and Kari et al. [44] set out to achieve just that. They considered mental workload as an independent variable and stress as a dependent variable, using EEG to perform human-centered experiments.

Kari et al. [44] utilized the wayfaring model to develop a proper EEG human-centered experiment. The wayfaring model [86–88] constitutes an exploration process that serves to generate new ideas rather than a pre-planned approach. It comprises four main steps: *(i)* probing ideas *(ii)* merging multidisciplinary *(iii)* speed *(iv)* agility. Kari et al. [44] developed two main scenarios: a low-workload scenario and a high-workload scenario. They then designed human-centered experiments suitable for simulating SCCs' remote monitoring work and gathering data using EEG EPOC Flex caps. During their study, brain activities of participants recorded using EEG EPOC Flex caps [44]. Figure 4.2 shows using EEG to record brain activities of a participant in an experiment environment.

Kari et al. [44] defined participants as officers of watch (OOWs) in the simulation environment which considered as an SCC monitoring ship bridges as remote-controlled ships. The ship bridges programmed as remote controlled ships with predefined routes. A self-reported questionnaire was used to assess stress where NASA TLX technique was used to assess the mental workload. In fact, self-reported questionnaire and NASA TLX technique were considered as supportive techniques to analyze EEG data [44]. Ultimately, they verified that EEG data are linked to human operators' mental workload and stress during remote ship operations. Thus, Kari et al. [44] answered Research Question 2 by verifying that EEG is a reliable tool for objectively assessing human factors. Hence, the next section (Paper C) presents a series of human-centered experiments to investigate the impact of high levels of mental workload on the stress levels and performance of remote operators during remote ship operations.

4.3 Exploring Mental Workload and Stress Levels Among Human Operators During Remote Ship Operations

Kari et al. [89] assessed mental workload and stress levels among human operators in a series of human-centered experiments surrounding remote ship operations. They developed two scenarios—low-workload and high-workload scenarios—and

Table 4.1: Type of the variables [89]

Variables	Type of variable	Manipulation	Measurements
Workload	Independent	Number of targets, number of ships to be monitored by SCC operators, difficulty of the route, weather, other events such as risk of accidents	NASA TLX technique Self-reporting questionnaire
Stress	Dependent	—	Physiological measurements of stress, EEG data. Self-reporting questionnaire

recorded the brain activity of participants using EEG while participants reported their perceived workload and stress using the NASA Task Load Index (TLX) and a questionnaire. Table 4.1 presents the ship-status indicators that Kari et al. [89] used to manipulate mental workload at a test SCC.

Kari et al. [89] manipulated the mental workload to test their hypotheses, adjusting the number of ships to be monitored, weather, visibility, accident risk, and VHF communication. Table 4.2 presents the characteristics of both the low- and high-workload scenarios. Kari et al. [89] developed the following hypotheses to evaluate the impact of the manipulation of status indicators on the human operators' mental workload and stress levels:

1. There is a significant change in the level of workload between the first and the second scenario in the experiments.
   Corresponding null hypothesis: There is no significant change in the level of workload between the first and second scenarios in the experiments.

2. There is a significant change in stress when workload increases.
   Corresponding null hypothesis: There is no significant change in stress level when workload increases.

3. There is a significant change in stress level when ships are operating in harsh weather.
   Corresponding null hypothesis: There is no significant change in stress when ships are operating in harsh weather.

4. There is a significant change in stress level when the number of ships in-

Table 4.2: Characteristics of both low and high workload scenarios in experiments [89]

Scenario	Low workload scenario	High workload scenario
Area	Kristiansund to Trondheim (low difficulty)	Vatlestraumen (moderate difficulty)
Number of ships	Three container ships (three-ship bridge simulators)	Five container ships
Visibility	Good visibility in daylight	Bad visibility, nighttime
Traffic	5+ targets	15+ targets
VHF communication	No VHF communication challenges	VHF communication challenges
Weather	Moderated wind, calm sea-state	Strong wind, choppy sea
Risk of accidents	No risk of accident	Two risks of accident

creases.
Corresponding null hypothesis: There is no significant change in stress level when the number of ships increases.

5. There is a significant change in stress level when operators establish VHF communication.
Corresponding null hypothesis: There is no significant change in stress levels when operators establish VHF communication.

6. There is a significant change in stress level when there is a risk of accident.
Corresponding null hypothesis: There is no significant change in stress level when there is a risk of accident.

Kari et al. [89] considered the instructor room of the Norsk Maritime Kompetansesenter navigation simulators as an SCC in which participants monitored and supervised ships in both scenarios. Figure 4.3 depicts a participant in the experiment environment engaged in monitoring in the low-workload scenario while Figure 4.4 shows the traffic situation of the same experiment in a bigger picture [89].

Kari et al. [89] recruited three healthy male participants for the experiment, with each scenario taking approximately 10–15 minutes. The participants then filled out NASA TLX forms and self-reported questionnaires that served to evaluate their mental workload and stress levels and reinforce the reliability of the EEG data. Notably, the participants received instructions before the experiment to ensure

Figure 4.3: A participant performing monitoring task in the low workload scenario in the experiment environment (adapted from Kari et al. [89], p.300)

that they were able to monitor ships' status indicators, including speed, turn rate, rudder status, propeller revolution, and engine status. The researchers calculated the participants' overall workload after each scenario using NASA TLX. Figure 4.5 presents the overall score of each participant across both the low- and high-workload scenarios. As shown in Figure 4.5, all of the participants perceived a higher level of mental workload during the high-workload scenario [89].

Kari et al. [89] developed the self-reported questionnaire, which included six questions that the participants expressed their level of stress in a scale from 0 to 7. The researchers used paired sample t-tests in SPSS to analyze the questionnaires. Table 4.3 presents the results of paired sample t-test analysis. After performing paired sample t-test analysis, four hypothesis were supported as follows [89]:

1. There was a significant change in the level of workload between the first and the second scenarios during the experiments.
2. There was a significant change in the level of stress when workload increased.
3. There was a significant change in the level of stress when ships were operated in harsh weather.
4. There was a significant change in the level of stress when the number of ships increased.

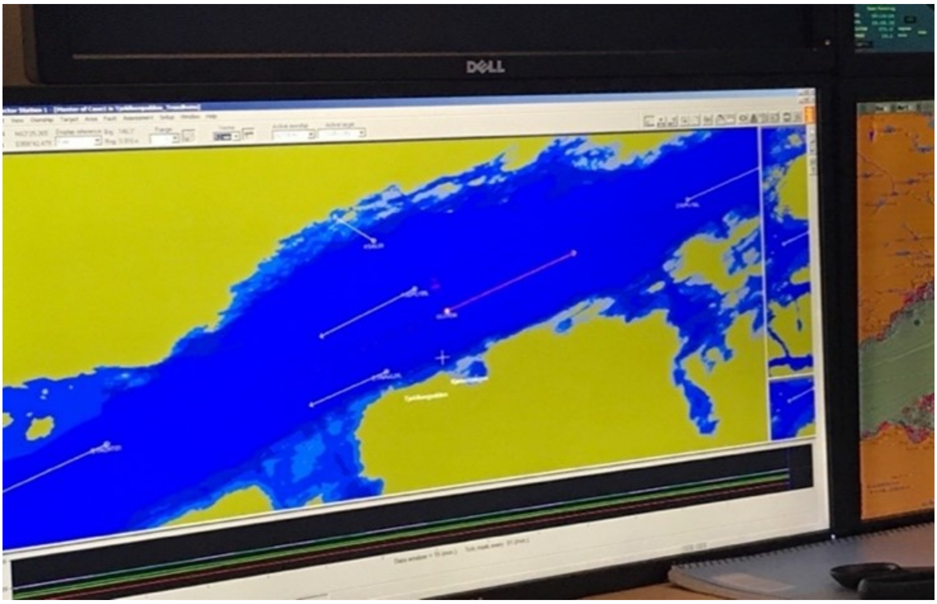

Figure 4.4: Traffic situation during the first scenario (low workload) in high resolution view

Kari et al.'s [89] EEG dataset contains 160 features (band powers) and a total of 42,082 data points, meaning that analyzing it manually would not be feasible. Therefore, the researchers visualized the EEG data using their cloud-based Elastic Stack platform. This enabled them to identify trends and correlations between brain-activity amplitude and workload [89]. The samples in this dataset were labeled with a binary workload value (high workload=1; low workload=0). Then, the researchers used the Pearson correlation coefficient to identify the EEG band powers that exhibited statistically significant changes when the level of workload increased. Indeed, they leveraged EEG signals to understand the variations in brain activity alongside changes in mental workload. They considered EEG band powers as the dependent variables and manipulated factors as the independent variables [89].

The results from Kari et al. [89] indicate that the amplitudes of beta and gamma band powers increase alongside mental workload when the number of ships to be monitored increased or the operators were forced to monitor in harsh weather. Figure 4.6 depicts the positioning of the EEG sensors and the corresponding correlation between the gamma and beta band powers and mental workload; high, moderate, and low correlations are depicted using purple, green, and blue, respectively [89].

Different regions of the brain are responsible for different functions. For example, the frontal lobes of the brain are associated with decision making, problem-solving,

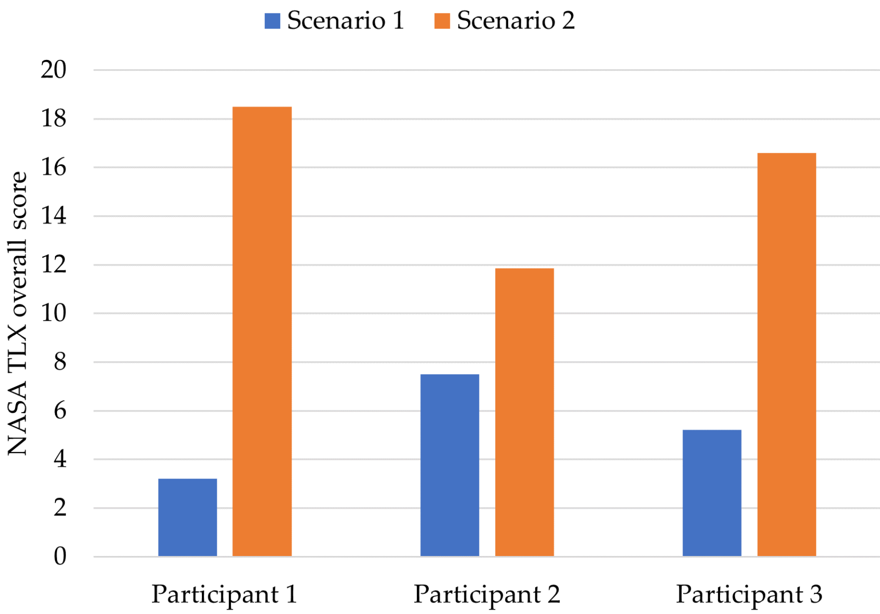

Figure 4.5: Overall perceived mental workload of participant in both low and high workload scenarios (adapted from Kari et al. [89], p.301)

and personality, while the temporal lobes are responsible for processing auditory information and memory. Therefore, EEG CAPs are introduced with various number of sensors starting from 5 to 64 sensors to cover different brain regions. On the other hand, band power of each sensor represents the activity of brain cognitive functions in four states including (i) awaked but relaxed (alpha), (ii) active concentration and alertness (beta) (iii) deep relaxation, deep meditation or light sleep (theta) (iv) deep sleep (gamma) for each region of brain [90, 91]. During remote ship operations, operators expected to be alerted while performing monitoring or remote operations. Therefore, beta band power of each sensor represents the activity of brain cognitive functions during remote ship operations. For example, increased beta power indicates increased attention and active concentration, while increased theta or gamma power may indicate mental fatigue or decreased alertness.

Beta EEG band power is typically associated with higher levels of brain activity and is often observed during cognitive tasks that require active concentration and attention. Therefore, an increased level of beta EEG band power can indicate higher cognitive function, as it reflects the activation of the neural networks involved in attention, working memory, planning and decision making. The beta activity in these regions is thought to reflect the engagement of neuronal networks that are

Table 4.3: Statistical analysis of the self-reported questionnaire [89]

Variable	Mean. Diff	t-value	Sig. (2-tailed)
Overall stress (baseline-low workload)	-1.666	-1.89	0.199
Overall stress (baseline-high workload)	-5.00	-8.66	0.013
VHF communication	-2.66	-3.02	0.94
Risk of accident	-1.333	-1.51	0.27
Weather	-3.66	0.11	0.008
Number of ships	-4.00	-6.92	0.02
Overall workload	-2.66	-8.00	0.15

responsible for these cognitive processes.

For example, during a task that requires sustained attention and visual perception, beta activity increased in the parietal lobe, reflecting the increased engagement of attentional networks when performing remote ship operation from SCCs. Similarly, during a task that requires working memory, beta activity increased in the prefrontal cortex, reflecting the activation of working memory affecting accuracy of response during remote ship operations. Hence, the level of EEG band powers, in particular beta band power indicates the state of the brain cognitive function during performing remote operation tasks. However, individuals may utilize different cognitive functions based on their approach and competence to perform the same task therefore different EEG sensors may capture the brain activity of operators during remote ship operations.

In case of a high level of stress, operators may give up performing a task due to a number of factors related to their cognitive and emotional state. When an individual is under high levels of stress, their cognitive abilities can be impaired, and their decision-making, problem-solving, and attentional abilities can be negatively affected. This can lead to a decrease in performance, motivation, and engagement with the task, as well as an increase in errors and accidents.

It is also possible to identify over-stressed operators with potential to mentally give up a task using EEG band powers. Mishra et al. presented that there is often an increase in the power of the beta and gamma band powers during high level of cognitive activity and physiological arousal [92]. In contrast, there may be a decrease in the power of the alpha band power, which is associated with relaxed states and reduced cognitive load [93]. Berka et al. asked participants to perform a sustained attention task while their EEG was recorded. They found that participants who eventually gave up on the task had higher levels of theta band power in the

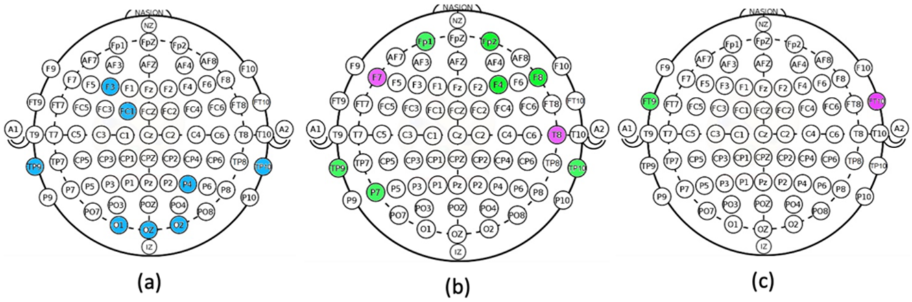

Figure 4.6: EEG sensors that indicated high (purple), moderate (green) or low (blue) correlations with the level of workload and stress; (a) depicts sensor correlation of participant 1, (b) depicts sensor correlation of participant 2, and (c) depicts sensor correlation of participant 3 (adapted from Kari et al. [89], p.302)

frontal and central regions of the brain compared to those who completed the task successfully [94].

Hence, it is possible to identify an over-stressed operator willing to mentally give up a task using EEG recordings. In addition, associating the level of stress inferred from EEG signals with the operators' performance indicates whether the operator mentally gave up the task during the training. Since this study only envisages EEG recordings for training programs, trainers can easily assess operators' performance during the training sessions to identify over-stressed trainees who mentally gave up the task.

In summary, Kari et al. [89] investigated factors that affect human operators' stress during remote ship operations with a particular focus on the remote monitoring mode. Their results verify that higher numbers of ships to be monitored and harsh weather conditions both increase operators' mental workload and stress levels. The results of the Pearson correlation coefficient also indicate that the amplitude of the beta and gamma band powers increase amid a higher number of ships to be monitored and harsh weather conditions. In this way they answered Research Question 3. The study of Kari et al. [89] verified findings of related works reporting correlation of brain activities recorded by EEG with the level of mental workload and stress. As analyzing EEG data using statistical methods is time-consuming and inefficient for training programs, the next section proposes a novel methodology with which to predict stress levels among human operators during remote ship operations using ML techniques.

4.4 ML-Enabled Stress Prediction in Remote Maritime Operations

Remote operations are gaining momentum in the maritime industry, as they are thought to boost the efficiency and safety of maritime operations. Along with the many technical challenges that come alongside remote operations, human factor issues constitute the main challenge facing the success of remote ship operations [1, 95]. Training programs are considered to be an effective solution to address these factors by preparing remote operators to appropriately handle difficult situations. Predicting stress levels among remote operators during remote operations enables training programs to tailor their training programs in a way that overcomes individual differences [96].

Kari et al. [96] identified two evaluation criteria to regulate the selection of the best ML model for predicting stress levels using EEG data. The criteria serve to choose the most accurate model while making predictions that can be understood by human observers. The first criterion is a classification accuracy of 99%, as binary classifications are able to achieve the highest accuracy. The second criterion is interpretability, meaning that human observers can understand the decision path of predictions and infer human factor issues that must be addressed by training programs. Indeed, the latter criterion enables training programs to extract knowledge captured by the ML model and either audit the ML process or detect biases. Kari et al. [96] identified decision trees as the ideal type of algorithm in terms of interpretability, as they allow for human observers to deconstruct decision paths into individual steps and extract relevant knowledge.

Based on these criteria, Kari et al. [96] proposed the smart training in remote operations (STiRO) methodology to predict stress levels among remote operators using EEG data. The process involved more than 10 experiments in which remote operators performed two different ship-ship crane operational scenarios. In the first scenario, operators performed a simple ship-ship crane operation, which is considered to be a low-workload and low-stress scenario. In the second scenario, the difficulty of the operation increased significantly, raising the remote operators' mental workload and stress levels. After each scenario, the participants filled out a NASA TLX form and a questionnaire. In addition, the brain activity of each participant was captured using an EEG equipped with 32 sensors during baseline, low-workload, and high-workload scenarios. The EEG EPOC FLEX was employed to capture brain activity with a frequency of 128 Hz. The questionnaires and NASA TLX forms were analyzed using paired sample t-test to verify the stress levels of the remote operators for each scenario [96].

In the pre-processing stage of the STiRO methodology, Kari et al. [96] labeled EEG data with the corresponding stress levels, resulting in a dataset with 22,000 data

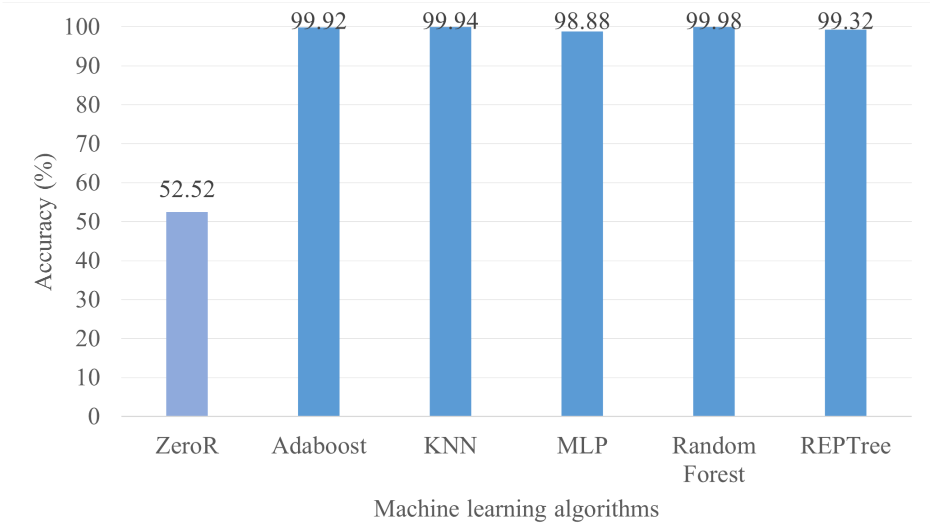

Figure 4.7: Percentage (%) of correctly predicting the level of stress by six algorithms (adapted from Kari et al. [96], p.8)

points. The initial dataset comprised 193 features, though unnecessary features were removed using a feature-reduction technique, reducing the number to 160 features. This reduction significantly increased the ML model's accuracy. In the main step, five different ML algorithms—REPTree, Random Forest, MLP, KNN, and Adaboost—were selected to be trained with the EEG dataset. In addition, the ZeroR majority-prediction algorithm was used as a baseline with which to compare the performance of the five other algorithms. Figure 4.7 presents the accuracy percentages of the ML algorithms trained with the EEG dataset. The random forest algorithm achieved highest accuracy of 99.98% among candidate algorithms predicting the levels of stress.

As the accuracy percentages are similar across all five algorithms, as shown in Figure 4.7, the researchers evaluated the ML algorithms using confusion matrices, on which all of the algorithms performed similarly. After all, classification accuracy is just one element that defines the "best" ML model [96]. Indeed, Kari et al. [96] also considered interpretability in their selection of the best ML algorithm. Thus, they chose the REPTree as the best algorithm for producing an ML model capable of objectively predicting stress levels among remote operators using EEG data. The REPTree algorithm predicted remote operators' stress levels with 99.32% classification accuracy. Table 4.4 presents an overall assessment of ML algorithms' accuracy and interpretability. Evidently, REPTree satisfies both criteria, which is why it was chosen as the best ML algorithm for predicting remote operators' stress

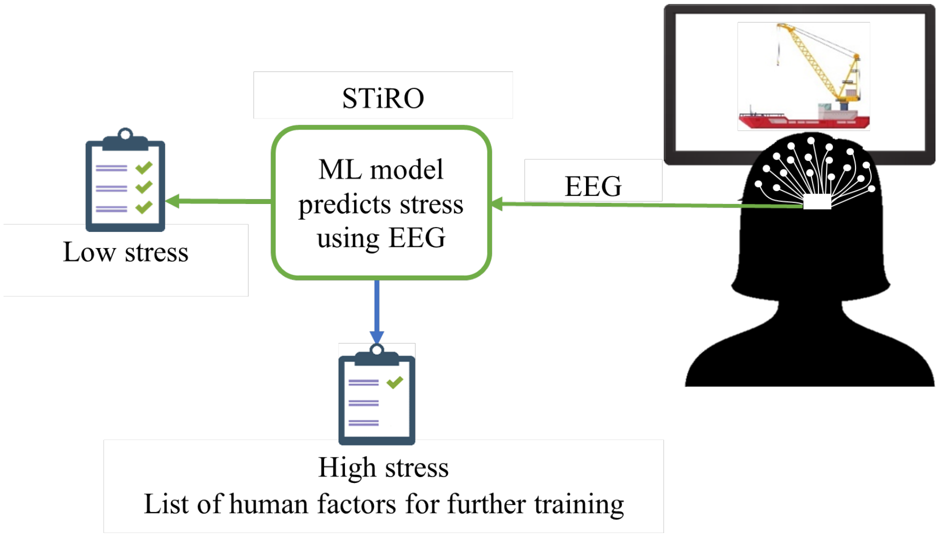

Figure 4.8: Architecture of STiRO methodology for training programs (adapted from Kari et al. [96], p.6)

levels [96].

The proposed STiRO methodology [96] produced an accurate and interpretable ML model for predicting remote operators' stress levels during maritime crane operations. The interpretability criterion ensures that observers can infer the human factor issues that must be specifically addressed by future training programs to improve the competence and efficiency of remote operators at SCCs. In effect, SCC designers, training programs, and standardization organizations can use the STiRO methodology to investigate the human factors that influence human operators' competence. Hence, Kari et al. [96] assert that each of these actors can utilize the results of their study to improve the efficiency of remote operations, particularly in the maritime industry. As depicted in Figure 4.8, training teams can utilize the proposed STiRO methodology to identify the human factor issues that impact stress levels during remote operations [96].

Table 4.4: Overall assessment of ML algorithms for accuracy (A) and interpretability (I) criteria [96]

	AdaBoost		KNN		MLP		Random forest		REPTree	
Dataset	**A**	**I**	**A**	**I**	**A**	**I**	**A**	**I**	**A**	**I**
EEG Dataset	++	–	++	–	–	–	++	–	+	+

Kari et al. [96] answered Research Question 4 and the general research question of this thesis by proposing the STiRO methodology to accurately predict stress levels among remote operators and identify the human factor issues that impact human operators' stress levels during remote operations. By enabling human observers to objectively identify these human factors, the proposed methodology aligns with the expected outcome previously defined in this thesis.

5 Conclusion

Today, remote operations have gained serious momentum in the maritime industry, moving human operators from onboard ships to on-land control centers. Incorporating new technologies into autonomous and remotely operated ships has introduced new challenges in ship operations. One of the most significant new challenges comprises the human factor issues impacting the performance and efficiency of the human operators behind autonomous and remotely operated systems. As unmanned and autonomous ships are under constant supervision from human operators at SCCs, human interactions (including human-human and human-machine interactions) significantly influence the performance and efficiency of remote ship operations.

Clearly, this relocation of the crew from onboard ships to SCCs has not eliminated human error. Therefore, human factors must be addressed properly to mitigate the impact of human error on ship operations. At SSCs, human operators play a backup role, primarily monitoring but able to intervene when a critical situation arise. Given this delicate position, mental workload and stress can influence the appropriateness of their decisions, hindering both safety and efficiency. Hence, this thesis employs a novel methodology—smart training in remote operations (STiRO)—to assess human operators' mental workload and stress levels using EEG and ML techniques. The proposed methodology enables maritime instructors to provide more modern, relevant training strategies that consider the relevance of human factors, especially in remote operations. More succinctly, the new strategy consists of the following phases:

- Perform the STiRO methodology to produce an accurate and interpretable ML model for predicting human operators' mental workload and stress levels.
  - Record the brain activity of human operators using EEG.
  - Calculate the mental workload and stress levels in the form of binary or ternary labels.
  - Label EEG data with mental workload and stress labels to produce a dataset.
  - Introduce accuracy and interpretability criteria for the evaluation of ML algorithms.
  - Train ML algorithms to produce an ML model and then test the model.
  - Identify the best model based on the predefined criteria: accuracy and interpretability

- Execute the interpretable model to identify human factor issues after the first round of operator training.

- Retrain human operators with customized trainings to mitigate human factor issues and improve efficiency and performance of human operators.

In addition to the accuracy evaluation criterion, this thesis considers interpretability as another criterion for selecting the best ML model. The interpretability criterion assesses how well a training instructor can understand the decision path that predicts stress levels and explain it to others. An interpretable ML model allows training instructors to extract knowledge captured by the ML model and either detect potential bias or audit the ML process. In this way, training instructors can infer the human factor issues driven by stress and administer customized training programs to mitigate them. In this sense, tree-like models are the most effective ML models at allowing instructors to deconstruct the decision path.

After testing the STiRO methodology in the use case of remote crane operations, the REPTree was found to be the best algorithm, exhibiting 99.32% classification accuracy. Among the five ML algorithms, the random forest algorithm achieved the highest accuracy at 99.98% but failed to produce an interpretable ML model from which training instructors could easily extract human factor issues.

Piloting remote crane operations demonstrates the accuracy and interpretability of the STiRO methodology in predicting remote operators' stress levels in remote ship operations. This methodology allows training instructors to interpret the decision path and infer the human factor issues impacting human operators' efficiency and performance. Furthermore, ML lowers the cost of competence assessment compared to traditional approaches, such as surveys, allowing instructors to more freely customize training programs. In effect, training programs, standardization organizations, and SCC designers can utilize the proposed methodology to objectively investigate the human factors that impact the efficiency and performance of human operators in remote ship operations, allowing for the mitigation of human error. In fact, training programs and standardization organizations can use the STiRO methodology to transform traditional technical training strategies into more predictable and measurable human-centered training strategies.

5.1 Summary of the Research

This thesis initially established four research questions to investigate human factor issues in remote ship operations. Each question sought to achieve specific goal to specify expected outcome of the research in the topic. Table 5.1 associates research goals with contribution of research papers and how much research papers addressed

Table 5.1: List of research goals, papers and the level of achievements.

Goals	Papers	Level of achievement
1	Paper A	Fulfilled
2	Paper B	Fulfilled
3	Paper C	Fulfilled
4	Paper D	Fulfilled

expected outcomes defined in each goal.

This study raised one general question and four specific questions. The general research question "*How can objective techniques including EEG and machine learning help to address human factor issues in remote ship operations?*" was answered by the four research papers published during the development of this PhD project. The general question sought to explore the topic and investigate opportunities presented by new technologies. The four specific questions served to sharpen the research by diving into more specific challenges.

The first research question "*Which human factors affect remote operations?*" was formulated to investigate common human-driven issues in remote operations implemented in various domains. The first research paper "Human Factor Issues in Remote Ship Operations: Lesson Learned by Studying Different Domains" investigated the various types of the human factor issues which can affect remote operations. In this paper, 13 groups of the human factor issues were identified that may affect the performance of the remote operators within the shore control centers (SCCs). These human factor issues include situation awareness, high mental workload, trust, boredom, fatigue, skill degradation, poor human-machine interfaces, lack of direct sensory, communication challenges, teamwork challenges, linguistic problems, cultural problems, and decision making issues. Then, this paper proposed a human factor classification for remote ship operations which presented major human factor issues that can affect remote operations. The proposed framework studied different industries and adopted human factor issues which can affect remote ship operations. Furthermore, this classification of human factors issues into human-human and human-machine interactions can be utilized by MET program designers. In line with Goal 1, the proposed classification presents human factor issues affecting remote operations.

The second research question "*How can EEG be utilized to objectively assess human factors in remote ship operations?*" was designed to assess the application of EEG in the objective assessment of mental workload and stress levels among human operators during remote ship operations. The second paper studied EEG applications across multiple domains and developed a framework to envisage the application of EEG in remote ship operations. This paper verified that EEG is a reliable tool with which to study human factors, including mental workload and stress. It proposed the use of low-workload/stress and high-workload/stress scenarios in human-centered experiments to assess human operators' mental workload and stress levels. In line with Goal 2, this paper identified EEG as a tool that can effectively be used to objectively assess human factors during remote ship operations.

The third research question "*How can EEG be utilized to objectively assess workload and stress as the two main human factors in remote ship operations?*" was designed to assess mental workload and stress levels via brain activity. The third paper designed and performed a series of human-centered experiments while recording the brain activity of human operators during remote ship operations. These experiments revealed the number of ships to be monitored and weather conditions as two factors that impact human operators' mental workload and stress levels. In addition, the third paper utilized both NASA TLX forms and self-reported questionnaires to correlate brain activities with human perceptions of mental workload and stress. It also generated a correlation coefficient matrix, which served to identify a correlation between EEG band powers and operators' workload and stress levels. In line with Goal 3, the paper verified that the brain activity of human operators is highly correlated with remote operators' mental workload and stress levels during remote ship operations and that EEG is a reliable tool with which to objectively assess those two factors.

The fourth question "*How can ML techniques be used to predict human factors in remote ship operations and enable providing customized training to address human factor issues?*" was designed to investigate the functionality of ML techniques in human factor predictions. Automated systems are increasingly prominent in the maritime industry, meaning that traditional training strategies are no longer sufficient. MET programs need to be updated to suit the industry's modern, human-centered dynamics. Hence, the fourth paper proposed the novel STiRO methodology to predict human operators' workload and stress levels during remote ship operations using ML algorithms. In fact, the STiRO methodology helps trainers to develop customized training programs based on individuals' competence and experience. It produces an ML model that is both accurate and interpretable, enabling trainers to infer human factor issues that impact remote operators' performance and efficiency. In effect, training programs, SCC designers, and standardization organizations can utilize the results of this study to objectively assess human factors in remote ship operations. In line with Goal 4, this paper proposed a methodology to improve the performance and efficiency of human operators through human-centered training programs.

The initial goal of this thesis was to identify the human factors that impact remote operators' performance and efficiency during remote ship operations. To do so, it investigated human-human and human-machine interactions. Eventually, it proposed the STiRO methodology to transform the strategy of training programs from a technical, ship-centered strategy to a human-centered strategy that considers individual differences and trains human operators to mitigate human factor issues.

With all of the thesis's findings established, the remainder of this chapter serves to highlight their implications for three audiences: practitioners, researchers, and maritime instructors.

5.2 Conclusions for Practitioners

Relocating human operators from onboard ships to SCCs leads to new human factor issues that must be considered when designing SCCs and their protocols. Thus, this thesis contributes to the literature by achieving a greater understanding of human factor engineering (HFE) within SCCs. The STiRO methodology can aid designers in inferring the human factors that influence operators' mental workload and stress level. This knowledge enables designers to properly consider human elements when developing the design of SCCs, especially with regard to human-machine interfaces. Overall, the results of this thesis have significant practical implications for professionals and practitioners in the field of modern maritime industry.

5.3 Conclusions for Researchers

This thesis focused on human factor issues and their impact on remote ship operations. It provides an overview of these factors, which are rooted in human-human and human-machine interactions. Thus, it theoretically contributes to the field of HFE during remote ship operations, providing new opportunities for human factor researchers to study these factors objectively. In addition, the proposed STiRO methodology can be utilized across other remote use cases. Future studies can test the STiRO methodology in different domains to extend the use cases of measuring human factors objectively. This proposed methodology enables researchers to use the knowledge captured by the ML model to identify human factors that require additional investigation. The interpretability of the ML model provides new opportunities for future studies. In addition, future studies can utilize the STiRO methodology to investigate other human factor issues, such as fatigue and boredom, during remote operations.

5.4 Conclusions for Maritime Education and Training

At SCCs, human operators monitoring and supervising remote operations significantly influence the efficiency and safety of remote ship operations. Since relocating onboard crew to land-based control centers does not eliminate human error, a new approach is required to enhance the competence of remote operators. Traditional MET strategies are largely focused on on-ship requirements or outdated technical elements. However, developments in remote and autonomous maritime operations require updated MET programs focused on human elements. Traditional MET strategies result in qualified seafarers, but modern strategies need to produce human operators capable of running modern ship operations. Thus, this thesis practically contributes to the MET field.

The proposed STiRO methodology enables MET to infer human factors that impact the performance and efficiency of remote operators. The methodology produces an interpretable ML model that allows designers and trainers to understand human factors that emerge amid high levels of stress and mental workload. This knowledge aids MET programs in customizing training sessions aimed at mitigating human errors in remote operations, significantly reducing human error in the long term.

5.5 Considerations and Suggestions for Further Research

While this thesis invited a limited number of participants to perform human-centered experiments, the proposed STiRO methodology produces a generic ML model to predict human operators' levels of mental workload and stress during remote ship operations. Thus, future studies should expand the scope of this method by analyzing the brain activity of a larger number of participants in human-centered experiments. Future works can use this methodology to produce ML models tailored to remote operations in specific domains beyond ship operations. While this study performed several experiments to record the brain activity of remote operators, it could not simulate all ship operations in all conditions. Therefore, future studies should record the brain activity of human operators during real-world scenarios to improve the generalization of the STiRO methodology. Indeed, deploying the STiRO methodology in real-world SCCs would further tune the ML model for industry-grade training.

This thesis identified 13 human factor issues. However, other human factors could certainly impact the performance and efficiency of human operators. Therefore, the STiRO methodology should be tested to predict the prevalence and impact of other human factors during remote ship operations. This would require an individual experiment for each new human factor.

The proposed STiRO methodology focuses on predicting levels of stress to enable training programs to identify the human factors that hinder efficiency among human operators. However, simply knowing these levels is not sufficient to improve human operators' competence. This knowledge must be coupled with HF training. Therefore, future studies must investigate methods that use the result of stress and mental workload predictions to automatically generate training programs aimed at improving the performance and efficiency of human operators during remote operations.

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PART II: Scientific Contributions

A Paper A: Human Factor Issues in Remote Ship Operations: Lesson Learned by Studying Different Domains

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Abstract The idea of remote controlling ships for operational and commercial uses has developed beyond concepts. Controlling and monitoring vessels from a distant location requires updating the concept and requirements of shore control centers (SCCs), where human operators control the fleet via cameras, GPS, and many other types of sensors. While remote ship operation promises to reduce operational and maintenance costs, while increasing loading capacity and safety, it also brings significant uncertainty related to both the human-machine and human-human interactions which will affect operations. Achieving safe, reliable, and efficient remote ship operations requires consideration of both technological, cultural, social and human factor aspects of the system. Indeed, operators will act as captain and crew remotely, from the SCC, introducing new types of hardware and software interactions. This paper provides an overview of human factor issues that may affect human-machine and human-human interactions in the course of remote ship operations. In doing so, the literature related to remote operations in the domains of shipping, aerial vehicles, cranes, train transportation, automobiles, and mining is reviewed. Findings revealed that human factor issues are likely to fall into 13 distinct groups based on the type of human interactions that take place in SCCs.

Keywords: remote ship operations; human factor issues; human-machine interac-

tions.

A .1 Introduction

Existing technologies such as sensor technologies and artificial intelligence, as components of the Industry 4.0 revolution, have enabled maritime companies to implement an early prototype of remotely controlled ships. Remote ship operation can improve the efficiency of ship operation by implementing novel concepts, such as Industry 4.0, which will improve safety and performance. In addition, remote ship operation enables more cost-efficient shipping by reducing or removing onboard manning and providing the advantage of being able to operate multiple ships from a control center simultaneously. According to ship operating reports, manning related costs can constitute 25% of total ship operating costs [1]; therefore, reducing or removing onboard manning can reduce a considerable portion of ship operating costs.

Various players in the maritime industry are pursuing the implementation of remote ship operations. In 2017, Wärtsilä [2] tested maneuvering an 80 m platform supply vessel in Scotland remotely from United State via satellite link. Rolls-Royce and Svitzer also tested remotely maneuvering a 28 m tugboat in Copenhagen harbor by a captain on shore in 2017 [3]. However, remotely controlled ships are not yet fully developed and their future is unknown.

Remotely controlled ships interact and communicate with human-operated systems. In this way, human operators program voyage planning, navigation and continuously monitor the vessel from the shore control center (SCC) to avoid accidents. The onboard systems follow well-established international regulations, whereas the implementation of SCCs is not standardized and companies develop their own SCCs.

Since human operators play a key role in monitoring and supervising remote ships from SCCs, human factors can significantly affect the performance and reliability of remote ships. On the other hand, remote ship operations are in the early stages and few SCCs have been implemented as a consequence of testing remote operations. Hence, investigating remote control experiences in different domains will help to improve the efficiency and reliability of SCCs in remote ship operations.

This paper investigates remote operations that have been implemented in different domains in the literature to identify the human factors that affect remote operations. In doing so, more than 50 articles were analyzed in order to identify factors that can affect remote ship operations; in particular, remote operations in SCCs. Then, inductive coding was utilized to categorize factors into human factors that affect human-human and human-machine interactions. As a result, 13 human factors were identified that can affect remote operations in SCCs, of which, three factors affect human-human interactions, eight factors affect human-machine interactions and two factors can affect both human-human and human-machine interactions.

The rest of this paper consists of three main parts. Section 2 presents the background and definitions, while Section 3 presents the methods used for the literature review. Section 4 classifies human factor issues identified in different domains. Finally, Section 5 concludes the study and mentions the limitations and future research directions.

A .2 Background

Remote Ship Operations

The process of teleoperation refers to the operation of a machine (teleoperator) at a distance such that there is continuous and direct human control of the machine [4]. In other words, teleoperation can be defined as the remote control of a vehicle by a human [5]. Remote ship operation is a process involving the control, manipulation, supervision, and administration of vessels from a distance, such that operators can collect vessels' operating information (e.g., fuel consumption and health status) from sensors and an onboard automated system.

Remote operations can be applied in different ways for different vessels. Table A .1 provides a general overview of how remote operations cover and complete the operations of three types of vessels, including manned vessels, unmanned vessels, and autonomous vessels, inspired by [6] and by the Maritime Unmanned Navigation through Intelligence in Networks (MUNIN) project. While most of the literature treats unmanned and autonomous vessels as identical; this paper distinguishes between these two concepts because only one of these types can have a crew onboard. Below, remote ship operation is explained in detail in relation to both of these types, and the role of human factors in relation to remote ship operations is described.

Unmanned and Autonomous Vessels

The concept of unmanned vessels relies on the land-based shore control center (SCC) [6], where the crew will monitor the vessel using crucial information transferred by satellite communication at short time intervals. If the autonomous system registers a problem—in addition to in several other situations—the crew at the SCC will take remote control of the vessel [7]. Porathe et al. [8] explain unmanned ships as:

"An unmanned ship is a ship with no humans onboard. An unmanned ship does not have to be autonomous; it can be under autonomous control but it can also be under

Table A .1: Three types of vessels and remote ship operations.

Type of Vessel	Crew	Operation
Manned (conventional)	Onboard	Manned operation (remote operation could be utilized for some tasks such as crane operation)
Unmanned	Ashore	Autonomous execution and control, remote operation, wireless monitoring and control, satellite communication, etc.
Autonomous	Ashore—a few crew members could be on board	Autonomous execution and control, remote operation, wireless monitoring and control, satellite communication, etc.

remote control from a [Shore Control Center], or from other places (e.g., a pilot or tugboat or a mooring supervisor)."

An autonomous ship is defined as a ship:

"with modular control systems and communication technology to enable wireless monitoring and control, including advanced decision support systems and the capabilities for remote and autonomous operation [9]"

Porathe et al. [8], explain that autonomous vessels have an automated software system that navigates and maneuvers the vessel. The system and the ship are under monitoring from the SCC. An autonomous ship has no crew in the engine room or bridge, but it may have a maintenance or service crew. The navigation and engine rooms have a programmed automatic system that typically reaches a particular level of artificial intelligence [7].

The MUNIN project describes the concept of an autonomous ship as a ship which is operated autonomously within specific limits by new systems onboard the ship. In this scenario, the functions of control and monitoring could be performed by operators in the SCC [10]. The crew continuously monitor the operation of the vessel from the SCC, implementing direct remote control in exceptional situations.

The operation of unmanned and autonomous vessels can be defined in four main states: autonomous execution, autonomous control (autonomous problem solving), remote control, and fail-to-safe mode [5]. Autonomous execution means that the onboard autonomous system constantly controls and measures the vessel's status to determine if the vessel can continue with its predefined plan. This involves providing regular data to the SCC so that the offshore crew can monitor the functioning of the vessel, while the SCC is not required to intervene, except in certain special cases. The vessel will enter into the autonomous control or autonomous problem solving states when a deviation from the predefined plan is required (e.g., crossing other vessels or harsh weather) [10]. At any time, the SCC can take remote control over the vessel and completely override the onboard autonomous ship controller (ASC) [5]. Fail-to-safe mode is the vessel's status if communication is lost and the autonomous system cannot resolve the problem [7].

Different Types of SCC Control Modes

Based on the control modes for unmanned and autonomous vessels, there are also different modes for the SCC. Rødseth et al. [5] argued that remote monitoring, remote operation, status investigation, ASC update, and intervention are the most important SCC control modes. During the remote monitoring mode, no action will be taken by the SCC and all ship status indicators are normal within the SCC. The SCC will enter into the ASC update and investigation mode when ship status indicators indicate an abnormality. During the investigation mode, the SCC operator will interact with the onboard system directly in order to obtain more details of the problem. However, during the ASC update mode, the SCC operator will update some aspects of the ASC plan [11]. When the ASC is not able to solve the problem, SCC will enter the remote ship operations mode. Furthermore, the SCC can be under intervention mode when more interactions with the onboard autonomous and navigation systems are required [5, 11].

Human Factors in the Context of Remote Ship Operations

Human factors examine the way human capabilities affect the system. Understanding the human factors involved can optimize the performance and reliability of the overall system. Human factor analysis is a scientific discipline that deals with understanding the interactions between humans and other components of a system; it involves applying theory, data, methods, and principles to design and optimize human well-being and overall system performance [12]. Despite the many advantages of remote operations, including more efficient cargo space, more efficient fuel usage and more efficient usage of crew and their skills [13], the technology complicates the interaction with humans. For example, SCC operators must make a new mental model, in which they are blind to the environment in order to monitor and control the vessel from shore. This requires transforming the "onboard mental model" so that it can be transferred to the SCCs [7]. Notably, such mental model is an internal representation of conceptual and causal interrelations between components that people utilize in order to understand phenomena [14].

Most maritime accidents occur due to human error [10]. In this respect, Uğurlu et al. [15] discussed several studies, concluding that 80–90% of maritime accidents are attributable to human error. This is true in other types of operations as well. For instance, a study of 68 unmanned aerial vehicle (UAV) accidents found that 65% of the 287 causal factors were associated with a human being [16]. Rasmussen's [17] theory and human factors analysis and classification system-maritime accidents (HFACS-MA) discuss risk assessments and provide human factors that are directly related to accidents. The HFACS-MA framework categorizes the causes of marine accidents into five levels including unsafe acts, preconditions, unsafe supervision, organizational influence and external factors [18]. On the other hand, this paper considers that skill-based errors, mistakes and violations are factors that affect control centers, in accordance with the health and safety executive (HSE). In light of this, it is necessary to understand the role of humans in the context of remote ship operations and to distinguish different types of human interactions and human factor issues that are likely to arise.

The first question is whether humans play a vital role in particular functions. In remote ship operations, operators in the SCC have to respond to sensor information immediately, especially in the case of a hazardous situation. The human acts as a backup system when the autonomous system fails. Thus, the human in the loop acts as a critical sub-system which affects the performance of the whole system. This involves both human-machine interactions—as humans interact with the software and hardware in the SCC and respond to the sensor information—and human-human interactions, as the operators, situation team (captain and engineer) [19], and supervisor all work together on remote ship operation within the SCCs.

Relocating onboard humans to onshore control centers introduces new human factor challenges compared to the existing challenges onboard manned ships and these may impact ship operations differently. Burmeister et al. [10] and MUNIN project [20] argued that human operators involved in the SCC are as follows

- SCC operators monitor the operations of autonomous or unmanned vessels from the SCC. Operators can give high-level commands such as changing the voyage plan.
- SCC engineers assist the operators with the technical aspects of ship operation and oversee the maintenance plan.
- The SCC situation team can take over direct remote control of a ship via the Remote Maneuvering Support System of the bridge of the vessel, which provides situation awareness (SA) to the crew in the SCC.

The rest of this paper consists of three main parts. The next section explains the methods used in this study. The third section classifies the human factor issues in different domains. The fourth part presents the conclusion, the main limitations of the study, and areas for future research.

A .3 Materials and Methods

For this study, the literature was investigated in order to classify the main human factor issues affecting operating ships in shore control centers. In the current research, various databases including ScienceDirect, IEEE Xplore, and Scopus were searched for related peer-reviewed studies using keyword including “remote operations”, “shore control center”, “human factors”, “autonomous vessels”, “ship operations” and “unmanned ships”. In addition, no publication time limit was considered while retrieving articles from digital libraries. The search domain was limited to the literature related to remote operations, teleoperations, human factors, human factor challenges, and automated environments. Search results were gathered in a non-structured way among industries that presented progress in applying remote operations. At the first stage, more than 50 papers were investigated, while during the second stage, the abstracts of the papers were investigated to select the most relevant literature to the topic. Finally, 38 papers that addressed the human factor issues of remote operations were selected in different domains in order to sharpen the literature review. This review primarily focuses on the operation of shore control centers, and therefore, issues relevant to the operation of remote ships in shore control centers were selected from the literature. This review also considered related work in regard to the shipping industry, unmanned aerial vehicles (UAVs), unmanned aircraft systems (UASs), remote operated cranes, self-driven trains, autonomous cars, and remote mining.

Results were analyzed based on an inductive coding process. Codes are constructs that are generated by the authors, which appear progressively through the qualitative data collection method. Codes are short phrases or words that are symbolically assigned to a portion of data [21]. The coding process in the present paper was conducted in two phases, including first cycle and second cycle coding. During first cycle coding, the author went through all gathered papers and identified empirically grounded codes which were related to human factors and the operation of automated systems. The portions of the data which were related to the mentioned fields were coded from a single code to a phrase. For example, fatigue, cultural problems, and linguistic problems. In this respect, the author developed a table including related portions of data and assigned codes in order to clarify, revise and identify final codes. During the second cycle of the coding process, the author grouped the first cycle codes into smaller categories and revised the codes to avoid overlapping. Finally, the author identified 13 codes, which are presented in the next section, as the main human factor issues. Additionally, during the second cycle of coding, the author developed pattern codes or meta codes. This refers to classifying the identified codes into bigger groups. In this respect, all 13 codes were classified into two main groups including human-human and human-machine interactions. These two groups indicate which human factor issues (codes) are related to human-human and human-machine interactions. Figure A .1 presents our literature review methodology starting with analysis of the literature and continuing with the inductive coding process in order to classify the human factors affecting each type of human interaction in shore control centers.

A .4 Results

The results of the literature review are classified as 13 main human factor issues which which are shown in Table A .2: (1) situation awareness (SA), (2) high workload, (3) trust, (4) are shown in Table 2: (1) situation awareness (SA), (2) high workload, (3) trust, (4) boredom, boredom, (5) fatigue, (6) skill degradation, (7) human–machine interface, (8) lack of direct (5) fatigue, (6) skill degradation, (7) human-machine interface, (8) lack of direct sensory sensory information in the SCC, (9) communication challenges, (10) decision-making, (11) information in the SCC, (9) communication challenges, (10) decision-making, (11) linguistic linguistic problems, (12) cultural problems, and (13) teamwork. These issues affect hu- problems, (12) cultural problems, and (13) teamwork. These issues affect human-human man–human and human–machine interactions. The sections below present the results of and human-machine interactions. The sections below present the results of the each of the each of these issues. these issues.

Situation Awareness (SA)

Endsley [40], defines situation awareness (SA) as "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future". Conception and cognition are two main key elements in achieving an adequate level of SA. SA has three levels: perception of the current situation, comprehension of it, and at the highest level, projection of the future situation [40]. Achieving levels two and three of SA (comprehension and prediction) is very critical for the performance of complex systems [33].

SA is commonly cited in human-automation errors. Aviation accidents and air traffic control errors frequently cite "lack of SA" or "failure to maintain SA" [33]. It is important to mention that lack of SA refers to a low level of SA in the environment. On the other hand, [22] discusses the relationship between harmony and SA in SCCs and discrepancies regarding SA requirements. Man et al. [22] argue that

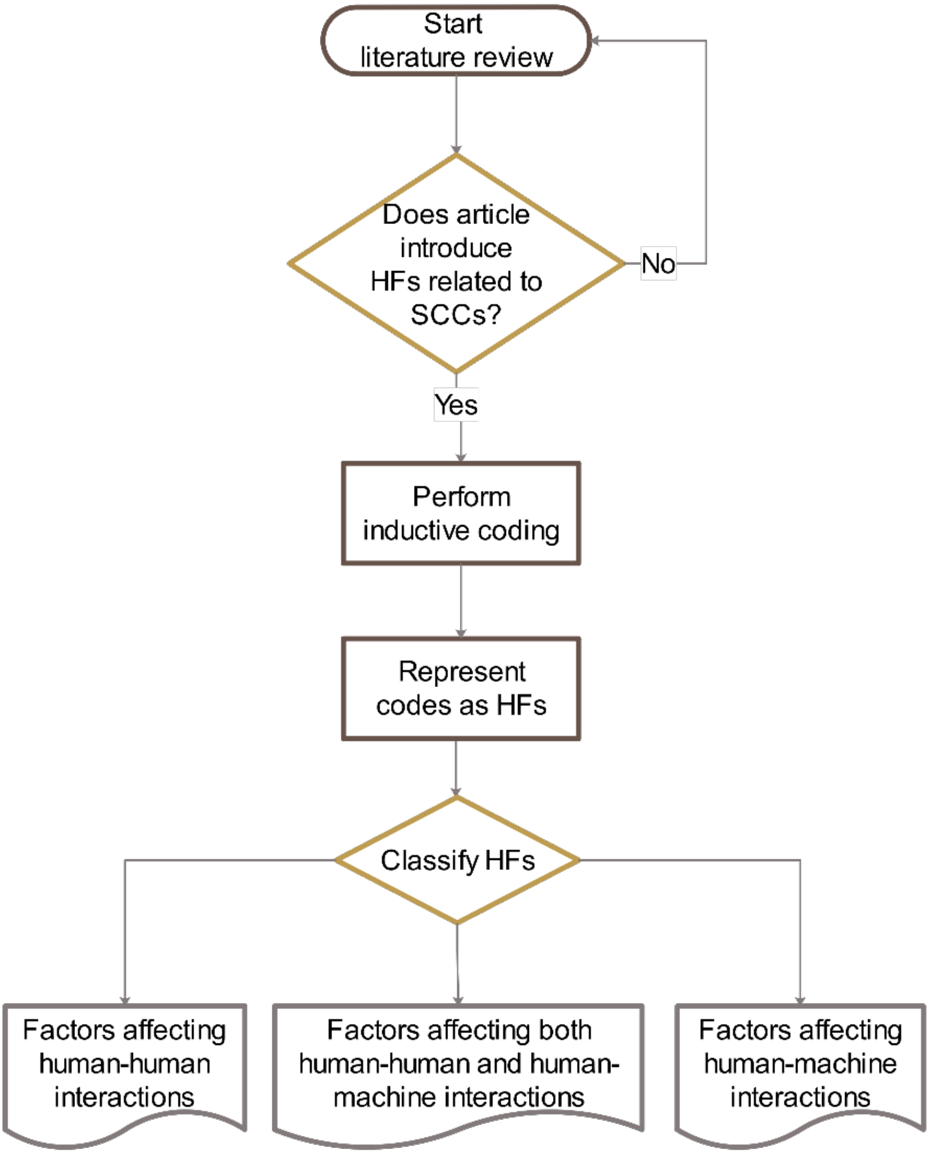

Figure A .1: Process flow for identifying human factors affecting shore control centers from the literature.

"harmony reveals the continuous balanced effect by tuning the ship to the dynamic environment under different situations that ship handlers strive for". According to their findings, loss of harmony hinders perception and makes it harder to obtain the higher levels of SA in the SCC. In addition, they mention that operators in SCCs

Table A .2: Human factor issues in remote operations.

		Human–Machine Interactions								Human–Human Interactions				
Authors	Domain	1	2	3	4	5	6	7	8	9	10	11	12	13
Burmeister et al. [10]	Shipping	✓	✓					✓		✓				
Man et al. [22]	Shipping	✓	✓	✓				✓	✓	✓	✓			
Porathe et al. [7]	Shipping	✓	✓						✓	✓	✓	✓		
Wahlströma et al. [23]	Shipping	✓	✓		✓		✓	✓	✓	✓		✓	✓	
Man et al. [24]	Shipping	✓							✓		✓			
Xue et al. [25]	Shipping										✓			
Olenderski et al. [26]	Shipping										✓			
IMO-NAV [27]	Shipping	✓						✓		✓				
IMO [28]	Shipping		✓					✓		✓		✓		
Kari et al. [29]	Shipping		✓	✓	✓		✓		✓	✓				✓
Zhang et al. [30]	Shipping	✓				✓					✓			
Wróbel et al. [31]	Shipping	✓						✓					✓	
Oncu and Yildiz [16]	Aviation (UAV)	✓	✓			✓	✓	✓	✓	✓	✓		✓	✓
Johnson [32]	Aviation (UAV)	✓	✓					✓					✓	
Nisser and Westin [33]	Aviation (UAV)	✓	✓	✓			✓	✓	✓		✓			✓
Williams [34]	Aviation (UAV)							✓		✓	✓			
Waraich et al. [35]	Aviation (UAS)							✓						
McCarley and Wickens [36]	Aviation (UAV)							✓	✓	✓				
Thompson et al. [37]	Aviation (Aircraft)				✓	✓								
Hobbs and Herwitz [38]	Aviation (UAV)								✓	✓		✓		
Drury and Scott [39]	Aviation (UAV)	✓						✓						
Endsley [40]	Aviation (Aircraft)	✓												
Lester and Thronson [41]	Airspace (telerobotic)									✓				
Baldwin [42]	Aviation (UAV)								✓			✓		
Karvonen et al. [43]	Remote operated container crane	✓	✓					✓	✓	✓				
Abdullah et al. [44]	Remote operated container crane							✓	✓	✓				
Abdullah and Handroos [45]	Remote operated container crane							✓	✓		✓			
Karvonen et al. [46]	Remote operated container crane							✓	✓					
Karvonen et al. [47]	Automated train	✓							✓		✓			
Wahlström et al. [48]	Metro control center	✓												
Dadashi [49]	Rail intelligent infrastructure	✓	✓	✓				✓			✓	✓		
Saffarian et al. [50]	Automated driving	✓	✓	✓			✓							
Wahlström et al. [51]	Rally control center	✓		✓		✓	✓	✓						
Lynas and Horberry [52]	Mining			✓	✓		✓	✓	✓					
Lynas and Horberry [53]	Mining	✓		✓	✓	✓	✓	✓						
Number of articles address each factor		20	12	8	5	5	8	21	16	14	12	6	4	3

require more time to develop SA, after which they react.

Achieving a high level of SA requires an incremental process of collecting information from the environment. SA in SCCs does not only depend on information; it also depends on the dynamic of the operating situation, which changes [7]. As sensors and satellite communications provide the required information for remote ship operations, the level of cognition and conception of the operators will lead to a lower level of SA in SCCs than they would have on board. This happens due to indirect sensory information within the SCC.

Various researchers who have examined SA argue that it should be considered in the case of land based unmanned ship handling [22, 58]. Furthermore, Porathe et al. [7] argue that misunderstandings a vessel's situation, which is an SA challenge, can lead to mis-takes in SCCs. Similarly, the operator of a remote crane must know the exact location of each container. As researchers note, remote operators cannot automatically gain the same information as a conventional crane operator [43]. In another example, the automation of the Helsinki Metro rapid transit system was cancelled due the fact that, without an in-trusion detection system, it will crash into a person or another object on the track. Other challenges researchers identified include “driving the train on the track”, “stopping at a station” and “interactions of the driver with other actors in the metro system” [47]. These issues refer to a lack of an adequate level of SA within the control center about the train and its surroundings and a lack of direct sensory information during the operation of automated trains, similar to the operations of autonomous vessels at sea. The report of the 58th session of Sub-Committee on Safety of Navigation (NAV) [27] also references SA in its discussion of various user gaps and preliminary potential solutions for the operational areas of e-navigation solutions; some of the solutions identified could possibly also be applied in the field of remote ship operations, for example, an integrated presentation of available information. Research has identified a lack of harmonized presentation of local infor-mation in order to increase SA for shore support services for remote ship operation [10]. In addition, future research can leverage machine learning techniques to assess the risk of e-navigation using performance parameters collected from e-navigation systems and human factors that resulted in accidents. In doing so, a machine learning model can predict the risk of human operations based on the way they use e-navigation systems. Zhang et al. [30] provide a model of human error assessment for an autonomous cargo ship, which highlights the effects of situation awareness and ship perception as two significant factors. This issue is related to the way that sensor data are presented in order to provide local information for both monitoring and controlling processes in SCCs. Thousands of sensors provide information about the ship’s status and voyage plan, however, the indirect sensory situation still remains, in addition to the fact that operators are not present onboard. This highlights SA as a significant challenge within the SCC.

It is important to mention that SA in the current paper—is discussed based on human–machine interactions. Other domains included here, such as UAV operation, show a similar focus [39]. However, SA could be investigated based on human–human interactions as well. In this respect, it is necessary to focus on the interactions between SCC operators, the captain and engineers in order to investigate how these human interactions affect the level of SA. SA based on human machine interactions could consist of the level of awareness of operators about the status of the unmanned or autonomous vessel, their surroundings, and also other vessels. This status comprises a wide range of factors in-cluding the ship’s health and route plan. Overall, SA, as an important factor, should be considered from both human–human and human–machine interaction perspectives in order to gain adequate information and achieve a satisfactory level of SA within the SCC.

High Workload

Human workload is the sum of the all task demands which are imposed on operators and the subjective response of the operators to those demands [33]. According to the organization of SCCs, one operator could be assigned to monitor more than one vessel (up to six vessels) [54]. In this situation, operators have a higher level of workload than op-erators onboard. This challenge is derived from human–machine interactions. The remote system constantly provides information to provide an optimal level of SA, which increases the risk that operators will experience information overload and a high level of workload in monitoring many different systems.

Man et al. [22] state that an SCC can present all of the information operators need and would have if they were onboard, but note that if this is the case, then the observation of multiple screens and simulators would lead to information overload. Other research studies have highlighted that information overload has two main reasons: (1) a constant flow of information designed to maintain SA, and (2) the fact that operators might be overseeing several ships at the same time [7]. Porathe et al. [7] also point out that human errors may occur because of the “carry over effect” when one operator monitors more than one vessel at the same time. These situations refer to higher mental workload as an important human factor challenge within remote control centers.

Furthermore, one of the major predictors of procedural error in the operation of UAVs is operators’ workload [16]. Increasing pilots’ workload was a cause of the Nogales UAS accident [32]. Nisser et al. [33] found that automation alters workload by decreasing manual load and increasing mental workload. In addition, in the field of crane remote operation, one study found that the tasks can be different every time without any previous information about its operation. Hence, the operators must be able to reorient immedi-ately on a received task [43]. This refers to operators performing multiple tasks in control centers, which creates a high level of mental workload.

The research reviewed here suggests that SCC workers could be exposed to too much information, which would make it impossible for them to understand the conditions of a ship they are overseeing. On the other hand, Saffarian et al. [50] discuss that insufficient and poorly designed automation leads to an erratic rise in operators’ workload, which has to be considered in the design of SCCs. In this case, a poor design may provide unnec-essary information which could lead to an erratic increase in operator’s workload, and finally, leads to a higher level of mental workload.

Trust

Researchers have discussed the possibility that the use of automation is likely to increase if humans' trust in systems increases. The perceived reliability, or trust, can be affected by operators' prior knowledge about the level of reliability, knowledge of the automation capabilities, and automation reliability [55]. Research suggests that if inter-actions between humans and machines become more similar to interactions between humans, teamwork between automated systems and humans will be more effective. Nisser et al. [33] suggest that operators' trust in automation is the main factor affecting human–machine teamwork.

In the field of remote ship operation, operators have to trust the sensor information, the autonomous system, and the remote controlled systems. Man et al. [22] discuss the need to ensure these systems are completely reliable so that operators will trust them completely. This raises the question as to how systems can engender such trust and how much trust is appropriate. Saffarian et al. [50] found that drivers who use adaptive cruise control over-rely on the system because they put excessive trust in it. A similar situation is possible with remote ship operation.

Kari et al. [29] considered the factors that affect the operators' trust in systems. They found that training programs affect the trust between operators and the automated sys-tem, suggesting that SCC operators should be trained well. On the other hand, high reliance on autonomous systems and sensor information over a long period of time leads to skill degradation. This issue requires attention because humans will act as a backup system even for ships with the highest level of autonomy.

Boredom

SCCs operators have to look at screens for several hours, which can lead to a high level of boredom. A study of operators of remotely piloted aircraft [37] found that 92% reported "moderate" to "total" boredom compared to 62% of sensor operators. Likewise, Wahlström et al. [23] highlighted boredom as a human factor challenge for unmanned ship operations.

Fatigue

A study that assessed fatigue indicated that UAV teams consisting of a pilot, sensor operator, and maintenance personnel show greater levels of fatigue than the crew of a manned aircraft [16]. However, another study found that operators consider remote monitoring and the shore control of unmanned vessels as a process full of "compliancy and relaxation". This study also highlighted that information overload is a problem [22].

Research on automated cars and automated driving shows that automation leads to a reduction in drivers' workload, but this leads to passive fatigue among drivers, leading to a reduction in overall performance [56]. Remote ship operators are also at risk of active and passive fatigue. Desmond et al. [57] describe active fatigue as a situation which "is derived from continuous and prolonged, task-related perceptual-motor adjustment". Active fatigue was highlighted by Saxby et al. [58], as a state which is associated with high cognitive workload. This situation can occur within an SCC during situations involving monitoring more than one vessel, accidental situations and high levels of workload. On the other hand, Desmond et al. [57] argue that "passive fatigue appears over several hours of doing what appears to be nothing at all", especially during system monitoring. This situation implies that SCC operators can be exposed to passive fatigue when SCC is only under the monitoring mode or they just monitor one vessel without any specific activity. The hu-man machine interface is another key factor in this field; for example, using multiple screens and insufficient furniture could also lead to a higher level of fatigue. In addition, Zhang et al. [30] argue that excessive fatigue is an important factor that leads to failure in emergency response processes.

Skill Degradation

Using autonomous systems over a long period of time may cause the operators' skill to degrade. A study of UAV operations highlighted this, stating that complacency and overconfidence are the main problems that experienced operators can have [33]. Operators who execute the same job for a long time think that they can perform the procedures and checklist operations by heart, which can lead them to miss a significant step in emergency situations and can blind them to hazards [16]. This situation refers to skill degradation in an automated environment over a long period of time, similar to auto-mated driving and automated mining domains.

Remote ship operators are at similar risk of skill degradation. During remote and autonomous operations, vessels are under constant human control and monitoring. Hence, a human is in the loop in all modes of unmanned and autonomous operations and may take full direct remote control over the ship even at the highest level of autonomy. This implies that humans must always be prepared to take over operations. However, high reliance on autonomy for a long period of time degrades operators' skills.

Human Machine Interfaces

Generally, human machine interfaces are an important factor supporting proper decision making in automated systems, introduced by the industry 4.0 concept to improve work conditions and enhance productivity. Hence, human–machine interfaces should provide collected information to the operators in the most user-friendly way possible [59]. In SCCs, human machine interfaces mostly refer to ergonomics. The organization of SCCs significantly imperils good ergonomics. The size and number of screens and design of automated and remote systems directly affect operators' performance. Waraich et al. [35] proposed four subcategories of ergonomically acceptable collaborative work systems that exist in SCCs: installed systems, input devices, furniture, and visual displays. Indeed, during the remote operation of UAVs, the operator interface is defined as a preliminary facilitator of human machine interactions and coordination, in addition to human human communication and coordination. Smooth UAV operation requires an interface which provides an adequate level of awareness, aimed at reducing information overload, miscommunication, distractions, and coordination breakdown [39].

A study comparing various human machine interfaces to onboard ship handling equipment found that participants considered SCC simulators to be ideal human machine interfaces because they use a joystick handle rather than a mouse. Participants suggest that the use of simulators as a human machine interface in SCCs would provide a 3D visualized environment in order to improve ship sense. However, researchers found that such a visualization would not provide adequate SA [22]. Wahlstrom et al. [23] discuss various solutions which could be applied in SCCs, such as a "large shared display" and "shared screen" that could be utilized in order to maintain shared awareness.

The 58th NAV session [27] prioritized various solutions to improve e Navigation processes, such as improving and harmonizing bridge design to make it more us-er-friendly and the presentation and integration of available information in graphical displays which were received from communication facilities. Burmeister et al. [10] and IMO [28] highlight the same human machine interfaces issues. These solutions are also critical in the design of SCCs because when humans start to interact with machines, an inefficient human machine interface may lead to various human factor challenges such as a higher level of fatigue, greater communication challenges, and distraction from nav-igational and monitoring tasks.

Lack of Direct Sensory Information

Industries are investing in smart technologies and are deploying sensor networks to collect data for supporting decisions. Nardo et al. suggest leveraging the industry 4.0 concept to collect data about the health status of equipment to predict safety incidents and avoid possible accidents [60]. In remote ship operations, there is no direct, physical connection between the ship and operator, and operators receive no direct information from the vessel's surroundings. This may lead to a loss of kinetic feeling and visual perception [22]. This lack of direct sensory information is one of the important human factor challenges in the field of remote ship operation. Porathe et al. [7] stated that ship sense is not only about the collection and use of presented information by the navigational equipment. Furthermore, they wrote that some tasks are mainly visual, for instance navigating in close proximity to other objects or harbor maneuvers. This refers to the challenge related to the lack of direct sensory information during remote ship operation via the SCC. This factor primarily affects SA.

Studies in other domains also reference the lack of sensory information. A study of UAV operations identified distance and the resulting loss of sensory information about obstacles as factors that hinder optimal human performance [16]. Studies of remote container crane operations also highlight this challenge [43, 45].

Communication Challenges

A reliable communication system is a significant challenge in SCCs, and misunderstandings especially in interactions with the crew of other ships—might occur due to lags in VHF communication, poor communication links, and language issues [7].

Man et al. [22] found that SCC operators observe a gyro and other sensors in shore-based unmanned ship handling, but the question is, are these sensors in real time? A concern for separation between operators and vehicle is data transmission delays, which lead to delays in operators' responses. A study of UAV operation discussed time delays during communication between operators and UAVs which could affect operators' feedback [36].

A study of the use of a telerobotic for space discussed the issue of communication latency due to the large distance. This latency refers to the time delay between the human brain, sensor and telerobotic effector [41]. This problem can be applied to SCC operations. Immediate operation of the ship can be challenging due to the long distance of com-munication; although the distance on the earth is less challenging than in space [23].

Another form of communication is strictly human human. Remote operators might not understand the local people, patterns of activity, their aims, or even their language, which leads to problems in some situations [23]. Language skills have been identified as essential for operators in e-navigation processes [28]. Linguistic problems are likely to arise during remote ship operations due to operating the vessel across long distances.

The 85th session of IMO [28] identified robust and effective communication between ship and shore as being a significant requirement among high level users in the field of e-navigation. Researchers found that effective communication between vessels and the shore reduces linguistic challenges and distractions of operators. In a study of the communication between ship, shore and shore support, officers were distracted from their navigational tasks due to extreme reporting requirements during e-navigation. They should avoid double reporting and harmonize all these communications; this leads to more time for navigational tasks in order to increase safety. On the other hand, most of the officers preferred to use broadband satellite communications for ship shore communications to keep VHF communications free for emergency safety communications [10].

The review of the literature on communication challenges suggests that sensor information in the SCC should be harmonized in order to avoid distracting operators from their monitoring and controlling tasks; this issue affects operators' responses, especially in emergency situations. Just as operators prefer to keep VHF channels free for emergency safety communications, SCCs require specific communication channels between the ship and shore to increase safety, especially for ships in the fail to safe mode. It is clear that SCCs should utilize wireless and satellite communications in order to communicate and control the vessels. The technical aspects of implementation may be complex, but it is vital to manage and harmonize these communications in SCCs in a way that prioritizes hu-man machine interactions. It is notable that the quality of communication channels in SCCs affects the level of SA and the process of decision making as well.

Decision Making

This human factor issue is derived from both human human and human machine interactions. Different types of technology, human machine interfaces, communication channels, level of situation awareness, and sense of ship affect the process of decision-making. Man et al. [24] discussed challenges and gaps that prevent teams and individuals from gaining appropriate SA in order to make decisions during the remote monitoring and controlling of unmanned ships. A study of UAV operations showed that obstacles to understanding the situation in hand led to poor decisions [33].

On the other hand, the onboard autonomous system has to provide adequate in-formation for operators in SCCs because operators' decisions depend on the provided information. For instance, one study drew attention to the problem that SCC operators may pay attention to information that is wrong or does not matter, wasting energy [22] and, hence, making poor decisions.

A study of remote ship operation argued that "intelligent decision-making capability" is a key element in automatic simulation systems and automatic ship navigation systems, which affect collision avoidance maneuvers and the planning of routes.

In traditional maritime navigation, a human pilot is responsible for assessing the situation and making the safest decisions, while an automatic ship navigation system is designed for autonomous navigation in a safe and efficient manner without human intervention or to guide navigators' decisions [25]. Danial et al. [61, 62] implemented a Markov logic network to model SA primarily for fire accidents and the emergency evacuation of offshore platforms. Through doing so, software agents created a method of simulating different behaviors in different situations in order to improve decision-making by facing trainees to different situations in a virtual training environment. Smith et al. [63] proposed a methodology to capture the knowledge of expert seafarers and establish a knowledge database to improve decision making capabilities by providing the best operating practice for offshore ice management. They stated that seafarers make the decision and choose their strategy based on different techniques and prescribed approaches they learned from training. This indicates how the operator's decisions are derived from situation awareness and local information which they gathered during the operations. However, in remote ship operations, decision-making occurs specifically in control centers.

Another study identified the challenges of creating a successful training simulator in order to train conning officers. One of the main challenges is the "readiness of response" of the automated boats when they face new situations which require controllers to act in real-time when they carry out the assigned task [26]. Actions in real time could be affected by different factors, although, ultimately, this leads to a real-time decision. Thus, human machine interactions and response times are also important in the context of decision making for unmanned and autonomous vessels.

The quality of human human interactions between operators, supervisors and the situation team also influence the process of decision making. When the autonomous vessel switches to full direct remote control, situation awareness and human interactions within the situation team significantly affect decision-making processes. Factors such as stress, memory limitations, and a dynamic environment could very easily disturb decision making and human cognitive work [33]. Furthermore, Porathe et al. [7] discussed delays that may occur due to SCC operators taking a long time to find out what is happening; this refers to the human out of the loop syndrome which affects the decision-making process. In another study, some remote crane operators explain that in unexpected situations, they stayed calm before making a decision [45]. Overall research implies that operators' decision-making is a process that is affected by both human–human and human–machine challenges during remote ship operations.

Cultural and Linguistic Problems

Communication challenges and misunderstandings during the interaction between autonomous and unmanned vessels with manned vessels might occur due to bad communications [7] and the organizational climate. This issue was highlighted by Wróbel et al. [31] as a working atmosphere which comprises structure, policies and culture within the organization. The organizational climate, which refers to the atmosphere of the organization which encompasses relationships, cultures, policies, and command and control structures. Past research suggests that problems with organizational values and culture have led to UAV accidents [16, 64].

Making and protecting a human centric culture is the way to create a peaceful atmosphere in an organization [16, 64]. The study of the Nogales UAS accident showed that a culture of "working around" previous failures was a factor. This culture led to the poor documentation of maintenance procedures, which created a lack of adequate information about the corrective process [32]. In relation to UAV operation, [38] a "model aircraft culture" was identified, in which radio control hobbyists usually perform operating and maintenance processes without formal checklists or procedures. They conclude that this culture must be changed if hobbyists are to join the UAV industry through the provision of training to change their habits and work culture.

The research suggests that cultivating an effective culture and sufficient linguistic skills among the teams that operate in SCCs is vital for the safety of remote ship operation. Whereas onboard crews travel based on the voyage-plan and are more familiar with different cultures and languages, remote ship operations will confront cultural and linguistic challenges that are not present in onboard operations.

Teamwork

Teamwork is the product of human human interactions between operators, supervisors, and the situation team inside the SCCs. It includes the integration between attitudes, knowledge, and certain skills that leads to members adapting and optimizing their performance [33]. According to Kari et al. [29], human interactions between operators affect the whole performance of a remote control system in both a positive and a negative way. A study of UAV accidents highlights the role of crew/team leadership and super-vision. Supervisors are responsible for guidance, leadership, motivation, steering team members toward training opportunities, and serving as effective role models. Researchers argue that UAV operators make more mistakes if supervisors fail to obtain these goals [16]. It seems likely that teamwork and supervision play an important role in SCCs.

Various factors, such as the organizational culture, may also affect the performance of teams. Team performance has a direct relationship with the process of decision making, in that SCCs are organized such that operators monitor ship operations and engineers assist them, when required. Furthermore, in remote control mode, the situation team take direct remote control over the vessel. Hence, teamwork is another significant human factor issue in the field of remote ship operations.

Relationships between Human Factor Issues

Table A .3 presents relationships between human factor issues in the context of remote ship operations and how these issues affect each other and human interactions. It high-lights decision making as a human factor issue that is highly integrated into the context of SCCs and reflects the impact of other human factor issues. In Table A .3, only the human factors that affect each other are presented. The negative and positive relationships between these issues are identified as well. Some human factors can have both a positive and negative effect on each other. For instance, good teamwork via effective work with team members, commitment to team processes and success [65]—derived from high-quality human human interactions—can positively affect the different aspects of decision making. In this respect, good teamwork does not include jealously [66] between the SCC operators, captain, and engineers, is centered around improving communication and takes all team members seriously [66]. On the other hand, poor teamwork can lead to poor decisions within an SCC.

The authors analyzed the literature and extracted the relationship between human factors. This information can provide knowledge in relation to the importance of each human factor and, therefore, it could form a baseline for future studies. For instance, the quality and design of human machine interfaces can affect the level of SA, workload, communication challenges and also decision making. Robert et al. [66] highlighted suitable data presentation at the human–machine interface as one of the technological aspects of decision making. This implies that good design and efficient human machine interfaces may solve a wide range of problems regarding communication, workload, level of SA and decision making.

As seen in Table A .3, a lack of direct sensory information leads to a lower level of SA. On the other hand, low level of SA and a lack of direct sensory information negatively affect the technological aspects of decision making [66]. It is clear that a high workload is one of the most significant factors that increases the operators' fatigue, while it also has a negative effect on certain aspects of decision making. Linguistic problems are another human factor issue that increase communication challenges, and finally, negatively affect the operator's decisions due to a lack of communication skills, misunderstanding or having no meaningful interpretation of the meaning of the words. This is highlighted by [66] as one of the human aspects of the decision making process. Skill degradation as a consequence of the high level of trust in automation is another factor that leads to inefficient decisions in control centers. Culture is another human aspect of the decision making process which can affect the operator's decisions. The quality of decisions, especially within a team, depends on the culture. For example, an individual may act according to his/her own experience, high ranking people, friends, or the regulations given [66]. Finally, a level of high reliance and trust in automation may result in procedural errors or out of the loop syndromes that can lead to irrational behavior and in-efficient decisions. In this respect, Robert et al. [66] refer to Sheridan's idea that individuals require trust for rational behavior, decisions and acceptance of automation.

A .5 Conclusions

Remote ship operations eliminate the role of humans in guiding ships on board, but they do not eliminate the human factors involved in monitoring and even—when nec-essary—controlling them, as human operators provide these interventions from the SCC. This paper provides insights for the design of SCCs and the understanding of humans as a critical sub-system in the context of remote ship operations. Remote operators have to gain an adequate level of SA and sense of ship during monitoring and controlling the vessel in order to make effective decisions. Hence, onboard autonomous systems need to provide updated data to the SCC via sensors and satellite communications, which leads to other human factor challenges such as communication problems, latency, lack of direct sense of ship and higher workloads compared to onboard operations.

Current forums of autonomous and unmanned vessels state that operators in SCCs will be assigned to monitor more than one vessel. While the situation team would take full direct remote control of one vessel in specific situations, operators would be exposed to a high workload, which is a human factor issue in need of greater attention. On the other hand, it is clear that the working environment in the SCC is completely different from the traditional onboard bridge and there is no direct connection between the operators and the vessel. SCC operators rely on sensor information and only onshore instruments; they have to work with screens and new types of interfaces. This implies the importance of human–machine interactions and how human–machine interfaces affect the operator's behavior. Additionally, human machine interfaces have a direct effect on the level of operator's boredom and fatigue in addition to workload and working hours.

Trust in the SCCs is another human factor issue; the main challenge is operators' trust in sensor information and eliminating factors that negatively affect the operators' trust. On the other hand, a high level of trust over a long period of time leads to another human factor challenge, namely skill degradation. Situation team

Table A .3: Relationship matrix (relationships between human factor issues).

	SA	Teamwork	Skill Degradation	High Level of Workload	Communication Challenges	Decision Making
SA						Low level of SA has a negative effect on decision making
Teamwork						The efficiency of teamwork can affect the decision making process both negatively and positively
Skill Degradation						Skill degradation affects the decision making negatively
High Level of Workload						High workload affects the decision making negatively
Boredom						Operator's boredom affects the decision making negatively
Communication Challenges		Communication challenges have negative effect on teamwork				Communication challenges affect the decision making negatively
Lack of Direct Sensory	Lack of direct sensory information affects the level of SA negatively				Lack of direct sensory information leads to communication challenges between shore and ships	Lack of direct sensory information has negative effect on decision making
Human machine Interfaces	Inefficient human-machine interface affects SA negatively, however, efficient human-machine interfaces affect SA in a positive way.			Inefficient interfaces affect workload negatively, efficient interfaces affect workload positively	Inefficient interfaces affect communication negatively, efficient interfaces affect it positively	The efficiency of the human-machine interface affects decision making positively and negatively
Fatigue						fatigue affects decision making negatively
Cultural Problems		Cultural problems affect teamwork negatively				Cultural problems affect the decision making negatively
Linguistic Problems	Linguistic problems affect effective teamwork negatively			Linguistic problems increase communication challenges	Linguistic problems negatively affect decision making	
trust			High trust leads to skill degradation over long period of time			High level of trust affects the decision making in a negative way

operators must be able to take full remote control over the vessel when needed, but this is infrequent. Decision making and teamwork also influence the process of monitoring and controlling the vessel in SCCs. Other human factor issues affect decision-making both directly and indirectly. The 13 identified human factor issues in the current study are as follows:

1. Situation Awareness (SA)

2. High workload

3. Trust
4. Boredom
5. fatigue
6. Skill degradation
7. Human–machine interfaces
8. Lack of direct sensory
9. Communication challenges)
10. Decision making
11. linguistic problems
12. Cultural problems
13. Teamwork

Most of the human factor challenges have been identified based on suggestive models and qualitative research conducted in remote control domains. Although few human factors have been tested in the real world with large and quantitative samples, this study provides a new perspective for human factor models, and future research should address experiments in the real world with large samples. In addition, this study focused on human factors affecting operations of shore control centers, which can be extended to investigate human factors affecting the safety of remote ship operation. Simulator experiments will also help to assess and evaluate the role of human machine and human human interactions, and the impact of each human factor issue. Additional research should also be conducted to identify methods for addressing problems related to human factor issues in SCCs.

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B Paper B: EEG Application for Human-Centered Experiments in Remote Ship Operations

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Abstract

Electroencephalography (EEG) is an exceptional technique in order to study human behavior via neurocognitive processes. EEG can be utilized in different domains to study the neurocognitive processes behind human-machine interactions. Furthermore, remote ship operations are an innovative approach in the maritime industry to improve the efficiency of operations. However, in the Shore Control Center (SCC), human-machine interactions are challenging and highly important in order to implement successful remote ship operations. In this respect, human operators are key components of the SCCs; performance and efficiency of their interactions directly affect remote monitoring and remote controls. Hence, the present study introduces the EEG EPOC Flex in order to objectively investigate human interactions. The current paper focuses on operator's stress in different levels of workload within the SCC. In effect, EEG will facilitate investigating human factor issues that may affect operators' interactions in the SCC. The result of this study can help SCC designers to design an efficient environment for SCC operators.

Keywords:Remote operations; Ship; EEG; Human experiments

B .1 INTRODUCTION

Today, studying the underlying mechanisms of human behavior is the center of interest for many researchers in different fields, especially for automated environments and remote-controlled vessels. Thus, different types of Human Factor Engineering (HFE), Human-Computer Interaction (HCI), and affective engineering experiments have been performed [1], [2]. While the concept of remote-controlled vessels and remote ship operations are in their early stage, study the human interactions will significantly improve the functionality and value of remote ship operations. Although the autonomous vessel might be in the form of an unmanned vessel, human operators still play an important role in the unmanned systems [3] within the SCC. In this respect, operators' stress due to information overload is one of the important identified human factor issues; because one SCC operator has to deal with several vessels at the same time [3], [4]. According to the communication requirements for an unmanned vessel, remote control and remote monitoring are two important control modes within the SCC [5] where humans play a critical role to monitor and control the vessels from distant locations.

The concept of SCC relies on a manned shore-based control center which is responsible for the ship operation. In this scenario, difficult or critical remote ship operations will be conducted by the SCC [5]. However, in order to decrease the workload on the SCC operators, assure the safety, or in the case of the limited or loss of the communication between the vessel and SCC, the vessel must be able to perform the normal operation without human supervision. There are several fails to safe strategies that are programmed and updated by the SCC and the vessel can enter one of the possible strategies when SCC cannot respond [5].

According to the concept of remote ship operation and SCC, the crew will be relocated from on board the vessel to shore-based control centers, and they will perform different tasks based on the organization and control modes of the SCC. This relocation does not mean the elimination of the human factors or solving all human errors; by contrast, more questions regarding human factors and human interactions will be raised, because SCC operators have to take the full control over the vessel at any time [4]. In addition, the SCC operator is defined as an Officer of Watch (OOW), who is responsible for monitoring the vessel at any time and interevent if needed [6]. This is highlighted in the remote monitoring mode of SCC as well [5].

Thus, human operators are key components of the SCC and their performance and efficiency directly affect remote ship operations. This implies that study the human-human and human-machine interactions are highly important in order to implement remote ship operations. In this respect, Electroencephalography (EEG) is a special tool that can be utilized for quantifying human interactions and study the neurocognitive processes underlying human behavior [7]. Although there are various studies that investigate the behavioral interactions in a qualitative manner, using physiological sensors especially EEG leads to quantify human interactions. EEG records brain waves and electrical activities by using electrodes on the scalp. Electrical activities of the brain indicate that how is the communication between different neurons in the brain network through electrical impulses [8].

The current study presents the application of EEG EPOC Flex in order to objectively investigate human factor issues affecting SCC operators. According to [9], there are different types of issues that affect human interactions during the remote ship operations especially within the SCCs. For example, a high level of mental workload and a lack of direct sensory. On the other hand, the main hypothesis of the successful implementation of the Human-Machine Interface (HMI) within the SCC introduces an SCC operator as a person who has to be able to monitor and control up to six vessels at the same time [10]. In this respect, the current paper focuses on using EEG EPOC Flex for measuring the stress of SCC operators during the remote monitoring and remote ship operations in different levels of workload. The paper presents stress as a dependent variable and workload as an independent variable, which can be manipulated during an EEG experiment.

Developing this type of human-centered experiment leads to the study of human interactions in a quantitative manner, which can boost the acceptability of results. But, the development process of a human-centered experiment requires fundamental knowledge in various domains, such as psychology, physiology, engineering design, electro-physics, and neuroscience [2]. This increases the complexity of the development process, especially when the experiment is to be designed from scratch and there is no clear experiment precedes for scenarios [2]. Thus, the current paper reviews some aspects of knowledge domains in order to build an EEG human-centered experiment within the SCC. In addition, an example case comprising a high workload and low workload scenarios is presented. The example case is developed based on the wayfaring model; this model supports the early concept creation stage of designing experiments including multi-disciplines and high levels of complexity [2].

The rest of the paper is organized as follows: the definition of remote ship operations and SCC in section II. Electroencephalography (EEG) and its characteristics appear in section III; this section reviews how stress can be investigated by using brain frequencies. Wayfaring model and example case is presented in section IV. Section V discusses the objective and EEG as an explicit tool to design a human-centered experiment regarding the stress of SCC operators. Finally, section VI presents the conclusion and future works.

B .2 REMOT SHIP OPERATIONS AND SCC

Today, technology is generally available to operate a vessel without on board crew, however, several developments and validations are required [5]. According to the definition of remote operation, a machine is under the continuing and direct human control from a distant location [11]. This implies that the concept of unmanned vessels will rely on an SCC, which is responsible for the operation of the vessel based on the different types of vessel and SCC control modes [5].

According to the baseline case from Maritime Unmanned Navigation through Intelligence in Networks (MUNIN), the SCC contains all on land functions, remote bridge, and engine control modules that can be utilized to take the direct control over the vessel in specific cases [12]. Furthermore, the initial voyage planning will be conducted in SCC, and all the voice communication to the vessel will be relayed

Table B .1: Ship indicators in SCC [5].

Indicator	Detailed description elements
Location position	Position, heading, speed, distance from planned as well as position quality flag.
Weather	Wind speed/ direction, wave and swell hight/length/ direction
Visibility	Visibility, radar range and culture. COLREG status of ship
Collision	Vectors to targets, status/heading/ speed of targets
Grounding	Depth measurement
Communication	Critical communication directly to ship, for example on VHF, GMDSS.
Stability	Trim, heel, draft, water tight integrity, void space, water ingress
Environment	Environmental performance and emission to air and sea
Economy	Fuel use and potential for late arrival/ off hire etc
Hull propulsion	Hull and equipment status, anchor, towing, ladders
Propulsion	Engine, auxiliaries, piping, fuel
Electric	Electric power systems, switch boards, emergency power
Safety	Fire, evacuation, extinguishing, escape
Cargo	Cargo status

to the SCC in order to handle by the SCC operators [12].

There are five main ship control modes for an onboard Autonomous Ship Controller (ASC) comprising autonomous execution, autonomous control, direct remote control, indirect remote control, and fail to safe mode [5]. According to different modes of ship control, it can be concluded that SCC will operate in various modes as well. Remote monitoring, remote operation, status investigation, ASC update, and intervention are the main SCC control modes [5]. Generally, the SCC will be in the remote monitoring mode, when all the ship status indicators are normal; in this case, no action will be taken from SCC. The ASC sends a set of ship status flags to SCC at short intervals (for example every 5 seconds). A set of ship status indicators are presented by [5] based on the hierarchical ship function decomposition [13] and the ship functional model [14]. Table B .1 indicates ship status indicators which are critical parameters for the SCC operators in different SCC control modes.

If one of the above indicators shows some abnormality, the SCC will enter to ASC update and investigation modes [5]. Remote ship operation mode is utilized to control the vessel manually when ASC cannot solve the problem in a certain situation. SCC will enter intervention mode when deeper interactions with onboard systems are necessary [5], [12].

B .3 ELECTROENCEPHALOGRAPHY (EEG)

Electroencephalography in short EEG means recording the electric activity of the brain. Most cognitive processes happen within tens to hundreds of milliseconds, this is much faster than the blink of an eye. On the other hand, events, which trigger cognitive processes happen in time sequences that span hundreds of million seconds to a few seconds [8]. EEG similar to a high-speed camera has a high time resolution; hence, it can capture the physiological changes of underlying cognitive processes better than other brain imaging techniques including Positron Emission Tomography (PET) scanners and Magnetic Resonance Imaging (MRI) [8].

The brain is continually active and generates electrical activities that are significantly less than a 9v battery. EEG sensors can pick up weak signals from the surface of the scalp [8]. The international brain research has been gaining important findings regarding EEG and established theories which are well-accepted on how the EEG signals relate to attentional, affective or cognitive processing [8]. The current paper utilized the Emotiv EEG EPOC Flex containing 32 channels. Each sensor records five main brain band powers consisting Theta (4-8Hz), Alpha (8-12Hz), Low beta (12-16Hz), High beta (16-25Hz), and Gamma (25- 45Hz). EEG researchers record the brain's electrical activities via sensors placed at the scalp surface; this applied first to humans by a German neurologist Hans Berger in the 1920s [8]. As the electrical signals are very small, the data is digitized and sent to an amplifier. Then, the recorded data can be displayed as a time series of voltage values [8].

American Encephalographic society (1994) has been provided the most common system in order to define and name the electrode locations/positions on the scalp. This system is called the 10-20 system such that electrodes are placed at 10% and 20% points along lines of longitude and latitude. In the 10-20 system electrode names start with one or two letters showing the general brain region or lobes where the electrode is placed [8].

Electrode's name end with a letter or a number showing the distance to the midline. Even numbers in the right hemisphere, and odd numbers in the left hemisphere. Larger numbers refer to the greater distances from the midline [8]. Electrodes placed at the midline are labeled with "z", which indicates zero distance from the midline. For instance, T7 is placed over the left temporal regions, Fp8 is placed over the right front-polar regions, and Cz is located over the midline central brain region [8].

Table B .2: Summary of EEG studies on stress and workload.

Authors	EEG band	EEG sensors	Results
[26]	Delta, Theta, Alpha, Beta, Gamma	F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF3, F7, AF4	The results indicate the feasibility of EEG in order to detect stress. The highest accuracy was obtained in the alpha band power.
[27]	Theta (fmq) Beta	71 EEG electrodes	Theta (fmq) increased consistently with memory load.
[28]	Beta	FC5, FC6, O1, O2,	Participants in the stress group had the highest level of Beta activity.
[29]	Theta	The locations of 48 electrodes (out of 171) are shown in the study	In more complex mazes there are more theta oscillations. Theta oscillations are more frequent through recall trials compare with learning trials.
[20]	Theta, Beta, Delta, Alpha	FP1, FP2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5, T6, FZ, CZ, PZ, OZ	During the most complex task, delta power increased. Delta only increases when attention to internal processing is required. During the performance of a task, alpha activity was suppressed, but low theta increased.
[23]	Alpha	C4–A2, C3, A1, O2–A2, O1–A1	During the visual stimulation, a decreased in Rhythmic Activity within the Alpha Band (RAAB) happened in occipital regions. During the auditory stimulation, power declined in the central regions.
[30]	Alpha, Beta, Theta	Fp1, AF3, F3, F7, FC5, FC1, C3, T7, CP5, CP1, P3, P7, PO3, O1, Oz, Pz, Fp2, AF4, Fz, F4, F8, FC6, FC2, CZ, C4, T8, Cp6, Cp2, P4, P8, PO4, O2	In the field of spectral centroids, 30 out of 32 electrodes indicated increased centroid frequency during stress (without significant effect). It is argued that negative valence stimuli lead to an increase in the right frontal activities. Besides, left frontal activity indicates the EEG response to positive valence stimuli.
[31]	Theta, Alpha, Beta	Fp1, Fp2, FpZ(prefrontal sites)	Stressful subjects showed a higher level of EEG complexity. The group with chronic stress had higher left prefrontal power. There was a significant difference in relative power of alpha between the normal group and the stress group.
[19]	Theta, Alpha	19 electrodes based on the 10–20 system (including O2, P4, F7)	Upper Alpha is dominant during retention (increasing the memory load). Theta and upper Alpha play an important role during the retrieval.

EEG frequencies

Brain oscillations with the 4-8 Hz frequency range are identified as theta band [15], [16]. Various studies highlight that frontal theta activities are correlated with the difficulty of mental operations; for instance, during learning, information takes up, focused attention or memory recall. In this respect, theta frequencies are more prominent when the task difficulty increase. Hence, theta is usually associated with the processes underlying working memory and mental workload [8], [17–19]. Workload refers to any cognitive process involving executive processes including problem- solving, working memory and analytical reasoning. Workload which is associated with the theta band power, increases in the case of a higher level of task demand and working memory load [8]. Theta frequency can be recorded from all over the cortex, this indicates that it is generated via a wide network involving central, parental, prefrontal and temporal cortices [8]. On the other hand, there is an improvement of theta waves in the case of mental stress. This implies a good correlation between EEG signals and mental stress [20], [21]. Table B .2 indicates a summary of studies on theta and other EEG bands focusing on stress and workload.

Alpha band as a rhythmic oscillatory activity with the frequency range between 8–12 Hz was discovered by Hans Berger in 1929 [15] cited by [8]. The alpha band is generated in posterior cortical areas, comprising parietal, occipital and posterior temporal brain areas [8], however, it is more active in frontal and occipital regions of the brain [22]. Figure B .1 indicates four main brain lobes and their responsibilities. In normal adults, alpha waves can be seen spontaneously during wakefulness and relaxed state [18]. The alpha band is correlated with sensory, memory, and motor functions. During the mental and physical relaxation with closed eyes, there is an increase in alpha band power. By contrast, alpha power is suppressed during mental and body activities with open eyes [8]. In other words, alpha suppression indicates that the brain is preparing to pick up information from different senses, focusing on what really matters in that specific moment, and coordinating attentional sources [8]. This implies that alpha suppression is a valid presentation of engagement and mental activities, for instance during focused attention to different types of the stimulus [23] cited by [8].

Importantly, in the case of no stress, when the brain is performing no activity alpha waves are dominant. In stressful conditions, the alpha power declines to indicate the change in the response under stress [21]. The power suppression of alpha band during the stressful situation is also highlighted by [24]. It is important to mention that in a study regarding functional roles of 10 Hz alpha band power, Magnetoencephalography (MEG) signals similar to EEG signals indicate that alpha oscillations are associated with semantic, spatial and social attention [25].

Oscillations within the range of 12-25 Hz are generally referred to as beta band activities [8], [16], [18]. Beta frequency is generated in both frontal and posterior regions of the brain. Higher beta power is generally correlated to active concentration and busy or anxious thinking [8], [32].

Another study indicates that there is a high beta activity at the FC5 electrode during the stress situation [28]. This means that there is a meaningful correlation between beta frequencies and levels of stress.

Oscillations above 25 Hz are referred to gamma frequencies which usually found during conscious perception. Due to high contamination by muscle artifacts and small amplitude [18]. Gamma frequencies are black holes of the EEG studies. Still, it is unclear that which parts of the brain generate gamma frequencies and what these frequencies reflect. Some studies argue that the gamma band is a by-product of other neural processes, hence, they do not reflect any cognitive processing at all [8]. Notably, high gamma activity in the temporal region is associated with memory processes [18]. Furthermore, some studies report that gamma activity is connected to attention, working memory and long-term memory processes [18], [33].

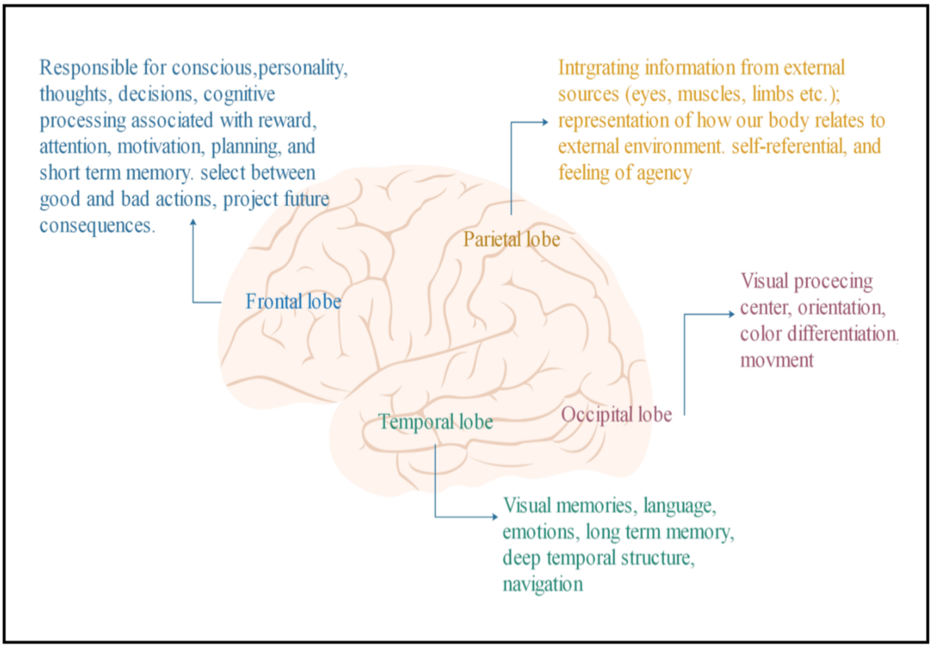

Figure B .1: Brain lobes and their responsibilities

HUMAN-CENTERED EXPERIMENT IN THE EXAMPLE CASE

This part presents an example of a human-centered experiment to study stress and workload within the SCC. The wayfaring approach is applied to the development of the experiment. The current example comprises two scenarios with different levels of workload. The research hypothesis is defined as follows:

H1: There is a significant difference in participant's stress between high workload and low workload scenarios.

Wayfaring approach

Wayfaring model [34], [35] can be utilized as an exploration journey instead of a planning-based approach to discover innovative ideas. The wayfaring model describes that "an optimum new solution to a problem cannot be preconceived as we do not have empirical evidence for the outcome of something that has not previously been done" [2]. In this respect, the model provides a methodology for a practical exploration of the problem and solution. According to [2], this methodology comprises four steps as follows:

1. Probing ideas: the exploration of opportunities, sometimes this phase includes

a low-resolution prototype in order to fail early and to abductive learning.

2. Merging multidisciplinary: comprising all knowledge domains from the beginning to discover interdependencies and develop interrelated knowledge

3. Speed: make a plan based on the short iteration timeframe to maximize the iteration numbers

4. Agility: opportunistically select the next step and let the development process shape the outcome. This phase can be followed in order to achieve serendipity findings and innovation outcomes

Scenario 1

This experiment uses EEG EPOC Flex to record the brain activity of a human operator while monitoring the vessel's operation in the simulation environment. The task takes 10 minutes due to limitations for using EEG EPOC Flex. The instructor room of the navigation simulators will be considered as an SCC and a ship bridge as a remote- controlled vessel. As we can see in Figure B .2, the instructor room is assumed as an SCC where one operator can monitor up to six vessels (SCC remote monitoring mode). In the current scenario, an SCC operator is defined as an OOW. As mentioned before, this person is responsible for monitoring the ship and intervening if required [6]; this means sending high-level commands in specific situations. The ship bridge will be operated by simulator assistants based on the predefined route. In this scenario, SCC operators will fill in a self-report stress survey after they finish the experiment. In addition, the paper-based NASA TLX forms will be used in order to assess the workload objectively.

In scenario number 1, SCC operator will monitor one remotely operated vessel from the instructor room (based on the monitor mode of SCC), and there is a ship-ship communication between the bridge operators and SCC operators. SCC operator is responsible to send high-level commands if needed in the case of accidents, crossing other vessels or harsh weather. In addition, SCC operator has to monitor the radar data, heading, propeller revolution, rate of turn, rudder and speed of each vessel to ensure that all the vessels are in an appropriate status. Independent variable will be manipulated as follows:

1. Area: Kristiansund to Trondheim (low difficulty)

2. One container ship as the main vessel

3. 5+ targets (traffic)

Figure B .2: Simulator instructor room.

4. Good visibility in daylight
5. Moderated wind, calm sea-state
6. No accidental situation

Scenario 2

Actors, environment, and components of scenario number 2 are the same as scenario number 1. The independent variable will be manipulated as follows:

1. Area: Vatlestraumen (moderate difficulty)
2. 5 container ships as the main vessels
3. 15+ targets (traffic)
4. Bad visibility, night time
5. Strong wind, wavy sea
6. Two accidental situation

It is notable that in this experiment physiological baseline will be performed before scenario 1.

B .4 DISCUSSION

Remote monitoring and remote controls have been merged in different types of control modes of unmanned vessels and SCCs. In this respect, SCC appears as a black box comprising human, hardware, software and different types of human-machine interfaces. It is clear that by relocating crew from on board the vessel to SCC, we will face more human factor challenges such as stress and information overloading. Hence, study human interactions within the SCC leads to gain more knowledge about different aspects of remote ship operations and decoding the black box of the SCC. The current paper presented EEG as a remarkable method in order to investigate the stress of SCC operators during the different levels of workload.

Moreover, the paper presented a very simple example case based on the wayfaring approach. The wayfaring model was an appropriate model in order to develop the experiment due to a lack of clear procedures and a high level of complexity. EEG EPOC Flex was defined as a tool to record the participant's brain signals during the experiment. According to the various studies regarding the EEG signals and stress, we suggest theta and alpha frequencies as two important EEG frequencies which can be considered to study stress. During the stressful situation, the power of alpha frequencies falls down, however, the power of theta waves increases. In addition, EEG electrodes in the frontal region of the brain including Fp1, Fp2, FpZ (prefrontal site), FC5 and FC6 can be considered as effective electrodes during the stress evaluation. However, a comprehensive analysis of stress requires considering more EEG electrodes in addition to different band powers.

Developing a human-centered experiment is a challenging task, as fundamental knowledge in the different domains is required. This implies one of the main challenges in developing human-centered experiments, especially in the field of EEG. Using a simulator environment rather than a real SCC is another issue, which can affect the results of the experiment. Furthermore, the availability of participants is another limitation during the human-centered experiments. It is important to mention that in the current high workload scenario, all the independent factors (number of targets, weather, route, etc.) were manipulated aiming to make a significant change in the level of workload; thus, the effect of each factor is not clear. Future experiments can provide more details regarding the independent variable.

B .5 CONCLUSION

In this paper, we studied general aspects of remote ship operations, SCC and EEG in order to a develop human- centered experiment. EEG is presented as an exceptional tool to study stress in different levels of workload within the SCC. Moreover, an example case including high and low workload scenarios was defined by applying the wayfaring approach. The current example case focused on the monitoring mode of the SCC. In this respect, future studies can investigate stress and workload in other SCC control modes. Moreover, future studies can investigate different analysis and pre-processing techniques in order to extract the required data of stress and workload from raw EEG data.

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C Paper C: EEG Based Workload and Stress Assessment During Remote Ship Operations

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Abstract Autonomous and remotely controlled ships present new types of human factor challenges. An investigation of the underlying human factors in such operations is therefore necessary to mitigate safety hazards while improving operational efficiency. More tests are needed to identify operators' levels of control, workload and stress. The aim of this study is to assess how increases in mental workload influence the stress levels of Shore Control Centre (SCC) operators during remote ship operations. Nine experiments were performed to investigate the stress levels of SCC operators during human-human and human-machine interactions. Data on the brain signals of human operators were collected directly by electroencephalography (EEG) and subjectively by the NASA task load index (TLX). The results show that the beta and gamma band powers of the EEG recordings were highly correlated with subjective levels of workload and stress during remote ship operations. They also show that there was a significant change in stress levels when workload increased, when ships were operating in harsh weather, and when the number of ships each SCC operator is responsible for was increased. Furthermore, no significant change in stress was identified when SCC operators established very high frequency (VHF) communication or when there was a risk of accident.

Keywords: Shore Control Center operators; remotely controlled ships; human factors; workload; stress.

C .1 INTRODUCTION

Autonomous ships that can be operated remotely have been envisaged as both safer and as a way of improving maritime operational efficiency while reducing crew-related costs. Several developmental and research projects on this topic are therefore being conducted globally. This technology is still in its infancy, and more knowledge about its operation is required. In remote ship operations, officers are relocated from onboard the ship to Shore Control Centers (SCCs). Technical autonomous ship controllers (ASCs) are placed onboard the ship to allow SCC operators to connect and interact with onboard control systems [1]. The SCC operational modes are a combination of monitoring and control modes [2]. Generally, SCC operators monitor status indicators for weather, location, collision, visibility, engine and propulsion. The control modes include status investigation, ASC updates, remote operation and intervention [3].

However, introducing new approaches to control ships remotely also introduces different types of human factor challenges from those found in traditional maritime systems, with regard to both human-machine and human-human interactions [4]. As a result, the 103rd session (5-14 May 2021) of the Maritime Safety Committee has approved the outcome of a regulatory scoping exercise for the use of Maritime Autonomous Surface Ships (MASS) [5]. At that session, terms such as master, responsible person, crew, remote control centers and remote operators as seafarers were identified as potential gaps in the operation of MASS, which should be addressed before extensive deployments of autonomous ships take place [5]. An investigation of the human factors underlying remote ship operations is therefore necessary in order to mitigate safety hazards while improving operational efficiency.

If the hypothesis that the human-machine interface (HMI) can be successfully implemented is confirmed, it is expected that SCC operators will control and monitor up to six ships simultaneously [6]. These operators will require appropriate levels of control, situational awareness and workloads. To find out what the appropriate levels are, a quasi-experimental project, MUNIN, has tested the hypothesis with data from SCC and maneuvering systems. The results indicate that the hypothesis that HMI can be successfully implemented should be accepted; however, tests of the remote maneuvering system were not fully successful [6]. More tests are therefore needed, and the aim of the current study is to assess how increases in mental workload influence the stress levels of SCC operators during remote ship operations.

To achieve this aim, we first performed a literature review to investigate the human factors which influence monitoring operations. The results of the review were then used to develop a series of hypotheses to (i) identify which types of variables (ship indicators) affect workload during monitoring operations, (ii) verify that workload and stress affect monitoring operations, and (iii) identify whether brain signals captured by electroencephalography (EEG) can be utilized to assess the stress levels and workloads of SCC operators during remote ship operations. Finally, two SCC experiments were performed to analyze low and high workload scenarios.

The remainder of this paper is organized as follows: Section 2 presents the literature review and hypotheses; Section 3 presents the material and methods; Section 4 presents the results of the experiments; Section 5 discusses the results; and Section 6 concludes this study and presents a roadmap for future research.

C .2 LITERATURE REVIEW

Remote Ship Operations

The Maritime Safety Committee of the International Maritime Organization (IMO) approved interim guidelines for MASS trials in 2019 that defined four degrees of ship autonomy. The first degree of ship autonomy includes ships with automated processes and decision support. Onboard seafarers operate and control shipboard functions and systems on ships with the first degree of autonomy. The onboard crew are ready to take control of automated and unsupervised operations [7]. The second degree of ship autonomy includes ships which are controlled remotely by onboard seafarers. On ships of this degree, the ship is operated and controlled from a distant location, but there are also crew onboard the ship who can take control of shipboard systems and functions [7]. The third degree of ship autonomy, the ship is remotely controlled without any seafarers on board: as with the second degree, the ship is controlled from another location, but in this case there are no crew on board. The fourth degree of ship autonomy includes fully autonomous ships which can make decisions and determine the actions to be taken by themselves [7].

It is important to mention that the operation of an autonomous ship can involve a combination of one or more control modes and levels of autonomy during a voyage [2, 7, 8]. For example, operators in the SCC can employ direct remote control when a ship approaches port traffic, in harsh weather or in unexpected traffic situations [9]. Hence, in a ship-shore system with any level of automation, operators (humans) are still involved, but are distributed in SCCs instead of operating conventionally onboard ships [7, 9].

Human SCC Operators

Human SCC operators are defined as officers of the watch who are responsible for monitoring the ship and intervening if necessary [2]. According to the MUNIN project, SCCs will be responsible for most supervisory monitoring and control operations [7]. In the course of a voyage, operators' dynamic navigation tasks are comprised of different aspects, such as: (i) planning the mission, confirmation and designation; (ii) handling critical situations during the voyage; (iii) monitoring the ship's status and health, judging whether the ship needs maintenance and preparing a maintenance plan if necessary [10]; (iv) communicating with other ships and shore elements; (v) maneuvering the ship in ports and waterways, either remotely or from on board; and (vi) gaining experience and learning from the outcomes of operations to improve future activities. Accordingly, the operator's performance depends on three factors: problem recognition, making correct and timely decisions, and acting correctly continuously and on demand [10].

Investigations have clearly indicated that human errors cause the majority of maritime accidents, and this highlights the importance of human factor studies. However, the main question is how human factors should be studied, since human errors do not occur in an isolated environment. Indeed, human errors are intermixed with other problems such as the complexity of human interactions, including human-human interactions and human interactions with other factors in the system [11]. Therefore, several studies [4, 12, 13] have investigated human factor issues that could affect human-human and human- machine interactions during remote ship operations and within SCCs. These studies have revealed mental workload and stress as the human factors with the highest impact on human errors.

Human SCC Operators

The mental workload caused by the various challenges of modern shipping, including complex systems, high levels of automation and decreasing crew sizes, has been identified as the main human factor affecting human performance in this context. This mental workload is cognitive or perceptual and is caused by the amount of mental effort which an operator must expend to perform a task or a series of tasks [11]. Kari et al. [4] have identified that SCC operators with workloads that are too demanding may have difficulties understanding the situation of the ship they are monitoring. Generally, the best operator performance occurs at an intermediate level of mental workload [11].

The operator's stress level is related to situations in which the operator perceives that the available resources are insufficient to manage the task and situation. High levels of stress can lead operators to focus on limited aspects of their tasks and overlook other aspects. As a result, high levels of stress can lead operators to take unsafe and risky actions [11]. This means that a perceived mismatch between the demands of a task or event and an individual's resources leads to an increase in stress levels [14]. Moreover, several studies have indicated that stress and mental workload are strongly interconnected. For instance, it has been found that there is a positive correlation between mental workload and stress, which implies that when operators are exposed to greater workloads their stress levels tend to increase [14].

Related Work

Dussault et al. [15] have studied the effect of mental workload without exposing participants to actual physical risk by using EEG and ECG to investigate the cortical and cardiovascular changes which occur during simulated flight. A total of 12 pilots participated in the experiment, which involved 10 sequences with different mental workloads. The results indicated that theta band power was lower at the central, parietal, and occipital regions of the brain during the two simulated flight rest sequences than it was during visual and instrument flight sequences. In addition, rest sequences resulted in higher beta (at the C4 region) and gamma (at the central, parietal, and occipital regions) band powers than active segments did. In another study, Qing et al. [16] investigated mental workload during the production process by using EEG and Galvanic Skin Response (GSR). Participants were divided into two groups according to whether they were novices or veterans. The novice participants had higher levels of mean voltages in the right hemisphere of their brains for SMR, theta, beta and gamma. This implies that the novice group presented a higher level of mental workload that was reflected by fatigue (reflected by theta band power), awakening level (reflected by beta band power), memory (reflected by gamma band power) and attention (reflected by SMR band power).

Another study, titled "An evaluation of mental workload with frontal EEG", recorded the frontal EEG signals of 20 participants during four activities (arithmetic operation, finger tapping, mental rotation and a lexical decision task) in order to investigate dynamic changes in mental workload. The EEG output indicated that theta activity increased as the difficulty of tasks increased [17]. Mohanavelu et al. [18] used EEG to demonstrate the relationship between dynamic workload and two elements of cognitive workload and attention. A total of 16 male fighter pilots participated in the experiment. The researchers found that alpha band power and both high and low beta band powers, as recorded by the FT10, FP1, FC1, P4, P7, Pz, T8, CP2 and C4 sensors, were more dominant during the cruise phase of the study. In addition, the FC2, FP2, FT10, and C4 sensors indicated more significant levels of total beta band power during the landing phase in comparison with the other workload tasks.

Umar Saeed et al. [19] classified long-term stress with machine learning algorithms which utilized resting state EEG recording signals. They revealed that beta and gamma band powers, as measured by the AF3 sensor, were statistically significantly different in the stress and the control group (with a label assigned by expert evaluators used as the reference).

Research Hypotheses

The current study involves the evaluation of mental workload and stress during remote ship operations using EEG signals. Six hypotheses to assess the level of stress during remote ship operations are proposed.

Kari et al. [4] have identified high mental workload as a human factor issue which affects the performance of operators in SCCs. In SCCs, remote control systems should promote an optimal level of situational awareness by providing a high level of information, which increases the risk of high workload during remote ship operations. The impact of high workload as a primary human factor issue during remote operation has also been highlighted in previous studies [14, 20, 21]. Since we wanted to make sure that our experiments succeeded in manipulating the workload, the first hypothesis tests whether the level of workload was successfully manipulated during the experiments. The level of workload was assessed using the NASA task load index (TLX) to identify whether operators perceived a higher level of workload during the second scenario.

Remote operators can also experience higher levels of stress when they face more demanding tasks and higher mental workloads [11]. This indicates that there are connections between high mental workload and stress [11, 14]. Hence, the second hypothesis of this study is designed to investigate whether operators perceived a higher level of stress when a higher level of workload was imposed on them.

The Autonomous Ship Controller (ASC) sends a set of ship status indicators to the SCC. The SCC operators use these ship status indicators to monitor the overall status of the ship [22]. Two ship status indicators, weather and risk of collision, highly affect the mental workload and stress levels of operators [1, 22]. Van Buskirk et al. (2019) have proposed heavy weather ship handling simulation training to improve the competence of seafarers, because the need to make correct and time-sensitive ship handling decisions in heavy weather increases human stress levels and the risk of error [23]. In addition, Yoshida et al. (2021) have established that weather conditions, such as heavy rain and fog, increase the mental workload and stress levels of operators during autonomous surface ship operations, particularly in highly congested areas [24]. Hence, the third hypothesis is designed to assess the impact of harsh weather on stress levels during remote ship operations.

The human-machine interface (HMI) can greatly affect human performance during interactions with machines. Since SCC operators receive all their information from the HMI, the HMI's design may affect the human operators' performance during remote ship operations. Moreover, a well-designed HMI can facilitate access to processable situational information, which decreases the level of stress that operators are exposed to during remote ship operations [25]. In addition, there is a significant probability of human errors associated with HMI, and human errors associated with HMI will highly affect performance factors such as stress during the operation of autonomous ships [26]. Hence, the fourth hypothesis is designed to investigate the impact of HMI on the stress levels of operators during remote ship operations.

Radio communication (voice over VHF) is a standard method of communication between remote operators [14]. Distorted communication and background radio communication have been identified as two main factors which create stress for aerial firefighting pilots during training [21]. Moreover, levels of theta, alpha and beta EEG band powers in the posterior and left front-central areas of the brains of air control traffic operators seem to increase during stressful radio communication with airplane pilots [27]. During stressful radio communications, the number of clear speech events on the part of air control traffic operators is reduced, probably due to faster pronunciation [27]. Hence, the fifth hypothesis is designed to investigate how VHF radio communication impacts the stress levels of operators during remote ship operations.

Operators must be completely focused to avoid collision risks when investigating the vectors, status/heading and speed of the targets depicted by the collision indicator [22]. Perceived collision risks seem to increase the stress level of operators because of anxiety about collisions or the difficulty of performing collision avoidance navigation in close head-on or crossing situations [28]. Hence, the sixth hypothesis is designed to assess the impact of situations in which there is a risk of accidents on operators' stress levels.

In summary, this study will test the following hypotheses:

1. There is a significant change in the level of workload between the first and the second scenario in the experiments.
    - Corresponding null hypothesis: there is no significant change in the level of workload between the first and second scenarios in the experiments.
2. There is a significant change in stress when workload increases.
    - Corresponding null hypothesis: there is no significant change in stress when workload increases.
3. There is a significant change in stress when ships are operating in harsh weather.
    - Corresponding null hypothesis: there is no significant change in stress when ships are operating in harsh weather.
4. There is a significant change in stress when the number of ships increases.
    - Corresponding null hypothesis: there is no significant change in stress when the number of ships increases.
5. There is a significant change in stress when operators establish VHF communication.

  - Corresponding null hypothesis: there is no significant change in stress when operators establish VHF communication.

6. There is a significant change in stress when there is a risk of accident.

  - Corresponding null hypothesis: there is no significant change in stress when there is a risk of accident.

C .3 MATERIALS AND METHODS

In this study, a series of experiments was performed to evaluate the impact of workload and stress on operators of SSCs and thus to evaluate the proposed hypotheses.

Instruments - EEG and NASA TLX

Generally, workload and stress are measured subjectively by means of interviews or questionnaires. However, it is also possible to investigate changes in brain activity directly by using tools which measure biological processes. In this study, both direct and subjective measures were used. EEG was used for direct measurements and the NASA TLX system was used for subjective measurements. NASA TLX was mainly employed as a supportive technique to verify that manipulation of the workload, the independent variable, was successful and that participants were exposed to a higher workload in the second scenario.

EEG is used to record human brain signals, and our previous study showcased the applicability of EEG to the assessment of the stress levels of SCC operators under different workloads [29]. EEG records the electrical activity of the brain using electrodes, also called sensors. The electrodes are attached to the scalp to record the electrical potential generated by the brain [30]. Types of EEG systems differ according to the type of connection between the electrodes and the scalp surface; these types include dry and wet electrode EEG systems. Wet electrode EEG systems include gel, saline and semi-dry or water-based systems [30] and require the use of electrolytic liquid to improve conductivity. The EMOTIV EEG EPOC Flex saline kits which were utilized in this study are comprised of 32 electrodes. The EMOTIV EEG cap uses electrodes in the following locations: AFz (driven right leg), FCz (common mode sense), Fp1, Fp2, F7, F3, Fz, F4, F8, FT9, FC5, FC1, FC2, FC6, FT10, T7, C3, Cz, C4, T8, CP5, CP1, CP2, CP6, TP9, TP10, P7, P3, Pz, P4, P8, O1, Oz, and O2 [31]. The EEG EPOC FLEX passes signals through a few stages of processing. First, it processes data to remove sharp spikes, then passes data through a high-pass filter to remove the DV offset and slow drift. It then applies a Hanning filter before performing a fast Fourier transform (FFT). Band power is calculated from the square of the amplitude in each frequency bin and output is presented as uV^2/Hz.

Table C .1: Types of workload and stress variables and how they were manipulated and measured.

Variables	Type of variable	Manipulation	Measurements
Workload	Independent	Number of targets, number of ships to be monitored by the SCC operators, difficulty of the route, weather, other events such as accidents	NASA-TLX technique Self-reporting questionnaire
Stress	Dependent		Physiological measurements of stress Raw EEG data Self-reporting questionnaire

The NASA TLX system was developed by NASA Ames Research Center in the 1980s and is used to subjectively assess the workload of human operators working with human-machine interaction systems [32]. The NASA TLX is comprised of two instruments, a self-reporting questionnaire and comparison cards, and measures overall workload as the mean of weighted ratings. The self-reporting questionnaire is comprised of six questions, answered on a scale of 1-7, which are designed to assess levels of perceived workload and stress. The measurement of workload includes six subscales reflecting the independent variables mental workload, physical workload, temporal demand, frustration, effort and performance. The NASA TLX is based on an assumption that some combination of the aforementioned variables is likely to indicate the workload [33]. In the NASA TLX form, participants rate the performance questions from "perfect" to "failure", and other questions from "very low" to "very high" [34]. The comparison cards include the same six variables, and participants are asked to choose one item in each card.

The experiments

The experiments were performed in the navigation simulators of Norsk Maritim Kompetansesenter (NMK), a department of the Norwegian University of Science and Technology, Alesund, Norway. Three healthy male participants with no psychiatric problems or neurological disorders, participated in the experiments as SCC operators. The participants worked in the maritime domain but were not experts in the use of simulators. Before the experiments started, they were informed about the process and received written instructions for the experiments. In addition, in-

Figure C .1: A participant reading a book in a calm and quiet environment to establish baseline EEG brain activity.

formed consent was obtained from all subjects involved in the study. During the experiments, navigation simulators were used to represent an SCC (specifically the instructor room) and three ship bridge simulators were used to represent remotely controlled ships.

During the experiments, workload and stress were considered to be the independent and dependent variables respectively. On the basis of the status indicators in SCCs [22, 35, 36], the independent variable was manipulated by changing the number of targets (traffic), the number of ships to the SCC operator had to monitor, the difficulty of the route, the weather, and by introducing accident risks and establishing VHF communication between the SCC and ships. Table C .1 illustrates the manipulation and measurement of the variables during the experiments.

Before the low and high workload scenarios, an initial scenario was performed to establish a baseline for the assessment of the impact of different levels of workload on brain activity, as well as for the identification of the trends and anomalies in the EEG signals. Figure C .1 depicts a participant performing the baseline scenario while the EPOC FLEX was recording the EEG signals of his brain activity. In the baseline scenario, each participant sat in a comfortable chair in a calm and quiet environment and read a newspaper or book for 10–15 minutes.

Table C .2: The high and low workload scenarios.

Scenario	First (low workload)	Second (high workload)
Area	Kristiansund to Trondheim (low difficulty)	Vatlestraumen (moderate difficulty)
Number of ships	Three container ships (three-ship bridge simulators)	Five container ships
Traffic	5+ targets	15+ targets
Visibility	Good visibility in daylight	Bad visibility, nighttime
Weather	Moderated wind, calm sea-state	Strong wind, choppy sea
VHF communication	No	Yes
Risk of accident	No risk of accident	Two risks of accident
Overall workload	Low	High

The content of the low and high workload scenarios, which was discussed and approved in advance by three pilots (as experts in this domain), are presented in Table C .2. Each of low and high workload scenarios were considered as a package of factors that may affect the level of workload perceived by remote ship operators.

Each experiment took 10–15 minutes due to the recording limitations of the EPOC Flex EEG. During the experiments, the EPOC Flex EEG recorded the brain activity of each participant via 32 sensors. Furthermore, a time recorder and a checklist were used to record events in order to synchronize the EEG data with external events. In addition, a video camera recorded activities in the SCC (instructor room) during the experiments to facilitate the correlation of external events with the operators' EEG signals. Each participant filled out the NASA TLX questionnaire and performed the comparison card exercise after each scenario in order to assess whether the workload increased in the second scenario and identify which factors were perceived by operators as demanding tasks during each experiment. In this way, the perception of high workload will be cross-validated by factors that operators perceived as demanding tasks during remote ship operations.. Figure C .2 depicts a human operator performing the first scenario in the SCC, where the human operator was responsible for monitoring a ship.

To simulate the monitoring mode of SCCs, during the experiments participants were responsible for monitoring the status and route of each ship and, if necessary, sending high-level commands to the ship. The participants monitored ships' status indicators, including speed, rate of turn, heading, engine status, rudder status, and propeller revolution. In cases of red alarms, participants were responsible for informing the ships via VHF communication.

Figure C .2: A participant performing the low workload scenario (first scenario) in the SCC.

Since the experiments involved three scenarios for three participants, nine sets of EEG data and NASA TLX self-reporting questionnaires and rating cards were produced. The scores of the rating sheet and rating cards were analyzed to calculate the overall workload.

C .4 Analysis

The EEG signals were analyzed by SPSS and a cloud- based visualization platform (Kibana). The EEG dataset comprised 160 features and a total of 42,084 samples, because signal of each EEG sensor preprocessed to generate five band powers including alpha, low beta, high beta, theta and gamma. Samples in the dataset were thus labeled with a binary value for the workload variable (where 0 = low workload and 1 = high workload). SPSS was used to calculate the Pearson correlation coefficient matrix and a correlation coefficient for each of 160 band powers. The Pearson correlation coefficient matrix was then used to identify which EEG band powers correlated with changes in workload and stress. A cloud-based visualization platform using Elastic Stack [37] was used to analyze the EEG data and identify trends and anomalies. Finally, the EEG data were correlated with workload variables to identify how the brain activity of human operators changes under changes in workload and stress.

The NASA TLX system analysis a two-part evaluation process comprised of rating and weighting processes. There were 15 pair-wise comparison cards for the six scales. On each card, participants circled the member of each pair that contributed more to the workload. In addition, participants filled out the rating sheet with a numerical rating for each scale. The overall workload score for each participant was calculated by multiplying each rating by the relevant weighting factor. Finally, the sum of the weighted ratings was divided by 15 (15 being the sum of the weights) [38].

C .5 RESULTS

The results of the NASA TLX analysis are presented graphically in Figure C .3 to distinguish the overall workloads perceived by each participant after each scenario. Based on the NASA TLX technique, the overall workloads of the first participant were calculated as 3.2 and 18.5 during the low and high workload scenarios respectively. The overall workloads of the second participant were calculated as 7.5 and 11.86 during the low and high workload scenarios respectively. The overall workloads of the third participant were calculated as 5.2 and 16.6 during the low and high workload scenarios respectively. Figure C .3 depicts the calculated perceived overall workload of each participant in the experiments. As can be seen in Figure C .3, all participants perceived a higher level of workload during the second scenario.

The results of a paired samples t-test, including the mean difference, t-value and two-tailed probability of each variable, are presented in Table C .3. According to the sampling distribution of t, the t-value was 4.303 for the two-degree field for the rejection of a null hypothesis, with a 95% confidence interval (CI) and 0.05 significance level. Furthermore, the 0.199 p-value was greater than the 0.05 alpha level, indicating that there was no significant change in overall stress between the baseline and low workload scenarios, with a 95% CI of mean difference [-5.46, 2.12].

The results indicate that there was a significant difference between the baseline and high workload scenarios: the 95% confidence interval [-7.48, -2.51] did not contain zero. In addition, the p-value was lower than the 0.05 alpha level, which also indicates there was a significant difference between baseline and high workload scenarios.

The participants did not report higher levels of stress when establishing VHF communication or when there was an increased risk of accident in the high workload scenario. For VHF communication, a 0.94 p-value that was greater than the 0.05

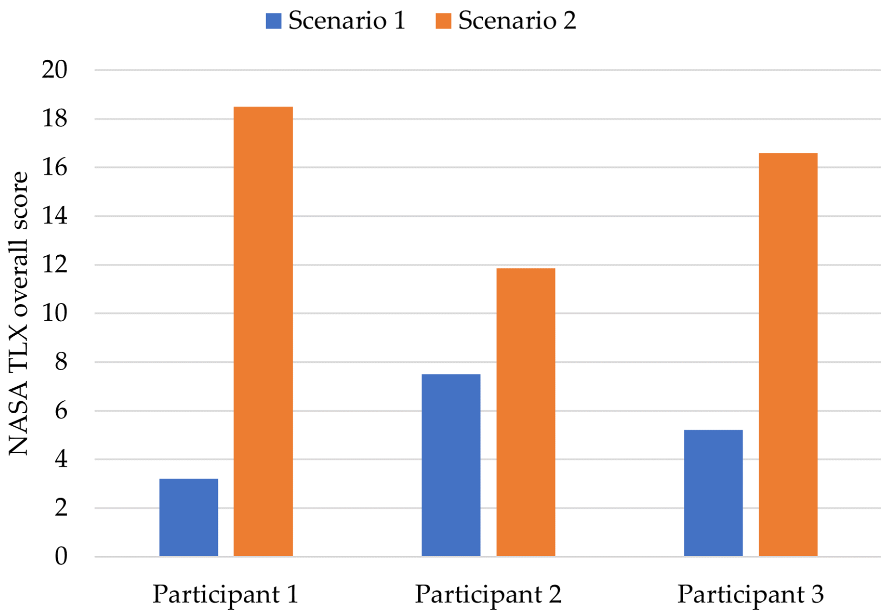

Figure C .3: Calculated perceived overall workload of each participant in the first and second scenarios.

alpha level indicated that there was no significant difference in stress between the low and high workload scenarios during VHF communication. In addition, the t-value (3.024) was less than the critical t-value, which also indicated there was no significant difference in stress between low and high workload scenarios during VHF communication. For increased risk of accidents, a p-value (0.27) greater than the 0.05 alpha level indicated there was no significant difference in stress between low and high workload scenarios when there was a risk of accident. In addition, the t-value (-1.51) was less than the critical t-value, which also indicated there was no significant difference in stress between low and high workload scenarios when there was a risk of accident.

Participants reported higher levels of stress in wavy waters and harsh weather and when the number of ships was increased. For weather, the p-value (0.008), t(2) (11.00) and the 95% CI [-5.10, -2.23] all indicated that there was a significant difference in stress between the low and high workload scenarios. In addition, the p-value was less than the 0.05 alpha level, which also indicated there was a significant difference in stress when the water was wavy and the weather was harsh. For the increase in the number of ships, the p-value (0.02) was less than the 0.05 alpha level, indicating that there was a significant difference in stress between the

Table C .3: Statistical analysis of self-reporting questionnaires.

Variable	Mean. Diff	t-value	Sig.(2-tailed)
Overall stress (baseline-low workload)	-1.666	-1.89	0.199
Overall stress (baseline-high workload)	-5.00	-8.66	0.013
VHF communication	-2.66	-3.02	0.94
Risk of accident	-1.333	-1.51	0.27
Weather	-3.66	0.11	0.008
Number of ships	-4.00	-6.92	0.02
Overall workload	-2.66	-8.00	0.15

low and high workload scenarios. In addition, the size effect (0.86) indicated that there was a positive correlation between the increase in the number of ships and the participants' stress levels.

Participants reported higher levels of overall mental workload during the high workload scenario. The statistical analysis indicated that there was a significant change in the overall mental workload during the high workload scenario: the p-value was 0.15, the t(2) was -8.00, and the 95% CI [-4.10, -1.23] did not contain zero.

Thus, based on the statistical analysis of the NASA TLX self-reporting questionnaires and comparison cards, it can be concluded that two variables—harsh weather and the number of ships—affected the workload, and consequently the stress levels, of the SCC operators in the experiments.

The samples in the EEG dataset were labeled with the corresponding values of the manipulated factors (weather, number of ships, risk of accident, etc). In this study, EEG band powers were considered as dependent variables, while the manipulated factors were considered as independent variables. According to the correlation coefficient matrix, two EEG band powers—gamma and beta—had the highest correlation with the independent variables. This indicates that gamma and beta band powers significantly increased when the number of ships that the participants had to monitor increased. This study follows the Pearson correlation coefficient classification: high ($\pm$ 0.50 $\leq$ high $\leq \pm$ 1), moderate ($\pm$0.30 $\leq$ moderate $<\pm$0.50) and low correlation ($\pm$0.1 $<$low $\leq \pm$0.29). Figure C .4 depicts the EEG sensors with high (purple), moderate (green) and low (blue) correlations with the weather and ship number variables in a 10–20 EEG sensor placement system. Figure C .4.a illustrates that EEG sensors for the first participant had low correlation with the number of ships and with weather status. In Figure C .4.a, sensors with low

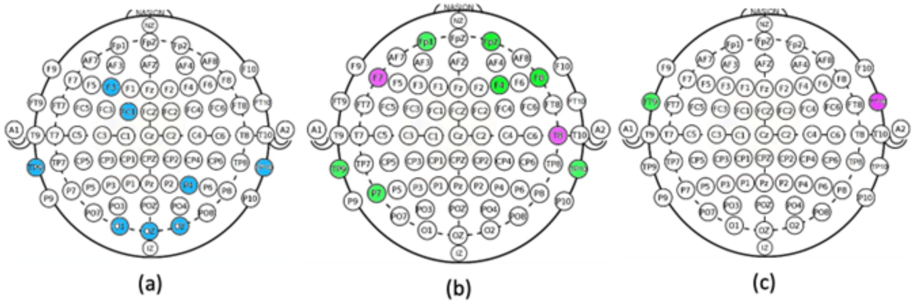

Figure C .4: EEG sensors that indicated high (purple), moderate (green) or low (blue) correlations with increases in workload and stress; (a) denotes participant 1, (b) denotes participant 2, and (c) denotes participant 3.

correlation to these two variables, including F3, FC1, TP9, TP10, P4, O1, Oz and O2, are colored in blue. Figure C .4.b depicts the EEG sensors for the second participant which had moderate and high correlations with the number of ships and with weather status. Sensors with high correlation, including F7 and T8, are colored in purple, while sensors with moderate correlation, including Fp1, FP2, F4, F8, TP9, TP10 and P7, are colored in green. Figure C .4.c depicts the EEG sensors for the third participant which had moderate and high correlations with the number of ships and with weather status. In Figure C .4.c the FT9 sensor with moderate correlation is colored in green, while the FT10 sensor with high correlation is colored in purple.

Figure C .5 depicts the EEG signals of beta and gamma band powers recorded during the experiments, where the first, second and third graphs illustrate baseline, low workload and high workload scenarios respectively in each sub-figure. The levels of EEG measurements were different in each scenario where sensors with moderate and high correlations presented considerable brain activity changes than sensors with low correlation. Hence, Figure C .5 depicts brain activity levels in each scenario for the low (participant 1), moderate (participant 2) and high (participant 3) correlation group of sensors. Figure C .5 illustrates the level of changes for low, moderate and high correlation sensors therefore sensors were selected randomly for demonstration of brain activity changes during baseline, low and high workload scenarios. While the calculated correlation of all EEG sensors of participant 1 were low thus Figures C .5.e and C .5.f depicts brain activity changes of low correlation sensors. Because sensors of participant 2 presented moderate and high correlations, Figure C .5.c depicts brain activity measured by a sensor with moderate correlation while Figure C .5.d depicts brain activity measured by a sensor with high correlation for participant 2. To show the changes of brain activity measured by different band powers, Figures C .5.a and C .5.b depict brain activity measured by different band powers of a sensor with high correlation for participant 3. Figure C .5.a indicates the

EEG signal of gamma band power of the FT10 sensor for the third participant. As can be seen in Figure C .5.a, the level of gamma band power significantly increased when the workload increased in the high workload scenario. Figure C .5.b indicates the EEG signal of beta band power of the FT10 sensor for the third participant. Figure C .5.b shows that levels of both beta and gamma band powers significantly increased when the workload increased in the high workload scenario. Figure C .5.c depicts the EEG signal of the gamma band power of the P7 sensor for the second participant. Figure C .5.c shows that the level of gamma band power also significantly increased in the high workload scenario. Figure C .5.d depicts the EEG signal of the gamma band power of the T8 sensor for the second participant. Figure C .5.d shows that the level of gamma band power also significantly increased when the workload increased in the high workload scenarios. Figure C .5.e depicts the EEG signal of the gamma band power of the FC1 sensor for the first participant. Figure C .5.e shows that the level of gamma band power changed slightly between the baseline, low workload and high workload scenarios. Figure C .5.f depicts the EEG signal of the gamma band power of the F3 sensor for the first participant. Figure C .5.f shows that the level of gamma band power also changed slightly between the low and high workload scenarios.

C .6 DISCUSSION

This study investigated human factor challenges during remote ship operations and highlighted the different human factors involved. It is evident that one of the main challenges is an increase in the mental workload of SCC operators due to operational tasks. SCC designers aim to identify the maximum workload level for the efficient performance of remote operations by SCC operators.

The current study focuses on variables that may increase the level of mental workload of SCC operators, such as the number of ships that they are responsible for, traffic, weather conditions, VHF communication and the risk of accidents. The correlation matrix of the EEG results indicates that the gamma and beta band powers of the FT10, P7 and T8 sensors were highly correlated with weather status and the number of ships to be monitored. The gamma and beta band powers were, in fact, the only band powers that recorded changes in workload and stress levels in all participants. The results from the statistical analysis of the self-reported NASA TLX data also indicate significant changes in stress levels when ships are operating in harsh weather and when the number of ships is increased. When the number of ships were increased, number of human machine interfaces (HMIs) that an operator should interact during experiments increased considerably. The way that operators received information from HMI also affected the level of stress because operators should collect critical information in a short time span for more than one ship. In addition, significant increase of P7 sensor (please see Figure 5c) which covers

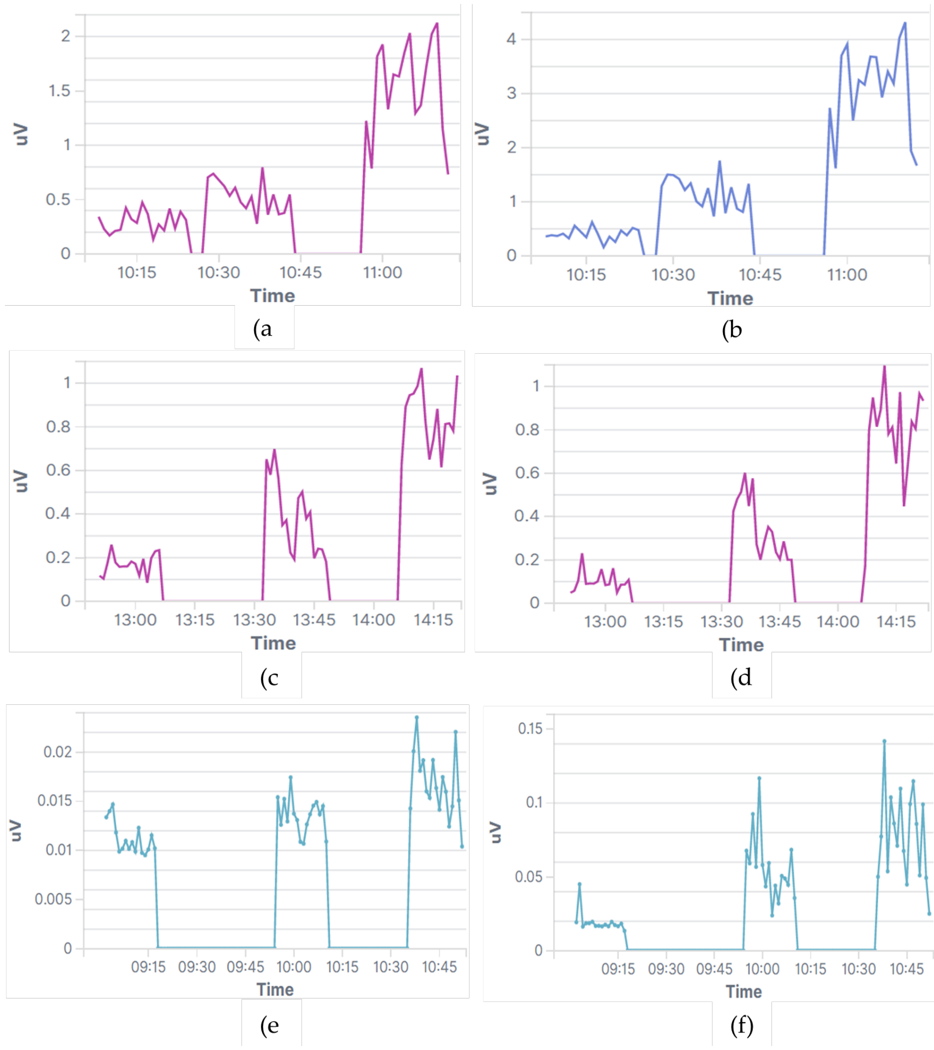

Figure C .5: Visualization of EEG band powers in uV during the baseline, low workload and high workload scenarios: (a) beta band power of FT10 sensor for participant 3; (b) gamma band power of FT10 sensor for participant 3; (c) gamma band power of P7 sensor for participant 2; (d) gamma band power of T8 sensor for participant 2; (e) gamma band power of FC1 sensor for participant 1 ; and (f) gamma band power of F3 sensor for participant 1

inferior lateral occipital cortex responsible for eye movements regarding object recognition in a visual information collection process supports the impact of HMI on stress when the number of ships increases. Furthermore, either low or no changes in stress were recorded when operators established VHF communication or when there was a risk of accidents. The direct measurement of brain activity by EEG

Table C .4: Hypotheses test results.

H#	Hypothesis	Result
1	There is a significant change in the level of workload between the first and the second scenario in the experiments	Supported
2	There is a significant change in stress when workload increases	Supported
3	There is a significant change in stress when ships are operating in harsh weather	Supported
4	There is a significant change in stress when the number of ships increases	Supported
5	There is a significant change in stress when operators establish VHF communication	Not supported
6	There is a significant change in stress when there is a risk of accident	Not supported

and the subjective self-reported findings therefore support each other with regard to hypotheses 3, 4, 5 and 6, which make the findings more credible.

All participants perceived a higher mental workload during the high workload scenario. Hence, this study successfully managed to manipulate mental workloads in the low workload and the high workload scenarios, which supports hypothesis 1. Since overall stress and workload increased during the high workload scenario, hypothesis 2 is also supported. Increase in the number of ships the operators were responsible for and worsening of the weather both had significant impacts on stress levels, and therefore hypotheses 3 and 4 are also supported. The results show, however, that establishing VHF communication and increasing the risk of accidents did not have significant impacts on operators' stress levels, and therefore hypotheses 5 and 6 are not supported. Hence, four hypotheses (1, 2, 3 and 4) were accepted, while two hypotheses (5 and 6) were not accepted. Support for each hypothesis according to the experimental results is summarized in Table C .4.

This study also has some limitations. The number of participants is low, and the participants are not experienced SCC operators.

C .7 CONCLUSION

This study performed human-centered experiments to investigate the stress levels of SCC operators during human-human and human-machine interactions, and tested six hypotheses to assess the human factors of workload and stress. Nine experiments were performed to collect the brain activity of human operators using EEG equipment, resulting in a dataset consisting of more than 42,000 samples.

In addition, the NASA TLX test was used so that the operators could self-assess workload and stress levels. On the basis of the statistical analysis, four hypotheses were accepted while two were rejected. In addition, a correlation coefficient matrix was generated to identify correlations between the brain activity of operators and workload and stress levels. This indicated that the beta and gamma band powers of the EEG recordings were highly correlated with workload and stress levels during remote ship operations. The results show that increases in workload result in significant changes in stress levels when ships are operating in harsh weather and when the number of ships each SCC operator is responsible for increases. The results also show that there is no significant change in stress levels when SCC operators establish VHF communication or when there is a risk of accidents. The practical implications of these findings are that SCC designers, SCC operator training programs and standardization bodies can utilize these results to improve the safety and efficiency of remote ship operations.

Future studies should investigate other human factors affecting workload and stress levels in remote ship operations. Future studies are also needed to perform these experiments with experienced SCC operators in order to improve the applicability of the results of this study. Moreover, studies with more participants are needed. It would also be interesting to extend this study by performing machine learning processes on EEG signals to provide a platform for customizing operator training programs and improving SCC designs and protocols.

C .8 References

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