HUMAN FACTORS IN MARITIME TRANSPORTATION AND MENTAL WORKLOAD ANALYSES FOR SEAFARERS IN BRIDGE SIMULATION

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This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.

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Abstract

Since the United States Coast Guard (USCG) reported in 1993 that human factors had essentially caused approximately 80% of maritime accidents and near misses, there has been an overwhelming understanding that human factors play a significant role in a considerable number of incidents or catastrophes by triggering chain events.

The work has initially documented a literature review underlining human factors in maritime accidents, mental workload study and functional Near-Infrared Spectroscopy (fNIRS) technique to imply how it can be studied for human factors in maritime transportation. It investigates how different risk factors generate an impact on different types of human-related maritime transportation accidents using a data-driven approach, and how mental workload influences neurophysiological activation and decision- making of seafarers by conducting an experimental study in bridge simulation.

The results of the developed models formalise the causal interdependencies between the risk factors with human factors perspectives and highlight the implications through scenario analyses. On the other hand, the findings of the fNIRS experimental study revealed the role of the prefrontal cortex and functional connectivity in watchkeeping and collision avoidance during maritime operations.

It is concluded that the understanding of risk factors contributing to human errors will help reduce the risk level or eliminate the potential hazards of ships, and provide the clue for accident investigation and generate insights for accident prevention. Also, the experimental study supports fNIRS as a valuable neuroimaging technique in realistic situations. It examines the mental workload and functional connectivity of seafarers, which helps generate insights for human performance and seafarers' training. Finally, the inclusion of a broader range of human factors and experimental methods shows promise by associating neurophysiological experiment in the maritime section.

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Nomenclature

AB	Able Seaman
ABN	Augmented naive Bayesian Network
ABS	American Bureau of Shipping
AHP	Analytical Hierarchy Process
AIBN	Accident Investigation Board Norway
ANOVA	Analysis of variance
ASEP	Accident Sequence Evaluation Program
ATHEANA	A Technique for Human Error Analysis
ATSB	Australian Transport Safety Bureau
BDD	Binary Decision Diagrams
BN	Bayesian Network
BNWAS	Bridge Navigational Watch Alarm System
BOLD	Blood Oxygenation Level Dependent
CBSI	Correlation-Based Signal Improvement
CM	Chief Mate
CPT	Conditional Probability Table
CREAM	Cognitive Reliability and Error Analysis ethod
CW	Continuous Wave
DA	Dissatisfaction Attitude
DAG	Directed Acyclic Graphical
DLPFC	Dorsolateral Prefrontal Cortex
ECDIS	Electronic Chart Display and Information System
ECG	Electrocardiograph
EDN	Event-Decision Network
EEG	Electroencephalography/Electroencephalogram
EMCIP	European Marine Casualty Information Platform
EMG	Electromyography
EMSA	European Maritime Safety Agency
ER	Evidential Reasoning
ETA	Event Tree Analysis
FAHP	Fuzzy Analytical Hierarchy Process
FCM	Fuzzy Cognitive Mapping
FFTA	Fuzzy Fault Tree Analysis

FMEA	Failure Mode and Effects Analysis
FSA	Formal Safety Assessment
FT	Fault Trees
FTA	Fault Tree Analysis
fMRI	functional Magnetic Resonance Imaging
fNIRS	functional Near - Infrared Spectroscopy
GISIS	Global Integrated Shipping Information System
GPS	Global Positioning System
HAZOP	Hazard and Operability
Hb	Haemoglobin
HbO	Oxygenated Haemoglobin
HbR	Deoxygenated Haemoglobin
HCR	Human Cognition Reliability
HFACS	Human Factors Analysis and Classification System
HOF	Human and Organisational Factor
HRA	Human Reliability Analysis
HRI	High Risk Inference
IMO	International Maritime Organization
LRI	Low Risk Inference
MAIB	Marine Accident Investigation Branch
MANOVA	Multivariate analysis of variance
MARDEP	Marine Department-Hong Kong
MC	Markov Chains
MM	Master Mariner
MPE	Most Probable Explanation
MPX	Master Pilot Exchange
MW	Mental Workload
NBN	Naïve Bayesian Network
NIR	Near-infrared
NTS	Non-technical skills
NTSB	United States National Transportation Safety Board
OOW	Officer of the Watch
PET	Positron Emission Tomography
PFC	Prefrontal Cortex
PFD	Personal Flotation Device
RCA	Root Cause Analysis

RIF	Risk Influencing Factor
ROI	Region of Interest
SA	Situational Awareness
SCC	Shore Control Centre
STCW	International Convention on Standards of Training, Certification and Watchkeeping for Seafarers
TAN	Tree Augmented Network
THERP	Technique for Human Error Rate Prediction
TLI	Task Load Index
TOPSIS	Technique for Order Preference by Similarity to an Ideal
TRI	True Risk Influence
TSB	Transportation Safety Board of Canada
UK MCA	UK Maritime and Coastguard Agency
USCG	United States Coast Guard
VTS	Vessel Traffic Service

Chapter 1 Introduction

1.1 Introductory remarks

This chapter gives a brief introduction to the research background that helps to understand the research necessity from a practical viewpoint. The research aims and objectives are stated to demonstrate the purpose of conducting this particular study, followed by the statement of the problem associated with human factors in the maritime transportation industry. Then, the thesis outline is provided to explain the logic of conducting human factors research within different perspectives, followed by both subjective and objective analyses. It is particularly innovative that the quantitative method is applied to model the risk factors contributing to human errors in maritime accidents. Besides, an experimental study integrated with neuroscience knowledge is conducted to simulate the scenario eliciting the neurophysiological changes of brain activities with the application of fNIRS and bridge simulation, which further investigates the individual factors – mental workload for seafarers. Meanwhile, the discussions and challenges in the research have been specified to demonstrate the deliverables to the knowledge and to indicate the achievements against the defined objectives.

1.2 Research background

95% of world trade by volume - raw materials, finished goods and energy supplies is transported by sea, and a significant amount of capital is invested in shipping (Trafford, 2009). However, about 75-96% of marine accidents are caused, at least in part, by human errors (Hanzu-Pazara et al., 2008). Human error is widely accepted to cover a variety of unsafe acts, behaviours, omissions and hazardous conditions. Besides, the activities on board or off board related to seafarers or mariners are influenced by internal and external factors. From a study analysing the specific onboard duties and off-board entities involving Greek-flagged ships, during 1993–2006, 57.1% of all accidents were attributed to the human element (Tzannatos, 2010). Among them, 75.8% of maritime accidents were detected on board, and 80.4% of the onboard human-induced accidents were linked to errors and violations by the ship's master. As the ship's master is responsible for decisions made on board, it is evident that the master's errors or violations affect other crews' working procedures, manoeuvring behaviours, and emergency responses, which illustrates the risks with respect to human and organisational factors in maritime transportation.

The questionnaire survey (Safahani, 2015) emphasised some issues: 75% stated that the team leader should discuss the work plan with other teammates; 90% thought monitoring the task provides an essential contribution to effective team performance; almost everyone in the survey believed that communication was a significant factor, and teams not communicating effectively increase their risk of committing errors. It broadens the definitions and classifications of human factors in maritime transportation. Thus, more attention has been paid to these skills to better understand the human factors in maritime accidents.

It is also agreed that there are numerous reasons for an individual making errors. These may include communication failure, ineffective training, memory lapse, inattention, poorly designed equipment, exhaustion or fatigue, ignorance, noisy working conditions, other personal and environmental factors. According to the annual report on marine casualties and incidents issued by European Maritime Safety Agency (EMSA, 2017), from a total of 1,170 accidental events during the investigations, shipboard operations represented the main contributing factor at 71% of the total, compared to the shore management. These statistics suggest the significance of studying ship officers' behaviours for navigation safety.

Not only wrong or delayed technical operational skills prevent the seafarers from manoeuvring effectively, but also numerous non-technical skills (NTSs) affect the performance of seafarers. The seafarer in the ship bridge (deck officer) is required to obtain plenty of skills, especially non-technical skills, including defining problems, managing workload, maintaining the standards of the watchkeeping, implementing the best solution, responding to the changes of information, anticipating future events, sending information clearly and concisely, maintaining concentration, coping with stressors, etc. (O'Connor and Long, 2011). Therefore, they are supposed to deal with multi-tasks during navigation within various levels of workload over the time and combined tasks. NTSs of cooperation, leadership and management, situation awareness and decision-making, are also considered in the training and assessment in the maritime industry (Saeed et al., 2016).

Also, crews working on board tend to be fewer owing to the automation revolution of vessels in the shipping industry. From this point of view, it is the advance in automation and reallocation of crew responsibility, as well as shore-based equipment and onboard devices, that permitted reductions in crew size (Council, 1990). In the late 1980s, European and Japanese governments supported greater automation, centralising navigation, engine control, communications, and administrative functions on the bridge to build the “ship operation centre”, as well as throughout the vessel. From this perspective, the fast pace of innovation and development in shipping is continuing worldwide.

Although the automation could eliminate the trivial stuff among the high workload seafarers, actually it induces unknown problems, as demonstrated by the grounding of the Royal Majesty (the Panamanian passenger ship grounded on Rose and Crown Shoal, Massachusetts in 1995) and evidence from other research results (Lutzhoft and Dekker, 2002). Automation has a prospecting expectation of human work and safety, which cannot merely replace human action thoroughly. Fewer crew numbers do not lead to less workload. There also exists an increased mental workload affecting situation awareness (Aguiar et al., 2015). Therefore, it is impossible that nobody is responsible for the ships.

More concisely, the humans will still work on monitoring, remote control, and maintenance, even for the high seas unmanned ships where it has to coexist with manned ship systems (Porathe et al., 2014). In this regard, automation in the vessel creates new error pathways, especially resulting from human errors, deficiencies in mission shifts, and postpones chances to correct errors in the system further into the future.

It is noteworthy that human error plays an essential role in exploring maritime transportation safety, no matter whether in the past or the future. Many cases of maritime accidents, as well as near-misses, reflect the risks and issues associated with maritime safety. With the revolution of advanced ships or even unmanned ships, there is an increasing number of research papers on inter-relationships between human factors to imply the potential measures taken for accident preventions, as well as introducing cross-discipline knowledge into the traditional marine safety research for new findings. Moreover, the practical evaluation of seafarers' mental workload will help understand the risks to which seafarers are exposed and improve navigation safety. Therefore, it is necessary to learn lessons from the past accidents with regards to human factors and explore the mental demands on duty for seafarers, which helps us to understand the risks in maritime transportation and introduce multi-discipline knowledge to human performance study in the maritime field.

1.3 Research aims and objectives

The primary purposes of this research are to investigate how human factors combined with common risk factors affect the safety of maritime transportation, and how an individual physiological factor - mental workload - influences neurophysiological activation, and decision making of experienced and inexperienced seafarers.

From the perspectives of human factors in maritime transportation, it aims at investigating how different risk factors generate an impact on different types of human-related maritime transportation accidents. Allowing for the drawbacks arising from traditional studies on human errors, it proposes a novel risk assessment of the human factors contributing to maritime accidents. Based on recorded maritime accident reports from maritime accident investigation organisations, a primary database for this study is developed. Moreover, a data-driven approach is used for modelling. In the developed models, it formalises the causal interdependencies between the risk factors. Furthermore, it highlights the implications through scenario analyses. The understanding of risk factors contributing to human errors will help reduce the risk level or eliminate the potential hazards of the novel ship in the future, and provide the clue for accident investigation and generate insights for accident prevention.

From the above human factors research derived from accident reports and works of literature, there is insufficient evidence to study individual factors which do not exist or contain limited information in the raw database, but are associated with the mental workload for seafarers. This research has to find a way to obtain the evidence of the mental workload of seafarers to support the hypothesis of the study. Therefore, it investigates how the mental workload induced by scenarios in the ship bridge influences neurophysiological activation and whether there is a difference between experienced and inexperienced seafarers. In order to understand the neurophysiological activation of the brain and the relations to human performance, an experimental study is designed and conducted for mental workload research. The results support fNIRS as a valuable neuroimaging technique, which can be used in realistic situations and reveal the role of the prefrontal cortex in watchkeeping and decision-making mental workload analysis of deck officers on a ship bridge. It examines changes in functional connectivity in the brains of seafarers and helps understand the relations between workload and human performance, which helps generate insights for seafarers' training and certification.

In order to achieve the research aims, the objectives are addressed as follows:

- To obtain the primary data representing frequencies of risk factors directly derived from maritime accident reports.

- To analyse the risk factors in maritime accidents.

- To incorporate human factors into causational analyses to maritime accident types.

- To develop a historical accident data-driven approach to train prior probabilities in the risk-based BN.

- To conduct an empirical study to provide insights for the prevention of a particular type of accident involving human errors.

- To design and conduct the experimental study aiming to study the mental workload of seafarers and the behavioural performance using fNIRS technology.

- To explore the patterns of functional connectivity in the dorsolateral prefrontal cortex (DLPFC) of experienced and inexperienced seafarers.

1.4 The statement of the problem

Ship accidents are caused by various types of failures, e.g. deck officer error (26%), equipment failure (9%), structural failure (9%), crew error (17%), mechanical failure (5%), among others. (Guedes Soares and Teixeira, 2001). Since the USCG reported in 1993 that human factors had essentially caused approximately 80% of maritime accidents and near misses, there has been an overwhelming understanding that human factors play a significant role in a considerable number of incidents or catastrophes by triggering chain events. Also, Branch et al. (2004) disclosed that watchkeeping manning levels and individuals' abilities to discharge duties were essential factors resulting in collisions and groundings. In order to study human factors in maritime transportation and analyse mental workload for seafarers in watchkeeping, the research questions are generated to ensure that the research objectives are met, and the methodological points are specified, which are shown as:

- What are the common human factors in maritime transportation?
- What are the most appropriate methods for analysing and evaluating the risk factors associated with human factors within the limited maritime transportation accidents, and how to implement the proposed methods?
- How to obtain the raw data to generate the database for human factors analyses?
- How to model the risk factors for human-related maritime transportation?
- What is the mental workload of seafarers on board, and how to quantify them?
- How mental workload influences neurophysiological activation?
- How to design the experiment for the measurement of mental workload and neurophysiological activation?
- How to reveal the decision-making of experienced and inexperienced seafarers in the experimental study within a ship bridge simulator?

To analyse human factors, the maritime accident database is used as one of the most valuable sources to obtain the primary data, including the global database like Global Integrated Shipping Information System (GISIS) (Pristrom et al., 2016), and the historical accident data collected from local maritime administration (Zhang et al., 2016). However, such databases contain less detailed and comprehensive information than the extractions from maritime accident reports. From this perspective, previous studies relying mainly on the secondary database, e.g. GISIS, were unable to present primary information from accident reports. Unlike the secondary database, investigation reports from public accident investigation organisations provide the navigational circumstance, process of the failure chain, environmental information, direct or indirect causes of the accidents, and the actions taken during the accidents. Even the hidden potential hazards and causal relations between various factors are demonstrated in some or part detail. However, few studies have utilised accident reports to obtain the raw data for risk factors and conduct human factors analyses due to the time-consuming process of extracting the context data from each report. Even studies utilising accident reports provided a small number of report sources and limited content of the risk factors, for example, 131 accident reports reviewed by Uğurlu et al. (2015b) and 27 collision reports reviewed by Chauvin et al. (2013).

Secondly, human factors have complex causal relations with each other. Lema et al. (2014) applied a K-means clustering method to indicate that human factors coexist with the condition of a ship and other external factors. It was widely accepted that human factors were associated with a variety of unsafe actions, behaviours, omissions and hazardous conditions, and the human element was a critical factor in maritime accidents (Antão and Guedes Soares, 2008). The annual report on marine casualties and incidents issued by European Maritime Safety Agency (EMSA, 2019) stated that, from a total of 4,104 accident events analysed during the investigations, 65.8% were attributed to a human actions category and 20% to system/ equipment failures. These statistics suggest the significance of studying seafarers' shipboard operations for navigation safety. Besides the operational skills, non-technical skills (NTS) of co-operation, leadership and management skills, situation awareness and decision-making, are also considered in the training and assessment in the maritime industry (Saeed et al., 2016). Much attention has been paid to the risk analysis of accidents' causes related to human factors. Celik and Cebi (2009) proposed a Human Factors Analysis and Classification System (HFACS) approach to identify human factors in shipping accidents. It revealed the hierarchy structure of human factors and the logic relations within the structure. Chen et al. (2013) modified the HFACS to make it more applicable to maritime accidents (*i.e.* HFACS-MA model), to comprehensively describe Human and Organisational Factors (HOFs) in the maritime sector. However, these given frameworks of HOFs illustrate several levels, but do not contain the patterns of risk factors contributing to human errors or the interdependencies between each factor. It calls for a methodology to incorporate human factors into maritime accident analysis, combined with common risk factors, and to generate new insights on critical human factors contributing to different types of accidents.

Thirdly, studying the human factors from these accident experiences or accident reports probably omits significant individual factors, e.g. mental workload, fatigue, stress, which is highly related to the human performance but cannot be reflected in the report recording or be described and quantified appropriately by words. Moreover, the research on patterns of the neurophysiological activation and behavioural performance of seafarers remains in blank space. In order to understand how mental workload influences neurophysiological activation and decision-making of experienced and inexperienced seafarers, it is necessary to develop an experimental study to quantify and measure mental workload and neurophysiological activation. The practical evaluation of the seafarer's workload will help understand the risk exposed to seafarers and improve navigation safety.

1.5 Scope and outline of the thesis

The research scope is set up to surround the core of the thesis, which offers integrated methods to identify the subjective and objective human factors, model the interdependency among Risk Influence Factors (RIFs), and proposes an experimental study on human factors using bridge simulation for maritime transportation. The proposed methods consider both subjective and objective ways concerning human factors and are combined with multi-discipline knowledge. Incorporating human factors into risk analysis for maritime accidents and applying fNIRS technology into seafarers' mental workload study, are particularly innovative, when being used to support the methodology of analysing human factors in maritime accidents, compared to the traditional human reliability research primarily based on the experts' knowledge or limited secondary data. This research provides a perspective to understand the inter-relationships among RIFs and changed patterns of brain activities of seafarers when faced with navigational duty. A graphical flowchart is presented in Figure 1.1 for outlining the structure of the thesis followed with the identification of research gaps, development of research, experimental study, and discussion. The thesis layout is highlighted and explained as follow.

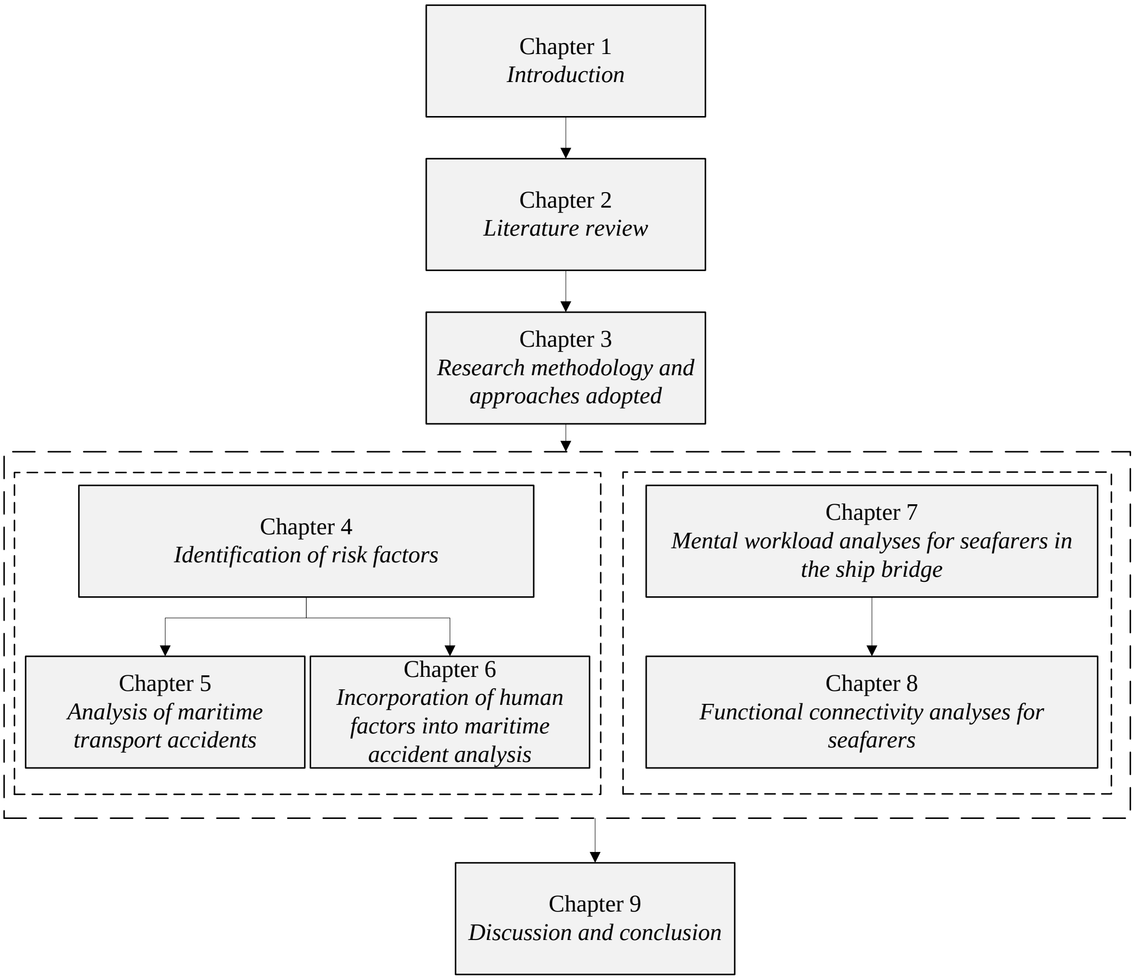


Figure 1.1 The structure of the thesis

This thesis is compiled in ten chapters. Following the introduction of the research process as presented in ***Chapter 1***, ***Chapter 2*** offers the first attempt at broadly understanding the human factors in maritime accidents, and discussing the state-of-the-art human reliability and neurophysiological research. Thematic analyses are conducted to gather the fragmental information to provide a systematic description of the research. It reviews the human factors in maritime accidents, risk assessment of HOFs, decision making theories, functional Near-Infrared Spectroscopy application in the field. From this perspective, it is evident that the human factors in maritime transportation influence the performance of seafarers and affect transportation safety. Besides, it finds that practically conducting human reliability research within novelty methodology and neurophysiological knowledge in maritime transportation are a fertile area emerging from growing challenges. The distinctive gaps existing in current literature provide a future research agenda.

In ***Chapter 3***, the approaches adopted in the research are presented and discussed. It lays down the foundation for the study by indicating the main philosophical views behind the research methodologies. The multi-discipline knowledge is provided to reveal the overall plan and the priorities of the research. Furthermore, the chapter describes the methodologies of BN modelling and the neurophysiological methods, which are employed to identify, extract, quantify, and analyse human factors and seafarers' mental workload.

To identify the risk factors contributing to human errors in maritime transportation, ***Chapter 4*** aims at analysing the human errors from the maritime accidents which happened from 2012 to 2017, and generating the contributing factors that influenced the human errors revealed in the reports and from the literature. From this perspective, it is evident that the common factors contributing to human errors existing in accident reports have valuable meaning for the shipping risk analysis and evaluation. Also, it will help reduce the risk level or eliminate the potential hazards of the novel ship in the future, and benefit the revolution of ship automation and innovation.

Based on the risk factors screened from ***Chapter 4***, ***Chapter 5*** aims at investigating how different risk factors generate an impact on different types of maritime accidents in terms of likelihood. Manual case by case analysis of recorded maritime accidents from the Marine Accident Investigation Branch (MAIB) and the Transportation Safety Board of Canada (TSB) that occurred from 2012 to 2017 is undertaken to develop a primary database to support this study, as they are among the most representative from the literature (Chauvin et al., 2013, Graziano et al., 2015, Kum and Sahin, 2015). A Bayesian

Network-based approach is proposed to analyse accident types in maritime transport. The results highlight the implications through scenario analyses.

Besides, there is another BN model developed for the RIFs influencing maritime accidents in the perspective of human factors. ***Chapter 6*** investigates how human factors combined with factors in ***Chapter 5*** affect maritime accidents in the perspective of risk analysis. It proposes a novel risk assessment of the human factors contributing to maritime accidents. Based on recorded maritime accident reports in ***Chapter 5***, a primary database is extended. Using the extended database, the Tree Augmented Network (TAN) model is developed to construct BN structure and train the data, so as to propose a data-driven BN-based approach for accident analyses accounting for inter-relationships among RIFs. It highlights the implications by providing a plausible explanation for the observed conditions.

From a neurophysiological perspective, an experimental study is conducted in ***Chapter 7*** to analyse the mental workload and neurophysiological activations of seafarers in the ship bridge. It is done with simulated watchkeeping tasks in a maritime bridge simulator and using fNIRS to measure neurophysiological activation. Research using this technique provides further support for the activation of the DLPFC as a result of mental workload. It investigates when and how the mental workload induced by scenarios in the ship bridge influences neurophysiological activation and whether there is a difference between experienced and inexperienced seafarers, which may generate insights for seafarers' training and certification in the future.

In ***Chapter 8***, it further analyses the functional connectivity of the brain area by conducting an experimental study. The functional connection between pairs of brain regions demonstrates the temporal correlation of regional haemodynamic. Thus symmetric correlation matrices are obtained of all pairwise combinations of channels in ***Chapter 7***, followed by a reasonable method on choosing the threshold applied to the matrices, so as to create the cross-correlation matrix to represent these data in a visualisation. In this way, it is supposed to demonstrate the patterns of brain activity for the watchkeeping and decision-making process, and explore an association between measures of functional connectivity and performance outcomes in an applied, safety-critical scenario.

Chapter 9 discusses the contributions of the research to the field, and highlights the novelty of the findings of the above chapters by adopting approaches in ***Chapter 3***. It corresponds to the research gaps in ***Chapter 2***. Then it briefly summarises the research objectives achieved and suggests the future work opportunities arising from the proposed methods. It highlights the research findings on the human factors analyses, modelling of the risk factors contributing to human errors, and the neurophysiological knowledge from the experimental study in all previous chapters. The research findings have been disseminated through academic publications in research journals and at international conferences making contributions to academic and industrial areas for further research on human factors in maritime transportation.

1.6 The novelty of the study

The novelty of the study lies in:

- It reveals new features including new primary data directly derived from maritime accident records by two major databanks, MAIB and TSB from 2012 to 2017; also, the quantification of the extent to which different combinations of the factors influence each accident type.

- It proposes BN-based risk analysis approaches to analyse the risk factors influencing maritime transport accidents. The network modelling the interdependency among the risk factors is constructed, then validated by sensitivity analysis.

- It incorporates human factors into causational analysis concerning different maritime accident types, and generates new insights on critical human factors contributing to different types of accidents using a historical accident data-driven approach. It also pioneers the analyses of various impacts of human factors on different maritime accident types.

- It investigates how mental workload influences neurophysiological activation of seafarers, which has not been used in maritime scenarios. This was done with simulated watchkeeping tasks in a maritime bridge simulator, and using fNIRS technology to measure neurophysiological activation. It demonstrates the developed scenarios which distracted the ship officers at specific points, which is the common task requiring temporal mental workload in the real world.

- It explores the decision-making mental workload analysis of deck officers on a ship bridge, which fulfils the blank space of application of the fNIRS technique in maritime transportation. And it reveals the patterns of brain activity of seafarers in different groups, which is evident to be one of the promising directions of multi-discipline research related to human factors.

1.7 Concluding remarks

The following are the most significant remarks comprised in the chapter, and emphasised in the form of bullet points for the reader’s ease:

- Human error is widely accepted to cover a variety of unsafe acts, behaviours, omissions and hazardous conditions. Although the automation in the shipping industry leads to fewer crew on board by eliminating the trivial stuff among the high workload seafarers, it probably induces problems and issues associated with human factors. Therefore it is necessary to learn lessons from past accidents with regards to human factors, which helps understand the risks in maritime transportation.

- Mental workload influences neurophysiological activation and decision-making of experienced and inexperienced seafarers. The practical evaluation of seafarers' mental workload will help understand the risk to which seafarers are exposed and improve navigation safety. Therefore it is necessary to explore the mental demand on duty for seafarers, which helps explain human performance study in the maritime field using multi-discipline knowledge. With respect to individual factors and cognitive demands for seafarers during navigation, there is scanty research on mental workload for seafarers with neuroscience and psychophysiological perspectives.

Chapter 2 Literature review

2.1 Introductory remarks

This chapter presents the process of carrying out a structured and comprehensive literature review in terms of human factors in maritime accidents, the evaluation of risk methods utilised in human reliability research, as well as new technologies derived from other transportation fields. The fragments of separate investigations are gathered within the research domain to provide critical insights into addressed human factors and mental workload. An emerging trend of using the technique - functional Near-Infrared Spectroscopy - for brain activity in the transport field, is also reviewed in a relatively broad range of research fields, in order to facilitate its further application in human factors study. The identified research gaps indicate the valuable points of additional work, which are used to clarify the research conducted in the following chapters.

2.2 Background information

In the late 1980s, European and Japanese governments supported greater automation, centralising navigation, engine control, communications, and administrative functions on the bridge to build the "ship operation centre", as well as throughout the vessel. From this perspective, the fast pace of innovation and development in shipping is continuing worldwide. It is the advance in automation and reallocation of crew responsibility, as well as shore-based equipment and onboard devices, that permitted reductions in crew size (Council, 1990). Although fewer crew are on board with the automation in the shipping industry, there are increasing risks and pathways for maritime accidents with human factor perspectives.

Human factors in this work are risk factors derived from unsafe actions or omissions of people, which are associated with human, ship, organisation, and environment. They not only reflect interactions with human's performance, response, and decision making, but also explain the pattern of failure chains and the clue of investigation on maritime accidents or near misses.

The maritime system is a human-machine system, and about 75-96% of marine accidents are caused, at least in part, by human errors (Hanzu-Pazara et al., 2008). Human error is widely accepted to cover a variety of unsafe acts, behaviours, omissions and hazardous conditions. SAFETY-II perspectives see human as a necessary resource that provides solutions to the potential problems rather than a hazard or problem to be fixed in the systems, with the purposed of ensuring that "as many things as possible go right" rather than "as few things as possible go wrong" (Hollnagel et al., 2015). The SAFETY-II assumes that everyday performance variability provides the adaptations that respond to varying conditions, and hence is the reason why things go right. From these perspectives, SAFETY-II is based on the agreement that human factors behind the incidents and accidents are complex and correlated with each other, so as the adaptations from everyday performance variability work well (Schröder-Hinrichs et al., 2012). In this way, human factors spread into a large number of causative factors in accidents.

From a study analysing the specific onboard duties and off-board entities involving Greek-flagged ships, during 1993–2006, 57.1% of all accidents were attributed to the human element (Tzannatos, 2010). The old view of human error treats it as a cause of accidents (Dekker, 2014). To explain the failure, it is important to find people's mistakes and wrong decisions. However, the new view of human error sees it as a symptom of deeper trouble in the system. To explain the failure, it is necessary to find how people's assessments and actions made sense at the time, instead of trying to find where people went wrong (Dekker, 2014). Woods (2010) emphasises that the enemy of the safety is not the human, but a complex story of how people succeed and sometimes fail in the way to get success. It cares human error after the fact. In addition, it is also agreed that there are numerous reasons for an individual making errors. These may include communication failure, ineffective training, memory lapse, inattention, poorly designed equipment, exhaustion or fatigue, ignorance, noisy working conditions, other personal and environmental factors. The questionnaire survey (Safahani, 2015) emphasised these issues: 75% stated that the team leader should discuss the work plan with other teammates; 90% thought monitoring the task provides an essential contribution to effective team performance; almost everyone in the survey believed that communication was a significant factor, and teams not communicating effectively increase their risk of committing errors.

2.3 Human reliability in maritime field

As one of the most significant factors causing maritime accidents, the elimination or minimisation of human error is vital in the process of navigation and operation on board. The naval system is a human-machine system. Various studies have been conducted on human errors and human factors in maritime transportation from different perspectives to illustrate the causal evolution from human errors to maritime accidents.

For human errors research, there are Human Reliability Analysis (HRA) methods that focus on the quantification of human operations (Precondition of human and contexts error). HRA is developed from engineering risk analysis and aims to predict likely failure event sequences quantitatively to analyse human factors in maritime accidents; error frequency and expert opinion have been used to predict reasons behind such accidents (Kirwan, 1994).

At the beginning, human reliability analysis methods assign a probability of failure of a human operator in performing tasks (Zio, 2009), including the Technique for Human Error Rate Prediction (THERP) (Swain and Guttmann, 1983), Accident Sequence Evaluation Program (ASEP) (Swain, 1987) and Human Cognition Reliability (HCR) (Hannaman et al., 1985). However, none of these studies went beyond individual human errors to consider personnel, situational or organisational factors. Consequently, this HRA approach has been developed further.

Latterly, methods including the Cognitive Reliability and Error Analysis Method (CREAM) (Hollnagel, 1998), considering the situational influences on human errors with local conditions and task-specific factors to categorise errors, and A Technique for Human Error Analysis (ATHEANA) (Cooper et al., 1996), try to model the relationship between the context and the probability of human failure (Zio, 2009). In this way, cognitive failures are traced back to the psychological and situational precursors with relatively fewer organisational conditions involved.

In recent research of human errors in maritime transportation, Celik and Cebi (2009) generated a HFACS derived from the aviation field (Wiegmann and Shappell, 2017) based on a Fuzzy Analytical Hierarchy Process (FAHP), to identify human errors in shipping accidents. In line with the HFACS, as well as Reason's Swiss Cheese Model and Hawkins' SHEL model, Chen et al. (2013) proposed HFACS for a Maritime Accidents (HFACS-MA) model to measure the HOFs. Some studies exist on human reliability to define human performance in accidents and estimate human failure probabilities (Yang et al., 2013, Yoshimura et al., 2015, Yang and Wang, 2012). Soner et al. (2015) combined Fuzzy Cognitive Mapping (FCM) and HFACS to generate a proactive model in fire prevention modelling on board ships. Also, Systems-Theoretic Accident Modeling and Processes (STAMP) was proposed by Leveson (2004) based on systems theory to help engineers to learn all the factors related to social and organizational structures. It provided a theoretical foundation for the introduction of new types of accident analysis, hazard analysis, accident prevention strategies.

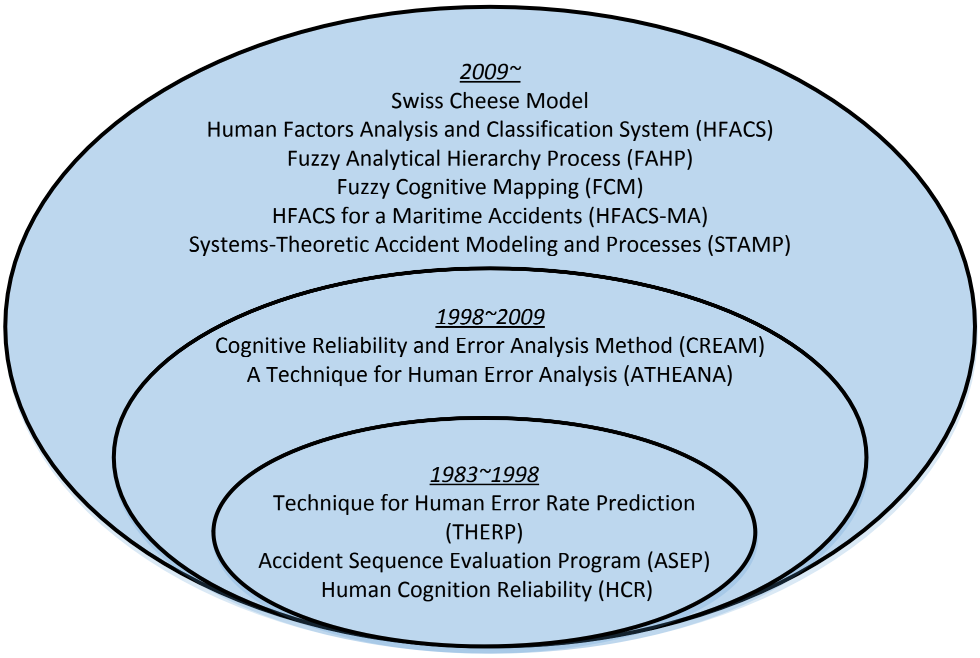


Figure 2.1 Human reliability analysis methods used in the maritime sector

As the human error in maritime operations raised the public's and industry's concern, more attention has been paid to accidents' causes related to human factors. John et al. (2014) proposed the methodology consisting of a FAHP, evidential reasoning (ER) approach, fuzzy set theory and expected utility to optimise performance effectiveness in seaport operation matters. It also reveals that human errors are a significant factor leading to the disruption of maritime operations with an enormous and long-term loss to the operator. Besides the concepts and theories of human errors research in naval operations, the investigation of human errors in maritime accident reports reveals more specific and realistic phenomena. There are frequent errors highlighted giving the practical human errors during the accidents.

i. Firstly, it is common for seafarers or passengers not to be routinely wearing lifejackets or personal flotation devices (PFDs) in the process of manoeuvring or navigation activities. It contributes to the miss or lose of chance to survive in emergency. From the accident report MAIB 3-2017, the master's intervention in the operation during the navigation, 14 seconds before the collision, was too late to be effective. Unlike the characteristics of transportation accidents that happen on the road, the reaction time left for the crew working on the ship during sailing is considerably more before the accidents. In many cases, the master has no choice if the chance of intervention in manoeuvring is missed, but waiting for when the collision or grounding comes.

ii. Secondly, insufficient passage planning by the command team appears commonly in the investigation. From the report, MAIB 20-2016, the submarine's command team misidentified Karen as a merchant ship primarily because no trawl noise had been heard on the same bearing. In this case, the submarine's command team did not take avoiding action to keep clear of Karen. It was associated with communication and cooperation with teammates or crew on the other ships.

iii. Thirdly, the loss of spatial awareness was proposed in maritime accident reports. Psychological effects of the relative motion illusion, for example, the cognitive costs of transferring from a different frame of reference, cannot be ignored during the navigation. Apart from the situation awareness proposed in the accident reports (MAIB 23-2017, TSBM16P0362), several psychological factors of individuals emerge in the maritime accidents, according to the higher workload from electronic navigation devices and automation application in the ship. Moreover, MAIB began to investigate and study the human factors in accidents associated with the use of advanced electronic navigation aids and the implementation of mandated navigation standards (MAIB 23-2017 reports). At the same time, the errors owing to the management team and organisation factors were revealed. It affects the violation and decision-making associated with the external and internal environment.

To meet the demand for human reliability in the engineering, it is essential to solve real problem based on theoretical principles by problem based learning (PBL) (Shekar, 2014). There are applications of PBL to engineering design courses (Hasna, 2008). Tse and Chan (2003) designed a group project for the class to designe a calculator using microcontroller, which provided students with cooperative learning atmosphere. Gavin (2011) applied PBL into civil engineering to develop problem-solving, innovation, group-working and presentation skills desired by graduate employers. In maritime sector, a framework was proposed using PBL for the final-year design project unit at Australian Maritime College, which facilitated the maritime design engineering undergraduates to learn human factors concepts and apply in design process (Abeysiriwardhane et al., 2016). Luis et al. (2013) used augmented reality for accessing to virtual materials including 3D models of objects and devices used for measuring, manipulate or processing, and video contents explaining related information. It developed PBL program with mobile devices which offering a better and a more engaging experience for students in higher maritime education.

2.4 Risk assessment in maritime systems and accidents

Since the UK Maritime and Coastguard Agency (UK MCA) proposed the formal safety assessment (FSA) framework to the International Maritime Organization, maritime accident risk models have been fast developed because of the goal-setting risk regime. It takes into account ship conditions, organisational management, human operation, and hardware (Guedes Soares and Teixeira, 2001). To assess the risks in maritime systems, quantitative risk assessments have been conducted to analyse maritime accidents. Yip et al. (2015) applied the econometrics method to conclude that the number of passenger injuries is positively related to the number of crew injuries in ferry, ocean cruise and river cruise passenger vessel accidents. Talley and Ng (2016) proposed a logical approach to select quality-of-service measures for port cargo, vessel and vehicle services, which can be used as port performance indicators for evaluating the service performance of multi-service ports. Ventikos and Psaraftis (2004) presented the relationship between an oil spill-assessing approach, namely the event-decision network (EDN) and the FSA to describe the spill-scenario analysis and to pinpoint its interconnections with the official instrument.

Besides that, risk analysis of maritime accidents would benefit the decision-making systems onboard. Balmat et al. (2009) presented a fuzzy approach to automatically define an individual ship risk factor, which could be used in a decision-making system. Wu et al. (2018) integrated evidential reasoning and TOPSIS into group decision making for handling ships that are not under command. A fuzzy logic-based approach was proposed by Wu et al. (2019) for ship-bridge collision alert, considering ship particulars, bridge parameters and natural environment, which can be used for the improvement of the ship handling in the bridge waterway area.

Moreover, the causation analysis and modelling of maritime risks have been conducted (Wang et al., 2019, Wan et al., 2019). Kum and Sahin (2015) used Root Cause Analysis (RCA) to clarify the causes and applied Fuzzy Fault Tree Analysis (FFTA) for a recommendation to reduce the occurrence probabilities of maritime accidents. Also, Zhang et al. (2014a) estimated the navigational risk of the Yangtze River using the BN approach. Montewka et al. (2014) developed the risk framework using BN for the estimation of the risk model parameters.

There are various risk methods developed for modelling in the maritime system, aiming at rational risk analyses. The interest in using BN as a tool in scientific risk analysis is continuously increasing, primarily related to its advantages in terms of learning and inference. According to the literature review by Weber et al. (2012), the number of academic papers on BN in risk analysis increased every year. Compared with other classical methods applied to dependability analysis, e.g. Markov Chains (MC) and Fault Trees (FT), BN sustains its advantages. Specifically, FT allows for calculating the probability by binary decision diagrams (BDD), which models the dependencies between events. However, it cannot represent the multiple state variables when multiple failures result in different consequences in a system.

On the contrary, BN displays similar capabilities as the FT, but has additional ability to model a multi-state variable and several output variables. Khakzad et al. (2011) and Weber et al. (2012) presented a comparison of FT and BN approaches, while previous studies also explained how FT could be transformed into BN (Mahadevan et al., 2001, Bobbio et al., 2001, Trucco et al., 2008a), involving dynamic FT transformation (Montani et al., 2006). As far as MC is concerned, it analyses the exact probability of a failure event with the dependencies among variables and integrates the knowledge to represent multi-state variables. However, system modelling tends to be sophisticated with increasing variables (Weber et al., 2012). In light of this characteristic, BN has required a relatively low number of parameters and a small-size conditional probability table (CPT).

BN is widely utilised in maritime risk analysis, e.g. ship navigational risk assessment, port safety assessment, Arctic water transportation, inland waterway transportation, and collision assessment (Zhang et al., 2016) (Yang et al., 2018) (Fu et al., 2016) (Baksh et al., 2018) (Hanninen and Kujala, 2012, Liu et al., 2016a). It is proved to be powerful to model maritime accidents since it enables quantitative analysis of HOFs (Akhtar and Utne, 2014, Castaldo et al., 2016, Thieme and Utne, 2017). It explicitly reveals probabilistic dependencies between factors and their causal relationships. Moreover, the feature that BN can take advantage of experts' knowledge makes it suitable for maritime risk modelling, in cases where failure data in the relevant investigations are incomplete. Therefore, experts' knowledge continues to be an essential data source for shipping accident modelling (Fu et al., 2016, Zhang and Thai, 2016), although it is subjectivity associated.

2.5 Human factors in maritime accidents

Since the USCG reported in 1993 that human factors had primarily caused approximately 80% of maritime accidents and near misses, there has been an overwhelming understanding that human factors play a significant role in a considerable number of incidents or catastrophes by triggering chain events.

The preliminary findings of the literature review on human factors in maritime accidents are stated in Table 2.1, which demonstrate the strengths and weakness of several typical studies. For organisational factors, Lu and Tsai (2008) studied the influence of the safety culture on ship accidents, concluding that the job safety, management safety practices and safety training were among the top influencers. On the other hand, people surrendered the level of vessel safety standards to a profitable activity due to commercial pressures (Vinagre-Ríos and Iglesias-Baniela, 2013). It showed that increase and decrease in the level of ship-owners' profits influenced the amount of risk tolerated in the ship operation.

From this point of view, human factors were also derived from the practices and operating policies established by shipping companies.

Table 2.1 Strengths and weaknesses of the relevant research

Researchers	Journals	Strengths	Weaknesses
Lu and Tsai, 2008	Accident Analysis & Prevention	Considered the organisational factors, and empirically evaluated the influence of safety climate on vessel accidents from a seafarer's perspective	Factors were limited, and it did not illustrate the interaction between organisational factors.
Vinagre-Ríos and Iglesias-Baniela, 2013	The Journal of Navigation	Mentioned the increasing incidence of human errors, and pointed out how commercial pressures of shipping market influence the risk behaviour of shipping business decision-makers.	Did not interact with other risk factors
Antão and Guedes Soares, 2008	Reliability Engineering & System Safety	Identified the difference in the pattern of human factors and other factors associated with high-speed crafts accidents, as compared with the more traditional ocean-going ships	Human factors were limited to human tasks, including set speed, set heading, lookout planning, trip maintenance, engine, and others.
Celik and Cebi, 2009	Accident Analysis & Prevention	Improved HFACS framework to identify the role of human factors in shipping accidents. Improvement of safety precautions in shipping companies	Did not reflect the influences between different factors' levels.
Chen et al., 2013	Safety Science	The use of HFACS-MA model with Why-Because Analysis can help ensure the relevant latent conditions and indicate the adverse influences between different factors' levels.	It needed a dedicated HOFs framework with particular items specified for marine accidents and the weights of the HOFs identified.
Yang et al., 2013,	Ocean Engineering	Proposed a modified CREAM to facilitate human reliability quantification in marine engineering; developed a quantitative human reliability analysis method using	It required appropriate consideration of the influence of the common performance conditions with neutral effects in the establishment of belief

		fuzzy Bayesian; realised real-time monitoring of marine engineers' failures under uncertainty	fuzzy rule bases.
Chauvin et al., 2013	Accident Analysis & Prevention	Used HFACS to identify contributory factors involved in 39 collisions; used Multiple Correspondence Analysis and hierarchical clustering to reveal three patterns of factors	The small number of collisions studied but the high number of variables.
Soner et al., 2015	Safety Science	Used FCM with HFACS to propose a novel proactive modelling and add value to predicting the root causes revealed in various levels.	Detailed predictions of suggested safety mechanisms will be studied in order to manage the operational level.
Pristrom et al., 2016	Reliability Engineering & System Safety	Used data collected from the Global Integrated Shipping Information System (GISIS) together with expert judgement	There was no detailed human factors data.
Zhang et al., 2016	Safety Science	A literature review on expert knowledge and BN modelling for shipping accidents in view of risk and uncertainty.	New methods for experts' knowledge elicitation should be developed to improve the model validity.
Kim et al., 2016	Safety Science	Conducted a STAMP-based accident analysis of the 2014 Sewol tragedy to uncover unsafe interactions among components leading to the hazards using system thinking.	Limited extensive data from available resources for thorough analysis.
Sotiralis et al., 2016	Reliability Engineering & System Safety	Proposed a collision risk model for the incorporation of human factors into quantitative risk analysis.	Focused on calculation of the collision accident probability due to human error, with limited causal analysis.
Sætrevik and Hystad, 2017	Safety Science	Demonstrated that inaccurate SA may be the proximal cause for operator error.	It calls for measuring objective safety indicators, rather than the crew's subjective risk assessment or self-report of incidents and actions.

Wang and Yang, 2018	Reliability Engineering & System Safety	Showed the key factors influencing waterway safety, including the type and location of the accident and conducted a novel scenario analysis to predict accident severity.	The completeness of the data mined from the text case was arguable. It focused more on objective variables rather than human factors.

Moreover, human factors have complex causal relations with each other. It was widely accepted that human factors were associated with a variety of unsafe actions, behaviours, omissions and hazardous conditions, and the human element was a critical factor in maritime accidents (Antão and Guedes Soares, 2008). Much attention has been paid to the risk analysis of accidents' causes related to human factors. Celik and Cebi (2009) proposed a HFACS approach to identify human factors in shipping accidents, which revealed the hierarchy structure of human factors and the logic relations within the structure. Chen et al. (2013) modified the HFACS to make it more applicable to maritime accidents (*i.e.* HFACS-MA model), to comprehensively describe HOFs in the maritime sector. In addition, human performance defined by human reliability in accidents was analysed, and the human failure probabilities were estimated to assess the risk level of the shipping industry (Yang et al., 2013, Yoshimura et al., 2015, Yang and Wang, 2012). Soner et al. (2015) combined FCM with HFACS to generate a proactive model in fire prevention, which revealed that human factors were significant factors on board ships, leading to the failures of maritime operations with an enormous and long-term loss. In STAMP, accidents are conceived as resulting not from component failures, but from inadequate control of safety-related constraints on the design, development, and operation of the system. Kim et al. (2016) conducted a STAMP-based accident analysis of the 2014 Sewol tragedy to uncover rationales behind the decision-makings and unsafe interactions among components leading to the hazards. Moreover, SA explained variation in unsafe actions and in subjective risk assessment (Sætrevik and Hystad, 2017). Variance in SA was in turn accounted for by captains' leadership, and inaccurate SA may be the proximal cause for operator error. In addition, the model took into account the human performance in different operational conditions leading to the collision, which could be used for calculation of human, economic and environmental risks (Sotiralis et al., 2016).

To analyse human factors, the maritime accident database is used as one of the most valuable sources to obtain the primary data, including the global database like GISIS (Pristrom et al., 2016), and the historical accident data collected from local maritime administrations (Zhang et al., 2016). However, such databases contain less detailed information than the extractions from maritime accident reports. From this perspective, the investigation reports of maritime accidents provide the navigational circumstance, process of the failure chain, environmental information, direct or indirect causes of the accidents, and the actions taken during the accidents. Even the hidden potential hazards and causal relations between various factors are demonstrated in detail. However, few studies utilised accident reports to conduct accident and human factors analysis due to the time-consuming process of extracting the data from each report. Therefore, even studies utilising accident reports provided limited content of the data sources. For instance, Chauvin et al. (2013) underlined 39 vessels involved in 27 collisions derived from the accident reports, identifying the importance of Bridge Resource Management for situations of navigation in restricted waters. Chen et al. (2013) utilised the accident reports of selected cases from MAIB for accidents analysis providing a complement measure. Wang and Yang (2018) analysed all accident investigation reports by China's Maritime Safety Administration (MSA), to conclude the key risk factors influencing waterway accident severity.

2.6 HOFs technologies and decision making theories

Celik and Cebi (2009) proposed a HFACS approach to identify human factors and their hierarchy structure and the logic relations in shipping accidents. Chen et al. (2013) modified the HFACS to make it more applicable to comprehensively describe HOFs in the maritime sector. Soner et al. (2015) combined FCM with HFACS to show that human factors lead to the failures of maritime operations with an enormous and long-term loss.

The STAMP proposed by Leveson (2004) was used to conduct accident analysis by Kim et al. (2016). It was based on systems theory to uncovered rationales behind the decision-makings and unsafe interactions among components leading to the hazards.

As for one of the most common approaches used for human factors studies, BN has been widely applied to maritime risk analysis, including collision risk assessment (Hanninen and Kujala, 2012, Ma et al., 2016), human reliability analyses (Martins and Maturana, 2013), and risk estimation (Montewka et al., 2014). Zhang et al. (2013) and Zhang et al. (2014a) estimated the navigational risk through FSA and BN to improve the navigational safety in the Yangtze River, and established the BN for the analysis and prediction of the congestion risk of inland waterways. Also, BN was constructed to represent the dependencies between the indicators and accident consequences (Zhang et al., 2016), revealing that the accident consequences were the most sensitive to the position where the accidents occurred.

Related to BN's learning and inference algorithms, Weber et al. (2012) pointed out that the number of publications on BN in risk analyses increased every year. However, the system modelling tends to be complicated with increasing variables, while leading to an apparent increase of parameters and related functions (Weber et al., 2012). Because BN can conduct bi-directional risk analysis, the transformation from the converging to diverging connections has no influence on the final BN results on risk analysis (Wang and Yang, 2018). That is to say, arrows' directions can be changed appropriately to fit the demand of a small-size conditional probability table in BN. In this way, the BN approach makes it applicable to a sophisticated system.

Moreover, BN is a competitive approach for maritime risk modelling owing to its abilities to utilise either expert knowledge or data-driven methods. Expert knowledge continues to be an essential data source for shipping accident modelling, when failure data in the relevant investigations are absent (Fu et al., 2016, Zhang and Thai, 2016). However, a data-driven BN was utilised to analyse RIFs and predict the probability of vessel detention, in order to help rationalise inspection regulations for port state control practice (Yang et al., 2018). In light of this characteristic, BN is appropriate for modelling maritime accidents since it enables quantitative analyses of HOFs (Trucco et al., 2008a, Castaldo et al., 2016, Akhtar and Utne, 2014).

As far as the maritime accident modelling is concerned, there are many approaches, *e.g.* Naïve Bayesian Networks (NBN), Augmented naive Bayesian Networks (ABN), and Tree Augmented Naive Bayes (TAN). Because the complexity of a data-driven BN structure super-exponentially increases with the growing number of variables in the network (Yang et al., 2018), NBNs are usually used in a simple network structure for the risk factors analyses of maritime accidents. To do so, there is a strong assumption in most NBN models that it has an independent node as the target node directly connected to all the other nodes without other links in the structure. NBN is a commonly used model aiming at improved classification (Friedman et al., 1997). On the other hand, in order to investigate the relations among risk factors considering more attributes in the network, NBN is not appropriate. Friedman et al. (1997) pointed out that TAN outperforms naive Bayes, at the same time, maintains the computational simplicity and robustness that characterise naive Bayes. Therefore, TAN is suitable for complex BN structure considering more human-related RIFs.

In addition, research suggested that significant work remained to be done after having the causations identified. Yang et al. (2018) proposed a Bayesian Network-based approach to analyse risk factors influencing Port State Control inspections and predict the detention probabilities under different situations. The findings could support port authorities to rationalise their inspection regulations as well as the allocation of the resources. Moreover, human factors are significant issues among decision making in accident preventions accounting for multiple criteria (Othman et al., 2015). For instance, Antão and Guedes Soares (2019) suggested to proactively optimise accident prevention through the development of specific procedures for fishing vessels and training for recreation vessels' crews, and reactively reduce the consequences of occurrence through equipping more life-saving equipment to the areas more prone to specific accidents. However, it revealed limited information regarding the direct impact of a human error into an occurrence. Othman et al. (2015) introduced TOPSIS method to maritime accident investigation and found that Senior Deck Cadets (SDC) are the most affected by distractions during the ship's operation. From this point of view, it is worth developing a methodology to introduce human factors into effective decision making in accident prevention.

Individually, the decision maker ranks alternatives after the qualitative or quantitative analysis of a set of criteria, and find the most desirable alternative based on the intersection of selected criteria (Yue, 2011). Besides, Multi Criteria Decision Making (MCDM) has been developed and applied to the maritime sector, especially for accident prevention. For instance, Hollnagel (2004) developed barrier functions and modelled barrier systems that will enable informed decisions for system changes for accident prevention rather than accident analysis. It was stated that accidents could be prevented through a combination of multiple criteria, including performance monitoring and barrier functions, rather than through the elimination of causes, which is a proactive approach. From this point of view, it provided insights for the recommendations in the cases of accidents and decision making of onboard operations for seafarers.

The seafarer’s decision making is associated with watchkeeping duties. Watchkeeping concerns those cognitive control processes of decision-making and preparation for action, which are activated when another vessel has been located and the potential for a collision is apparent. Koechlin et al. (2003) described a hierarchical model of cognitive control, wherein selection of motor actions in response to task stimuli (sensory control) are informed by existing stimulus-response associations for the situational context (contextual control), which in turn, are determined by recall of previous experience (episodic control). This model hypothesised that sensory control was localized to motor cortex, whereas contextual and episodic levels of control were associated respectively with bilateral activation of caudal (BA44/45) and rostral (BA46) regions of the lateral prefrontal cortex (LPC). This model was further developed by Koechlin and colleagues (Koechlin and Summerfield, 2007, Domenech and Koechlin, 2015) who proposed two methods of arbitration for executive control: (1) a peripheral system located in the premotor/caudal/orbitofrontal regions for action selection based on perceptual cues and reward values that are stable, and (2) a core system incorporating regions of the ventromedial, dorsomedial, lateral and polar PFC that adjust between the exploitation/adjustment of a previously learned behavioural set, and exploration/creation of new behavioural set in a variable environment. According to this model, the possibility of a desirable outcome via a specific behavioural task set is explored via the ventromedial region of the PFC. If there is a mismatch, the system reverts to the dorsomedial and lateral regions of the PFC to either create a new task-set or select an alternative task-set with a greater chance of a desirable output; for elaborated model and further explanation, see Koechlin (2016).

2.7 Mental workload and functional Near-Infrared Spectroscopy in transportation fields

Although the above human factors research indicates the patterns of risk factors influencing accidents, there is insufficient evidence to study individual factors which do not exist or about which only limited information is contained in accident reports or the literature, but are associated with the mental workload for seafarers. In order to find a way to obtain the evidence of the mental workload of seafarers to support the hypothesis of the study, a literature review has been conducted below.

Accounting for multi tasks on duty for seafarers, understanding the cognitive demands and their relations to human performance during the navigation helps provide insights for better performance training for seafarers. Mental workload is one of the fundamental factors for individuals on board in some transportation fields. Moreover, it has been used in a wide range of applications to evaluate task performance of operators or the practical aspect of system design (Ngodang et al., 2012, Dijksterhuis et al., 2011). Although mental workload related research has been conducted in road traffic accidents (Boyle et al., 2008, Rakauskas et al., 2008) and aviation transportation (Ayaz et al., 2012, Gateau et al., 2015), seafarers' mental workload analysis in maritime transport is scanty (Lim et al., 2018, Fan et al., 2018). The mental workload has been described as being responsible for the majority of road traffic accidents (Dijksterhuis et al., 2011). Both high and low levels cause insufficient perception and attention, which in turn leads to driver errors.

Mental workload is the amount of demands or resources requiring an operator to complete specific tasks. The more sophisticated the tasks, the more mental workloads are required to accomplish the tasks. Moreover, the mental workload is also linked to the experience of operators. Experienced drivers have acquired more effective automation through practice so that a lower level of mental workload was induced compared to novices (Patten et al., 2004). In the maritime sector, the majority of trainees had less workload when the experienced captain was present, and the latter had the highest workload levels while the former revealed low workload and stress because of the shared work and responsibility (Lim et al., 2018). Besides, neuroimaging techniques demonstrated increases in PFC activation with increases in mental workload (Ayaz et al., 2012). There is a threshold for workload, beyond which leads to worse performance and decreases in PFC activity (Molteni et al., 2008).

Brain activity in the transport field has previously been measured using a range of techniques, including functional magnetic resonance imaging (fMRI), positron emission tomography (PET), and electroencephalogram (EEG). The above three techniques are extremely sensitive to motion artefacts, making them difficult to deal with natural cognitive tasks in realistic scenarios (Chiarelli et al., 2017). Typically, fMRI and PET have physical limitations for participants, requiring them to be in a supine position (Foy et al., 2016). However, along with the high sensitivity for muscle movement, the EEG signal is weak during collection as it is affected by other noise. However, functional near-infrared spectroscopy (fNIRS) is a portable technique for both simulated environment and real-world operation. It is more robust to motion artefacts and has a higher temporal resolution (Noah et al., 2015). Besides, the hardware cost of fNIRS is significantly lower than most functional brain imaging techniques, including fMRI, PET, and EEG (Chiarelli et al., 2017).

fNIRS is an emerging non-invasive brain imaging modality for measuring and recording cortical haemodynamic activity (Fishburn et al., 2014). It does not need to confine the subject in a small space compared to fMRI, and is also able to generate montages covering the whole head or precisely the parts of the cortex that contain relevant activations. This functional neuroimaging technique can record changes in brain activation by measuring changes in the concentration of oxygenated and deoxygenated haemoglobin, which is based on the different absorption spectra of near-infrared light. It is a sensitive and consequent mature measurement technique for identifying different mental workloads.

To quantify the mental workload, fNIRS is a common technique applied in real-world scenarios (Christian et al., 2013), as fNIRS is sensitive to the cognitive load and state and can be used as a viable alternative of fMRI (Fishburn et al., 2014). Brain changes discussed above may also be evident in changes in haemodynamic concentrations measured by fNIRS according to a study on the association between haemoglobin levels and white matter conducted by Rozanski et al. (2014). More specifically, the increases in prefrontal activation are associated with increases in development by using fNIRS (Schroeter et al., 2004, Franceschini et al., 2007), which also have been found using fMRI (Adleman et al., 2002). Brain activity has a linear relationship with the working memory load of the left and right prefrontal cortex (Fishburn et al., 2014). Statistically different levels of oxygenation change result from significant changes in task difficulty. However, smaller differences in task difficulty were not reliably differentiated in some cases (Ayaz et al., 2012). In this way, fNIRS can be used to design optode holders to analyse the region of interest of the brain for the investigated tasks.

2.8 Research gaps

This chapter presents a comprehensive review of a broad range of literature and the available maritime accident database from the MAIB of UK and TSB of Canada organisations from 2012 to 2017. Because MAIB adapted European Marine Casualty Information Platform (EMCIP) in 2011, and since then the records on maritime accident reports have been in uniform style. The number of maritime accidents from two databases in five years is reasonable for academic research referring to literature review.

It provides the comprehensive summaries of the research development of human errors, the realistic phenomena in accidents, common errors highlighted concerning human errors during the accidents, decision-making theories, and mental worload analysis, see Table 2.2.

Table 2.2 Summarise the literature review

Categorise	**Main contents**
Human reliability in maritime field	1.Human reliability analysis methods and models used in the maritime sector 2.The investigation of human errors in maritime accident reports
Risk assessment in maritime systems and accidents	1.Maritime accident risk models have been fast developed 2.Risk analysis of maritime accidents would benefit the decision-making systems onboard 3.The causation analysis and modelling of maritime risks, including BN
Human factors in maritime accidents	1.The strengths and weakness of several typical studies on human factors 2.The maritime accident database used to obtain the primary data 3.BN’s advantages as a competitive approach for human factors research
Decision making in maritime accidents	1.The importance of introducing human factors into effective decision making in accident prevention

	2.Individually, seafarer's decision making is associated with watchkeeping duties
Mental workload and fNIRS in transportation fields	1.The reason why this work introduces mental workload into human factors study 2.Definition of mental workload for seafarers 3.fNIRS's advantages and applications in transportation fields

More importantly, the research on the common elements contributing to human errors in maritime accidents can be complicated and multi-dimensional effects given multi-disciplines. Consequently, the studies carried out on this topic are relatively rare and can be developed. Based on the literature review, some research gaps are discussed as follows.

i. Redefining the risk factors

As stated in the maritime accident reports, there are several new factors related to human errors compared to the factors highlighted in the past, for example, ergonomic impact of ship design, unfamiliar with the automatic equipment on board, cognitive overload, lack of situation awareness due to the advanced devices, and over-reliance on AIS (Automatic identification system).

With the development of automation in the shipping industry, fewer crew are on board. It is the advance in automation and reallocation of crew responsibility, as well as shore-based equipment and onboard devices, that permitted reductions in crew size (Council, 1990). To some extent, the automation could relieve the human errors in shipping by simplifying the operational procedures and raising the emergency alarm in time. However, it could aggravate a dangerous situation in the condition of situational awareness being lost or unfamiliarity with the automatic devices, even in the case of inability to terminate the specific automatic action of ships. Moreover, automation has a prospecting expectation of personal work and safety, which cannot merely replace human work thoroughly. Humans will still work on monitoring, remote control, and maintenance, especially on the high seas unmanned ships where it (automation) has to coexist with manned ship systems (Porathe et al., 2014). In this regard, automation in the vessel creates new error pathways, primarily resulting from human errors-related factors, deficiencies in mission shifts, and postpones chances to correct errors in the system further into the future. It is noteworthy to redefine and explore the potential hazards and risks related to human errors to peruse safe navigation, especially associated with psychophysiological factors.

ii. Incorporating quantitative methods into human errors assessment

Integrating the primary data with the advanced quantitative BN analysis approach facilitates maritime accident analysis and prevention from an innovative perspective. Despite previous attempts at using BN to model objective data from accident reports (Wang and Yang, 2018), the relevant investigation relied on a small scale database constrained in a pre-defined water/region. It requires more experiments based on a wide range of maritime accident data to be conducted to generalise the finding on BN's feasibility on RIF analyses and more importantly, to reveal the most critical RIF from a global perspective, particularly concerning different accident types. Previous studies relying mainly on the secondary database for RIFs identification were unable to present primary information from accident reports. However, the data acquisition through the investigation of accident reports brings new insights, which cannot be achieved from the existing databases. One of the research gaps of this study is to propose database for quantitative analysis and assessment, and to incorporate human factors derived from accident reports into accident analysis, combined with other external factors.

On the other hand, compared with the studies on the probability and/or the frequency of maritime accidents, those addressing the relationship between risk factors and accident types are scanty in the literature. For example, the risk factors contributing to collision may be different from the risk factors contributing to sinking. It reveals another new feature that is the analysis of accident types in maritime transportation and a new understanding of differentiation among critical factors contributing to different types of accidents. Also, compared to the studies using expert judgements in BN construction, data-driven BN in maritime risk analyses is scarce, requiring more experimental evidence to be collected before its wide practical applications. To fulfil this gap, the study conducts a data-driven BN to generate the structure of RIFs. Consequently, it will provide new insights into the differentiation among critical human factors contributing to each of the different types of accidents.

iii. Achieving the control measures of human errors

Literally the potential human errors during the manoeuvring procedures or navigation process could be mitigated at the beginning of ship design. In recent years, the innovation of ship development and the increasing complexity of updated manoeuvring-related procedures has caused more attention to be paid to the ergonomic issues of vessels, particularly within the bridge design. Specifically, visual blind sector ahead and motion illusion not only lead to inaccurate or non intuitive data and blurred information in regard to observing deviation, but also be vulnerable for the increasing workload and distraction of multi-tasks conducting which is a common phenomenon in sailing or navigation process. As illustrated in the MAIB 26-2013 and MAIB 03-2017, the bridge design led the officer on duty to sit down and then increased the potential for him to fall asleep and caused the pilot’s disorientation. It implies that ergonomic design should be considered into human factors research in maritime safety.

Another clue to controlling the human factor risks will be in and after the process of the emergency. Understanding the human errors attributes benefits the intervention of people or automatic auxiliary system during the emergency process. It is imperative to take adequate measures to prevent further hazards from spreading and decrease costs for recovering. These issues as to how to reduce the risk level of human errors scenarios and the possible potential intervention remain unclear.

iv. Neurophysiological methods for human factors research

There is literature on the framework of human errors and human factors analyses, to generate the risk assessment of human mistakes. Relevant studies (Xi *et al.*, 2017, Akyuz and Celik, 2014, Chen *et al.*, 2013) focus on the concepts of HOFs, HRA, and human errors, human failure etcetera. Most of such studies are unable to measure the specific factor changing, especially the quantitative data of psychological and physiological characteristics of the human responses. As the method of analysing the questionnaire or accident report is one of the subjective ways of data collection, novel quantitative methods tend to be further applied in the assessment of human errors. It is necessary for the proposed framework to incorporate the novel quantitative approach given multi-discipline, for example, the cognitive load of seafarers from the psychophysiological domain, and the knowledge for feature extraction of human performance. Among them, activities of the subject's central nervous system or neurobehavioral parameters could be imperative to one of the novel quantitative methods. As is shown in an EEG-based CogniMeter system (Hou et al., 2015), emotion, mental workload, and stress using cognitive algorithms were detected. With the rising psychological concern, drivers' workload, pressure, emotional stress and environmental stress, can also be monitored associated with advanced systems (Liu et al., 2016b, Fan et al., 2017).

Physiological signals (Hou et al., 2015) are collected to quantify human factors using sensors like EEG, ECG, EMG, blood volume pulse, skin electrical response, and eye movement. However, the relationship between psychophysiological signals and human performance was not demonstrated. Although studies on angry driving in road transportation (Yan et al., 2015, Zhang et al., 2014b, Lafont et al., 2018) have been conducted to identify the emotional connection between drivers and behaviours, there is rare research on similar perspectives in the maritime field.

Furthermore, research using fNIRS technique provides further support for the activation of the dorsolateral prefrontal cortex (DLPFC) as a reflection of mental workload. However, much of this research does not use naturalistic tasks in the maritime field, and none has focused on differences in DLPFC activity between experienced officers and novice officers. In this regards, another research gap lies in considering more variables (e.g. experience, distraction) influencing the mental states of seafarers, and involves psychophysiological methods to design human error-oriented scenarios affecting seafarers' performance and measure their mental state in association with these factors. Therefore, to fulfil this gap, this study investigates how the mental workload induced by scenarios in the ship bridge influences neurophysiological activation, which may generate insights for seafarers' training and certification.

The above demonstration presents research gaps in the current research field. Also, the identified research gaps indicate the valuable points of this work, which clarifies the research conducted in the following chapters.

2.9 Concluding remarks

The following are the most significant remarks comprised in the chapter, and emphasised in the form of bullet points for the reader's ease:

- The maritime system is a human-machine system, and most marine accidents are caused, at least in part, by human errors.
- There are numerous reasons for an individual making errors. These may include communication failure, ineffective training, memory lapse, inattention, poorly designed equipment, exhaustion or fatigue, ignorance, noisy working conditions, other personal and environmental factors.
- Automation in the vessel creates new error pathways, primarily resulting from human errors-related factors, deficiencies in mission shifts, and postpones chances to correct errors in the system further into the future. It is noteworthy to redefine and explore the potential hazards and risks related to human errors.
- There are risk factors resulting in human errors in the maritime domain from maritime accident reports. The risk factors contributing to collision may be different from the risk factors contributing to sinking. A systematic procedure for searching

the maritime accident reports database, and selecting the reviewed reports has been applied.

- Since the UK MCA proposed the FSA framework to the International Maritime Organization, maritime accident risk models have been fast developed because of the goal-setting risk regime.
- Modelling of maritime accidents since it enables quantitative analysis of HOFs explicitly reveals probabilistic dependencies between factors and their causal relationships.
- BN is appropriate for modelling maritime accidents since it enables quantitative analysis of HOFs.
- Compared to the studies using expert judgements in BN construction, data-driven BN in maritime risk analysis is scarce, requiring more experimental evidence to be collected before its wide practical applications.
- Physiological signals can be collected to quantify human factors using sensors like EEG, ECG, EMG, blood volume pulse, skin electrical response, and eye movement.
- Mental workload is linked to the experience of operators. Experienced drivers have acquired more effective automation through practice so that a lower level of mental workload was induced compared to novices.
- In the maritime sector, the majority of trainees had less workload when the experienced captain was present, and the latter had the highest workload levels while the former revealed low workload and stress because of the shared work and responsibility.
- To quantify the mental workload, fNIRS is a common technique applied in real-world scenarios, as fNIRS is sensitive to the cognitive load and state.
- Considering more variables (e.g. experience, distraction) influencing the mental states of seafarers, and involving psychophysiological methods to design human error-oriented scenarios affecting seafarers' performance and measure their mental state may generate insights for seafarers' training and certification.

Chapter 3 Research methodology and approaches adopted

3.1 Introductory remarks

This chapter discusses the research approaches, which have been implemented to reach the defined aims and objectives. One of the objectives is to provide a novel risk assessment method for defining, assessing, and analysing the risk factors in maritime accidents with human factors perspectives. Due to the insufficient specific data, the literature review and maritime accidents review are conducted to generate the raw database in risk identification and risk data collection. A systematic procedure for searching the maritime accident reports database, and selecting the reviewed reports has been applied. BN offers a methodological approach that learns the structure of modelling and describes the significant interdependencies between the RIFs. The application of the proposed modelling method enhances the practice of risk modelling, which can be used to address human factor risk effects and potential risk reduction outcomes in maritime accidents, see the left part of Figure 3.1.

Another aim of this study is to investigate the mental workload and neurophysiological activation of seafarers during navigation duty. With this regard, it conducts an experimental study using the fNIRS technique. Much of the research does not use naturalistic tasks in the maritime field. Therefore this chapter proposes an approach to design the experiment, combined with functional connectivity analysis, to explore how the mental workload induced by scenarios in the bridge simulation influences neurophysiological activation. In order to illustrate the change of brain activity and its relations to human performance, relevant theories have been applied for the research, see the right part of Figure 3.1.

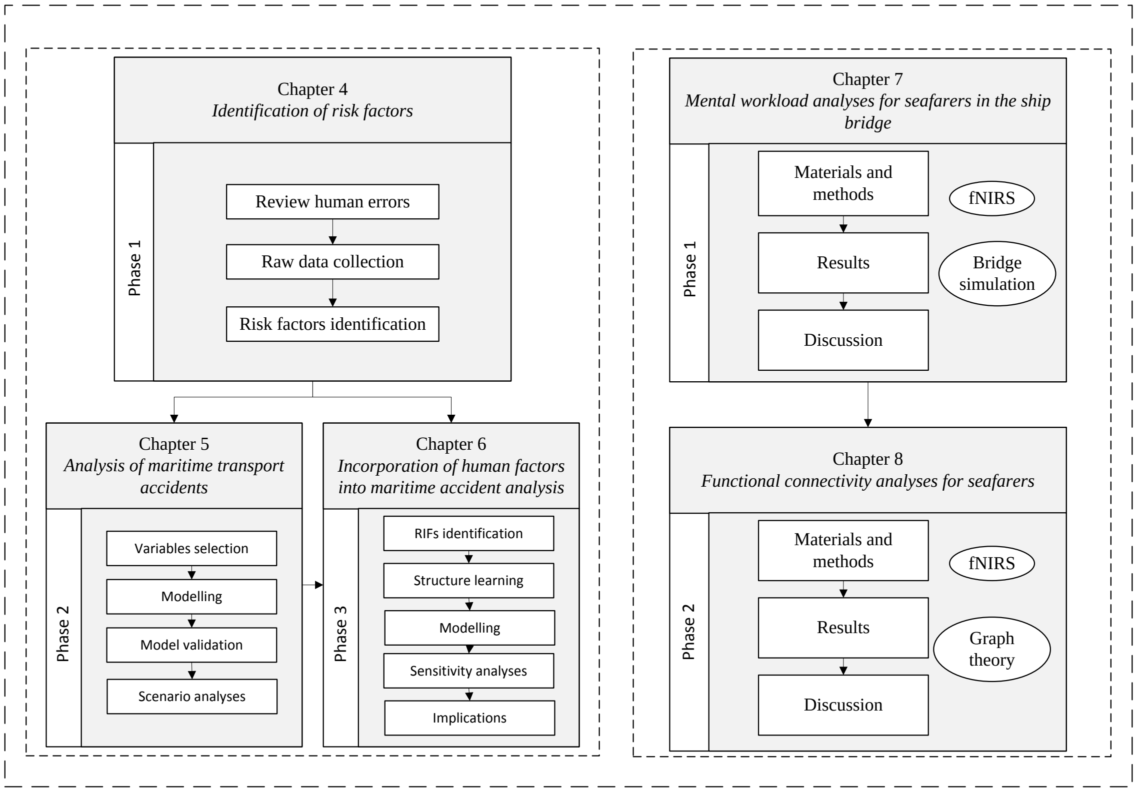


Figure 3.1 Detailed technical chapters of the work

3.2 Identification of risk factors

In order to review human factors in maritime transportation and common factors resulting in human errors, a systematic procedure for searching the maritime accident reports database, and selecting the reviewed reports has been applied. To begin with, it is necessary to conduct a systematic procedure to search the maritime accident reports and select the reviewed reports, referring to Macrae (2009), Chauvin et al. (2013), Uğurlu et al. (2015a), Wan et al. (2017). The procedure consists of three stages: (1) online database searching; (2) reports screening and selecting; (3) refining and analysis. In this process, there are 152 accident reports in MAIB and 61 accident reports in TSB from 2012 to 2017.

In the screening process stage, the accident reports were filtered into human error-related accidents to ensure the representativeness and relevance of the reviewed accident reports. To begin with, some of the accident reports involving passengers disobeying rules or drowning in the swimming pool on cruise ships, and extreme accidents which occurred in small fishing vessels, tugs etcetera were discarded, as their reduced manning requirements would easily lead to a distortion of results about the human element influence (Tzannatos, 2010). On the other hand, the accident reports on mechanical failures or severe weather without serious or obvious human errors were not to be screened, considering the relevance of human errors in maritime accidents. In this way, there are 109 accident reports extracted from 152 reports in MAIB and 52 accident reports obtained from 61 reports in TSB. It is noted that, on rare occasions, an accident report (4 of 109 in MAIB) may contain two similar or related incidents or accidents from the database, where it is counted as one accident for analysis due to the characteristics similarity and information integrity.

In the final stage, these reports had been further refined and analysed through review, especially the 'safety issues' and 'common factors' section in the accident reports. Some details of information associated with maritime accidents were involved in refining, such as accident report number, accident type, vessel type, a summary of accidents, date of occurrence. Specifically, ship operation and voyage segment of the accident were analysed from the MAIB database.

This is a significant process for analysing the accident reports because human factors described in reports are not literally classified in the procedures of investigation, where more information on human errors is closely linked with near-misses or demonstrated in the way of "what if" sentences in reports. To summarise the human error-related factors among the accident reports, some descriptions including the behaviour of crews or seafarers and key chapters focused on direct or indirect factors of accidents were highlighted and extracted as the human error attributes in the study. Although some sentences reveal only potential hazards associated with human errors, the majority are stated in a causal relationship. Finally, these formulated the database of human error attributes in the study. The distribution of accident reports by source database, year of occurrence, accident type, vessel type, ship operation, and voyage segment were generated. In addition, the analyses of human errors exist in accident reports and the common factors contributing to human errors are analysed in maritime accident reports. From the perspective of maritime accident human error related factors, such a thorough review will be valuable in the evaluation research of human error in maritime accidents and hence provide applicable insights in terms of reducing the risk of navigation or manoeuvring related to ships in the future.

With respect to RIFs in maritime accidents, it is necessary to identify the critical factors from accident investigation reports. According to the filtered reports, risk factors are derived among them according to their appearance frequency in accident reports to eliminate the factors of trivial effect (i.e. appearing less than twice across all the searched reports). As a result, RIFs are identified for modelling in the next step.

3.3 RIFs analysis – model structure learning

BN is a probabilistic directed acyclic graphical (DAG) model (Pearl, 1988) for modelling RIFs in this study, which is composed of nodes with the links between them, representing variables and influences of one node on the other(s), respectively. The directional arc from node *A* to node B refers that variable *A* has a direct causal effect on *B*, representing conditional dependencies. In addition, the nodes that are not directly linked are conditionally independent of each other. A BN model usually consists of the following steps: data acquisition, BN structure learning, BN analysis, and sensitivity analysis and model validation (Zhang et al., 2013).

3.3.1 Naïve Bayesian Network (NBN)

Once RIFs are identified, a BN structure is to be generated by using the factors as the nodes. There are mainly two approaches to BN structure learning. One is based on expert knowledge, which is used to conduct qualitative analyses based on subjective causal relationships. An alternative approach for BN structure learning is the data-driven approach to represent the interactive dependencies between variables. This study developed BN modelling by the latter data-driven method.

As far as the data-driven approach is concerned, there are many approaches, *e.g.* NBN, ABN, and TAN. First of all, a simple network structure is used for the risk factors analyses of maritime accidents. Because the complexity of a data-driven BN structure super-exponentially increases with the growing number of variables in the network (Yang et al., 2018), NBNs are usually used. To do so, there is a strong assumption in most NBN models that it has an independent node as the target node directly connected to all the other nodes without other links in the structure. NBN is a commonly used model aiming at improved classification (Friedman et al., 1997).

3.3.2 Tree Augmented Naive Bayes (TAN)

On the other hand, a more complex structure is considered in another model, so as to investigate the interdependencies and relations among RIFs further. Besides, more human factors are considered for RIFs selection. Among many data-driven approaches, Friedman et al. (1997) pointed out that TAN outperforms naive Bayes, at the same time, maintains the computational simplicity and robustness that characterise naive Bayes.

3.4 Quantitative methods on inter-relationships among RIFs

In order to illustrate the inference process in the above models, as well as reveal inter-relationships among RIFs, there are quantitative methods applied to the model, including mutual information, sensitivity analysis etcetera .

3.4.1 Mutual information

In the probabilistic theory, the mutual information is a measure of the mutual dependence between two variables. It describes the amount of information obtained about one random variable, through the other random variables (Yang et al., 2018). Mutual information is also interpreted as entropy reduction, measuring the mutual dependence of different variables. Since the objective of this study is to identify the relationship between RIFs and ‘accident type’, ‘accident type’ is determined as the fixed variable in mutual information.

The larger the value of mutual information, the stronger the relationship between individual RIF and ‘accident type’. In this way, calculating the mutual information is able to filter out the RIFs that are relatively less important in the model. Then the remaining RIFs are selected as significant variables with regards to a pre-defined accident type.

3.4.2 Sensitivity analysis - True Risk Influence (TRI) of risk variables

Based on the significant RIFs screened from mutual information calculation, there is another form of sensitivity analysis, e.g. scenario simulation, to determine the effects of different variables, particularly in a combined way. The traditional way is to set a scenario in which all the other nodes (apart from the investigated ones) are locked, and the target node is updated accordingly. It means, for example, 10% up and down for the node reveals the effects of the variable in the model. It is considered applicable for variables with two states, but not suitable for variables with more than two states. For example, when the state value of a bi-state variable is increased from 0% to 10%, the value of the other state will decrease from 100% to 90% accordingly. However, the integration of the other states of multi-state variables makes it difficult to appropriately decrease their values when a selected state increases its value by 10%. In this case, the traditional scenario simulation is inappropriate.

In order to overcome the drawback of the traditional way, a new method proposed by

Alyami et al. (2019) is applied here. This method increases the probability of the state within the highest influencing on a type of accident to 100% to obtain the High Risk Inference (HRI) of this type of accident. Then it increases the probability of the state generating the lowest influence on the accident type to 100% to obtain the Low Risk Inference (LRI). In this way, calculating the average value of HRI and LRI concludes the True Risk Influence (TRI) of each variable in the case of a particular accident type.

3.4.3 Model validation

There are two axioms that have at least to be satisfied in the sensitivity analysis for the inference process (Yang et al., 2009, Zhang et al., 2013). The axioms are expressed as follows:

Axiom 1: A slight increase/decrease in the prior probabilities of each test node should contribute to the corresponding increase/decrease in the posterior probability of the target node.

Axiom 2: The total influence of the combination of the probability variations of x parameters (evidence) should be no smaller than the one from the set of y ($y \in x$) risk factors.

3.4.4 Scenario analysis

BN modelling can also explain the most probable scenario with reference to a particular accident type, which is helpful to demonstrate inter-relationships among RIFs in TAN model. Providing a plausible explanation for the observed findings is called the most probable explanation (MPE). It is a particular case of the maximum a-posteriori probability. In the case that results of regular belief updating are questionable, the MPE can be used to identify the states of RIFs to provide a scenario for which the beliefs are upheld. It finds a completely specified scenario easier to understand. Then the study gains insights by putting the Bayes net in MPE mode, entering the evidence, and observing the most probable configuration for the maritime accident type.

3.5 fNIRS technique for maritime transportation

In order to explore the mental workload for seafarers in the experimental study, the Nirsport 88 (NIRx Medical Technologies LLC, USA) continuous wave (CW) fNIRS device was used to measure DLPFC activity of seafarers. This particular device records at a frequency of 8.9286Hz and performs dual-wavelength CW near-infrared (NIR) diffuse tomographic measurements. It consists of 8 sources and 8 detectors that emit near-infrared light at 760nm and 850nm wavelengths, which are absorbed primarily by deoxygenated and oxygenated haemoglobin, respectively. These objective measurements help understand mental workload of seafarers and the situational awareness obtained during the watchkeeping.

3.6 Subjective workload measurement

Developed initially as a paper and pencil questionnaire by NASA Ames Research Center's (ARC) Sandra Hart in the 1980s, NASA Task Load Index (TLX) has become the gold standard for measuring subjective workload across a wide range of applications (Hart, 2006). NASA TLX questionnaire is used to assess subjective levels of perceived workload. An extended NASA Task Load Index (TLX) questionnaire is supposed to be completed for the scenario developed in bridge simulation. This is a self-assessed measure based on six 10-point scales, with 1 being "Very Low" and 10 "Very High." The scales are Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, and Frustration. Additional information about education degree, STCW qualification, and practical maritime seafaring experience (month or year) are also supposed to be given by participants. On the other hand, the staff in the control room next to the simulator should record the target spotted time with corresponding distance (distance 1) and the course changed time with corresponding distance (distance 2). The above information and questionnaires are used to analyse behavioural performance and task load.

3.7 fNIRS experiment for seafarers in the bridge simulator

The experiment uses a mixed design, where two groups of participants are allocated to 1) experienced group and 2) inexperienced group, depending on their STCW qualification and nautical experience. Specifically, the experienced group included a master mariner (MM), chief mate (CM), and officer of the watch (OOW), while the inexperienced group contained able seamen (AB) and cadets. Both groups undergo the scenario with the timeline of baseline, watchkeeping, and decision-making. However, it is presented in 1) non-distraction condition or 2) distraction condition. The non-distraction condition is shown in the workflow of ***Chapter 7***. The distraction condition is demonstrated by setting the reporting points (*Rn*) at the same intervals while watch-keeping and decision-making. It distracts the participants' attention by requiring them to report the vessel's position every 10' of difference in longitude, as well as answering the questions from the staff in the control room, which is the same as the seafarers' daily work.

The participant wears the NIRx Sport apparatus, which is an fNIRS skullcap containing infrared sensors and detectors allowing the operator to see the blood volume, oxygenated and deoxygenated blood flow in the DLPFC indicating how the state of the seafarer changes during the navigation scenario and showing what the difference is between experienced and inexperienced. The scenario lasts on average no longer than 30 minutes. Then the NASA- TLX questionnaire is collected after each scenario. The following process demonstrates the trials in a ship bridge simulator:

a) Taking blood pressure if necessary (hypertension self-reported by participants): this step is to exclude the participants suffering from high blood pressure since this may affect the results from fNIRS.

b) Read information sheet and give informed consent: this step is compulsory, and no participant will be allowed to take part in the study before having read the information provided, understood the conditions of the experiment and having signed the consent form.

c) Training on the simulator: All the participants will be asked to take several minutes to attend the training session of the bridge simulator to familiarise them with the bridge and the mission.

d) fNIRS placement: the equipment will be placed on participants' heads to measure oxygenated and deoxygenated haemoglobin with seven sensors, and seven detectors relaying information on the blood volume and flow in the prefrontal cortex of the brain by the emission of infrared light during the experiment.

e) Simulator trial: participants will be allocated to the experienced group (20) or inexperienced group (20). Moreover, each group will undergo the scenario in the bridge simulator, 10 participants of each group are in 1) non-distraction condition and 10 participants are in 2) distraction condition.

f) Questionnaire: after the scenario test, the participant is supposed to finish the questionnaire about the subjectively perceived workload.

g) Debrief: review the performance.

3.8 Functional connectivity and graph theory

The functional connection between pairs of brain regions demonstrates the temporal correlation of regional haemodynamics. Thus symmetric correlation matrices are obtained from the partial correlation coefficients of all pairwise combinations of the 15 channels, for each group or segment, shown in Figure 3.2. The rows and columns of the matrix represent the channels, while cells of the matrix reflect the correlation coefficient of the corresponding channels. From these matrices, weak links are representing spurious connections, where they should be discarded by thresholding (Rubinov and Sporns, 2010). It is necessary to decide on a threshold level for the correlation scores to demonstrate where the strong connections are. In order to calculate various threshold levels, the percentile distribution of all correlation values is obtained. For example, a very liberal threshold (50th percentile), a more conservative threshold (75th percentile) and extremely conservative threshold (95th percentile) are selected. Obviously, there are many connections for the liberal threshold and very few for the threshold based on the 95th percentile. Only coefficients greater than or equal to the chosen threshold value are kept as connections assigned with a value of 1. Otherwise, the coefficient is replaced with a 0, thus creating a binary adjacency matrix (in Figure 3.3). In this way, it creates a cross-correlation matrix to represent these data in a visualisation.

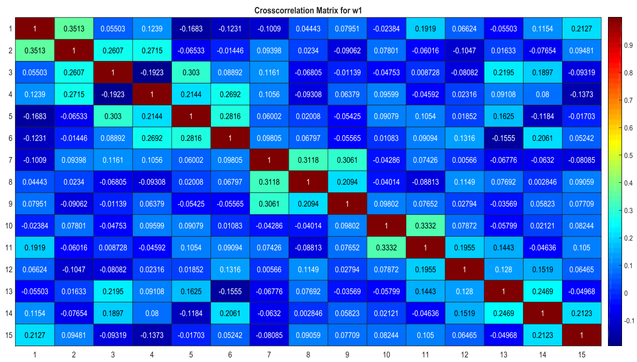


Figure 3.2 Constructing a binary functional connection network from fNIRS-data. Partial correlation coefficients were calculated for all pairwise combinations of channels to obtain a symmetrical cross-correlation matrix

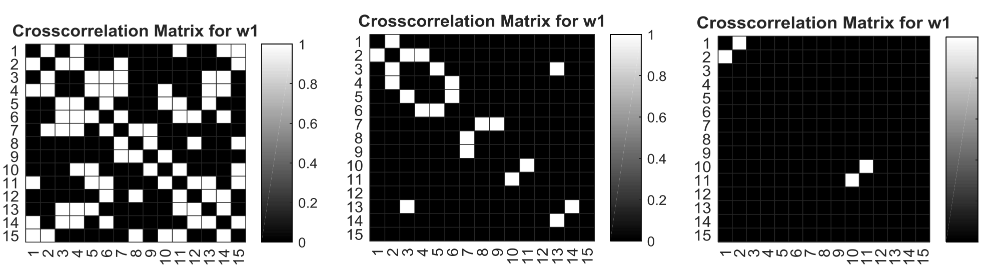


Figure 3.3 Constructing a binary functional connection network from fNIRS-data. Binary adjacency matrices were calculated by thresholding along with different threshold values

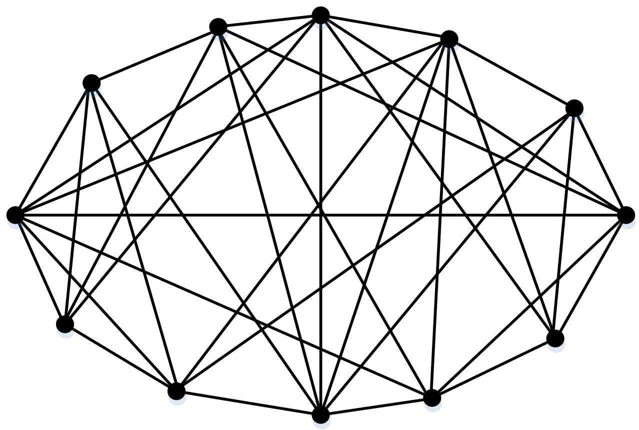


Figure 3.4 Constructing a binary functional connection network from fNIRS-data. Network metrics density and clustering coefficient were obtained on the functional connectivity networks (binary connection work) described by the adjacency matrices

In order to reflect the characteristics of networks (Figure 3.8), there are two most commonly used parameters (Racz et al., 2017) to describe it: the connection density (D), and the local clustering coefficient (C). The connection density of a network is the fraction of the existing connections to all possible connections. The density is used to describe the overall 'wiring cost' of the given network (Racz et al., 2017). In addition, the clustering coefficient for an individual node, defines the fraction of its neighbours which are also neighbours of each other (Watts and Strogatz, 1998), i.e. reflecting the number of triangles around the given node (Rubinov and Sporns, 2010).

To sum up, the above approaches aim at analysing the risk factors in maritime accidents with human factors perspectives and conducting experimental research on mental workload for seafarers. That is to say, a novel risk assessment method on human factors research has been proposed to generate a raw database for risk factors identification, learn the structure of the model, and describe the interdependencies among RIFs with human factors perspectives using methodologies in Section 3.2, 3.3, 3.4. By doing this, it generates insights for countermeasures for human errors in maritime accidents.

On the other hand, an experimental study using the fNIRS technique has been conducted to complement the insufficient data in the former risk-based study and further explore the mental workload for seafarers from subjective and microcosmic perspectives. It explores how the mental workload induced in the bridge simulation influences neurophysiological activation using neurophysiological methods. The descriptions on how these methodologies will be applied to bridge the gaps previously identified can be seen in Figure 3.5.

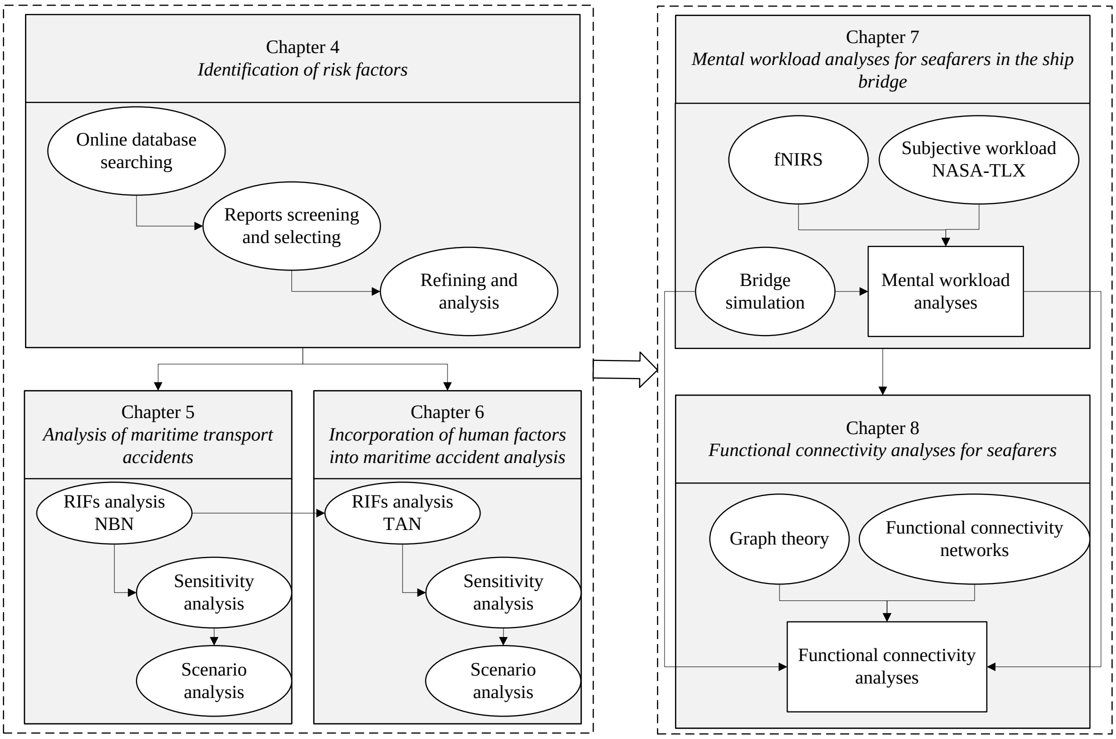


Figure 3.5 Methodology adopted in all technical chapters

3.9 Concluding remarks

The following are the most significant remarks comprised in the chapter, and emphasised in the form of bullet points for the reader's ease:

- The analysis of human errors exists in accident reports, and the common factors contributing to human errors are analysed in maritime accident reports. From the perspective of maritime accident human error related factors, such a thorough review will be valuable in the evaluation research of human error in maritime accidents and hence provide applicable insights in terms of reducing the risk of navigation or manoeuvring related to ships.

- BN is a probabilistic DAG model, which is composed of nodes with the links between them, representing variables and influences of one node on the other(s), respectively. A BN model usually consists of the following steps: data acquisition, BN structure learning, BN analysis, and sensitivity analysis and model validation.

- There are mainly two approaches to BN structure learning. One is based on expert knowledge, which is used to conduct a qualitative analysis based on subjective causal relationships. An alternative approach for BN structure learning is the data-driven approach to represent the interactive dependencies between variables. This study developed BN modelling by the latter data-driven method.

- Quantitative methods on inter-relationships among RIFs reflect in the sensitivity analyses of the BN model with regard to human factors in maritime accidents.

- In order to measure the neurophysiological activation in the experimental study, the Nirsport 88 continuous wave fNIRS device is used to measure the DLPFC activity of seafarers.

- Associated with the fNIRS technique, scenarios designed with bridge simulator and NASA-TLX questionnaires are utilised to conduct the experiment and subjectively quantify mental workload.

- The functional connection between pairs of brain regions demonstrates the temporal correlation of regional haemodynamics, reflecting the activity of brain areas and specific patterns in various conditions.

Chapter 4 Identification of risk factors

4.1 Introductory remarks

In order to identify risk factors contributing to human errors in maritime accidents, this chapter describes the procedure of generating a source database for risk factors to fulfil further risk analyses. It aims at illustrating the features of maritime accidents, the description of human errors, and risk factors related to human errors from the accident reports investigated by maritime organisations. Accidents related to human errors in the process of navigation and sailing that happened in the six years from 2012 to 2017, integrated with literature, are analysed to identify risk factors in maritime accidents from different views. From this perspective, this chapter provides a general demonstration of maritime accidents and rational classification of related risk factors as procedure factors, individual factors, vessel factors, environmental factors, regulation and management factors.

4.2 Data collection of maritime accidents

4.2.1 Distribution by the source database

Among the database composed of 161 accident reports (selected from ***Chapter 3***), 109 accident reports are from MAIB and 52 reports from the TSB. They are selected based on the methodology in Section 3.2. Besides MAIB and TSB, there is the fact that numerous maritime accident investigation organisations exist, e.g. United States National Transportation Safety Board (NTSB) and American Bureau of Shipping (ABS) in USA, Marine Department-Hong Kong (MARDEP) in China, Australian Transport Safety Bureau (ATSB) in Australia, Accident Investigation Board Norway (AIBN) in Norway etcetera. However, considering the flexibility of obtaining the data and representativeness of the maritime accident reports, the MAIB and TSB were selected as source database in this study, as they are among the most representative from the literature (Chauvin et al., 2013, Graziano et al., 2015, Kum and Sahin, 2015).

MAIB examines and investigates all types of marine accidents happening to or on board UK ships worldwide, and all vessels in UK territorial waters (MAIB, 2015). And, TSB is an independent agency that investigates occurrences in several modes of transportation, including the marine section. The maritime accident reports databases from these two organisations are the two most frequently used databases in maritime accident analysis, referring to Chauvin et al. (2013) and Uğurlu et al. (2015b). The details of accident reports are in the below Table 4.1.

Table 4.1 Code of maritime accidents reports

No	Code	Source	No	Code	Source
1	26-2017	MAIB	83	2-2014	MAIB
2	25-2017	MAIB	84	1-2014	MAIB
3	24-2017	MAIB	85	SB3/2014	MAIB
4	23-2017	MAIB	86	26-2013	MAIB
5	22-2017	MAIB	87	24-2013	MAIB
6	21-2017	MAIB	88	23-2013	MAIB
7	20-2017	MAIB	89	22-2013	MAIB
8	19-2017	MAIB	90	20-2013	MAIB
9	17-2017	MAIB	91	18-2013	MAIB
10	16-2017	MAIB	92	17-2013	MAIB
11	14-2017	MAIB	93	14-2013	MAIB
12	11-2017	MAIB	94	11-2013	MAIB
13	10-2017	MAIB	95	10-2013	MAIB
14	8-2017	MAIB	96	9-2013	MAIB
15	7-2017	MAIB	97	8-2013	MAIB
16	5-2017	MAIB	98	7-2013	MAIB
17	4-2017	MAIB	99	6-2013	MAIB
18	3-2017	MAIB	100	5-2013	MAIB
19	1-2017	MAIB	101	4-2013	MAIB
20	27-2016	MAIB	102	3-2013	MAIB
21	26-2016	MAIB	103	1-2013	MAIB
22	25-2016	MAIB	104	SB3/2013	MAIB
23	24-2016	MAIB	105	27-2012	MAIB

24	20-2016	MAIB	106	26-2012	MAIB
25	19-2016	MAIB	107	25-2012	MAIB
26	18-2016	MAIB	108	24-2012	MAIB
27	17-2016	MAIB	109	11-2012	MAIB
28	16-2016	MAIB	1	m16p0362	TSB
29	15-2016	MAIB	2	M16P0241	TSB
30	14-2016	MAIB	3	M16P0162	TSB
31	13-2016	MAIB	4	M16P0062	TSB
32	12-2016	MAIB	5	M16C0036	TSB
33	10-2016	MAIB	6	M16C0014	TSB
34	8-2016	MAIB	7	M16C0005	TSB
35	6-2016	MAIB	8	M16A0327	TSB
36	4-2016	MAIB	9	M16A0141	TSB
37	3-2016	MAIB	10	M16A0140	TSB
38	2-2016	MAIB	11	M16A0115	TSB
39	1-2016	MAIB	12	M15P0347	TSB
40	28-2015	MAIB	13	M15P0286	TSB
41	27-2015	MAIB	14	M15P0037	TSB
42	26-2015	MAIB	15	M15P0035	TSB
43	25-2015	MAIB	16	M15C0094	TSB
44	24-2015	MAIB	17	M15C0045	TSB
45	20-2015	MAIB	18	M15C0006	TSB
46	18-2015	MAIB	19	M15A0189	TSB
47	17-2015	MAIB	20	M15A0045	TSB
48	16-2015	MAIB	21	M15A0009	TSB
49	15-2015	MAIB	22	M14P0150	TSB
50	14-2015	MAIB	23	M14P0121	TSB
51	13-2015	MAIB	24	M14P0110	TSB
52	12-2015	MAIB	25	M14P0023	TSB
53	11-2015	MAIB	26	M14P0014	TSB
54	10-2015	MAIB	27	M14C0219	TSB
55	9-2015	MAIB	28	M14C0193	TSB
56	7-2015	MAIB	29	M14C0156	TSB
57	6-2015	MAIB	30	M14C0106	TSB
58	5-2015	MAIB	31	M14C0045	TSB
59	3-2015	MAIB	32	M14A0348	TSB
60	1-2015	MAIB	33	M14A0289	TSB
61	32-2014	MAIB	34	M14A0051	TSB
62	31-2014	MAIB	35	M13W0057	TSB
63	30-2014	MAIB	36	M13N0014	TSB
64	29-2014	MAIB	37	M13N0001	TSB

65	28-2014	MAIB	38	M13M0287	TSB
66	25-2014	MAIB	39	M13M0102	TSB
67	24-2014	MAIB	40	M13L0185	TSB
68	21-2014	MAIB	41	M13L0123	TSB
69	19-2014	MAIB	42	M13L0067	TSB
70	18-2014	MAIB	43	M13C0071	TSB
71	17-2014	MAIB	44	M12W0207	TSB
72	16-2014	MAIB	45	M12W0070	TSB
73	15-2014	MAIB	46	M12N0017	TSB
74	13-2014	MAIB	47	M12L0147	TSB
75	12-2014	MAIB	48	M12L0098	TSB
76	11-2014	MAIB	49	M12L0095	TSB
77	10-2014	MAIB	50	M12H0012	TSB
78	9-2014	MAIB	51	M12F0011	TSB
79	8-2014	MAIB	52	M12C0058	TSB
80	7-2014	MAIB			
81	6-2014	MAIB			
82	4-2014	MAIB			

4.2.2 Distribution by year of occurrence

According to the database established, their distribution by year from January 2012 to December 2017 is represented in Figure 4.1. It is noted that the specific number of maritime accidents or near misses which happened during this period is much larger than the number of accident reports. In order to refine and analyse common factors contributing to human errors in maritime accidents, only the accidents described and investigated in the way of accident reports are considered. It is noted that four accidents reports from MAIB in the database contain eight accidents' details, so that they are counted as 113 cases of MAIB instead of 109. The way of counting is according to the date of accidents' occurrence rather than the date of reports published. Hence, the number of accident reports in 2017 is only one, due to the uncertainty for the period of the maritime accident investigation.

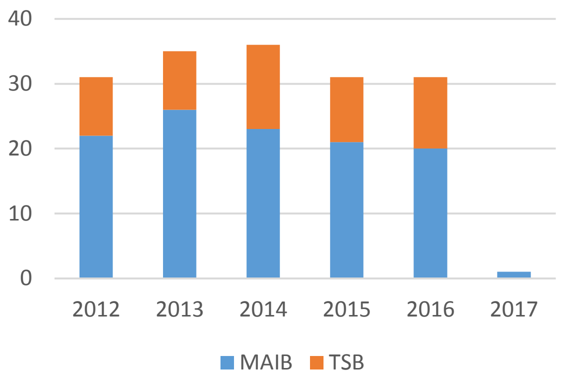


Figure 4.1 Distribution of reports by year of occurrence, by January 2018

4.2.3 Distribution by accident type

According to the database reviewed, their distribution by accident type is stated in Figure 4.2. In both MAIB and TSB sources, grounding accidents are the most frequently occurring accidents in the maritime transportation, accounting for 21.10% of total accidents in MAIB, and 26.92% of them in TSB. The grounding accidents are usually linked with human fatigue and human errors (Akhtar and Utne, 2014, Uğurlu et al., 2015b). Although the number of collision accidents ranks second among the accident type, it reveals the severe consequences once they have happened in maritime transportation according to the accident reports and literature (Rudan et al., 2012, Macrae, 2009, Sandhaland et al., 2015).

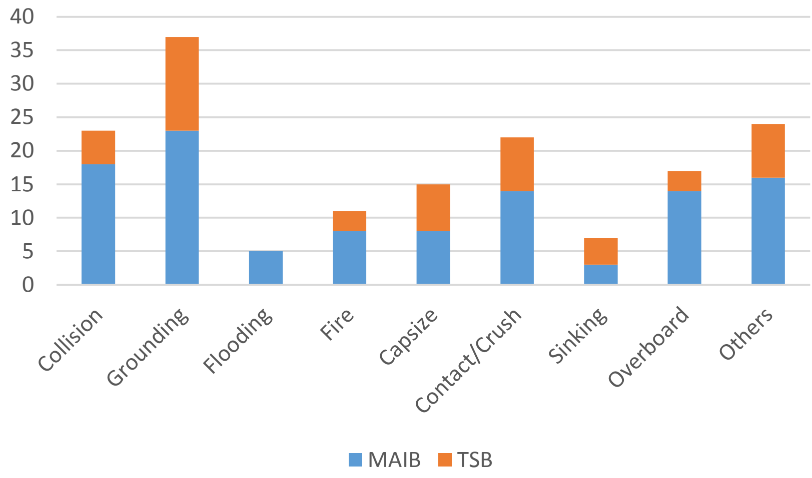
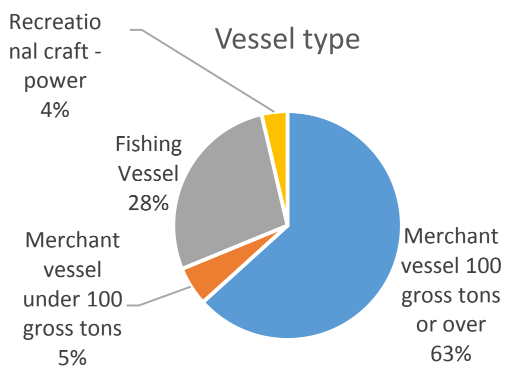


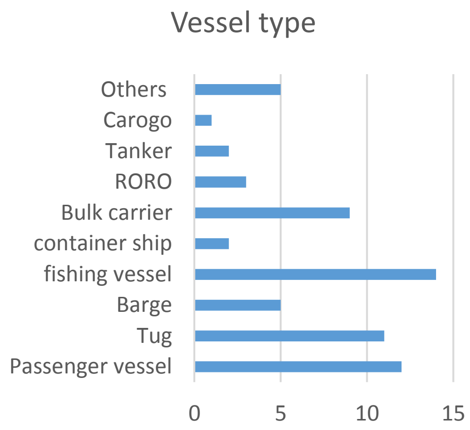
Figure 4.2 Distribution of reports by accident type

4.2.4 Distribution by vessel type, ship operation, and voyage segment

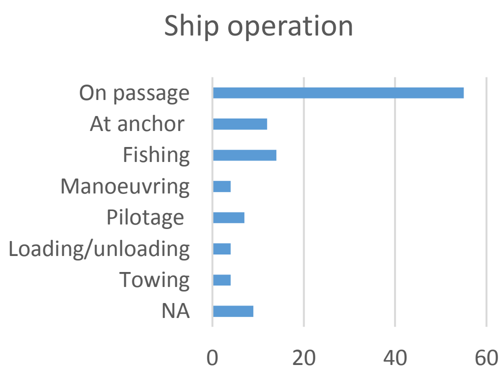
From the accident reports from MAIB, it is demonstrated that the accidents occurring on merchant vessels of 100 gross tons or over account for the majority of accidents, followed by fishing vessels (Figure 4.3). In addition, fishing and passenger vessels tend to be involved in maritime accidents according to the data from TSB. Most of the accidents happened when the ship was on passage rather than other ship operations, e.g. fishing, pilotage, at anchor. Due to the fact of the long period of voyage path compared to arrival or departure, the mid-water is regarded as the most likely accident area during the voyage segment. However, the arrival segment holds more hazards than the departure segment of the voyage.



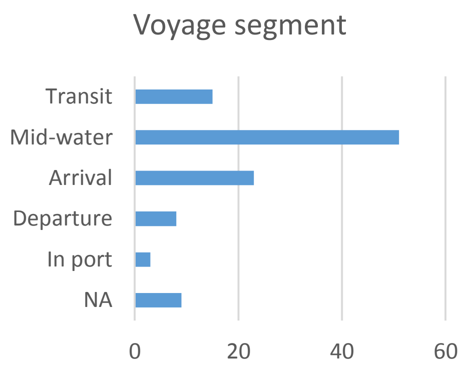
(A) Vessel type from MAIB



(B) Vessel type from TSB



(C) Ship operation from MAIB



(D) Voyage segment from MAIB

Figure 4.3 Distribution by (A)(B) vessel type, (C) ship operation, and (D) voyage segment

4.3 Common factors contributing to human errors

According to the data collected from maritime accident, common risk factors are extracted from the primary reports. Some factors including communication and coordination, lookout, use of navigation equipment, supervision and supports, are related to the working procedure of people; some factors are individual factors, such as fatigue and situational awareness (SA), which are related to the individual themselves; vessel factors are the condition of vessels, devices onboard, the ergonomic impact of design;

environment factors are weather condition, sea condition, the density of fairway traffic, and the noisy acoustic environment; regulation and management factors are associated with code, endorsement, regulations, procedure, instruction, formally published guidance, operation manual, and requirement.

4.3.1 Procedure factors

Human errors may be caused by procedures during the sailing or manoeuvring, especially for improper planning and communication problems. Macrae (2009) maps the typical patterns of human and organisational causes in grounding and collision maritime accidents to point out that groundings are more likely caused by inadequate passage planning, problem locating vessels, or communication on the bridge. While collisions commonly resulted from the inadequate planning process. Chauvin et al. (2013) found that most collisions were due to decision errors by a modified HFACS model in collisions, and Bridge Resource Management deficiencies and Inter-ship communications problems are more likely occurring in restricted waters and including vessels that are carrying pilots. Research on the prevention of grounding accidents involving human errors was conducted using the Analytic Hierarchy Process (Uğurlu et al., 2015b). It suggested the most significant causes are, lack of communication and coordination in Bridge Resource Management, position-fixing application errors, lookout errors, interpretation errors, use of improper charts, inefficient use of bridge navigation equipment, and fatigue. A study using the FTA method (Uğurlu et al., 2015a) found that reasons leading to human-error-originated initial events for collision accidents are, lack of education and experience, unfamiliarity with bridge and devices, lack of coordination in the bridge resources management, and inconvenient work hours. For grounding accidents, there is a lack of education and experience, errors in the passage plan and chart, failure to use the echo sounder, lack of communication, and inconvenient working hours.

‘Careless talk costs lives’, a phrase from some British propaganda during WWII neatly sums up the dangers of ineffective communications (Winbow, 2002). It illustrated the importance of effective communications between seafarers or between ship and shore, and the severe dangers if they go badly wrong. Meanwhile, it pointed out that ineffective or misunderstood communications often occur partly due to cultural differences but also due to language ‘barriers’ (TSB M14C0193). Research interviewing crew managers and seafarers in Greek shipping (Theotokas and Progoulaki, 2007), showed predominant problems like communication with multicultural crews, are rooted in cultural incompatibility and inadequate training, which inevitably affected the crew management and operation on board. It concluded that culture management could improve crew team coordination, communication, working environment and the overall performance of the team. Latterly, support of human operation, especially improving the ship’s navigation and aiding the master’s command, is proved to be necessary for shipping safety (Tzannatos, 2010).

Apart from this, ineffective supervision and supports, and improper supervision of loading operation are frequent during the navigation. Lone watchkeeper or working isolated makes the procedures on board vulnerable to the hazards due to the workload pressure or onboard culture. From MAIB 17-2016 report, although required by the Arco Avon’s SMS, the third engineer did not inform the chief engineer or the bridge OOW of the leaking problem of fuel or his intention to fix it. The reason for him not doing so was probably influenced by the onboard culture of routinely working isolated and the absence of adequate and frequent communication. Also, Arco Avon’s chief engineer’s standing orders requiring the duty engineer to progress routine duties and conduct planned maintenance while on watch, effectively condoned working alone and disobeyed the guidance provided in section 15.9.1 of COSWP, and with the guidance provided in the Code of Safe Working Practices for Merchant Seafarers 2015 edition. It all contributes to the mistakes the third engineer made. Moreover, from the MAIB 8-2014 report, the master and chief officer kept lone watched on the bridge with the functional Bridge Navigational Watch & Alarm System (BNWAS) switched off. According to this accident, and several similar others in the past, MAIB demonstrated that it was not safe for only two bridge watchkeepers to operate vessels because of the workloads placed on watchkeeping officers.

From the maritime accident reports (MAIB 6-2014), the bridge team's action was too late to be taken to prevent the collision with the method of recognising the high speed. Also, from the grounding accident (TSB M14P0014), upon initiating the turn, the vessel's rate of speed limited the time available to respond to the surrounding developing situation, resulting in that the vessel was on a course for the silting of the channel. It is also evident that relying on a single navigational device produced the risk of undetected potential errors or inaccuracies. From the perspective of pilotage, there is a risk that pilots make decisions referring to imprecise information if they do not take advantage of the accurate navigational aids available.

4.3.2 Individual factors

The human error relates to individuals themselves or the crew in teamwork, especially fatigue-related problems. Faced with the unique environment, seafarers on board take the irregular sleep patterns within the existence of time-zone crossings, noise, heat, cold, vibration and motion of vessels. It means sleep under such conditions is often interrupted, and the risk of fatigue induced by inadequate sleep and rest is relatively high. Also, seafarers are involved in multi-tasks. These include navigation, cargo handling, watchkeeping, communication, emergency response, paper charts, maintenance, administration and human resources management that is interacted with other vessels and a shore-based centre.

The research demonstrated three levels of reference to sleep - either being asleep without fatigue, conflicting pressures of work and sleep, and the nature of sleeping and work (Phillips, 2000). It revealed contributing factors of sleepiness among crucial crew members, and associated either being asleep, or being sleep deprived with accidents, but not with fatigue all the time. Hetherington et al. (2006) found that fatigue is more significant in the near sea than in support shipping. Exposure factors predicting fatigue are the length of working hours, sleep problems, tour length (more extended tours equate to less fatigue), shift length, job demands, stress or pressure, and standing watch. For ship types, seafarers on ferries reported higher levels of fatigue than other ship types. Strauch (2015) proposed a systematic method to determine whether fatigue adversely affected mariner performance in an accident. Akyuz and Celik (2015) adopted Cognitive Reliability and Error Analysis Method (CREAM) to assess human reliability along with the cargo loading process, and Akhtar and Utne (2015) used it to study common patterns of interlinked fatigue factors. It illustrated that “inattention”, “inadequate procedures”, “observation missed”, and “communication failure” were related to fatigue factors that influenced the human cognitive processes in accidents. The bridge team should be trained to recognise fatigue and exercise caution related to the fatigue factors.

Lack of SA is another focus of the individual factors contributing to human errors, which is also associated with being distracted, use of recreational drugs or alcohol. Prospect (MAIB 07-2014) grounded because the skipper was distracted due to a telephone conversation and his intention to check whether an email had been received during the departure, resulting in the loss of situation awareness. Also, from the MAIB 12-2016, the master, owing to lack of adequate assistance, was unable to maintain his situational awareness, resulting in a grounding accident. Due to the loss of situation awareness, the bridge team or masters have difficulties identifying the hazards around the ships, as well as dealing with the proper manoeuvring. Specifically, it will take a long time for the OOW to realise the vessel is in trouble even with the information shown in the navigational aids display, for example, the Electronic Chart Display and Information System (ECDIS) (MAIB 24-2014). As stated in MAIB 28-2015, the master and the third officer lost situation awareness before the collision, resulting in that the bridge team did not monitor another ship’s position and movement during the eight minutes from the pilot’s disembarkation. It reveals the significance of forming and maintaining the situation awareness of the seafarers on board. Moreover, it is demonstrated that the master's lack of situational awareness is contributed by stress, panic and poor communication regarding the status of the ship control (MAIB 20-2017).

In the maritime sector, Lim et al. (2018) suggested the majority of trainees had less workload when the experienced master was present, and the latter had the highest workload levels while the former had low workload because of the shared work and responsibility. Mental workload is the number of demands requiring a person to complete specific tasks. The more sophisticated the tasks, the more mental workload is required to do the tasks. It has been used in a wide range of applications to evaluate task performance of operators or the practical aspect of system design (Ngodang et al., 2012, Dijksterhuis et al., 2011). Moreover, the mental workload is linked to the experience of operators. Experienced drivers have acquired more effective automation through practice, so that a lower level of mental workload was induced compared to novices (Patten et al., 2004).

4.3.3 Vessel factors

As the maritime accident reports present, vessel factors containing the condition of vessels, devices onboard, the ergonomic impact of design, updated information supports are concluded. Lema et al. (2014) used The K-means clustering method with 15 a priori defined clusters to indicate that human factors coexist with the condition of the ship and other external factors. From the perspective of the state of vessels, the increasing complexity of propulsion arrangements, modifications made to vessels, and the change of the size of ships are consistent with the development of ship automation. It is also related to the ergonomic impact of innovative bridge design, for example, visual blind sector ahead and motion illusion. From the MAIB 26-2013, the bridge design led the second officer on duty to sit down and then increased the potential for him to fall asleep. The same ergonomic problem exists in the collision accident reported in MAIB 03-2017 in which the pilot's actions resulted from a 'relative motion illusion'. It was the off-axis bridge windows and lack of visual references that led to the pilot's disorientation.

The devices and equipment on board not being fully utilised or operated correctly leads to the human errors directly or indirectly, for example, the BNWAS is switched off; alarm systems are not in the recommended position or not noticed. Moreover, the insufficient or lack of updated information aggravated the situation. Poor quality of equipment data and falsified records of data contribute to the failure of transforming data into effective information for decision making, as well as the difficulties for the accident/incident investigation. The automatic means or indicators for necessary observing, e.g. working signs or lights, are the critical way to decrease the workload or the possibility of overload among the seafarers. From the MAIB 27-2016, it is evident that in this collision case, radar, visual and Automatic Identification System (AIS) information could have been utilised more efficiently. Furthermore, using all the information available on the bridge makes a high standard of watchkeeping to obtain and maintain a good sense of the situation.

4.3.4 Environmental factors

Environmental factors, especially in port service, contribute to human errors. The weather condition, sea condition, the density of fairway traffic, and the noisy acoustic environment are all considered in the environmental factors. Hsu (2012) utilised a fuzzy AHP model to identify ports' service attributes for ship navigation safety, and the Dissatisfaction attitude (DA) was used to determine the attributes priorities. It concluded that the traffic control of fairway is the most critical aspect to be improved according to human errors contributors. Moreover, the Master Pilot Exchange (MPX) that is a document of debatable value in pilotage waters is designed to reflect local navigational challenges and port requirements (Wild and Constable, 2013). However, investigation recommendations are not consistently reflected in MPX forms, and there is a gap between them and what should be recorded. Besides, port safety evaluation, a fuzzy analytical hierarchy process was used to evaluate the importance of the factors, to rank the factors affecting navigation safety, and to rank the safety level of ports in Korea (Pak et al., 2015). The results showed that the element of weather was of higher importance than others.

Lee and Kim (2013) used the AHP to analyse the relative importance of the risk factors for the maritime traffic environment. It showed that the relative importance of visibility restriction is the highest among risk factors, and the relative importance of the traffic condition is the most senior among risk categories. From the MAIB 20-2016, the submarine's command team did not perceive any risk of collision or need for avoiding action. It is highly likely that the density of shipping traffic and the other factors contributed to cognitively overloaded crews. The reduced passing distances, the traffic density, bridges, moorings, tidal streams and the possibility of interaction on the vessel make the voyage a significant challenging area in which to navigate, as demonstrated in the report MAIB 13-2015. On the other hand, the repetitive nature of the route increases the individual errors like overconfidence on the duties or underestimation of the severity of the condition with a low state of alertness.

The noisy and vibrating environment and sea condition containing a strong tidal stream, current, and waves, influence the performance or behaviours of crews in the process of operation. It contributes to the emotional response and psychological effects on the crews. From the MAIB 10-2014, the master did not take the tidal condition into account, and it was without a plan in conjunction with experienced staff, resulting in the collision due to lack of appreciation of the hazards from tidal effects on the tow when anchoring.

4.3.5 Regulation and management factors

Regulation and management factors reflect the organisational factors in the maritime system. It is regarded as the essential cause of human errors. Inappropriate or ambiguous code, endorsement, regulations, procedure, instruction, formally published guidance, operation manual, and requirement contribute to the complicated causal relationship with human errors. Branch et al. (2004) illustrated that the hours of working and lookout requirement contained in the International Convention on Standards of Training, Certification and Watchkeeping for Seafarers, 1995 (STCW 95) and the principles of safe manning, endorsed by the experiences of the MAIB during accident investigation, have insufficient impact on those factors.

In addition, a lack of safety culture and precautionary thought are critical factors for human errors. Lu and Tsai (2008) conducted the factor analysis revealed six safety climate dimensions, and used logistic regression analysis to evaluate the effects of the safety climate on vessel accidents. The results suggested that job safety has the most critical impact on vessel accidents, followed by management safety practices and safety training dimensions.

Risk assessment in maritime and several management systems benefits the safe operation of ships and manoeuvring. A valid risk assessment conducted provides a good view of the potential hazards and risks existing in the activities on board, while improper risk assessment leads to less than adequate crew emergency preparedness, onboard management, safety management, and practical training. At the same time, it can identify the appropriate fitness requirements for pilots by their specific duties at their port of employment (MAIB 21-2017). The robust vessel's risk assessments may make the onboard working environment safer. From the investigation of MAIB 24-2014, it is evident that the onboard management of Ovit was dysfunctional, as well as the safety culture developed on the bridge provided by the insufficient leadership of the master.

Meanwhile, there are serious shortcomings highlighted in the reports that had not been realised from the vessel's audits and inspections. By the way, the assessment of competence plays a role in crew management. It means judgement as to whether a seafarer is competent, or what a seafarer needs to know and what skills and knowledge he or she requires to learn, before that person is deemed to be competent. Many accidents occur due to a person performing incompetently at that time.

As the literature shows, people tend to exchange the level of safety standard of the vessel for a profitable and riskier activity, considering the commercial affairs of ships (Vinagre-Ríos and Iglesias-Baniela, 2013). It highlights the existence of human errors derived from the practices and manning policies established by the managers of shipping companies. Namely, crews can choose the risky or dangerous way to complete the operation or manoeuvring process due to commercial pressure. As stated in MAIB 12-2015, it was proved that financial constraints, rather than lack of experience or the sense of safety, caused the skipper to work single-handed and induced him not to maintain the ship and its equipment on board safe. Under the pressure of finance, industry, and public, more attention and concentration is assigned to deal with the cost calculation behind every decision. It results in the potential risk of human errors causing maritime accidents.

4.4 Identification of risk factors

Furthermore, maritime accidents reports during 2012-2017 have been reviewed for the human error attributes. The accident database utilised is the MAIB in UK and the TSB in Canada. There are 109 accident reports extracted from 152 reports in MAIB and 52 accident reports obtained from 61 reports in TSB.

The procedure consists of three stages: (i) online database searching, (ii) reports screening and selecting, (iii) refining and analysis. Then, the maritime accident data is obtained according to the filtered accident reports.

Concerning RIFs in maritime accidents, it is necessary to identify the critical factors from accident investigation reports. According to the filtered reports, the factors (i.e. 32 risk factors) contributing to accidents are classified and described in five categories, as seen in Table 4.2. However, risk factors are derived among them according to their appearance frequency in accident reports to eliminate the trivial effect of the factors appearing once or twice across all the searched reports.

According to the source or origin that human errors come from, the common factors contributing to human errors are classified and described in 5 categories with 32 attributes. The categories are based on the descriptions in Section 4.3, and consulted by the experts in maritime sector and human factors research filed, which are selected for better illustrating the 32 attributes. The specific common factors derived from the maritime accidents reports are stated.

Table 4.2 Attributes of common factors contributing to human errors.

Categories	Attributes	Source representatives
Procedure	poor communication and coordination with team	MAIB23-2017, MAIB20-2017, MAIB24-2016 TSBM16C0005, TSBM14P0014, TSBM13M0287
	ineffective supervision and support (lone watchkeeper or working isolated, improper supervision of loading operation)	MAIB23-2017, MAIB12-2016, MAIB30-2014 TSBM16P0062, TSBM14P0014, TSBM13L0067
	no detailed passage plan or revised passage plan was unsafe	MAIB23-2017, MAIB22-2017, MAIB12-2016 TSBM16P0362, TSBM14P0150, TSBM12L0147
	swift duty between pilots and seafarers or change of the steering mode	MIAB15-2015 TSBM16C0005
	over-reliance on devices (AIS, GPS…), or poor lookout	MAIB9-2014, MAIB4-2014, MAIB26-2013 TSBM16P0362, TSBM15C0006, TSBM14P0150
	fast speed	MAIB20-2017, MAIB14-2013
	no clear order (not accurately interpret and apply the requirements of a safe manning document)	MAIB23-2017, MAIB22-2017, MAIB24-2016 TSBM16C0005
	limited time to respond	TSBM14C0045, TSBM16P0062
Individual	lack of situation awareness	MAIB23-2017, MAIB20-2017,MAIB11-2017 TSBM16P0362, TSBM15C0006, TSBM12L0147
	fatigue/asleep/tiredness and desire to rest	MAIB22-2017, MAIB8-2014, MAIB4-2014

	emotion (low level of arousal, panic, anger, unhappiness)	TSBM15C0006, TSBM12L0147 MAIB22-2017, MAIB20-2017, MAIB14-2016
	unfamiliar with/lack of equipment knowledge, inexperienced, ill-prepared	MAIB20-2017, MAIB24-2016, MAIB14-2016 TSBM16C0005, TSBM14P0014, TSBM14C0015
	complacent about the duties or underestimation of the severity of the condition (low state of alertness)	MAIB22-2017, MAIB18-2015, MAIB12-2014 TSBM13M0287, TSBM12C0058
	recreation drugs, alcohol	MAIB25-2015, MAIB7-2014
	cognitively overload	MAIB20-2016
	physical incapacitation	MAIB9-2013 TSBM12L0147
	distracted/insufficient attention	MAIB11-2017, MAIB12-2016, MAIB30-2014 TSBM16P0362, TSBM13L0067, TSBM12H0012
	stress	MAIB20-2017
Vessel	the poor condition of the vessel, increasing complexity of propulsion arrangements, and modifications made to vessels, size	MAIB23-2017, MAIB20-2017, MAIB19-2017
	devices and equipment on board not fully utilised or operated correctly (BNWAS switched off, alarm system not in the recommended position or not noticed)	MAIB23-2017, MAIB22-2017, MAIB11-2017 TSBM15C0006, TSBM14P0014, TSBM14C0106
	ergonomic impact of innovative bridge design (visual blind sector ahead, motion illusion)	MAIB18-2015, MAIB26-2013, MAIB9-2013 TSBM16P0362, TSBM16C0005, TSBM14C0045
	insufficient or lack of updated information (poor quality of equipment data, falsified records of information, relies on a single piece of navigational equipment); no automatic means or without indicators for necessary observing (working indicators, light)	MAIB23-2017, MAIB22-2017, MAIB19-2017 TSBM16P0362, TSBM16C0005, TSBM15C0006
Environment	weather condition: wind, visibility(dense fog)	MAIB19-2017, MAIB8-2013
	sea condition: falling tide, current, waves	MAIB22-2017, MAIB19-2017, MAIB24-2016 TSBM16P0362

	noisy and vibrating environment	MAIB20-2016
	fairway traffic (traffic density, repetitive nature of the route)	MAIB23-2017, MAIB18-2015 TSBM15C0006
Regulation and management	inappropriate or ambiguous code, endorsement, regulations, procedure, instructions, formal published guidance; operation manual, requirement	MAIB232017, MAIB14-2017, MAIB24-2014 TSBM16P0062, TSBM16C0005, TSBM13M0287
	lack of risk assessment	MAIB25-2015, MAIB24-2014, MAIB4-2014 TSBM16P0062, TSBM13L0067, TSBM12C0058
	dysfunctional management system (shore management, maintenance management, bridge source management, onboard management, safety management systems, port service, qualification examination, inadequate training, practice, emergency drill)	MAIB23-2017, MAIB22-2017, MAIB20-2017 TSBM13M0287, TSBM13M0102, TSBM13L0067
	lack of safety culture, precautionary thought	MAIB 25-2015, MAIB24-2014, MAIB4-2014 TSBM12L0147
	no medical and fitness standards for crews	MAIB17-2016 TSBM12W0070
	commercial pressure, public pressure or industrial pressure (financial constraints)	MAIB12-2015 TSBM12N0017

4.5 Concluding remarks

The following are the most significant remarks comprised in the chapter, and emphasised in the form of bullet points for the reader's ease:

- To provide the comprehensive summaries of the research development of human errors, the realistic phenomena in accidents, and common errors highlighted concerning human errors during the accidents, common factors contributing to human errors are analysed on several given categories and concluded from the accident reports as well as literature.

- Maritime accidents reports during 2012-2017 have been reviewed for the human error attributes. The accident database utilised is from MAIB and TSB. There are 109 accident reports extracted from 152 reports in MAIB and 52 accident reports obtained from 61 reports in TSB.

- According to the source or origin that human errors come from, the common factors contributing to human errors are classified and described in 5 categories with 32 attributes.

Chapter 5 Analysis of risk factors for maritime transport accidents

5.1 Introductory remarks

This chapter proposes a Bayesian Network-based risk analysis approach to analyse the risk factors influencing maritime transport accidents. Comparing with previous studies in the relevant literature, it reveals new features including new primary data directly derived from maritime accident records by two major databanks, MAIB and TSB from 2012 to 2017; also, the quantification of the extent to which different combinations of the factors influence each accident type. The network modelling the interdependency among the risk factors is constructed by using NBN and validated by sensitivity analysis. The results reveal that the common risk factors among different types of accidents are ship operation, voyage segment, ship type, gross tonnage, hull type, and information. Scenario analyses are conducted to predict the occurrence likelihood of different types of accidents under various situations. The findings provide transport authorities and ship owners with useful insights for maritime accident prevention.

5.2 Background information

Waterborne transportation accounts for approximately 90% of the world's trade by volume, representing one of the essential transportation modes in ensuring the prosperity of international trade and the global economy. Maritime accidents have revealed new features in the past few years. According to the 'Safety and Shipping' Annual Report of 2017 (Specialty, 2018), published by Allianz Global Corporate & Specialty, more than a quarter of ship losses in 2016 occurred in the South China, Indochina, Indonesia and Philippines regions. Although the number of maritime casualties has declined over the years, there is increasing complexity of navigation risk exposure in the shipping industry (e.g. high demand on human reliability in complicated operations introduced by advanced technologies). The questionnaire survey on maritime operations conducted by Safahani (2015) emphasised the non-technical skills: 75% stated that a team leader should discuss the work plan with his/her teammates; 90% thought that monitoring the task provided an essential contribution to effective team performance; almost everyone in the survey believed that communication was a significant factor, and that teams who do not communicate effectively would increase the possibility of making errors. Branch et al. (2004) disclosed that watchkeeper manning levels and a master's ability to discharge his duties were significant factors influencing collisions and groundings.

Studies on maritime accident analysis rely on the discretional context and experts' knowledge to extract the causal relations among the process of accidents, as well as data-driven methodologies. Specifically, causal relations were connected to one type of accidents through accident analysis methods, specifically for grounding or collision (Hanninen and Kujala, 2012, Macrae, 2009, Uğurlu et al., 2015a). Moreover, some studies focused on the probability or the frequency of maritime accidents. Fabiano et al. (2010) investigated the occupational accident frequency affected by the organisation, job experience, and productivity. Pristrom et al. (2016) estimated the likelihood of a ship being hijacked in the Western Indian or Eastern African region by using the GISIS database together with expert judgement. Other studies concentrated on the severity or the consequence of maritime accidents. Zhang et al. (2016) predicted the accident consequences in the Tianjin port by statistical analysis of historical accident data. Wang and Yang (2018) analysed the key risk factors influencing waterway accident severity by using Bayesian Networks (BN). In addition, some studies investigated the combination of the above two (i.e. likelihood and consequence) (Bouejla et al., 2014, Balmat et al., 2011). However, few studies have been carried out to investigate the issues on how risk factors affect maritime accident types, leaving a research gap to fill for effective accident prevention. The key factors contributing to collisions are probably quite different from those resulting in groundings. Also, understanding differentiation among the key factors contributing to different types of accidents will help generate useful insights for reasonable risk control measures.

This chapter aims at investigating how different risk factors generate, in an individual or combined manner, an impact on different types of maritime accidents in terms of likelihood. Manual case by case analysis of recorded maritime accidents from MAIB and TSB that occurred from 2012 to 2017 is undertaken to develop a primary database to support this study. A BN-based approach is proposed to analyse accident types in maritime transport.

5.3 Raw data collection and RIFs selection

The accident reports are from MAIB in UK and TSB in Canada, as they are among the most representative from the literature (Chauvin et al., 2013, Graziano et al., 2015, Kum and Sahin, 2015). The raw data derived from the MAIB and TSB contains general information of the ship and the voyage, accident evolution process, and details related to the management and organisational factors. In the screening process stage, the accident reports were screened with a focus on error-related accidents to ensure their representativeness and relevance. In the final stage, these reports had been further refined and analysed, especially the ‘safety issues’ and ‘common factors’ section in the accident reports. Some details of information associated with the accident process were involved in the refining. According to such analysis, there are 109 accident reports extracted from 152 reports in MAIB and 52 accident reports obtained from 61 reports in TSB, as shown in ***Chapter 4***.

In total, the 161 maritime accidents involving 208 vessels reported in MAIB and TSB between Jan. 2012 and Dec. 2017 were carefully reviewed and analysed manually. The search was conducted in Jan. 2018 and the general statistical analysis and findings are presented in Figure 5.1, Figure 5.2, and Figure 5.3, which provide the raw data for the subsequent in-depth analysis using NBN.

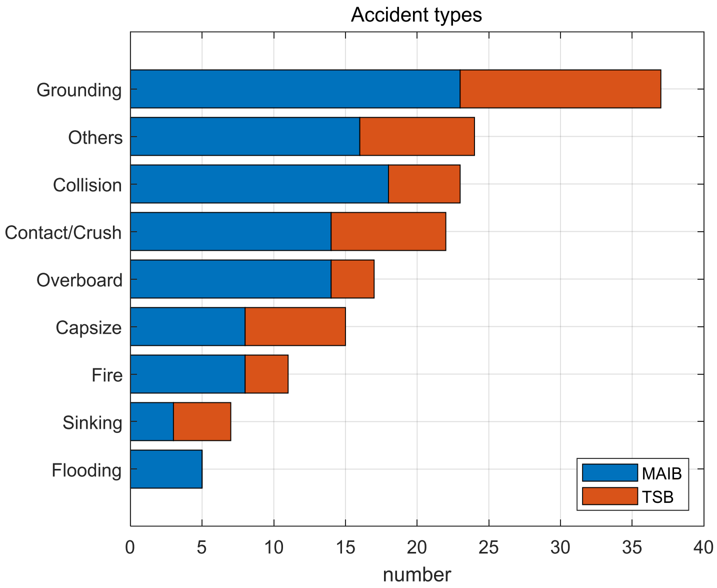


Figure 5.1 Accident distribution by accident types

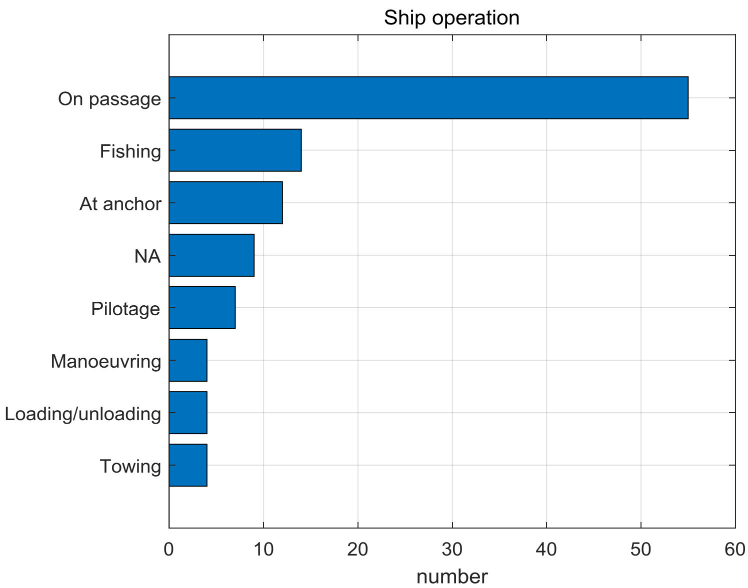


Figure 5.2 Accident distribution by ship operations from MAIB

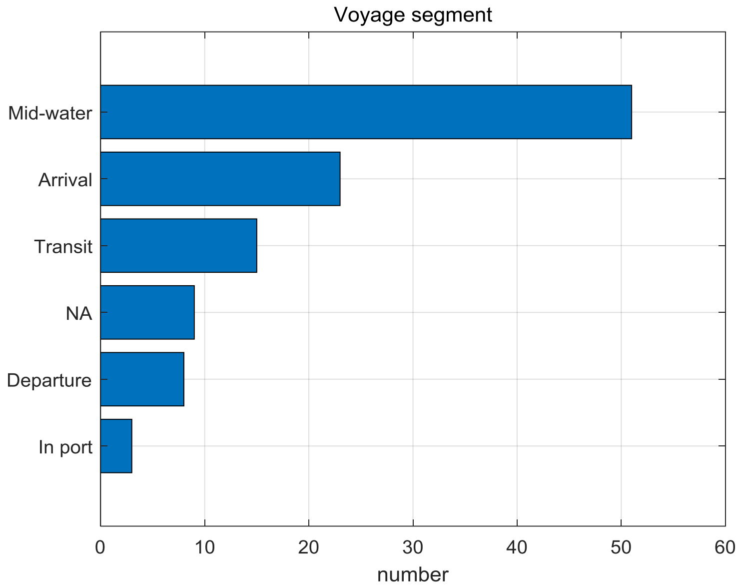


Figure 5.3 Accident distribution by voyage segments from MAIB

As is indicated in Figure 5.1, grounding, collision and contact/crush accounted for more significant percentages than other kinds of accidents while sinking and flooding accounted for lower percentages. Specifically, there were 23 grounding accidents from MAIB and 14 from TSB, while there were 3 sinking accidents from MAIB and 4 from TSB. And Figure 5.2 and Figure 5.3 show accident distributions by ship operation and voyage segment from MAIB. The number of accidents happening on passage was much higher than those others, followed by 'fishing' and 'at anchor'. However, the number of accidents that happened in mid-water was much higher than others like 'departure' and 'in port'.

These reports had been further refined and analysed. Furthermore, special attention is paid to the 'safety issues' and 'common factors' in the accident reports. Some details of information associated with the accident process were involved in the refining. According to such analysis, the common factors contributing to the accidents are generated.

Concerning the accident type, a maritime accident can be classified into collision (*S1*), grounding (*S2*), flooding (*S3*), fire/explosion (*S4*), capsize (*S5*), contact/crush (*S6*), sinking (*S7*), overboard (*S8*), and others (*S9*), which refer to the combined description and definition in MAIB and TSB. These 9 types of accidents consist of 9 states ($S1$~ $S9$) of the variable 'accident type' in the study.

Furthermore, the accident-related RIFs are retrieved in Table 5.1. In the quantitative analysis of BN modelling, the accident type is defined as a dependent variable, variables in Table 5.1 are defined as independent variables.

Table 5.1 The accident-related RIFs

RIFs	**Notation**	**Description**	**Values of state in BN**
Ship type	R_{ST}	Passenger vessel, tug, barge, fishing vessel, container ship, bulk carrier, RORO, tanker or chemical ship, cargo ship, others.	1, 2, 3, 4, 5, 6, 7, 8, 9, 10
Hull type	R_{HT}	Steel, wood, aluminium, others	1, 2, 4, 5
Ship age (years)	R_{SA}	(0 5], [6 10], [11 15], [16 20], >20, NA	1, 2, 3, 4, 5, 6
Length (metres)	R_L	≤100, >100, NA	1, 2, 3
Gross tonnage (GT)	R_{GT}	≤300, 300 to 10000, >10000, NA	1, 2, 3, 4
Ship operation	R_{SO}	Towing, Loading/unloading, Pilotage, Manoeuvring, Fishing, At anchor, On passage, others	1, 2, 3, 4, 5, 6, 7, 8
Voyage segment	R_{VS}	In port, Departure, Arrival, Mid-water, Transit, others	1, 2, 3, 4, 5, 6
Weather condition	R_{WC}	Good or poor considering rain, wind, fog, visibility	1, 2
Sea condition	R_{SC}	Good or poor considering falling/rising tide, current, waves	1, 2
Time of day	R_{TD}	07:00 to 19:00, other	1, 2
Fairway traffic	R_{FT}	Good or poor considering complex geographic environment, dense traffic, or repetitive nature of the route contributing to ignorance	1, 2
Ship speed*	R_{SS}	Normal, Fast	1, 2
Vessel condition	R_{vc}	Good condition of vessels, or the condition of vessel has nothing to do with the accidents; Poor condition of vessels, or increasing complexity of propulsion arrangements, or modification made to vessels and size contributes to the accidents	1, 2
Equipment/device	R_E	Devices and equipment on board operate correctly; Devices and equipment not fully utilised or operated correctly (e.g., BNWAS switched off, alarm system not in the recommended position or not noticed)	1, 2
Ergonomic design	R_{ED}	Ergonomic friendly or ergonomic aspects have nothing to do with accidents;	1, 2

		ergonomic impact of innovative bridge design (e.g., visual blind sector ahead, motion illusion)	
Information	R_I	Effective and updated information provided;	
		Insufficient or lack of updated information (e.g., poor quality of equipment data, falsified records of information, relies on a single piece of navigational equipment, without working indicators or light for necessary observing)	1, 2

*The ship speed is grouped into normal and fast states based on the description in the MAIB accident reports.

A majority of definitions of variables' states are derived from accident reports. To quantify such states, the majority of variables are defined and quantified based on ***Chapter 4***. However, variables, e.g. accident type, ship type, hull type, ship operation, and voyage segment, are divided into different states according to the classification of MAIB or TSB investigation. The 'vessel condition' is quantified into two states based on whether it is blamed for the faults in accidents, as described in the reports. The grading of 'ship speed' is based on the description in the MAIB accident reports, rather than the grading method by Wang and Yang (2018). The main reason is that accurate speeds of vessels involved in accidents are not clearly indicated in the source database.

5.4 Bayesian networks model for maritime accidents

In the study, the only child node of BN is 'accident type', i.e. the class variable (*S*). The parent node set $R = \{R_{ST}, R_{HT}, R_{SA}, R_L, R_{GT}, R_{SO}, R_{VS}, R_{WC}, R_{SC}, R_{TD}, R_{FT}, R_{SS}, R_{vc}, R_E, R_{ED,} R_I\}$ is the set of risk variables (R_k) including the RIFs (in a matching order), for example, ship type, hull type, ship age, length, gross tonnage, ship operation, voyage segment, weather condition, sea condition, time of day, fairway traffic, ship speed, vessel condition, equipment, ergonomic design, and information. Then, the structure learning is simplified to demonstrate the relationship between *S* and R_k.

As demonstrated in Figure 5.4, the NBN structure is one in which 'accident type' is the only child of each RIF. The ‘Accident type’ is assigned to *S*, representing 9 different accident types, and has 16 influencing parent nodes. Each node is assigned with multiple states. Then the number of conditional probability distributions $P(S|R_{ST}, R_{HT}, R_{SA}, \cdots, R_I)$ is more than 2E+09 for any observation set $R = \{R_{ST}, R_{HT}, R_{SA}, \cdots, R_I\}$, That is to say, the size of the conditional probability table increases exponentially, resulting in the complex computation in this converging BN.

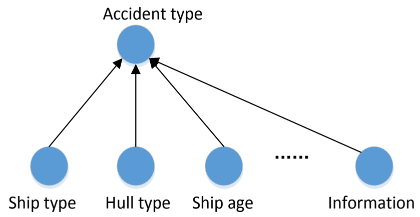


Figure 5.4 ‘Accident type’ as a child node

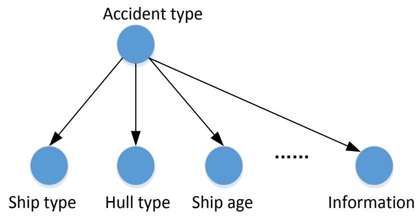


Figure 5.5 ‘Accident type’ as a parent node

To simplify the BN structure, a modified diverging NBN structure in which ‘Accident type’ has no parents but is the only parent of other RIFs is presented, as shown in Figure 5.5, by referring to Wang and Yang (2018). In this way, this NBN structure includes the prior distribution $P(S)$ and the conditional probability table with relatively small number of conditional probability distributions $P(R_k|S)$. Compared to the structure in Figure 5.4, this structure significantly reduces the computation and number of conditional probability distributions. Hence, it is adopted to express the relationship between risk variables in the NBN structure. Because BN can conduct bi-directional risk analyses, the transformation from the converging to diverging connections will be well reflected by the adapted CPT and hence has no influence on the final BN results on risk analyses (e.g. Wang and Yang

(2018)).

Although the assumption that the variables are completely independent is not always valid in reality, modified diverging NBN simplifies the structure by reducing the number of conditional probability distributions. Moreover, such an assumption does not significantly affect the posterior probabilities calculated, which does not affect the scenario analysis in the study (Wang and Yang, 2018), given the fact that the statistical analysis of all the accidents did not indicate strong correlation among the RIFs. Therefore, assuming that all the variables, i.e. the child nodes, are independent of each other, the NBN is constructed.

Based on the NBN model, the parameter learning of CPTs from the cases is conducted by the software 'Netica' using the counting-learning algorithm. They are calculated by the manual collected database from accident reports. Once the CPTs are constructed and obtained in Table 5.2, the posterior probabilities of each variable can be calculated.

Table 5.2 Conditional probability tables (CPT) for RIFs

	Ship type									
Accident type	1	2	3	4	5	6	7	8	9	10
1	7.5472	11.3207	3.7736	13.2076	5.6604	9.4340	5.6604	7.5472	15.0943	20.7547
2	18.1818	7.2727	7.2727	10.9091	9.0909	9.0909	3.6364	7.2727	21.8182	5.4546
3	5.8824	5.8824	5.8824	23.5294	5.8824	11.7647	11.7647	11.7647	11.7647	5.8824
4	9.5238	9.5238	4.7619	23.8095	4.7619	4.7619	9.5238	4.7619	19.0476	9.5238
5	6.0606	18.1818	9.0909	30.3030	6.0606	6.0606	3.0303	6.0606	3.0303	12.1212
6	12.5000	6.2500	3.1250	12.5000	3.1250	12.5000	12.5000	12.5000	12.5000	12.5000
7	11.1111	11.1111	16.6667	22.2222	5.5556	5.5556	5.5556	5.5556	5.5556	11.1111
8	10.3448	6.8966	3.4483	41.3793	6.8966	3.4483	3.4483	3.4483	10.3448	10.3448
9	17.5000	12.5000	10.0000	12.5000	2.5000	12.5000	2.5000	2.5000	15.0000	12.5000

	Equipment_ device	
Accident type	1	2
1	64.4445	35.5556
2	48.9362	51.0638
3	66.6667	33.3333

4	69.2308	30.7692
5	60.0000	40.0000
6	62.5000	37.5000
7	30.0000	70.0000
8	80.9524	19.0476
9	65.6250	34.3750

Ergonomic design		
Accident type	1	2
1	71.1111	28.8889
2	85.1064	14.8936
3	88.8889	11.1111
4	92.3077	7.6923
5	96.0000	4.0000
6	75.0000	25.0000
7	90.0000	10.0000
8	95.2381	4.7619
9	96.8750	3.1250

Fairway traffic		
Accident type	1	2
1	66.6667	33.3333
2	74.4681	25.5319
3	66.6667	33.3333
4	92.3077	7.6923
5	92.0000	8.0000
6	79.1667	20.8333
7	90.0000	10.0000
8	95.2381	4.7619
9	90.6250	9.3750

Gross tonnage				
Accident type	1	2	3	4
1	36.1702	23.4043	29.7872	10.6383
2	18.3674	48.9796	28.5714	4.0816
3	36.3636	18.1818	36.3636	9.0909
4	46.6667	26.6667	20.0000	6.6667
5	62.9630	18.5185	7.4074	11.1111

6	19.2308	38.4615	38.4615	3.8462
7	75.0000	8.3333	8.3333	8.3333
8	52.1739	26.0870	13.0435	8.6957
9	38.2353	29.4118	20.5882	11.7647

Hull type				
Accident type	1	2	4	5
1	72.3404	10.6383	8.5106	8.5106
2	81.6327	6.1225	4.0816	8.1633
3	45.4545	27.2727	9.0909	18.1818
4	53.3333	33.3333	6.6667	6.6667
5	59.2593	7.4074	11.1111	22.2222
6	76.9231	7.6923	7.6923	7.6923
7	41.6667	25.0000	8.3333	25.0000
8	52.1739	4.3478	4.3478	39.1304
9	67.6471	2.9412	5.8824	23.5294

Information		
Accident type	1	2
1	64.4445	35.5556
2	31.9149	68.0851
3	33.3333	66.6667
4	69.2308	30.7692
5	68.0000	32.0000
6	25.0000	75.0000
7	60.0000	40.0000
8	71.4286	28.5714
9	68.7500	31.2500

Length			
Accident type	1	2	3
1	58.6957	34.7826	6.5217
2	60.4167	37.5000	2.0833
3	50.0000	40.0000	10.0000
4	71.4286	21.4286	7.1429
5	84.6154	7.6923	7.6923
6	52.0000	44.0000	4.0000
7	81.8182	9.0909	9.0909

8	77.2727	18.1818	4.5455
9	63.6364	30.3030	6.0606

Sea condition		
Accident type	1	2
1	55.5556	44.4444
2	31.9149	68.0851
3	66.6667	33.3333
4	61.5385	38.4615
5	24.0000	76.0000
6	54.1667	45.8333
7	40.0000	60.0000
8	47.6191	52.3810
9	59.3750	40.6250

Ship age						
Accident type	1	2	3	4	5	6
1	18.3674	16.3265	8.1633	8.1633	26.5306	22.4490
2	13.7255	13.7255	11.7647	11.7647	45.0980	3.9216
3	15.3846	7.6923	23.0769	7.6923	38.4615	7.6923
4	11.7647	11.7647	17.6471	5.8824	35.2941	17.6471
5	17.2414	10.3448	10.3448	13.7931	34.4828	13.7931
6	21.4286	10.7143	10.7143	14.2857	21.4286	21.4286
7	7.1429	14.2857	21.4286	7.1429	35.7143	14.2857
8	12.0000	12.0000	12.0000	16.0000	24.0000	24.0000
9	13.8889	19.4444	5.5556	11.1111	36.1111	13.8889

Ship operation								
Accident type	1	2	3	4	5	6	7	8
1	1.9608	1.9608	1.9608	5.8824	5.8824	1.9608	78.4314	1.9608
2	18.8679	1.8868	18.8679	11.3207	1.8868	5.6604	39.6226	1.8868
3	6.6667	6.6667	13.3333	6.6667	20.0000	6.6667	33.3333	6.6667
4	5.2632	10.5263	5.2632	5.2632	5.2632	10.5263	52.6316	5.2632
5	29.0323	3.2258	3.2258	16.1290	22.5806	3.2258	16.1290	6.4516
6	10.0000	6.6667	13.3333	16.6667	6.6667	6.6667	33.3333	6.6667
7	18.7500	6.2500	6.2500	6.2500	6.2500	12.5000	37.5000	6.2500
8	7.4074	7.4074	7.4074	11.1111	37.0370	3.7037	22.2222	3.7037
9	18.4210	21.0526	7.8947	13.1579	10.5263	7.8947	18.4210	2.6316

Ship speed		
Accident type	1	2
1	80.0000	20.0000
2	89.3617	10.6383
3	88.8889	11.1111
4	92.3077	7.6923
5	92.0000	8.0000
6	70.8333	29.1667
7	90.0000	10.0000
8	95.2381	4.7619
9	93.7500	6.2500

Time of day		
Accident type	1	2
1	42.2222	57.7778
2	51.0638	48.9362
3	55.5556	44.4444
4	53.8462	46.1538
5	60.0000	40.0000
6	58.3333	41.6667
7	70.0000	30.0000
8	52.3810	47.6191
9	65.6250	34.3750

Vessel condition		
Accident type	1	2
1	84.4445	15.5556
2	68.0851	31.9149
3	77.7778	22.2222
4	53.8462	46.1538
5	60.0000	40.0000
6	79.1667	20.8333
7	20.0000	80.0000
8	80.9524	19.0476
9	62.5000	37.5000

Voyage segment

Accident type	1	2	3	4	5	6
1	2.0408	12.2449	2.0408	51.0204	30.6123	2.0408
2	1.9608	15.6863	29.4118	39.2157	11.7647	1.9608
3	7.6923	7.6923	7.6923	46.1538	23.0769	7.6923
4	5.8824	5.8824	17.6471	52.9412	11.7647	5.8824
5	13.7931	17.2414	3.4483	44.8276	17.2414	3.4483
6	7.1429	10.7143	42.8571	10.7143	14.2857	14.2857
7	7.1429	7.1429	21.4286	28.5714	28.5714	7.1429
8	8.0000	4.0000	8.0000	60.0000	8.0000	12.0000
9	19.4444	5.5556	22.2222	36.1111	13.8889	2.7778

Weather condition		
Accident type	1	2
1	66.6667	33.3333
2	46.8085	53.1915
3	44.4444	55.5556
4	61.5385	38.4615
5	60.0000	40.0000
6	62.5000	37.5000
7	60.0000	40.0000
8	66.6667	33.3333
9	65.6250	34.3750

The statistical analysis of the probability of variables reveals interesting initial findings in terms of safety caution and accident prevention as follows.

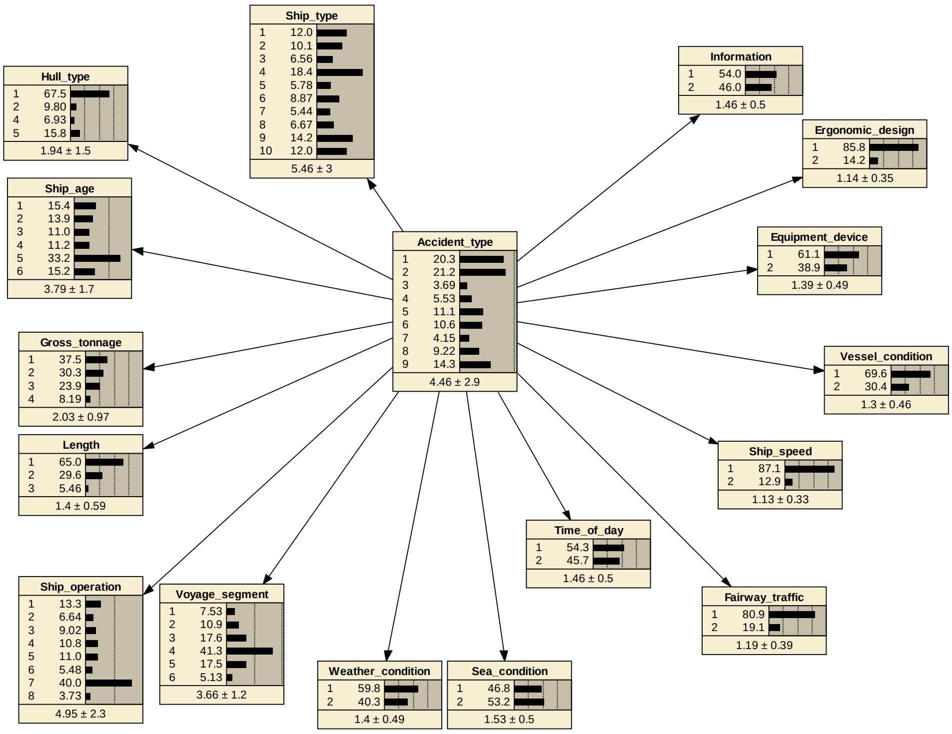


Figure 5.6 Results of NBN

Figure 5.6 presents the results of NBN involving all the retained 16 RIFs. Among the accidents, grounding and collision are the two most frequently occurring types of accidents: accounting for 20.3% and 21.2%, respectively. A majority of vessel lengths (i.e., 65%) are less than 100*m*. Vessels with gross tonnages less than 300 account for 37.5% of shipments involved in accidents. In addition, 67.5% of vessels are made of steel.

In light of environmental factors, 40% of vessels in the accidents are involved in the ship operation of ‘on passage’, 41.3% are involved in the voyage segment of ‘mid-water’. Besides this, only 19.1% of ships involved in accidents are in poor fairway traffic in the process of accidents, 45.7% are at night time. Severe weather condition accounts for 40.2% of accidents, while tough sea condition accounts for 53.2%.

With regard to ship factors, fishing vessels constitute the most substantial proportion (i.e.

18.4%) of shipments in accidents. Ships older than 20 years are presented in 33.2% of accidents. Also, 46% of vessels convey insufficient information, 14.2% have ergonomic design problems, 38.9% are faced with invalid equipment or devices on board, and 30.4% experience the condition of modification or increasing size.

5.5 Sensitivity analyses and model validation

5.5.1 Mutual information analysis

Table 5.3 demonstrates the mutual information shared between ‘accident type’ and RIFs. When ‘accident type’ is the parent node, “ship operation” with the corresponding mutual information value of 0.28294, has the most potent effect on the accident type. To select important variables, a threshold of the mutual information value is set as 0.09, which is the average mutual information value. The variables with $I(S,R_k)$ larger than 0.09, i.e. ‘ship operation’, ‘voyage segment’, ‘ship type’, ‘gross tonnage’, ‘hull type’, and ‘information’, illustrate essential impacts on ‘accident type’. Thus, these variables are to be computed for the factor analysis in the next step. In addition, variables that have less impact on ‘accident type’ mainly include ‘ship age’, ‘vessel condition’, ‘ergonomic design’, ‘length’, ‘fairway traffic’, ‘sea condition’, ‘equipment or device’, ‘ship speed’, ‘time of day’, and ‘weather condition’.

Table 5.3 Mutual information shared with ‘accident type’

Node	**Mutual Info.**	**Percentage**	**Variance of Beliefs**
Accident_type	2.95073	100	0.7352824
Ship_operation	0.28294	9.59	0.0156048
Voyage_segment	0.21515	7.29	0.0076025
Ship_type	0.13632	4.62	0.0048136
Gross_tonnage	0.12415	4.21	0.0037518
Hull_type	0.10076	3.41	0.0024178
Information	0.09665	3.28	0.0032523
Ship_age	0.07052	2.39	0.0019386
Vessel_condition	0.06771	2.29	0.0010538

Ergonomic_design	0.05944	2.01	0.0030873
Length	0.05745	1.95	0.0009204
Fairway_traffic	0.05660	1.92	0.0022666
Sea_condition	0.05270	1.79	0.001587
Equipment_device	0.03650	1.24	0.0008695
Ship_speed	0.03372	1.14	0.0012873
Time_of_day	0.01941	0.658	0.000732
Weather_condition	0.01907	0.646	0.0009535

5.5.2 Sensitivity analysis

In order to overcome the drawback of the traditional way, a new method proposed by Alyami et al. (2019) is applied here. This method increases the probability of the state within the highest influencing on a type of accident (e.g. collision) to 100% to obtain the High Risk Inference (HRI) of collision. Then it increases the probability of the state generating the lowest influence on the collision to 100% to obtain the Low Risk Inference (LRI) of collision. In this way, calculating the average value of HRI and LRI concludes the True Risk Influence (TRI) of each variable in the case of a particular accident type. It is described as:

$$TRI = \frac{HRI + LRI}{2}$$

where HRI refers to ‘High Risk Inference’ which is calculated for a variable influencing ‘collision’, LRI is ‘Low Risk Inference’ calculated for a variable influencing ‘collision’, and TRI refers to ‘True Risk Influence’ for a variable influencing ‘collision’. To obtain the variable influence on ‘accident type’, a similar analysis procedure is applied to other accident types, ‘grounding’ and ‘flooding’ etcetera. Then TRIs for a variable influencing all accident types are obtained. After applying this method for each variable, the TRIs for all variables for all accident types are available. Therefore, the sensitivity analysis illustrates the ranking of variables’ influences on accident types according to the value of TRI. The higher a TRI is, the higher its corresponding RIF’s effect on ‘accident type’.

In terms of sensitivity analysis, Table 5.4 demonstrates the TRI value of ‘ship operation’ against collision, where *S*1 refers to collision. Table 5.5 indicates the values of all RIFs for all accidents, where *S*1~ *S*9 are defined in Section 5.3.

Table 5.4 TRI of a risk variable (ship operation) for collision

Ship_operation											
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**S1***	**HRI**	**LRI**	**TRI**
/	/	/	/	/	/	/	/	20.30	19.50	17.31	18.41
100%	0	0	0	0	0	0	0	2.99			
0	100%	0	0	0	0	0	0	5.99			
0	0	100%	0	0	0	0	0	4.41			
0	0	0	100%	0	0	0	0	11.00			
0	0	0	0	100%	0	0	0	10.80			
0	0	0	0	0	100%	0	0	7.26			
0	0	0	0	0	0	100%	0	39.80			
0	0	0	0	0	0	0	100%	10.70			

*S1 - Collison

Table 5.5 TRI of risk variables for all accident types

Node	**TRI**									
	S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**	**Average**
Ship_operation	18.41	20.33	2.37	4.21	10.07	6.24	3.56	12.94	19.36	10.83
Voyage_segment	16.44	14.94	1.96	2.06	9.07	13.38	2.03	9.06	14.82	9.30
Ship_type	11.70	11.82	3.09	3.35	8.72	9.63	4.44	8.61	8.23	7.73
Gross_tonnage	5.35	11.90	1.70	1.19	7.59	6.01	3.58	3.89	4.10	5.03
Hull_type	7.00	7.30	3.91	8.23	4.67	3.47	4.02	9.41	8.51	6.28
Information	4.25	9.40	1.53	1.70	3.11	6.20	0.51	3.24	4.25	3.80

Specifically, in Table 5.4, the first row denotes the base-case scenario where the value of *S*1 is ‘20.3’, and the following rows represent the different scenarios with each state of the variable reaching 100%, for example, the second row increases the probability of the state 1 of ship operation to 100% to obtain the value of *S*1 (2.99). The same process is applied to all states of ship operation. According to column ‘S1’, ‘39.8’ is the largest, which means the state 7 of ship operation is the state within the highest influencing on *S*1 (collision), and the difference between ‘39.8’ and ‘20.3’ (base-case scenario) is the HRI, i.e. ‘19.5’. However, ‘2.99’ is the smallest value, which means the state1 of ship operation is the state within the lowest influencing on *S*1 (collision), so the LRI is obtained as '17.31'. Then the TRI is calculated by averaging them. In this way, TRIs of each RIF of each accident type are obtained in Table 5.5.

To obtain the impact levels of such RIFs in accident types, TRIs are compared and ranked. Generally, the most important variables lists for 'accident types' are as follows:

Ship operation > Voyage segment > Ship type > Hull type > Gross tonnage > Information

In detail, the most important variables lists for different accident types are demonstrated in Table 5.6.

Table 5.6 The most important variables

Accident type	**Ship operation**	**Voyage segment**	**Ship type**	**Hull type**	**Gross tonnage**	**Information**
S1 Collision	1	2	3	4	5	6
S2 Grounding	1	2	4	6	3	5
S3 Flooding	3	4	2	1	5	6
S4 Fire/explosion	2	4	3	1	6	5
S5 Capsize	1	2	3	5	4	6
S6 Contact/crush	3	1	2	6	5	4
S7 Sinking	4	5	1	2	3	6
S8 Overboard	1	3	4	2	6	5
S9 Others	1	2	4	3	6	5

5.5.3 Model validation

To validate the model, another sensitivity analysis is conducted by investigating the results of the model given RIFs. It is also used to test the combined effect of multiple RIFs to the accident types. There are two axioms that have at least to be satisfied for the inference process (Yang et al., 2009, Zhang et al., 2013), referring to ***Chapter 3***.

Accounting for different states of the parent nodes, this study calculates the changed value of each state. The ‘information’ is selected as the first node, the state generating the highest changed value of state 1 in ‘accident type’ is increased by 10%, while the state generating the lowest changed value of state 1 in ‘accident type’ is decreased by 10%. This procedure is written as ‘~10%’ in Table 5.7. Then, the same approach is applied to the next RIF, and the cumulative changed value is obtained and updated. The updating procedure would continue until all the RIF nodes are involved. Similarly, the same updating procedure is applied into the state 2, 3… 9 in ‘accident type’ respectively, until all states of accident type are included, as seen in Table 5.7.

Table 5.7 Accident rate of minor change in variables

Node	**Accident rate of minor change**						
Information	/	**~10%**	**~10%**	**~10%**	**~10%**	**~10%**	**~10%**
Hull type	/	/	**~10%**	**~10%**	**~10%**	**~10%**	**~10%**
Gross tonnage	/	/	/	**~10%**	**~10%**	**~10%**	**~10%**
Ship type	/	/	/	/	**~10%**	**~10%**	**~10%**
Voyage segment	/	/	/	/	/	**~10%**	**~10%**
Ship operation	/	/	/	/	/	/	**~10%**
S1	20.30	20.70	21.00	21.20	21.40	22.00	23.40
S2	21.20	22.20	22.60	23.40	23.60	24.20	24.60
S3	3.69	3.85	4.04	4.14	4.18	4.23	4.27
S4	5.53	5.71	5.90	5.96	6.01	6.08	6.17
S5	11.10	11.40	11.50	11.90	12.10	12.30	12.50
S6	10.60	11.30	11.40	11.70	11.80	12.20	12.30
S7	4.15	4.20	4.51	4.77	4.85	4.91	4.99
S8	9.22	9.57	9.84	10.10	10.40	10.50	11.00
S9	14.30	14.7	15.00	15.10	15.20	15.40	15.80

The first column of the data in Table 5.7 shows the original values of 9 states of accident types in NBN, and the rest of the columns state the updated, changed values of results. However, each state of ‘accident type’ is calculated separately, i.e. each row is computed through the change of states of RIFs in each accident type. Specifically, for the first row, ’20.30’ is the original value of accident type $S1$ (grounding). Moreover, ‘20.70’ is calculated by the way that the state of ‘Information’ generating the highest changed value of $S1$ is increased by 10% while the state generating the lowest changed value of $S1$ is decreased by 10%. A further step is conducted based on ‘20.70’ to obtain ’21.00’ in the table, which means the state of 'Hull type' generating the highest changed value of *S*1 is increased by 10% while the state generating the lowest changed value of *S*1 is decreased by 10%. Then 'Gross tonnage', 'Ship type', 'Voyage segment', 'Ship operation' apply this method sequentially. Furthermore, the same updating procedure is applied into the *S*3, *S*4, …, *S*9, respectively, until accident types are included. Besides that, the updated values of the target node demonstrate this model is in line with Axiom 1. Moreover, Axiom 2 is examined by comparing the initial target value with the updated one under all states. From Table 5.7, the updated values of the target node are gradually increasing or decreasing, along with the continuous updating of RIFs.

5.6 Implication: scenario analyses

The study enables the understanding of differentiation among critical factors contributing to different types of accidents. BN modelling is applicable to analyse the occurrence likelihood of each accident type in different scenarios involving vessel condition and environmental factors. To do this, two scenarios are proposed for useful research implications and managerial contributions.

5.6.1 Scenario 1: environmental factor

In the first scenario, maritime accidents under specific shipping environmental factors are estimated. Shipping environmental factors contain ship operation, voyage segment, weather condition, sea condition, time of day, fairway traffic in this scenario. For different assigned states of these factors, maritime accidents reveal different types.

When the nodes are assigned with the specific states in Figure 5.7, the effects of the shipping environment are revealed. The probability of collision is the highest among the 'accident type', accounting for 85.1%, followed by grounding only accounting for 4.52%. Such probability indicates the considerable increase in the risk of collision compared to the other types of accidents.

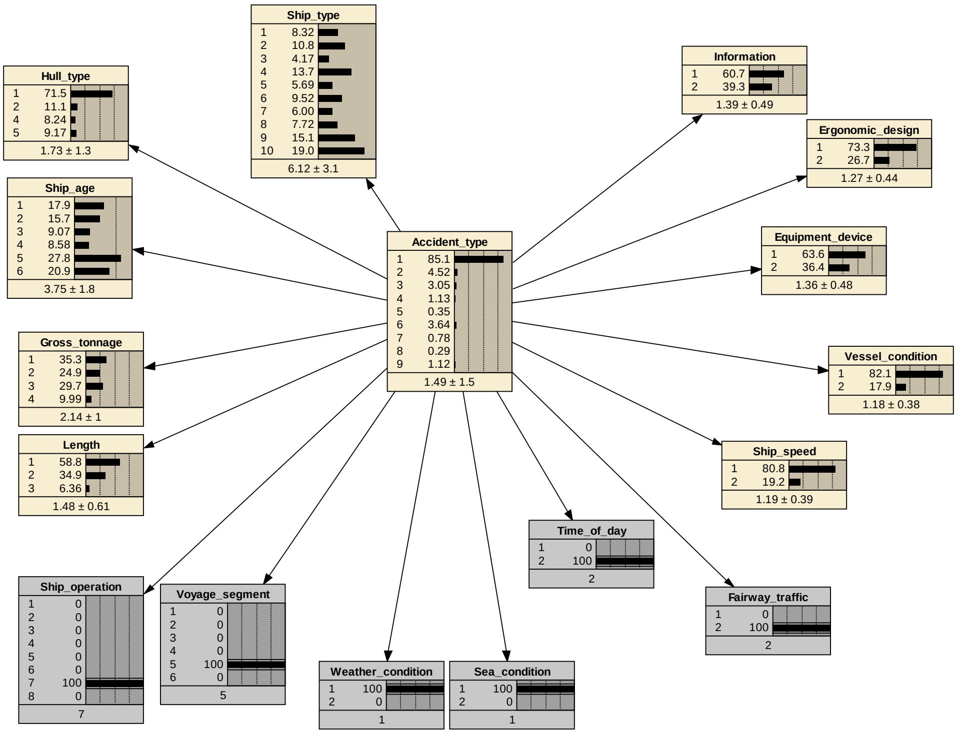


Figure 5.7 Posterior probability analysis in Scenario 1 - collision

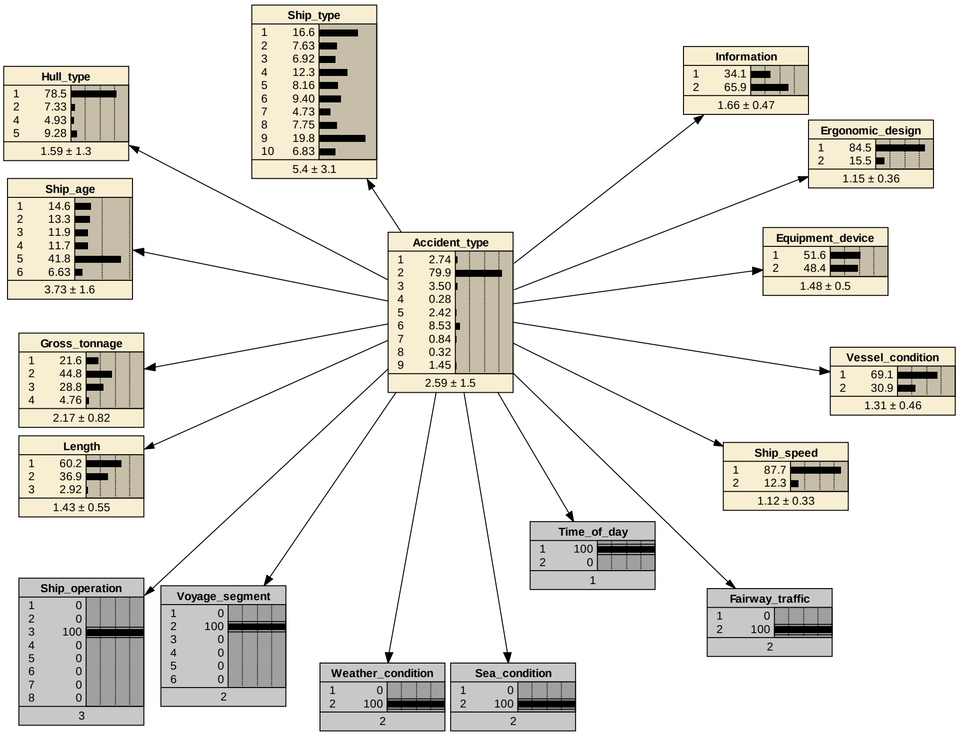


Figure 5.8 Posterior probability analysis in Scenario 1 - grounding

Concerning the following states in Figure 5.8, the effects of the environment are revealed. The probability of grounding is the highest among the ‘accident type’, accounting for 79.9% of the accident types. Therefore, transport authorities and ship owners should pay more attention to risk-reduction measures for collision or grounding under specific navigational environment, especially the strongly related variables, i.e. ship operation, voyage segment, fairway traffic, and sea condition.

5.6.2 Scenario 2: vessel factor

In the second scenario, attention has been paid to vessel factors associated with maritime accident types. The variables include ship age, ship type, information, ergonomic design, equipment/device, vessel condition, and ship speed. For different assigned states of these vessel factors, maritime accident types have shown different likelihoods.

Assuming that variables are assigned with the specific states in Figure 5.9, the effects of vessel factors on accident types are illustrated. The probability of collision is the highest among ‘accident type’, accounting for 82.1%. This probability indicates the considerable increase in the risk of collision compared to the initial states in Figure 5.6 due to the combined effect of the involved RIFs.

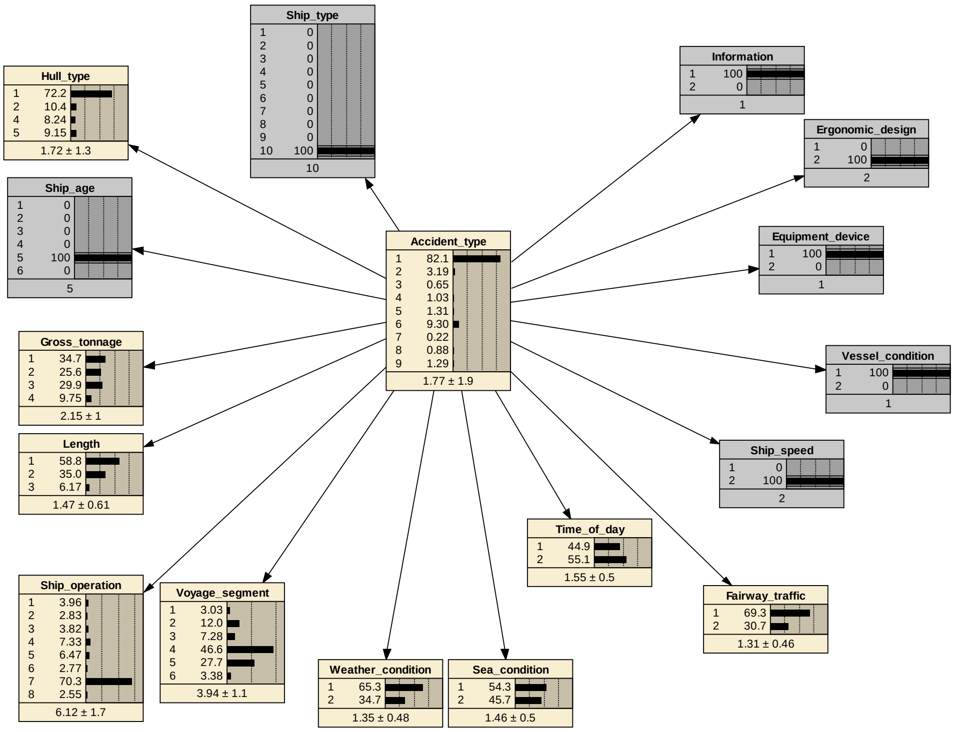


Figure 5.9 Posterior probability analysis in scenario 2 - collision

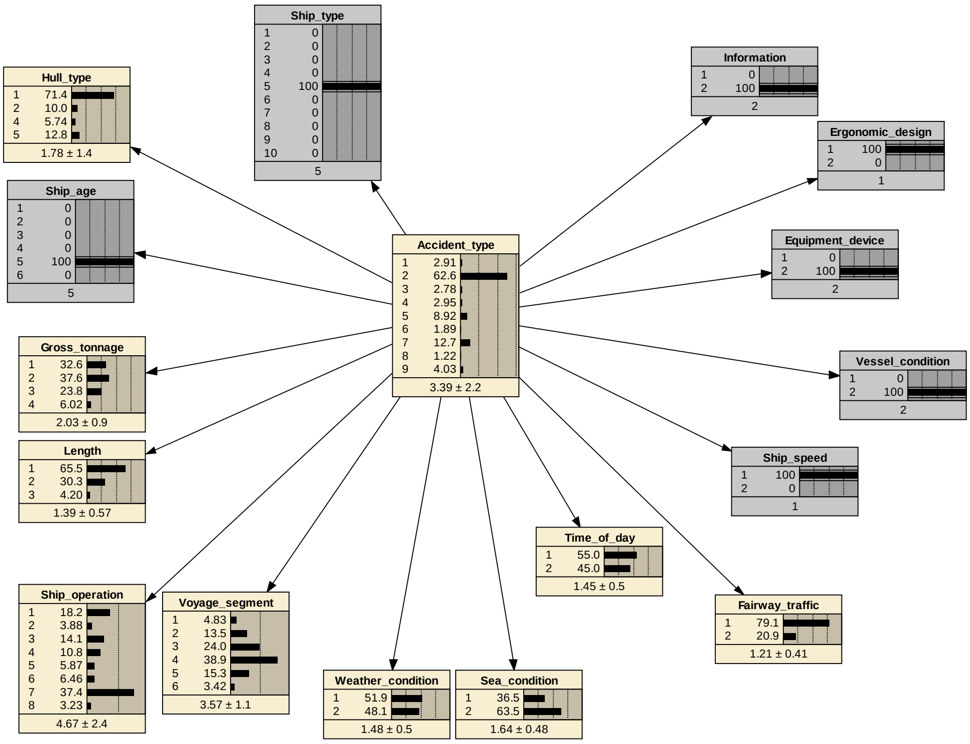


Figure 5.10 Posterior probability analysis in scenario 2 - grounding

Assuming that the variables are assigned with the specific states in Figure 5.10, the effects of vessel factors are indicated. The probability of grounding is the highest among ‘accident type’, accounting for 62.6%, followed by sinking (i.e., 12.7%). This probability indicates a significant increase in the risk of grounding and sinking compared to the initial states in Figure 5.6.

According to the above analysis, transport authorities and ship owners can use these findings to put forward the most effective risk control measures for different types of accidents derived from various vessel factors, especially the strongly related variables, i.e. ship type, information, ship age, vessel condition, and ergonomic design.

5.7 Discussion

Compared to previous studies focusing on causal factors related to the severity and the probability of maritime accidents, this study uses an NBN approach to investigate how different risk factors pose an impact on different types of maritime accidents. To identify RIFs, maritime accident reports from MAIB and TSB within a five-year period are extracted and reviewed to develop a primary database on maritime accidents. Then the risk-based NBN model is constructed to analyse RIFs in maritime accidents. At last, the sensitivity analysis is conducted, as well as scenario analysis to indicate research contributions. In general, the results from the NBN model present the distinctions among the key factors contributing to different types of accidents, which helps generate insights for accident prevention.

In summary, the findings of this study can be summarised as follows:

(1) According to the calculations of the mutual information, crucial RIFs are ranked under different accident types. The results reveal that critical RIFs for maritime accident types are ‘Ship operation’, ‘Voyage segment’, ‘Ship type’, ‘Gross tonnage’, ‘Hull type’, ‘Information’.

(2) There is the highest probability of overboard occurring on fishing vessels. When the ship operation is ‘towing’, the accident type has a high likelihood of being ‘capsize’; ‘manoeuvring’ and ‘on passage’ operation contribute to the higher probability of grounding; ‘pilotage’ is closely related to ‘contact/crush’.

(3) When ships are in ‘mid-water’ and ‘transit’ voyage segments, there is a higher probability of being in a collision. Grounding is more likely to happen in ‘departure’ and ‘arrival’ segments.

(4) The situation of poor information on board exposes a higher risk of grounding.

Among them, the scenario analysis reveals that environmental factors and vessel factors of maritime accidents generate a significant impact on accident types.

With respect to the environmental factors, the probability of collision is the highest among the ‘accident type’ when a ship is in the following states: ‘voyage segment – transit’; ‘ship operation - on passage’; ‘before 7:00 am or after 7:00 pm’; ‘good weather and sea condition’; ‘not considering the fairway traffic appropriately’. The probability of grounding is the highest when a ship is in the following states: ‘voyage segment – departure’; ‘ship operation – pilotage’; ‘between 7:00 am and 7:00 pm’; ‘severe weather and sea condition’; ‘not considering the fairway traffic appropriately’.

Concerning the vessel factors, the probability of grounding is the highest among ‘accident type’ if a ship is in the following states: ‘older than 20 years’, ‘effective and updated information provided’, ‘ergonomic problem’, ‘equipment operates correctly’, ‘good condition of vessel’, ‘fast ship speed’. The probability of grounding is the highest among ‘accident type’ if a fishing ship is in the following states: ‘older than 20 years’, ‘lack of updated information’, ‘ergonomic design friendly’, ‘equipment not fully utilised’, ‘modification made to vessels and size’, ‘normal ship speed’. Therefore, such conclusions can effectively assist maritime authorities in developing countermeasures for accident prevention.

There are also limitations in this study. The small number of flooding data makes the results not significant and robust. Although BN can conduct bi-directional risk analysis, the transformation from the converging to diverging connections does not intuitively represent the accident development. Moreover, more human factors, underlining communication, situation awareness, fatigue, etcetera, will be processed to conduct further research to illustrate the influence of human errors on maritime accidents.

5.8 Concluding remarks

The following are the most significant remarks comprised in the chapter, and emphasised in the form of bullet points for the reader's ease:

- New primary data is analysed directly from maritime accident records.
- Analysis of risk factors for rational prevention.
- Evaluation of RIFs contributes to different types of maritime accidents.
- The findings help assist maritime authorities in developing countermeasures for accident prevention.

Chapter 6 Incorporation of human factors into maritime accident analysis

6.1 Introductory remarks

Based on the results of the NBN model in ***Chapter 5***, more human factors need to be included, as well as the inter-relations among different risk factors. With this perspective, another data-driven Bayesian Network is used to investigate the effect of human factors on marine safety in maritime accident analyses. Its novelties consist of 1) incorporation of human factors into causational analysis concerning different maritime accident types, and 2) modelling by a historical accident data-driven approach, to generate new insights on critical human factors contributing to different types of accidents. The modelling of the interdependency among the risk influencing factors is structured by TAN and validated by sensitivity analyses. The findings reveal that the critical risk factors for all accident types are ship age, ship operation, voyage segment, information, and vessel condition. More importantly, the findings also present the differentiation among the vital human factors against different types of accidents. Most probable explanation (MPE) is used to provide a specific scenario in which the beliefs are upheld, observing the most probable configuration. The work pioneers the analyses of various impacts of human factors on different maritime accident types. It helps provide specific recommendations for the prevention of a particular type of accidents involving human errors.

6.2 Background information

Most shipping accidents (e.g. collisions, groundings, crash, fire and explosions) are characterised with a feature of low probability-high consequence. Catastrophic maritime accidents may cause a huge loss of human lives, damage to the society and environment (Zhang and Thai, 2016). To mitigate the risk and improve the safety of marine transportation, the IMO introduced FSA methodology for its applications to the rule-making process (IMO, 2002, IMO, 2013). Although modern ships are highly equipped with advanced technologies (*e.g.* navigation technology, onboard information, bridge resource management systems), human factors present a significant contribution to accidents. There is no consensus on the statistical analysis of the causations leading to maritime accidents, due to the different perspectives on the analysis and use of various investigation approaches. According to the literature, the organisation, working condition, and navigational environment are the major driving forces to maritime accidents (García-Herrero et al., 2012). However, human errors, technical failures, and mechanical failures are traditionally highlighted as the main root causes of accidents (Celik and Cebi, 2009). It is widely accepted that the human element, accounting for 75%-96% of maritime casualties, plays an essential role in accidents involving modern ships (Trucco et al., 2008b, Fan et al., 2018, Tzannatos, 2010). Human factors are often viewed as causes behind anything that goes improperly at sea.

Human factors are usually adopted as a concept that considers other relevant factors, including workplace conditions, physical and natural environment, procedures, technology, training, organisation, management, as well as seafarers (*i.e.* fatigue, task load, mental state, etcetera) (Psarros, 2015). Several researchers have studied the contribution of human and organisational factors to ship accidents (Chauvin et al., 2013, Chen et al., 2013, Xi et al., 2017). The majority of accidents occurred due to one of or a combination of the following causes: poor crew competence, fatigue, lack of communication, lack of proper maintenance, lack of application of safety culture and protocols or other procedures, inadequate training, poor situation assessment, and stress (Vinagre-Ríos and Iglesias-Baniela, 2013, Fan et al., 2018). Generally, seafarers often face more accidents than the crews working onshore, as reported by Roberts and Hansen (2002). Also, there is a consideration that a system for the training and assessment of the non-technical skills (NTS) needs to be established in the maritime industry (Saeed et al., 2016). Thus, the effective control of these causes will help reduce the risk and improve safety.

Risk analyses are an effective way of devising mitigation measures that prevent accidents. Among the studies on the risk analyses for maritime transportation, historical data analyses have been widely used. A number of papers have used historical accident data for such purposes (Zhang et al., 2013, Zhang et al., 2016). Ronza et al. (2003) investigated 828 accidents in port areas using event trees to predict the frequency of accidents. Kujala et al. (2009) included detailed accident statistics over a ten-year period in a collision model, to analyse the safety in the Gulf of Finland. Jin and Thunberg (2005) proposed the logic regression model based on accident data from 1981-2000 to analyse fishing vessel accidents. Quantitative risk and reliability analyses techniques have been widely used to reduce the probability of failure in offshore sectors, including Hazard and Operability Studies (HAZOP), Failure Mode and Effects Analysis (FMEA), Fault Tree Analysis (FTA), Event Tree Analysis (ETA) and BN. (Yeo et al., 2016, Zhang and Thai, 2016). BN became popular for maritime risk modelling during the period of 2004–2013. Experts' knowledge was also found to play an essential role in Bayesian Network structures, regarding the definition of the relative probabilities due to insufficient historical data (Hänninen and Kujala, 2014, Zhang and Thai, 2016).

This chapter investigates how human factors, combined with other factors, affect maritime transportation using risk analysis. Allowing for the drawbacks arising from traditional studies, this study proposes a novel risk assessment of the human factors contributing to maritime accidents. Since 75-96% of maritime accidents involve human elements, to which extent a maritime accident is defined to be a human-related maritime accident. This study aims at investigating how different risk factors generate, in an individual or combined manner, an impact on different types of human-related maritime accidents. Based on recorded maritime accident reports from MAIB and TSB between 2012 and 2017, a primary database is developed. Owing to the use of accident data, the TAN model is developed to construct BN and train the data, so as to propose a data-driven

BN-based approach for accident analyses.

6.3 RIFs identification

To analyse the maritime accident types under various RIFs, identifying and selecting the RIFs from the accident reports is necessary. The data was obtained from case-by-case analyses of recorded maritime accidents from MAIB and TSB that occurred from 2012 to 2017. These reports are among the most representative from the literature (Chauvin et al., 2013, Graziano et al., 2015, Kum and Sahin, 2015).

To generate the RIFs, the procedure consists of four stages: (1) online database searching, (2) reports screening and selecting, (3) refining and analysis, (4) RIFs selecting, as demonstrated in ***Chapter 3***. Through online database searching, the maritime accident reports from MAIB and TSB between Jan. 2012 to Dec. 2017 were obtained. In order to ensure the human element relevance, these accident reports are screened with a focus on human factors-related accidents. Therefore, the study generates the database with 161 reports involving 208 vessels. Then, the reports are further refined and analysed, 32 risk factors contributing to human errors are identified and described in ***Chapter 4***, shown in Table 6.1. Then factors with high occurrence frequencies are selected as common factors, and the others are excluded due to low frequencies and hard measurement.

Table 6.1 The risk factors contributing to human errors in maritime accidents

Number	Risk factors	Frequency
24	Sea condition: falling tide, current, waves	53.37%
22	Insufficient or lack of updated information (poor quality of equipment data, falsified records of information, relies on a single piece of navigational equipment); no automatic means or without indicators for necessary observing (working indicators, light)	45.67%
29	Dysfunctional management system (shore management, maintenance management, bridge source management, on board management, safety management systems, port service, qualification examination, inadequate training, practice, emergency drill)	40.87%
23	Weather condition: wind, visibility (dense fog)	39.42%

20	Devices and equipment on board not fully utilised or operated correctly (BNWAS switched off, alarm system not in the recommended position or not noticed)	37.98%
7	No clear order (not accurately interpret and apply the requirements of a safe manning document)	37.50%
2	Ineffective supervision and support (lone watchkeeper or working isolated, improper supervision of loading operation)	32.69%
12	Unfamiliar with/lack of equipment knowledge, inexperienced, ill-prepared	32.69%
1	Poor communication and coordination	30.77%
19	Poor condition of the vessel, increasing complexity of propulsion arrangements, and modifications made to vessels, size	28.85%
28	Lack of risk assessment	26.92%
30	Lack of safety culture, precautionary thought	24.52%
13	Complacent about the duties or underestimation of the severity of the condition (low state of alertness)	21.63%
27	Inappropriate or ambiguous code, endorsement, regulations, procedure, instructions, formal published guidance; operation manual, requirement	19.71%
17	Distracted/insufficient attention	16.35%
26	Fairway traffic (traffic density, repetitive nature of the route)	16.35%
5	Over-reliance on devices (AIS, GPS…), or poor lookout	15.38%
9	Lack of situation awareness	14.42%
3	No detailed passage plan or revised passage plan was unsafe	13.46%
10	Fatigue/asleep/tiredness and desire to rest	13.46%
8	Limited time to respond	12.50%
21	Ergonomic impact of innovative bridge design (visual blind sector ahead, motion illusion)	11.06%
6	Fast speed	9.62%
14	Recreational drugs, alcohol	6.73%
15	Cognitively overload	4.81%
32	Commercial pressure, public pressure or industrial pressure (financial constraints)	4.33%
31	No medical and fitness standards for crews	2.40%
11	Emotion (low level of arousal, panic, anger, unhappiness)	1.92%
4	Swift duty between pilots and seafarers or change of the steering mode	1.44%
16	Physical incapacitation	0.96%
25	Noisy and vibrating environment	0.96%
18	Stress	0.48%

However, human factors in maritime accidents are usually combined with other external factors, such as sea condition, weather condition, fairway traffic, and vessel condition, to affect the safety procedure in navigation. From this perspective, it is beneficial to combine human factors with other such factors to investigate their combined effect on maritime safety. The average frequency of all common factors was calculated as the threshold of RIFs selection. Therefore, the top 14 common factors whose frequencies were higher than the average value, 19.35%, were extracted as RIFs in the study. Besides, combined with the factors identified from ***Chapter 5***, encompass a total of 25 RIFs, seen in Table 6.2.

Table 6.2 25 RIFs defined in maritime accidents

No	**RIFs**	**Notation**	**Description**	**Corresponding values**
1	Ship type	R_{ST}	Passenger vessel, tug, barge, fishing vessel, container ship, bulk carrier, RORO, tanker or chemical ship, cargo ship, others.	1, 2, 3, 4, 5, 6, 7, 8, 9, 10
2	Hull type	R_{HT}	Steel, wood, aluminium, others	1, 2, 4, 5
3	Ship age (years)	R_{SA}	(0 5], [6 10], [11 15], [16 20], >20, NA	1, 2, 3, 4, 5, 6
4	Length (m)	R_{L}	≤100, >100, NA	1, 2, 3
5	Gross tonnage (GT)	R_{GT}	≤300, 300 to 10000, >10000, NA	1, 2, 3, 4
6	Ship operation	R_{SO}	Towing, Loading/unloading, Pilotage, Manoeuvring, Fishing, At anchor, On passage, others	1, 2, 3, 4, 5, 6, 7, 8
7	Voyage segment	R_{VS}	In port, Departure, Arrival, Mid-water, Transit, others	1, 2, 3, 4, 5, 6
8	Ship speed	R_{SS}	Normal, fast	1, 2
9	Vessel condition	R_{vc}	The condition of vessel has nothing to do with the accidents; Increasing complexity of propulsion arrangements, modification made to vessels, size contributes to the accidents	1, 2
10	Equipment /device	R_{E}	Devices and equipment onboard operate correctly; Devices and equipment not fully utilised or operated correctly (*e.g.*, BNWAS switched off, alarm system not in the recommended position or not noticed)	1, 2
11	Ergonomic design	R_{ED}	Ergonomic friendly or ergonomic aspects have nothing to do with accidents; Ergonomic impact of innovative bridge design (*e.g.*, visual blind sector ahead, motion illusion)	1, 2
12	Information	R_{I}	Effective and updated information provided; Insufficient or lack of updated information (*e.g.*, poor quality of equipment data, falsified records of information, relies on a single piece of navigational equipment, without working indicators or light for necessary observing)	1, 2

13	Weather condition	R_{WC}	Good/poor considering rain, wind, fog, visibility	1, 2
14	Sea condition	R_{SC}	Good/poor considering falling/rising tide, current, waves	1, 2
15	Time of day	R_{TD}	07:00 to 19:00, other	1, 2
16	Fairway traffic	R_{FT}	Good or poor considering complex geographic environment, dense traffic, or repetitive nature of the route contributing to ignorance	1, 2
17	Communication	*A1*	Good or poor communication and coordination	1, 2
18	Supervision	*A2*	Effective or ineffective supervision and supports (lone watchkeeper or working isolated, improper supervision of loading operation)	1, 2
19	Clear order	*A6*	Good or unclear order from documents (not accurately interpret and apply the requirements of a safe manning document)	1, 2
20	Experienced	*A11*	Familiar or unfamiliar with/lack of equipment knowledge, experienced or inexperienced, good or ill-prepared;	1, 2
21	Complacent	*A12*	Properly understand or complacent about the duties/underestimation of the severity of the condition (low state of alertness)	1, 2
22	Regulation	*A18*	Good or inappropriate/ambiguous code, endorsement, regulations, procedure, instructions, formal published guidance; operation manual, requirement	1, 2
23	Risk assessment	*A19*	Good or lack of risk assessment	1, 2
24	Management	*A20*	Good or dysfunctional management system (including shore management, maintenance management, bridge source management, onboard management, safety management systems, port service, qualification examination, inadequate training, practice, emergency drill)	1, 2
25	Safety culture	*A21*	Good or lack of safety culture, precautionary thought	1, 2

Most of the definitions of variables' states can be seen in accident investigation reports. For example, 'accident type', 'ship type', 'hull type', 'ship operation', and 'voyage segment', are classified into different states according to the classification of MAIB or TSB. Some variables are degraded according to the literature, like 'ship age', 'length', and 'gross tonnage'. Also, 'vessel condition', 'communication', 'supervision', etcetera, are graded based on whether they are blamed for the faults in accidents, as described in the reports.

In the quantitative analysis of BN modelling, the accident type is defined as a dependent variable, as presented in Table 6.3.

Table 6.3 Accident type

No.	**Accident type**
S1	Collision
S2	Grounding
S3	Flooding
S4	Fire/explosion
S5	Capsize
S6	Contact/crush
S7	Sinking
S8	Overboard
S9	Others

6.4 TAN Modelling for maritime accidents

A Bayesian network encodes a joint probability distribution over a set of random variables *U*, which is an annotated directed acyclic graph (DAG). Let $U=\{A_1,\dots A_n,C\}$ where *n* stands for the number of RIFs, the variables $A_1,\dots A_n$ are the RIFs and *C* is the class variable (accident types). Consider a graph structure where the class variable is the root, that is, $\prod C=\varnothing$ ($\prod C$ denotes the set of parents of *C* in *U*), and each RIF has the class variable as its unique parent, *i.e.* $\prod A_i=\{C\}$ for $1\le i\le n$. A BN defines a unique joint probability distribution over *U* given by

$$P(A_1,\dots A_n,C)=P(C)\cdot\prod_{i=1}^{n}P(A_i\,|\,C)$$

The DAG on $\{A_1,\dots A_n\}$ is a tree if $\prod A_i$ contains only one parent for all A_i, except for one variable without parents (referred to as the root). There is a function π which can define a tree over $A_1,\dots A_n$ if there is exactly one *i* such that $\pi(i)=0$ (*i.e.* the root of the tree), and there is no sequence $i_1,\ldots i_k$ such that $\pi(ij)=i_{j+1}$ for $i \leq j< k$ and $\pi(i_k)=i_1$ (*i.e.*, no cycles). Such a function defines a tree network where $\prod A_i=\{C,\ldots A_{\pi(i)}\}$ if $\pi(i)>0$, and $\prod A_i=\{C\}$ if $\pi(i)=0$.

Learning a TAN structure is an optimisation problem. Solving this problem follows the general procedure proposed by Chow and Liu (1968), who used conditional mutual information between attributes. The function can be defined as

$$I_P(A_i, A_j \mid C)=\sum_{a_{ii},a_{ji},c_i} P(a_{ii},a_{ji},c_i)\log\frac{P(a_{ii},a_{ji}\mid c_i)}{P(a_{ii}\mid c_i)P(a_{ji}\mid c_i)}$$

where I_P represents the conditional mutual information, a_{ii} is the i^{th} state of RIF A_i, a_{ji} is the i^{th} state of RIF A_j, c_i is the i^{th} state of 'accident type'. The optimisation problem, *i.e.* learning a TAN structure, is to find a tree defining function π over $A_1,\ldots A_n$ such that the log likelihood is maximised.

This function measures the information that A_i provides about A_j when the value of C is known. The procedure of TAN modelling consists of five steps:

(a) Compute $I_P(A_i, A_j \mid C)$ between each RIF given 'accident type', $i \neq j$. 'Accident type' is the class variable.

(b) Build an undirected graph in which the vertices are the RIFs $A_1,\ldots A_n$. Annotate the weight of an edge linking RIF A_i to RIF A_j by $I_P(A_i, A_j \mid C)$.

(c) Build a maximum weighted spanning tree, *i.e.* the tree that has a maximum sum of $I_P(A_i, A_j \mid C)$.

(d) Transform the undirected tree to a directed tree, *i.e.* choose a root variable from the

RIFs according to (c) and setting the direction of all edges linking RIFs to be outward from it.

(e) Construct a TAN structure by adding a vertex labelled by ‘accident type’ and adding an arc from ‘accident type’ to each RIFs.

To generate the BN model, 25 RIFs are involved in demonstrating their relationships with the dependent variable (*i.e.* accident type). The Netica software package (Norsys, http://www.norsys.com) is applied to assist the calculation. It has a ‘learning network’ function that develops the TAN network. The structure of the BN is presented in Figure 6.1.

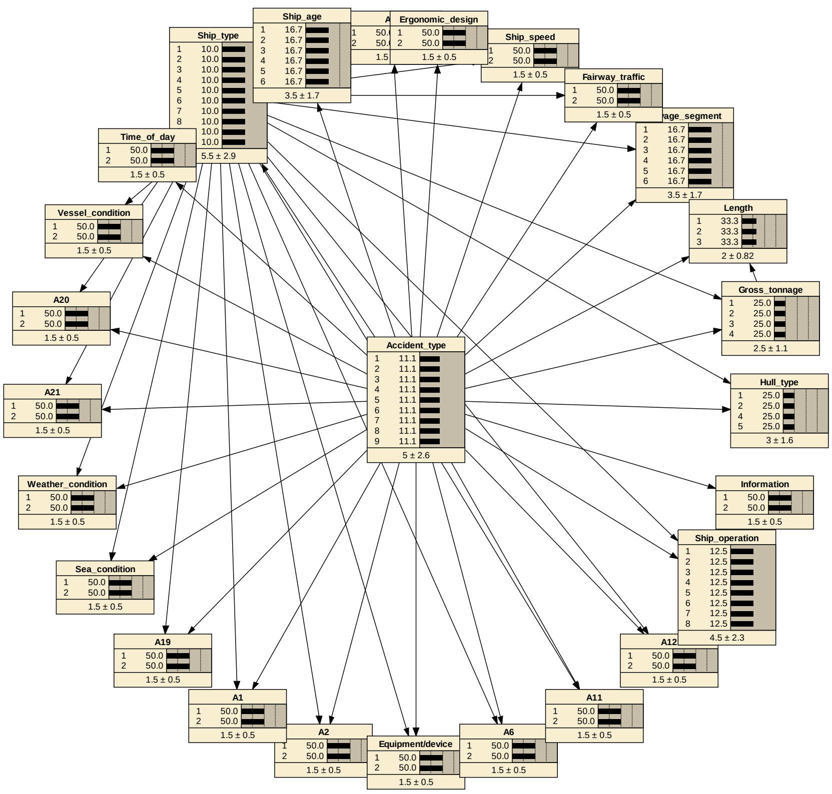


Figure 6.1 Proposed BN for analysis of accident types’ probability

Based on the TAN model, the parameter learning of CPTs from the cases is conducted by Netica Software. Once the CPTs are constructed and obtained, the posterior probabilities of each variable can be calculated. The statistical analysis of the probability of variables, reveals interesting initial findings of useful insights regarding safety caution and accident prevention as follows.

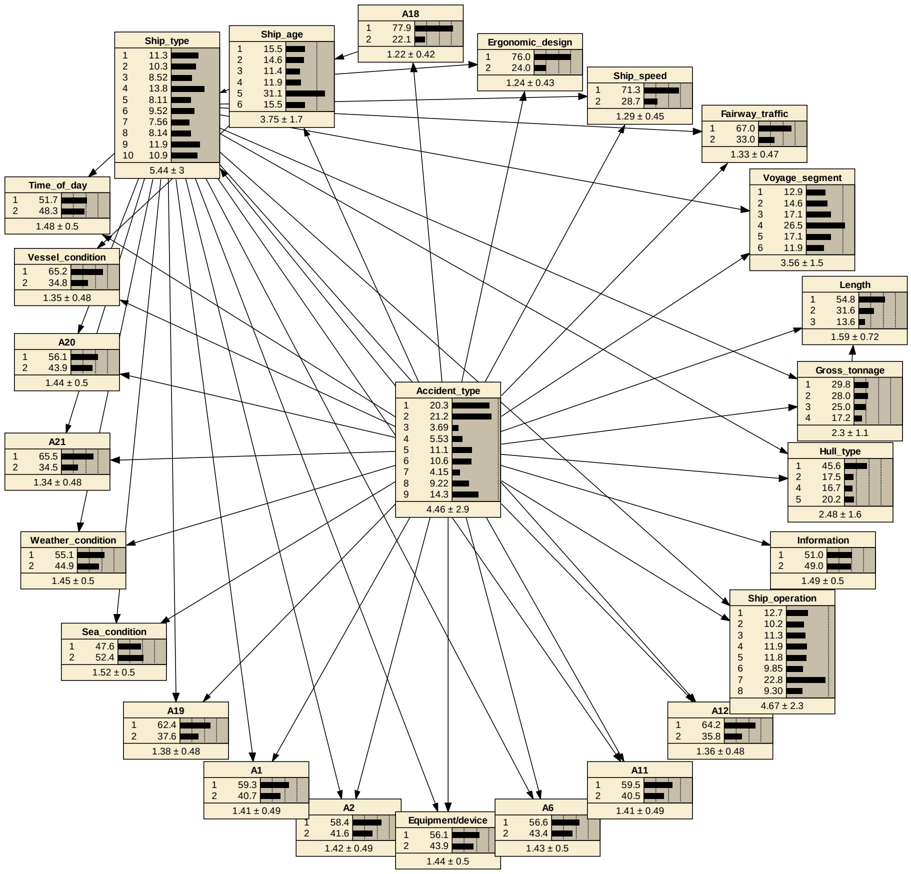


Figure 6.2 Results of TAN

Figure 6.2 presents the results of TAN involving all the retained 25 RIFs. Among the accidents, grounding and collision are among the most frequent accident types, accounting for 20.3% and 21.2%, respectively.

6.5 Sensitivity analysis

6.5.1 Mutual information

The mutual information between ‘accident type’ and RIFs is demonstrated in Table 6.4.

From this point of view, the variables with higher $I(S,R_k)$ reflects essential impacts on 'accident type'. When 'accident type' is the parent node, 'ship age' with the corresponding mutual information value of 0.05422, has the most significant effect on the accident type. Meanwhile, variables 'ship age', 'ship operation', 'voyage segment', and 'information', are selected to be calculated for the factor analysis in the next step.

Table 6.4 Mutual information shared with 'Accident type'

Node	Variance Reduction	Percentage (%)	Mutual Info	Percentage (%)	Variance of Belief
Ship_age	0.02399	0.284	0.05422	1.84	0.0015433
Ship_operation	0.3115	3.69	0.05132	1.74	0.0030026
Voyage_segment	0.11	1.3	0.03595	1.22	0.0013546
Vessel_condition	0.07391	0.874	0.03171	1.07	0.0006767
Information	0.06113	0.723	0.03042	1.03	0.0010573
Ship_type	0.03119	0.369	0.02891	0.98	0.0011112
A21	0.01585	0.188	0.02871	0.973	0.000501
Hull_type	0.1171	1.39	0.02838	0.962	0.0008351
Gross_tonnage	0.0414	0.49	0.02482	0.841	0.0010064
A18	0.01091	0.129	0.02306	0.782	0.0005812
Length	0.02874	0.34	0.02151	0.729	0.0003882
Ergonomic_design	0.07421	0.878	0.0194	0.657	0.0006816
Sea_condition	0.0168	0.199	0.01774	0.601	0.0006831
A19	0.06751	0.799	0.01466	0.497	0.0004953
A11	0.000957	0.0113	0.01271	0.431	0.0003126
Ship_speed	0.006733	0.0797	0.01172	0.397	0.0003134
Weather_condition	0.004131	0.0489	0.00889	0.301	0.0004858
A20	0.02553	0.302	0.00851	0.288	0.0001854
A6	0.01196	0.142	0.00707	0.24	0.0002377
Fairway_traffic	0.03498	0.414	0.00704	0.238	0.0001619
Time_of_day	0.04428	0.524	0.00671	0.227	0.0002614
A12	0.003327	0.0394	0.006	0.203	0.000211
A1	5.57E-05	0.000659	0.00547	0.185	0.0000786
Equipment/device	0.003186	0.0377	0.00541	0.183	0.0001612
A2	0.01893	0.224	0.00399	0.135	0.0001467

6.5.2 Sensitivity analysis

With regard to the most important variables influencing each of the investigated accident types, the next step is to figure out how these variables (the states of variables) affect the target accident type. To do so, the calculation of a joint probability of each variable and 'accident type' is presented in Table 6.5.

Table 6.5 The joint probability of the TAN model

					Ship age				
	S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
1	23.6	19.8	3.69	3.88	12	13.9	**2.56**	7.7	12.9
2	22.4	21.1	2.2	4.99	**8.81**	8.73	3.8	8.21	**19.7**
3	**14.8**	23.5	**7.24**	**8.87**	8.93	11.2	**7.74**	8.92	**8.82**
4	15.8	22.5	2.69	**3.72**	**13.7**	12.6	3.33	12.9	12.8
5	16.8	**27.7**	4.27	5.58	11.7	**7.02**	4.11	**7.15**	15.7
6	**29.3**	**6.95**	**2.07**	6.52	10.6	**14.3**	4.13	**13.2**	13
					Ship operation				
	S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
1	**12.8**	25.3	3.3	**4.74**	15.2	9.75	4.48	7.9	16.5
2	15.9	16.3	4.1	**6.5**	10.3	11.1	4.57	9.81	**21.4**
3	14.4	**28.4**	4.08	5.32	9.28	11.9	4.14	8.9	13.6
4	16.5	21.6	3.51	5.05	12.5	12.2	3.92	9.36	15.4
5	16.9	**14.2**	4.45	5.12	**15.4**	9.69	3.98	**15.9**	14.3
6	16.6	20	4.26	6.75	10.7	11.6	**5.26**	9.27	15.7
7	**35.7**	22.8	**2.64**	5.19	**6.51**	**8.71**	**3.14**	**6.08**	**9.23**
8	17.5	18	**4.51**	6.48	12.7	**12.2**	5.03	9.82	13.7
					Voyage segment				
	S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
1	15.3	**15.6**	4.24	6.03	**13.5**	11	4.72	9.95	**19.6**
2	20.3	23.5	3.73	5.31	12.6	10.6	4.16	7.96	11.8
3	**11.5**	**28.5**	3.2	5.44	**7.72**	**15.9**	4.29	7.54	15.9
4	25.4	22.1	**3.17**	5.34	11.3	**5.86**	**2.99**	10.6	13.3
5	**27.5**	17.7	3.89	**5.02**	10.9	9.84	4.67	**7.51**	**13**
6	16.5	16.9	**4.6**	**6.53**	11.1	14.2	**5.12**	**11.8**	13.3
					Vessel condition				
	S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
1	**24.3**	**21.191**	**3.63**	**4.46**	**9.56**	**11.5**	**2.22**	**10.1**	**13.1**
2	**12.8**	**21.212**	**3.8**	**7.53**	**13.9**	**8.99**	**7.76**	**7.52**	**16.5**
					Information				
	S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
1	**21.8**	**15.8**	**3.33**	**6.17**	**13.2**	**7.28**	**4.28**	**10.6**	**17.6**
2	**18.7**	**26.8**	**4.06**	**4.86**	**8.86**	**14.1**	**4.01**	**7.82**	**10.8**

According to Table 6.5, the state of each variable that poses the highest influence on an accident type is shown (in bold value), as well as the state of each variable that poses the lowest influence on an accident type (in bold value). For example, when a ship is in the state of ‘on passage’, there is the highest probability for the accident to be ‘collision’ (35.7%); when ‘ship operation’ is the state of ‘towing’, there is the lowest probability to be ‘collision’ (12.8%). However, when a ship is in ‘pilotage’, there is the highest probability to be ‘grounding’ (28.4%); in ‘fishing’ operation, there is the lowest probability to be ‘grounding’ (14.2%). For the voyage segment, when in the state of ‘transit’, a ship has the highest probability to be in ‘collision’ (27.5%); when in ‘arrival’ segment, it has the lowest probability to be in ‘collision’ (11.5%), but has the highest probability to be in ‘grounding’ (28.5%). As far as the ship age is concerned, a ship with age from 11 to 15 years has the lowest probability to be involved in ‘collision’(14.8%), whereas a more than 20-year-old ship has the highest probability to be involved in ‘grounding’(27.7%). Although with good vessel condition and the condition of good information, the ship associates with ‘collision’, whereas the situation of poor information on-board ship exposes the highest risk of ‘grounding’.

In this way, it demonstrates the influence of the certain state of a single variable on an accident type. Moreover, it illustrates how different states of a single variable contribute to the probability of a particular accident type.

In terms of TRI sensitivity analysis, Table 6.6 demonstrates the TRI value of ‘ship age’ against collision. Table 6.7 indicates the values of all RIFs for all accidents. Moreover, by comparing the updated value of the target node, it is claimed that the model is in line with Axiom 1.

Table 6.6 TRI of a risk variable (ship operation) for collision

Ship age									
1	**2**	**3**	**4**	**5**	**6**	**Collision**	**HRI**	**LRI**	**TRI**
/	/	/	/	/	/	20.3	9.0	5.5	7.25

100%	0	0	0	0	0	23.6
0	100%	0	0	0	0	22.4
0	0	100%	0	0	0	14.8
0	0	0	100%	0	0	15.8
0	0	0	0	100%	0	16.8
0	0	0	0	0	100%	29.3

Table 6.7 TRI of risk variables for all accident types

Node	**TRI**									
	S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**	**Average**
Ship age	7.25	10.38	2.59	2.58	2.45	3.64	2.59	3.03	5.44	4.44
Ship operation	11.45	7.10	0.94	0.88	4.45	1.75	1.06	4.91	6.09	4.29
Voyage segment	8.00	6.45	0.72	0.76	2.89	5.02	1.07	2.15	3.30	3.37
Vessel condition	5.75	0.01	0.09	1.54	2.17	1.26	2.77	1.29	1.70	1.84
Information	1.55	5.50	0.37	0.66	2.17	3.41	0.14	1.39	3.40	2.06

Specifically, in Table 6.6, the first row denotes the base-case scenario, and the following rows represent the different scenarios when each state of the variable reaches 100%. To obtain impact levels of such RIFs in accident types, TRIs are compared and ranked. Generally, based on Table 6.7, the most important variables for ‘accident types’ are as follows:

Ship age > Ship operation > Voyage segment > Information> Vessel condition

Ship age is ranked as the most important variable, and vessel condition is ranked as the fifth important variable for ‘accident types’. Compared to the results in Chapter 5, it shows that the majority of the results remain the same. However, the ship age and vessel condition reveal more contribution to the accident types when more human factors are considered within their interactions in the model. Both of them are vessel factors, which implies that vessel factors attribute more interactions considering human factors.

In detail, the most important variables list for different accident types is demonstrated in Table 6.8.

Table 6.8 The most important variables

Accident type	Ship age	Ship operation	Voyage segment	Vessel condition	Information
S1 Collision	3	1	2	4	5
S2 Grounding	1	2	3	5	4
S3 Flooding	1	2	3	5	4
S4 Fire/explosion	1	3	4	2	5
S5 Capsize	3	1	2	4	4
S6 Contact/crush	2	4	1	5	3
S7 Sinking	2	4	3	1	5
S8 Overboard	2	1	3	5	4
S9 Others	2	1	3	5	4

From this point of view, different accident types are correlated to different variable priorities. For example, 'vessel condition' is the most important RIF for 'sinking', but the least important RIF for 'contact/crush'. And 'ship operation' contributes more to the accidents like 'collision', 'capsize', and 'overboard', than the accidents like 'sinking' and 'contact/crush'.

6.5.3 Model validation

To validate the model, it is examined by testing the combined effect of multiple RIFs to the accident types. Accounting for different states of the parent nodes, this study calculates the changed value of each state. The 'information' is selected as the first node, the state generating the highest changed value of state 1 (*i.e.* collision) in 'accident type' is increased by 10%, while the state generating the lowest changed value of state 1 in 'accident type' is decreased by 10%. This procedure is written as '~10%' in Table 6.9. Then, the same approach is applied to the next RIF, and the integrated changed value is obtained and updated. The updating procedure would continue until all RIF nodes are included. Similarly, the same updating procedure is applied into the state 2, 3… 9 in 'accident type' respectively, until all states are included.

The first column of the data in Table 6.9 shows the original values in TAN, and other columns state the updated, changed values of results. However, each state of 'accident type' is calculated separately from each other, *i.e.* each row is computed through the change of states of RIFs in each accident type. From Table 6.9, the updated values of the target node are gradually increasing or decreasing along with the continuously changing RIFs, so that Axiom 2 is examined.

Table 6.9 Accident rate of minor change in variables

Information	/	**~10%**	**~10%**	**~10%**	**~10%**	**~10%**
Vessel condition	/	/	**~10%**	**~10%**	**~10%**	**~10%**
Voyage segment	/	/	/	**~10%**	**~10%**	**~10%**
Ship operation	/	/	/	/	**~10%**	**~10%**
Ship age	/	/	/	/	/	**~10%**
S1	20.3	20.4	21.2	21.5	22	22.2
S2	21.2	21.761	21.765	22	22.2	22.6
S3	3.69	3.72	3.74	3.76	3.79	3.8
S4	5.53	5.6	5.8	5.82	5.85	5.91
S5	11.1	11.3	11.6	11.7	11.8	11.9
S6	10.6	10.9	11.1	11.371	11.426	11.6
S7	4.15	4.16	4.52	4.57	4.61	4.68
S8	9.22	9.36	9.53	9.61	9.79	9.91
S9	14.3	14.6	14.86	14.945	15.1	15.3

6.6 Implications

The study enables the understanding of differences among critical factors, contributing to different types of accidents by incorporating human factors into the analysis. BN modelling can also explain the most probable scenario with reference to a particular accident type.

To enable the MPE function, each variable will have a belief-bar at the 100% level, and usually, some bars in RIFs are at lower levels, as seen in Figure 6.3. It reveals the most probable configuration by assuming the state with the bar at the 100% level for each variable. The shorter bars indicate the relatively low probabilities of the other states, given that the other variables are in the most probable configuration. In addition, they are scaled by the same factor used to bring the longest bar to 100%.

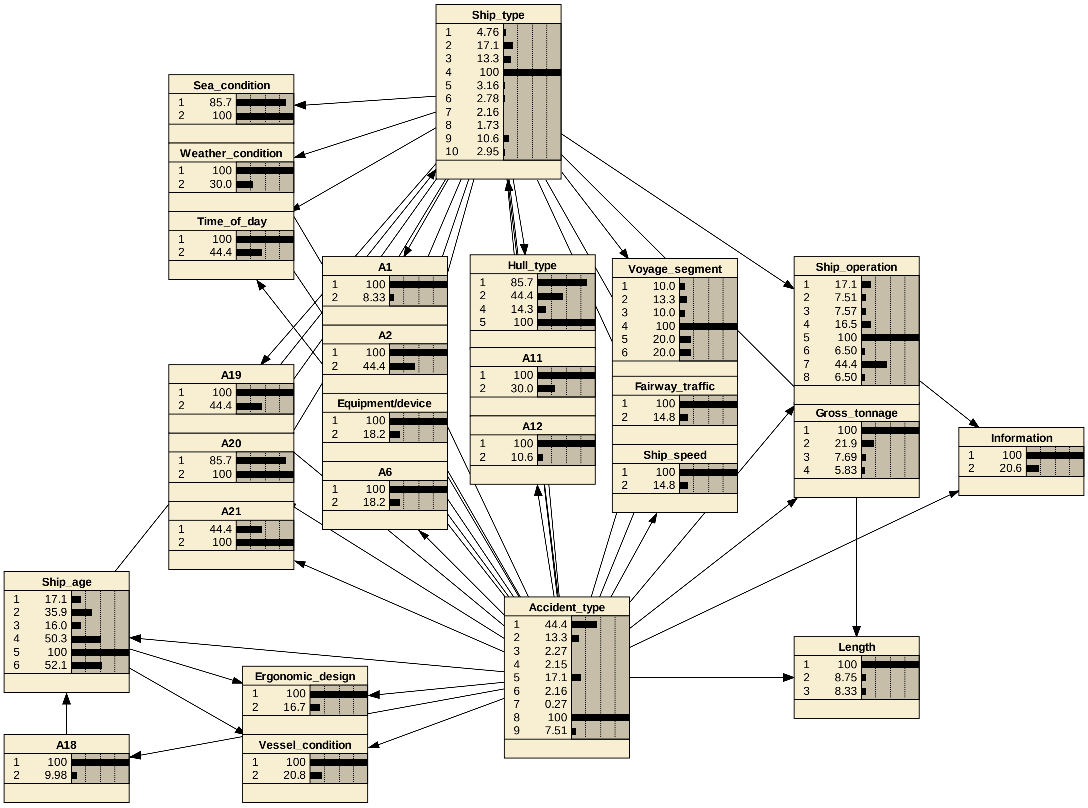


Figure 6.3 Most Probable Explanation for the BN model

From Figure 6.3, ‘overboard’ is the most probable accident type, as its high occurrence frequency indicates, and other RIFs reveal the corresponding most probable states. That is to say, a ‘fishing vessel’ tends to be ‘overboard’ within these conditions:

1) Ship age ‘more than 20’, ship length ‘100m or less’, gross tonnage ‘300GT or less’, in ‘finishing’ operation and ‘mid-water’ voyage segment with ‘normal’ speed, in ‘good condition’, with friendly ergonomic design and correctly operating device, and with effective navigational information;

2) Bad sea condition, during the time from 7:00 to 19:00;

3) Dysfunctional management system, lack of safety culture.

With regard to this explanation, it emphasises the critical causal relation between the dysfunctional management system and overboard. The management system refers to shore management, maintenance management, bridge source management, onboard management, port service, inadequate training, emergency drill, etcetera, which is a complex system as a significant variable influencing human factors for overboard. Besides, the lack of safety culture explains some dangerous behaviours of passengers or crew, so as to cause overboard.

Similarly, when ‘accident type’ is selected as state 1 (collision), the MPE is displayed in Figure 6.4.

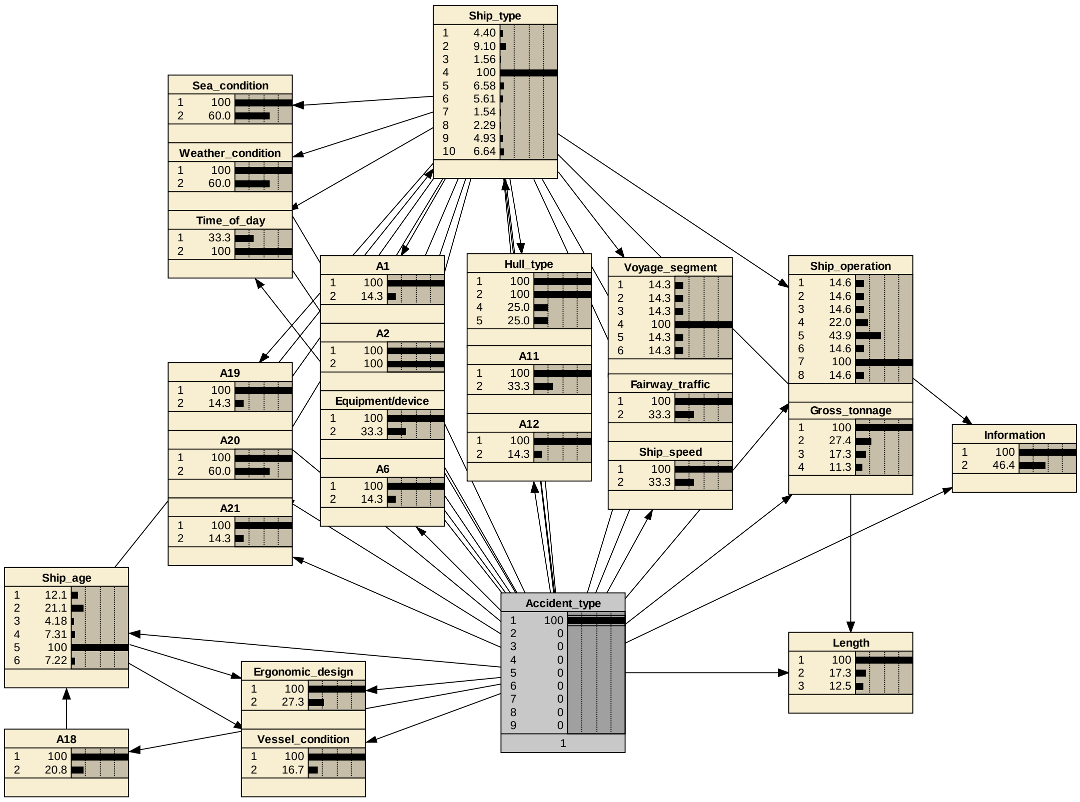


Figure 6.4 Most Probable Explanation for ‘collision’

From Figure 6.4, there are multiple 100% bars for ‘hull type’. Typically, when two or more states of the same variable have bars that are at the 100% level, it indicates that there is more than one configuration with the highest probability (*i.e.* the configurations have equal probability). Then one of the states is to be entered with an artificial finding that the variable is in that state, to see how it changes the multiple 100% bars of other variables. When accident type is selected in Figure 6.4, there is a high probability for the ‘fishing vessel’ to collide under these circumstances:

1) Ship age ‘more than 20’, ship length ‘100m or less’, gross tonnage ‘300GT or less’, ‘on passage’ operation and ‘mid-water’ voyage segment with ‘normal’ speed, in ‘good

vessel condition’, with friendly ergonomic design and correctly operating device, and adequate navigational information;

2) During the time before 7:00 or after 19:00;

3) Ineffective supervision or support of operation.

Under this circumstance, ineffective supervision or support of operation is strongly related to the collision. Branch et al. (2004) reported that at least three of the fifteen ships which failed to keep a proper lookout at night for collision had lone watchkeepers on the bridge. Working isolated or improper supervision increases the risk of human errors in navigation compared to operating under supervision.

By trying each of the possibilities, all the configurations that are at the highest probability level are revealed. Table 6.10 illustrates the MPE for all accident types. Although there are influences between different RIFs, poor vessel condition such as increasing complexity of propulsion arrangements or modification made to vessels size has a strong relation to sinking. Insufficient or lack of updated information, such as falsified records of information, relies on a single piece of navigational equipment, or without working indicators for necessary observing, contributes to grounding, contact, and other incidents. Ergonomic impact of innovative bridge design (e.g., visual blind sector ahead, motion illusion) is strongly related to fire and sinking. Also, it emphasises several human factor related variables under different accident types. For example, there is a high probability for a collision to happen under the case of lone watchkeeper or working isolated. Grounding usually happens under the circumstance with inadequate risk assessment, dysfunctional management system, unclear order from documents, and ineffective supervision. The most probable explanation given human factors for flooding is the lack of safety culture and precautionary thought. Human factors for capsize are related to lack of risk assessment, unclear order, and ineffective supervision. The situation with poor safety culture, dysfunctional management, and unclear order is strongly associated with sinking.

Table 6.10 Most Probable Explanation for all accident types

Variable	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
Ship age	5	5	5	5	1	6	5	5	2
Ship operation	7	1	5	7	1	7	1	5	2
Voyage segment	4	2	4	4	5	3	5	4	1
Vessel condition	1	1	1	1	1	1	2	1	1
Information	1	2	1	1	1	2	1	1	2
Ship type	4	3	4	4	2	7	2	4	9
A21	1	1	2	1	1	1	2	2	1
Hull type	2	1	2	2	1	1	1	5	1
Gross tonnage	1	2	1	1	1	3	1	1	2
A18	1	1	1	1	1	1	1	1	1
Length	1	1	1	1	1	2	1	1	1
Ergonomic design	1	1	1	2	1	1	2	1	1
Sea condition	1	2	1	2	2	1	2	2	1
A19	1	2	1	1	2	1	1	1	2
Ship speed	1	1	1	1	1	2	1	1	1
Weather condition	1	2	2	2	1	1	1	1	1
A20	1	2	1	2	1	1	2	2	1
A6	1	2	1	2	2	2	2	1	2
Fairway traffic	1	1	1	1	1	1	1	1	1
Time of day	2	1	1	1	1	2	1	1	1
A12	1	1	1	1	1	1	1	1	1
A2	2	2	1	1	2	1	1	1	1

6.7 Discussion

Compared to previous studies focusing on causal factors related to the severity and the probability of maritime accidents, this study uses a data-driven TAN approach, to investigate how different risk factors generate an impact on different types of maritime accidents with a focus on human factors. To identify RIFs, maritime accident reports from MAIB and TSB within a five-year period of 2012-2017, are extracted and reviewed to develop a primary database on maritime accidents. Then the risk-based TAN model is constructed to analyse RIFs incorporating human factors in maritime accidents. Lastly, the sensitivity analysis is conducted, as well as scenario analysis and MPE to indicate research contributions.

According to the calculations of the mutual information, crucial RIFs are ranked under different accident types. The results reveal that critical RIFs for maritime accident types are ‘ship age’, ‘ship operation’, ‘voyage segment’, ‘information’, and ‘vessel condition’. Meanwhile, it is evident that:

(1) The management system, including shore management, maintenance management, bridge source management, onboard management, port service, inadequate training, emergency drill etcetera, is a significant variable influencing human factors for overboard. Besides, the lack of safety culture explains dangerous behaviours on board, so as to cause overboard.

(2) Ineffective supervision is strongly related to the collision. Working isolated or improper supervision increases the risk of human errors in navigation compared to operating under supervision.

(3) Collision tends to happen under the case of lone watchkeeper or working isolated. Grounding is a probability under the circumstance with inadequate risk assessment, dysfunctional management system, unclear order from documents, and ineffective supervision. The most probable explanation given human factors for flooding is the lack of safety culture and precautionary thought. Human factors for capsize are related to lack of risk assessment, unclear order, and ineffective supervision. The situation with poor safety culture, dysfunctional management, and unclear order is strongly associated with sinking.

The scenario analysis provides a plausible explanation for the observed findings, revealing the most probable scenario under specific accident type. Therefore, it can help identify the potential hazards and effectively assist maritime authorities in developing countermeasures for accident prevention.

Generally, results from the TAN model present differentiation among the vital human factors contributing to different types of accidents, which helps provide the clue for accident investigation and generates insights for accident prevention. The stakeholders, such as ship owners and maritime authorities, will benefit from the findings and obtain the clue for accident investigation and prevention. However, there is a drawback in the MPE method for implications. Generally, its results can change with the introduction of irrelevant variables, and be deceptive in situations where even the most probable explanation is improbable. In addition, there is insufficient evidence to study individual factors which do not exist or contain limited information in the raw database, but are associated with the mental workload for seafarers. Further work should be conducted to propose a way to quantify or measure the mental workload of seafarers to support the human factors study.

6.8 Concluding remarks

The following are the most significant remarks comprised in the chapter, and emphasised in the form of bullet points for the reader's ease:

- Incorporate human factors into causational analysis of maritime accident types.
- Develop a historical accident data-driven approach to train prior probabilities in the risk-based BN.
- Conduct an empirical study to provide insights for the prevention of a particular type of accidents involving human errors.

Chapter 7 Mental workload analyses for seafarers in the ship bridge

7.1 Introductory remarks

From the above human factors research derived from accident reports and works of literature, there is still a gap for individual factors which contain limited information in the raw database, but are associated with the mental workload for seafarers. This research has to find a way to obtain the evidence towards the mental workload of seafarers to support the hypothesis of the study. This chapter investigates how mental workload influences neurophysiological activation and decision making of experienced and inexperienced deck officers concerning collision avoidance. This last was done with simulated watch-keeping tasks in a maritime bridge simulator, and using fNIRS technology to measure neurophysiological activation. It demonstrates that the developed scenario distracted the ship officers by reporting vessel position at specific points, which is the common task requiring temporal mental workload in the real world. The results show that experienced participants were considered to believe they have better performance than inexperienced people. It also illustrates better performance for experienced seafarers because they made decisions earlier, which leads to collision avoidance successfully. Participants under distraction were considered to require more temporal demand than without distraction. In terms of fNIRS data, it shows significant differences in the right DLPFC of the brain. Greater oxygenation is found during decision time for participants with distraction. Higher oxygenation is observed for experienced participants at the end of watchkeeping.

7.2 Background information

Human factors are often viewed as sophisticated causes behind anything that goes improperly at sea. Out of nearly 62% of pollution and maritime accidents (Er and Celik, 2005), human factors were comprised of 30% deck officer error, 7% shore-based personnel error, 2% engine officer error, 8% pilot error. Compared to the offshore crews, ship officers are faced with higher risks during ship navigation.

The deck officer is required to obtain plenty of skills, especially non-technical skills, including defining problems, managing workload, maintaining the standards of the watch-keeping, implementing the best solution, responding to the changes of the information, anticipating future events, sending information clearly and concisely, maintaining concentration, coping with stressors, etcetera (O'Connor and Long, 2011). Therefore, they are supposed to deal with multi-tasks during navigation. Among them, watchkeeping is one of the significant duties along the voyage and needs to be done with other missions simultaneously, especially for Officers of Watch (OOWs). During this duty, OOWs keep a proper lookout to know what is happening near the ship and obtain the information from various sensors to be aware of the situation in which they are immersed.

MAIB stated that of the 1,647 collisions, groundings, contacts and near collisions that were reported to MAIB between 1994 and 2003, two-thirds of vessels involved in collisions were not keeping a proper lookout (Branch et al., 2004). Watchkeepers have to deal with various issues including observing and recording the vessel position at intervals, paying attention to the radio or alarm, checking onboard equipment or devices, while they do watchkeeping. The workload of deck officers varies along with time and combined tasks. Thus, the effective evaluation of the deck officer’s workload during watchkeeping will help understand the risk to which seafarers are exposed and improve navigation safety.

Mental workload is the amount of demands or resources requiring an operator to complete specific tasks. Furthermore, the more sophisticated the tasks, the more mental workload is required to accomplish the tasks. It has been used in a wide range of applications to evaluate the task performance of operators or the practical aspect of system design (Ngodang et al., 2012, Dijksterhuis et al., 2011). Although mental workload related research has been conducted in road traffic accidents (Boyle et al., 2008, Rakauskas et al., 2008) and aviation transportation (Ayaz et al., 2012, Gateau et al., 2015), seafarers' mental workload analysis in maritime transport is scanty (Lim et al., 2018, Fan et al., 2018).

Moreover, mental workload has been described as being responsible for the majority of road traffic accidents (Dijksterhuis et al., 2011). Both high and low levels cause insufficient perception and attention, which in turn leads to driver errors. However, in the maritime sector, Lim et al. (2018) suggested the majority of trainees had less workload when the experienced captain was present, and the latter had the highest workload levels while the former revealed low workload and stress because of the shared work and responsibility.

Mental workload is also linked to the experience of operators. Experienced drivers have acquired more effective automation through practice, so that a lower level of mental workload was induced compared to novices (Patten et al., 2004). Besides, neuroimaging techniques demonstrated increases in PFC activation with increases in mental workload (Ayaz et al., 2012). There is a threshold for workload, beyond which it leads to worse performance and decreases in PFC activity (Molteni et al., 2008).

For ship officers, the ship bridge simulator is widely used for crew training and further understanding of human factors in these dedicated systems. The IMO utilised the simulation for crews' training based on the simulation training requirements (A-I/6: Training and Assessment) in the Standards of Training, Certification and Watchkeeping Convention (STCW 78-95). The awareness of the significance of human factors among navigation and maritime safety was aroused, and this stimulated studies on human performance in the ship bridge, which is commonly conducted in the bridge simulator. However human performance in the ship bridge is related to many elements, such as task demands, prior experience, personality, voyage segment, workload, etcetera (Ngodang et al., 2012); therefore, an acceptable measurement is required for credible evaluation.

To measure the mental workload of seafarers, especially ship officers, brain activity needs to be recorded. Brain activity in the transport field has previously been measured using a range of techniques, including fMRI, PET, and EEG. The above three techniques are extremely sensitive to motion artefacts, making them difficult to deal with natural cognitive tasks in realistic scenarios (Chiarelli et al., 2017). Typically, fMRI and PET have physical limitation for participants, requiring them to be in a supine position (Foy et al., 2016). EEG has the advantage of greater time resolution. The functional near-infrared spectroscopy (fNIRS) is a portable technique for both simulated environment and real-world operation. Along with the high sensitivity for muscle movement, both EEG and fNIRS are susceptible to head movement. However, the use of short-leads for fNIRS can isolate effects of blood flow in the scalp. The advantage of fNIRS over EEG is greater spatial resolution of the signals and less crosstalk between sites. It is more robust to motion artefacts and has a higher temporal resolution (Noah et al., 2015).

Besides, the hardware cost of fNIRS is significantly lower than most functional brain imaging techniques, including fMRI, PET, and EEG (Chiarelli et al., 2017). fNIRS is an emerging non-invasive brain imaging modality for measuring and recording cortical haemodynamic activity (Fishburn et al., 2014). It will not confine the subject in a small space compared to fMRI, and is also able to generate montages covering the whole head or precisely the parts of the cortex that contain relevant activations. This functional neuroimaging technique can record changes in brain activation by measuring changes in the concentration of oxygenated and deoxygenated haemoglobin, which is based on the different absorption spectra of near-infrared light. It is a sensitive and consequently mature measurement technique for exploring different mental workloads.

The current research investigates how mental workload influences neurophysiological activation and decision-making of experienced and inexperienced deck officers concerning collision avoidance. This last was done with simulated watchkeeping tasks in a maritime bridge simulator and using fNIRS to measure neurophysiological activation.

However, much of similar research does not use naturalistic tasks in the maritime field, and none has focused on differences in DLPFC activity between experienced officers and novice officers. Therefore, this study investigates how the mental workload induced by scenarios in the ship bridge influences neurophysiological activation and whether there is a difference between experienced and inexperienced seafarers, which may generate insights for seafarers' training and certification.

7.3 Materials and methods

7.3.1 Participants

A total of 41 participants were recruited from the Nautical Institute London Branch and Liverpool John Moores University. Inclusion of participant recruitment is limited to adults (>18 years old), without head injury conditions or suffering from high blood pressure since this may affect the results from fNIRS. In the study, any person suffering from anxiety condition or receiving medication for anxiety condition is excluded. Participants were divided into two groups based on their navigation experience. Twenty experienced seafarers whose average age is 44.60 (SD = 15.47) include master mariner (MM), chief mate (CM), and officer of the watch (OOW). Twenty-one inexperienced seafarers whose average age is 24.76 (SD = 5.25) are AB and cadets. Raw NASA-TLX data of 41 participants were kept for behaviour performance analysis. However, there was a severe 'detector saturation' of data collection for one inexperienced participant. This raw fNIRS data was deleted for not being recorded correctly. Therefore 20 pieces of data for experienced seafarers who had 213.4 months (SD=188.8) experience at sea, and 20 for inexperienced seafarers who had 27.2 months (SD=30.5) experience at sea, were obtained for further analysis, see Table 7.1. Exclusion criteria included: history of head injury, high blood pressure, anxiety or currently taking medication for anxiety.

Table 7.1 Background data on experienced and inexperienced groups

Group	Average age (year)	STCW qualification	Experience at sea (month)
Experienced	44.60 (SD = 15.47)	MM,CM,OOW	213.4 (SD=188.8)
Inexperienced	24.76 (SD = 5.25)	AB, Cadets	27.2 (SD=30.5)

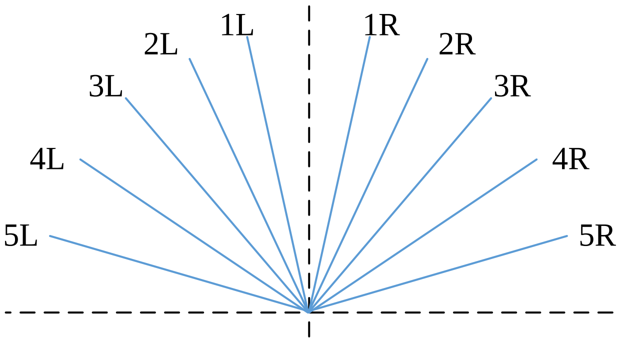
The experimental procedure is in accordance with the principles set out in the Declaration of Helsinki and was reviewed and approved by the ethics committee at Liverpool John Moores University. The experimental protocol for the study was approved by the institutional ethics committee prior to data collection. All participants received a full explanation of the purpose, procedures, risks, and benefits of the experiment. They were provided written informed consent for participation and well trained for the study. More details are demonstrated in Appendix B.

7.3.2 Bridge simulator and scenarios

The experiment took place in a ship bridge simulator (Transas) fitted with instrument panels located at Liverpool John Moores University. An illustration of the participant view of the facility is provided in Figure 7.1A. The Transas simulator is configurable for specific ship types using ship-modelling software which manages the simulation environment, allowing for positioned interactive tides, currents, geographically-variable wind, and sea, and changing conditions such as light, visibility, fog and rain. The bridge simulator can deliver a 360° field-of-view but the display was constrained to a 180° field-of-view for the purpose of the current study for two reasons: (1) the scenario involved watchkeeping in the forward view only, and (2) it tried to avoid significant movement of the head and upper body to minimize artifacts in the fNIRS data.

The task scenario was designed to occur along a North/South axis to better accommodate a realistic reporting system that kept the participant occupied in a time framework. All participants were required to keep watch over 180° field-of-view of the open sea. This watchkeeping period was terminated when participants spotted a ‘target’ vessel that appeared randomly at one of 10 locations in the field of view, see Figure 7.1B. The target vessel was the only other craft on the ocean in the whole of the task simulation.

(A)



(B)

Figure 7.1 (A) View of the participant in the ship bridge simulator, (B) The position of the target vessel appeared from 10 different directions in the exercise

Referring to the implications of specific scenarios in ***Chapter 6***, collisions tend to happen under the case of lone watchkeeper or working isolated. Hence the exercise for this chapter was conducted for lone watchkeeper under the collision avoidance scenario.

Participants were required to press the button of the buzzer when they spotted the target vessel. And its approximate location was recorded by the staff in the control room. On average, this duration of this watchkeeping phase of the task was 19min:42sec. The distance in nautical miles between the target vessel and the participants' ship when the former was spotted was captured as a dependent variable. The target vessel approached the participants' ship on a course that would lead to a collision if the participant failed to make an evasive manoeuvre. Once participants had spotted the target vessel, the scenario enters a decision-making phase that was terminated when the participants made the evasive manoeuvre; the experiment also ended at this point. On average, all participants made an evasive manoeuvre at 24min: 26sec; the distance in nautical miles between target vessel and participants' ship when the manoeuvre was made was recorded as a dependent variable.

To generate different task demands, the navigation scenarios in the study were formed into two mental workload levels based on the experts' opinions, who are an experienced captain and chief mate.

In addition to the scenario described in the previous section, half of the participants (10 experienced and 10 inexperienced) were required to perform an additional reporting task as a distractor. This task was based on existing maritime reporting procedures and participants were required to make a verbal report of the position of their vessel, then followed by replying questions from the control room, i.e. vessel's flag, type of vessel, speed, IMO number. Participants in the distraction group were required to make this verbal report whenever the position of their vessel had changed by 10 degrees of longitude, i.e. approx. every 2 minutes.

7.3.3 fNIRS montage and data collection

In this study, the montage (Figure 7.2, Figure 7.3) was designed using NIRSite software. To measure the haemodynamic activity of DLPFC which is associated with brain functions of working memories and decision-making, 7 sources and 7 detectors were utilised to design the montage, resulting in a total of 15 channels of HbO and HbR. In the montage, the specific brain area has been divided into three sub-areas: left dorsolateral prefrontal cortex, left DLPFC (channel 1-5); central dorsolateral prefrontal cortex, central DLPFC (channel 6-10); right dorsolateral prefrontal cortex, right DLPFC (channel 11-15).

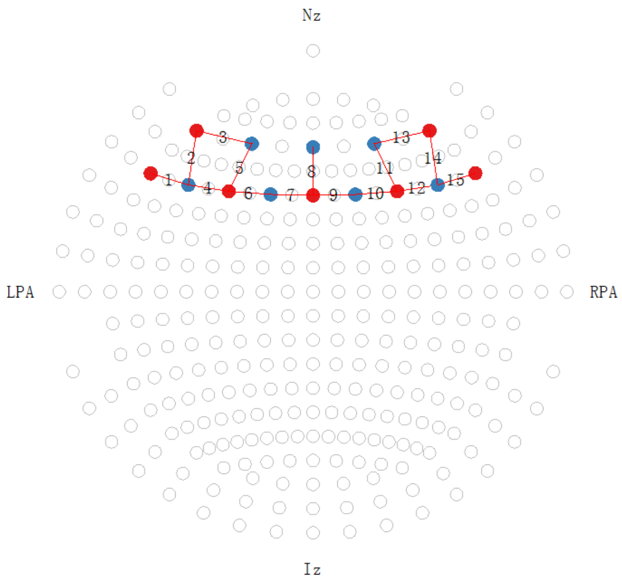


Figure 7.2 fNIRS probe placement - 2D montage, where red point refers to ‘Source’, blue point refers to ‘Detector’, and red lines refer to channels in the montage

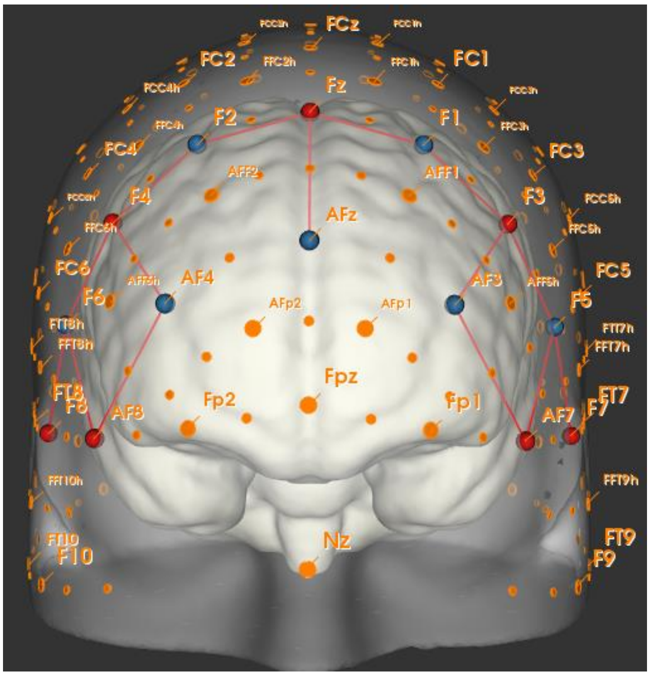


Figure 7.3 fNIRS probe placement - 3D montage, where red point refers to ‘Source’, blue point refers to ‘Detector’, and red lines refer to channels in the montage

The software used for recording the fNIRS data is the NIRStar, and nirsLAB software was used for the pre-processing of fNIRS data. The fNIRS device was placed on the desk behind the participant in the bridge simulator. Care was taken to avoid hair from the eyebrows or side of the head interfering with detectors and sources.

7.3.4 Questionnaires

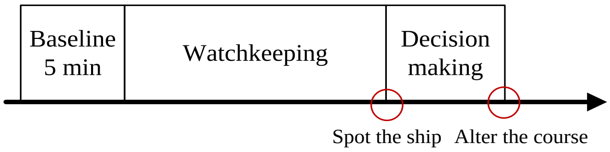
At the beginning of the experiment, participants were required to complete a brief form prior to the experiment recruitment. This form was used to record the participant’s age, gender, nationality, and seafarer experience. The experience was measured by the qualification license they obtained.

To conduct the questionnaires, an extended NASA Task Load Index (TLX) questionnaire (see Appendix A) was completed after the scenario. The participant was supposed to finish the questionnaire about the subjectively perceived workload, rating 1-10 in each questions referring to six different scales, followed by adding their other information and experience. The questionnaires were completed based on their feelings of the whole test. Once the participant carefully filled the form, it was returned to the researcher for further analysis.

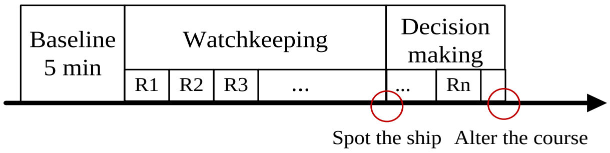
The questionnaire is a self-assessed measure based on six 10-point scales, with 1 being “Very Low” and 10 “Very High.” The scales are Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, and Frustration. They also gave additional information about education degree, STCW qualification, and practical maritime seafaring experience (month or year). On the other hand, the staff in the control room next to the simulator recorded the target spotted time with corresponding distance (distance 1), and the course changed time with corresponding distance (distance 2). The above information and questionnaires were used to analyse behavioural performance and task load.

7.3.5 Experiment procedure

The experiment used a mixed design, where two groups of participants were allocated to 1) experienced group and 2) inexperienced group, depending on their STCW qualification and nautical experience. Specifically, the experienced group included master mariner (MM), chief mate (CM), and officer of the watch (OOW), while the inexperienced group contained AB and cadets. Both groups underwent the scenario with the timeline of baseline, watchkeeping, and decision-making. However, it was presented in 1) non-distraction condition or 2) distraction condition. The non-distraction condition was shown in the above workflow. The distraction condition was demonstrated by setting the reporting points (*Rn*) at the same intervals while watch-keeping and decision-making. It distracted the participants' attention by requiring them to report the vessel's position every 10' of difference in longitude, as well as answering the questions from the staff in the control room, which is as same as seafarers’ daily work. The procedure for the non-distraction group and distraction group is stated in Figure 7.4.



(A)



(B)

Figure 7.4 The fNIRS data collection procedure for (A) non-distraction group and (B) distraction group, where *R*1 is reporting point 1, *n* represents reporting times

The participant wore the NIRx Sport apparatus, which is an fNIRS skull - cap containing infrared sensors and detectors allowing the operator to see the blood volume, oxygenated and deoxygenated blood flow in the DLPFC indicating how the state of seafarers changes during the navigation scenario and showing what is the difference between experienced and inexperienced. The scenario lasted on average no longer than 30 minutes. Then the NASA- TLX questionnaire was collected after each scenario.

7.3.6 Performance evaluation

Subjective data from questionnaires were analysed for performance evaluation. The analysis is to determine whether distraction influenced the time when participants spotted the ship and altered the course, and whether there was difference between experienced and inexperienced deck officers. 2 (distraction) × 2 (experience) analysis of variances (ANOVAs) were conducted for the time and distance when participants spotted the vessel, and the time and distance when they changed the course. Also, ANOVA was conducted to observe whether the position of the target vessel influenced the performance of deck officers.

7.3.7 fNIRS data pre-processing

Raw fNIRS data (15 channels × 2 wavelengths) was pre-processed using nirsLAB software. The Interpolate function was used to fill the data in each channel where there was detector saturation. However, for those channels which lost too much data, this function was not applicable. Then the data quality function was applied to check and identify any ‘poor quality’ channels in which the signal was too weak. After removing discontinuities (STD threshold is 5) and spike artefacts (artefacts replaced by nearest signals), a low-pass filter was applied in order to reduce high-frequency instrument noise and physiological noise such as fast cardiac oscillations (e.g. heartbeat 1~1.5Hz) with the frequency of 0.04Hz. The pre-processed data was imported for haemodynamic states calculation using the modified Beer-Lambert law (Sassaroli and Fantini, 2004). It reveals changes in oxygenated haemoglobin (HbO), deoxygenated haemoglobin (HbR) and total haemoglobin (Hb). It should be noted that HbO and HbR tend to be most highly correlated with other neuroimaging measures such as the fMRI measured blood oxygenation level dependent (BOLD) response (Huppert et al., 2006, Schroeter et al., 2006, Foy et al., 2016), and strong correlations with HbO and Hb have also been found (Strangman et al., 2002). All fNIRS results were reported in micromoles (μM). The focus of this study highlights HbO.

7.3.8 Data analysis

For fNIRS data analysis, there was a transformation on the data called Correlation-Based Signal Improvement (CBSI) that forces HbO and HbR to be negatively correlated and controls for head movement, which was developed by Cui et al. (2010). As HbR is transformed into the inverse of HbO after this point, only HbO data were used in the subsequent analyses.

The analysis was conducted to investigate how distraction influenced neurophysiological activation and decision-making of experienced and inexperienced seafarers with respect to collision avoidance. Moreover, it determined whether there were differences between left, central, and right DLPFC activity. However, the HbO in the baseline period of the experiment procedure revealed that the majority of participants had active brain activities, which was opposite to the expectation of the experiment design. Because the heavy fog over the sea introduced uncertainty for professional seafarers who were more conscious of the navigational environment, reflecting active mental states of seafarers. Therefore, the baseline data was ignored and deleted. In order to create ANOVA models for statistical testing, the 15 channels of HbO were divided into three regions of interest: left DLPFC (channel 1-5); central DLPFC (channel 6-10); right DLPFC (channel 11-15) (Figure 7.2). In addition, the period of watchkeeping during the task scenario was divided into four periods of equal duration for each participant (w1, w2, w3, w4) and the decision-making phase of the task was divided into two periods of equal duration (d1,d2), seen in Figure 7.5.

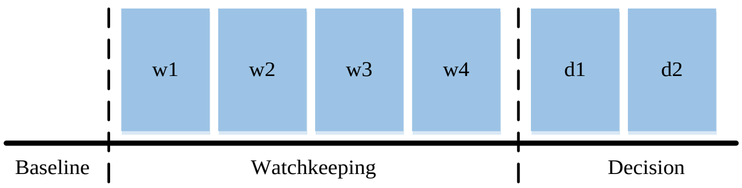


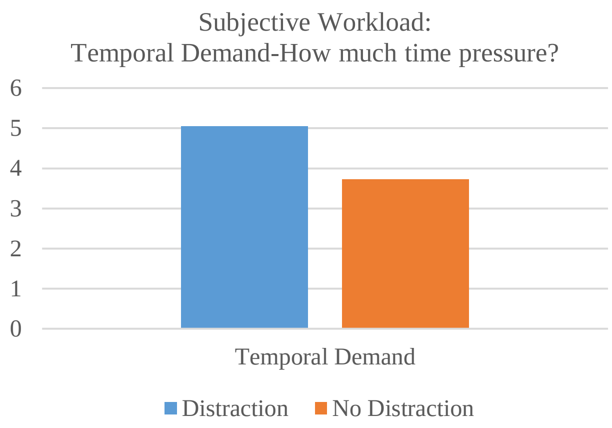
Figure 7.5 Averaged fNIRS data in the procedure

7.4 Results

The results section is divided into two sections: subjective mental workload and behavioural data, and the average level of HbO at specific sites. Data are subjected to statistical analyses via ANOVA and MANOVA models. Outliers are defined as any data point that lay more than 3 standard deviations from the mean for that ‘cell’ in either a positive or negative direction. For those models with a repeated-measures component, sphericity is tested using Mauchly's Test and the Greenhouse-Geisser adjustment is performed. The average levels of HbO are obtained in MATLAB software, and the analysis is conducted in SPSS software.

7.4.1 Subjective mental workload and behavioural data

Raw TLX data scores from 1 to 10 were used for analysis, as they are more sensitive than other methods of data treatment such as scale weighting (C. Hendy et al., 1993). Between distraction and non-distraction groups, one-way ANOVAs showed a main effect of distraction for Temporal Demand ('How much time pressure?') ($F(1, 39) = 4.229$, $p = .046$; Figure 7.6A). Participants under distraction ($M = 5.05$, $SD = 2.139$) were considered to require more temporal demand than participants without distraction ($M = 3.76$, $SD = 1.868$). There was no disadvantage on any performance indicators for distracted participants. However, performance ('How successful were you at meeting the goals of the task?') showed a significant main effect of experience ($F(1, 39) = 11.0342$, $p = .002$; Figure 7.6B). Experienced participants ($M = 9.05$, $SD = .945$) were considered to have better performance than inexperienced people ($M = 7.86$, $SD = 1.315$). And experienced participants were more confident/did not work as hard (effort). Between experienced and inexperienced groups, one-way ANOVAs showed there was not significant effect for Distance 1 ($F(1, 39) = .438$, $p = .512$). No advantage for spotting ship for the experienced participant.



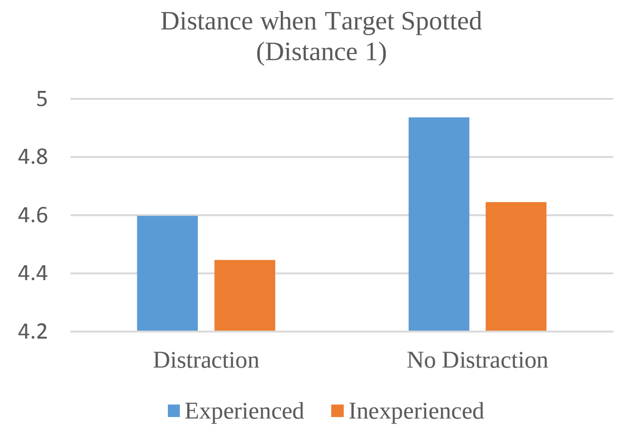
(A)

(B)

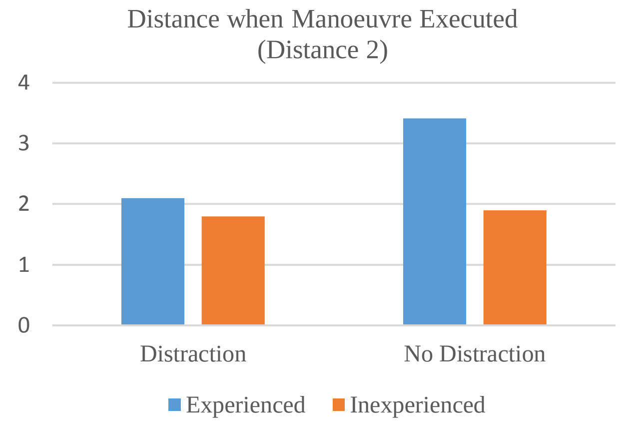
Figure 7.6 NASA-TLX scores (A) Temporal demand - 'How much time pressure did you feel due to the pace at which task elements occurred?' - scores in NASA-TLX (B) Performance - 'How successful do you think you were in completing the goals of the task?' - scores and Effort - 'How hard did you have to work (mentally and physically) to accomplish your level of performance?' - scores in NASA-TLX

There was no statistically significant interaction effect between experience and distraction on the combined dependent variables ($p > .05$). From MANOVAs results, the estimated marginal means for the dependent variables 'Distance 1 – distance when target spotted' and 'Distance 2 – distance when manoeuvre executed' were shown in Figure 7.7A and Figure 7.7B. It showed a main effect of experience for Distance2 ($F(1,39) = 4.762$, p

= .036, η_p^2 = .114). The distance of two ships when experienced participants changed the course (Distance 2) (M = 2.755, SD = .298) was farther than the distance when inexperienced participants did (M = 1.847, SD = .291), shown in Figure 7.7C. It demonstrated that experienced participants executed manoeuvres at a higher distance.



(A)



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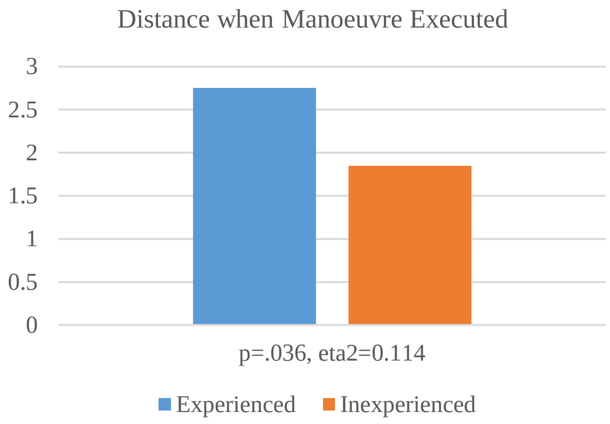


(C)

Figure 7.7 (A) Distance 1 – distance when target spotted, (B) Distance 2 – distance when manoeuvre executed, (C) Distance when manoeuvre executed (Distance 2) for experienced and inexperienced groups

Exercises in the experiment were selected randomly from 10 samples which were in the same scenario but from 10 different directions, seen in Figure 7.1. One-way ANOVAs were also conducted to analyse whether there was a significant difference in the exercise for the subjective mental workload. It showed there was not significant effect of exercise direction for Distance 1 ($F(9, 31) = 1.057$, $p = .420$), Distance 2 ($F(9, 31) = .681$, $p = .720$), Mental Demand ($F(9, 31) = .590$, $p = .795$), Physical Demand ($F(9, 31) = .827$, $p = .596$), Temporal Demand ($F(9, 31) = 1.423$, $p = .221$), Performance ($F(9, 31) = 2.086$, $p = .062$), Effort ($F(9, 31) = .604$, $p = .784$), or Frustration ($F(9, 31) = .887$, $p = .548$). It revealed that the experimental design of randomly selecting directions that the ship appears from, did not affect the mental workload or behavioural performance.

7.4.2 Average level of HbO at specific sites

There were in total 40 participants' fNIRS data which was valid for the analysis.

The fNIRS data were divided into three Regions Of Interest (ROI) corresponding to the left-lateral, medial and right-lateral areas of the DLPFC. After signal processing, oxygenated haemoglobin (HbO) data were averaged for each period of the task, i.e. four periods of watchkeeping and the two periods of decision making. HbO data for each ROI were subjected to a 2 (experienced/inexperienced) x 2 (distraction/no-distraction) x 6 (task period) ANOVA.

Analyses of left-lateral and medial ROI failed to reveal any statistically significant main effects or interactions. However, analysis of HbO data from the right-lateral ROI revealed a significant main effect for Task Period [$F(5,30) = 3.76$, $p=.02$, $\eta_p^2=0.4$], as well as significant interactions between Distraction x Task Period [$F(5,30) = 3.99$, $p<.01$, $\eta_p^2=0.43$] and Experience x Task Period [$F(5,30) = 2.30$, $p=.05$, $\eta_p^2=0.27$]. Post-hoc testing indicated that average HbO at the right-lateral ROI was significantly lower during W3 and W4 than all other periods ($p<.05$); this effect is illustrated in Figure 7.8.

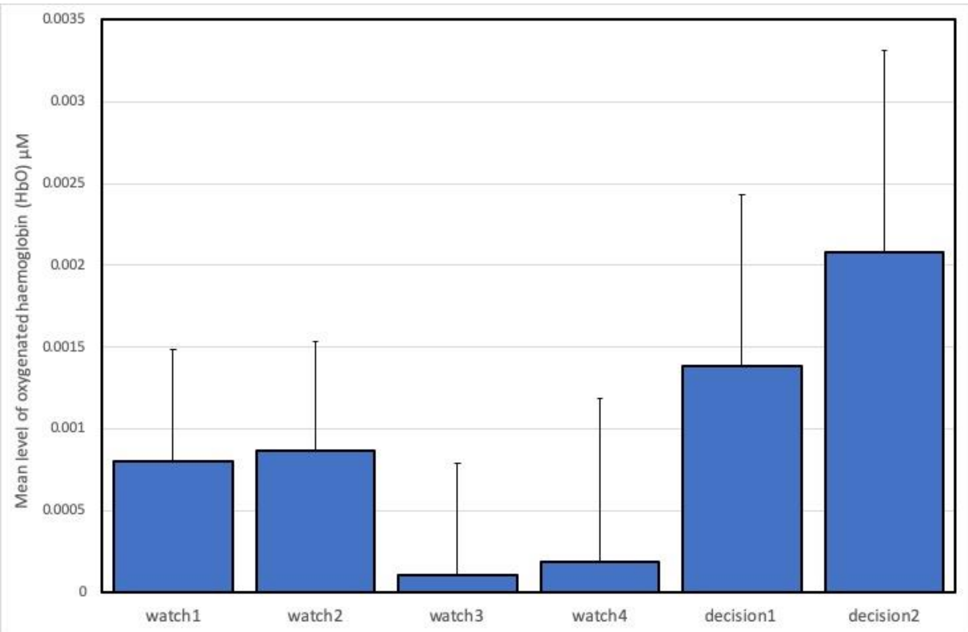


Figure 7.8 Mean HbO and standard error during all Task Periods for Right-Lateral ROI (N=38), i.e. 2 participants were omitted as outliers from this model.

A number of post-hoc t-tests were conducted to analyse the two interaction effects. It was found that average HbO was significantly higher for participants who performed the distraction task during the two periods of decision-making that occurred once the ship had been spotted: D1 [t(36)=2.17, p=.04], D2 [t(36)=2.69, p=.02]. This effect is illustrated in Figure 7.9.

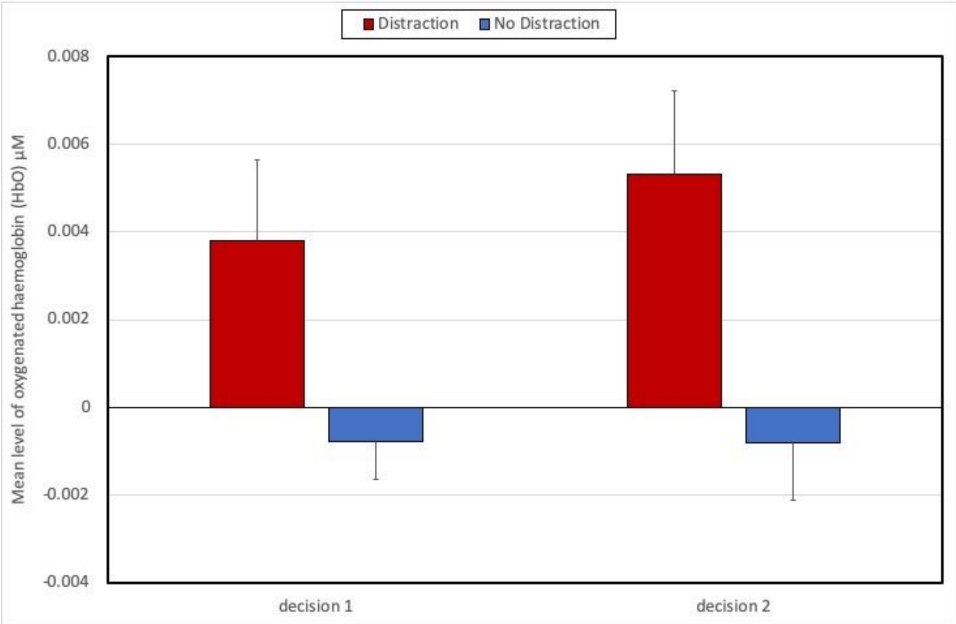


Figure 7.9 Average HbO/standard error in the Right-Lateral ROI for Task Period x Distraction Interaction (N=38)

The interaction effect between Experience x Task Period was also explored using t-tests. These tests revealed that average HbO was higher for experienced participants at the right-lateral ROI, but only during the fourth period of watchkeeping (W4) when the ship was spotted [t(36)=2.78, p<.01]. This interaction is illustrated in Figure 7.10.

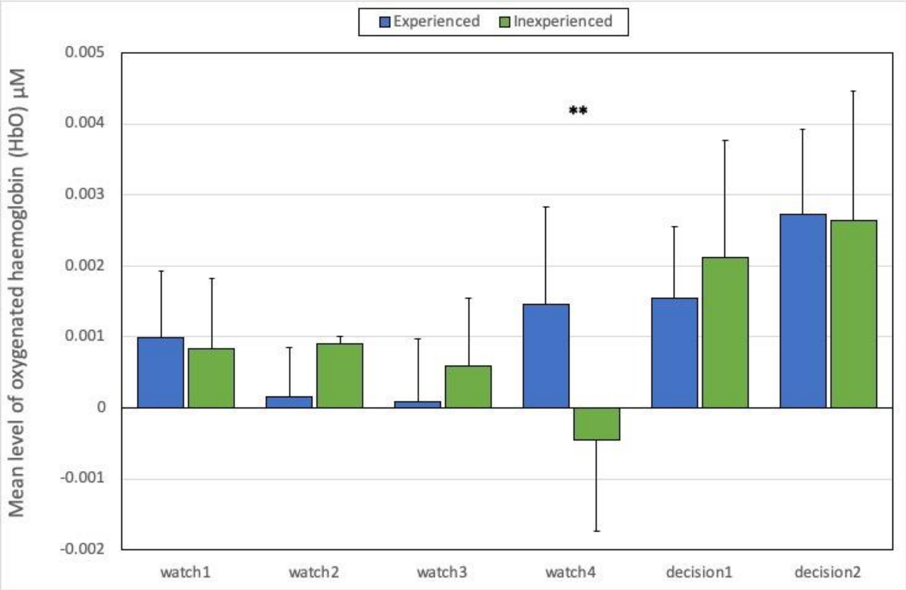


Figure 7.10 Average HbO/standard error in the Right-Lateral ROI for Task Period x Experience Interaction (N=38). Note: ** = significant difference at p<.01

7.5 Discussion

This research aimed to investigate how mental workload influences neurophysiological activation and decision-making of experienced and inexperienced seafarers with respect to collision avoidance, both of which have been linked to human performance during navigation and also changes in DLPFC activity.

With respect to the behavioural data, experienced participants were considered to believe they have better performance than inexperienced people do. Due to sufficient training and outstanding experience, experienced seafarers who have a higher level of STCW qualifications also believed they had better performance. In addition, experienced seafarers tended to change the course earlier than inexperienced participants did when they faced the collision condition. It also illustrates better performance for experienced seafarers because they made decisions prior to an event, which leads to successful collision avoidance. Meanwhile, participants under distraction were considered to require more temporal demand than participants without distraction. It demonstrated that the developed scenario distracted the ship officers by reporting vessel position at certain points, which is the common task requiring temporal mental workload in the real world.

Generally, research has demonstrated a correlation between brain activity and performance of a task (Ullman et al., 2014). Right-lateral ROI showed increased oxygenation during the decision phase of the task, due to a more significant mental workload/decision-making – there was some evidence that decreased oxygenation during w3 and w4 was due to boredom. Greater oxygenation was found during decision time for participants with distraction, because of higher workload when simultaneously performing a distraction task and making the decision to change course. Higher oxygenation was observed for experienced participants at the end of watchkeeping, due to more considerable attention being focused on the duty – which may have contributed to superior performance.

From the perspective of designed scenarios in the bridge simulator, actually, zero visibility was proved to be invalid for the baseline design, as experienced seafarers tend to be more cautious about the environment with uncertainty, which is opposed to the expectation that they will be relaxed. Because seafarers were not told whether the ship appeared in the baseline phase or not. The heavy fog over the sea introduced uncertainty for professional seafarers who were more conscious of the navigational environment, reflecting active mental states of seafarers. Therefore, the baseline data which did not meet expectations was deleted in this study.

The current study was not without a number of significant limitations. The task simulation used during the experiment was highly simplistic and designed to facilitate collection of neurophysiological data. It could be argued that the ecological validity of the simulation was compromised by our desire to reduce artefacts in the fNIRS data. For example, the task simulation failed to accommodate any aspect of team work, which is the more common operational situation on the bridge of a large ship; in addition, watchkeeping duty is often part of a multitasking activity that includes monitoring weather conditions and running communications tasks. These characteristics of high workload multi-tasks are typically found in the real world, which is also the environments that demonstrate the highest accident rates (Foy et al., 2016). In addition, the decision not to utilize the 360° field-of-view capability in the bridge simulator (once again in order to minimize the influence of physical artifacts in the fNIRS signal) was problematic, as it enormously simplified and artificially constrained the challenge of the vigilance task in a maritime environment. Our decision to seat participants at the helm of the vessel was also uncharacteristic of the bridge environment and participants were seated to minimize those systemic influences on the fNIRS signal that were likely to occur if the participants were standing and ambulatory.

Moreover, complicated or combined tasks such as introducing weather forecast or communication while watchkeeping could be used to manipulate mental workload in a naturalistic navigation task.

In conclusion, the results of this study support fNIRS as a valuable neuroimaging technique which can be used in realistic situations such as ship navigation and could be implemented in the assessment and prediction of ship officer overload and subsequent manoeuvre (Franceschini et al., 2007). This research achieves its aim of investigating deck officers' mental workload during watchkeeping and decision – making.

7.6 Ethics statement

This study was carried out in accordance with the recommendations of Liverpool John Moores University with written informed consent from all subjects. All subjects gave written informed consent in accordance with the Declaration of Helsinki. The protocol was approved by Liverpool John Moores University. See appendix A, B.

7.7 Concluding remarks

The following are the most significant remarks comprised in the chapter, and emphasised in the form of bullet points for the reader's ease:

- It was done with simulated watch-keeping tasks in the maritime bridge simulator, and using fNIRS technology to measure neurophysiological activation.

- The results show that experienced participants were considered to believe they have better performance than inexperienced people do. It also illustrates better performance for experienced seafarers because they made decisions earlier, which leads to successful collision avoidance.

- Participants under distraction were considered to require more temporal demand than those without distraction.

- In terms of fNIRS data, it shows significant differences in the right DLPFC of the brain. Greater oxygenation was found during decision time for participants with distraction. Higher oxygenation was observed for experienced participants at the end of watchkeeping.

Chapter 8 Functional connectivity analyses for seafarers using bridge simulation

8.1 Introductory remarks

This chapter was done further with simulated watchkeeping tasks in the maritime bridge simulator and fNIRS technology to measure neurophysiological activation. Besides the mental workload and fNIRS data analysis in ***Chapter 7***, this chapter conducts the functional connectivity analyses for seafarers with bridge simulation. The results show that reduced connection density and a higher level of local clustering across a frontal montage of 15 channels was associated with action selection in comparison to the earlier watchkeeping period of vigilant attention. Activity in the right DLPFC and the level of local clustering decline across the watchkeeping period for participants. The study also demonstrates a significant association between connection density and behavioural responses to a safety-critical scenario.

8.2 Background information

Brain changes may indicate evident changes in haemodynamic concentration measured by fNIRS according to a study on the association between haemoglobin levels and white matter conducted by Rozanski et al. (2014). More specifically, the increases in prefrontal activation are associated with increases in development by using fNIRS (Schroeter et al., 2004, Franceschini et al., 2007), which also have been found using fMRI (Adleman et al., 2002).

Brain activity has a linear relationship with the working memory load of the left and right prefrontal cortex (Fishburn et al., 2014). Statistically different levels of oxygenation change result from substantial changes in task difficulty. However, smaller differences in task difficulty were not reliably differentiated in some cases (Ayaz et al., 2012). In this way, fNIRS can be used to design optode holders to analyse the region of interest (ROI) for the investigated tasks.

The current research investigates how functional connectivity changes when measuring the mental workload of seafarers by fNIRS, which explains neurophysiological activation and decision-making of experienced and inexperienced deck officers. This last was done further with simulated watch-keeping tasks described in ***Chapter 7***.

8.3 Materials and methods

8.3.1 Participants

A total of 41 participants were recruited from the Nautical Institute London Branch and Liverpool John Moores University, as demonstrated in ***Chapter 7***. And 40 sets of data were used for the analysis in this chapter.

8.3.2 fNIRS data

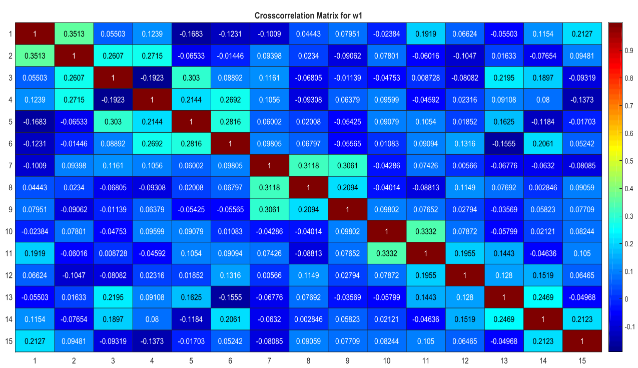
Raw fNIRS data were collected and pre-processed from ***Chapter 7***. The first step of the data analysis was obtained from Section 7.3.7, followed by network analysis.

8.3.3 Functional connectivity

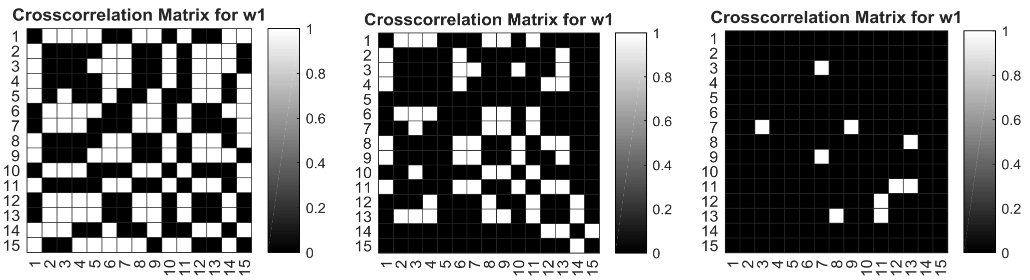
In order to find out how brain connectivity changes during the periods, a functional connection network was generated. Network analysis was performed on HbO after CBSI treatment of the signals in ***Chapter 7***. The functional connection between pairs of brain regions demonstrated the temporal correlation of regional haemodynamics. Concerning functional connection, symmetric correlation matrices were obtained from the partial correlation coefficients of all pairwise combinations of the 15 channels, for each group or task period, shown in Figure 8.1A. The rows and columns of the matrix represented the channels, while cells of the matrix reflected the correlation coefficient of the corresponding channels, explaining the connectivity between channels.

Among these matrices, there were cells with weak links representing spurious connections between pairs of brain regions, where they should be discarded by thresholding (Rubinov and Sporns, 2010). On the other hand, cells with strong links represent significant connections and reveal reliable information on the patterns of brain activities, where they should be kept for next-step analysis. Therefore, it was necessary to decide on a threshold level for the correlation scores to demonstrate where the strong connections are. Moreover, it should be a consistent procedure for threshold calculation for each participant across all task periods.

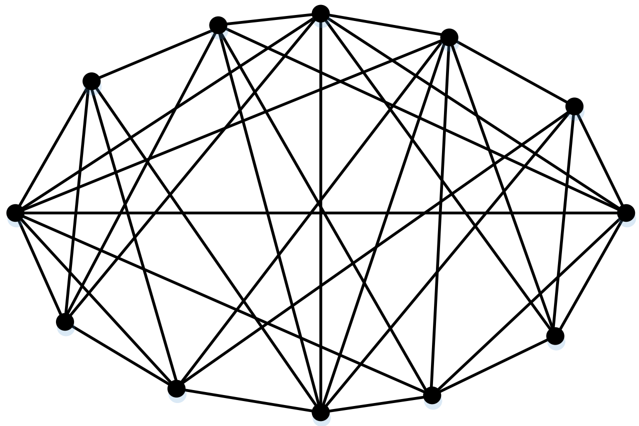
In order to obtain the reasonable standard for threshold calculation, various threshold levels were calculated to compare with each other, and then the percentile distribution of all correlation values was obtained. Specifically, a very liberal threshold (10^{th} percentile), a more conservative threshold (50^{th} percentile) and extremely conservative threshold (90^{th} percentile) were selected. The percentiles determined the absolute threshold values for each participant across all task periods. There were many connections for the liberal threshold based on the 10^{th} percentile and very few for the threshold based on the 90^{th} percentile.



(A)



(B) P=10th ,50th ,90th percentiles



(C)

Figure 8.1 Constructing a binary functional connection network from fNIRS-data, (A) Partial correlation coefficients were calculated for all pairwise combinations of channels to obtain a symmetrical cross-correlation matrix, (B) Binary adjacency matrices were calculated by thresholding along with different threshold values, (C) Functional connection networks were described by the adjacency matrices

It is noticed that all negative correlation values should be eliminated before conducting thresholding, as its influence on the functional connectivity was not considered (Rubinov and Sporns, 2010). Only coefficients greater than or equal to the chosen threshold value were kept as connections assigned with a value of 1. Otherwise, the coefficient was replaced with 0, which creates a binary adjacency matrix (in Figure 8.1B). Furthermore, it created a cross-correlation matrix to represent these data in a visualisation. In this way, the functional connectivity network was developed by adjacency matrices, seen in Figure 8.1C, which explained the activities of the specific area of the brain by various parameters (Racz et al., 2017).

Unlike those authors, the analysis of functional connectivity in this study was based upon a matrix of partial correlations, i.e. the association between two channels of HbO while controlling for the effect of all remaining 13 channels. A matrix of partial r values was calculated for all 15 channels of HbO for each of the six periods (watch1, watch2, watch3, watch4, decision1, decision2) for each participant.

A process of thresholding was applied in order to construct a binary functional connection network based on these matrices of partial correlations. The first step of this analysis was to remove any partial correlation coefficients that fell below zero so only positive associations were considered as part of the thresholding process. A criterion level of 0.28 was selected in order to remove weak or spurious levels of correlation, this value represents the critical value for a one-tailed test of Pearson's coefficient at $p<.05$ for $N=40$. This process of thresholding converted the original matrices of partial correlations into binary adjacency matrices that were suitable for graph-theoretic analyses.

8.3.4 Graph theory

In order to reflect the characteristics of the above networks, there are two most commonly used parameters (Racz et al., 2017) to describe it in graph theory: the connection density (D), and the clustering coefficient (C). This study used these two parameters to describe the functional connectivity for brains.

The connection density of a network is the fraction of the existing connections to all possible connections, which is used to describe the overall 'wiring cost' of the given network (Racz et al., 2017), calculated as

$$D = \frac{1}{2n(n-1)} \sum_{i \in n} \sum_{j \in n} a_{ij}$$

where n is the number of channels in the network, and a_{ij} equals 1 if there is a connection between channel i and j, 0 otherwise.

In addition, the local clustering coefficient for an individual node is a parameter to define the fraction of its neighbours which are also neighbours of each other (Watts and Strogatz, 1998), i.e. reflecting the number of triangles around the given node (Rubinov and Sporns, 2010). Therefore, the local clustering coefficient is calculated as

$$C = \frac{1}{n}\sum_{i\in n}\frac{1}{k_i(k_i-1)}\sum_{j,h\in n} a_{ij}a_{ih}a_{jh}$$

Where k_i is the degree of channel i, C is how the neighbouring channels in the network form connected groups.

The above functions for the graph theory metrics were obtained from the Brain Connectivity Toolbox (Rubinov and Sporns, 2010). Statistics were performed with IBM SPSS statistics 26 with differences considered significant in the case of $p<0.05$. Measures of D and C were calculated per participant for each period of the task and subjected to statistical testing.

8.4 Results

Activation of the PFC is assessed using a 15-channel fNIRS montage. Partial correlations of each channel across all periods are calculated, followed by the selection of the threshold. Then 2 (Experienced/Inexperienced) x 2 (Distraction/No Distraction) x 6 (Task Period) ANOVA is performed on density and clustering. Outliers are defined as any data point that lay more than 3 standard deviations from the mean for that ‘cell’ in either a positive or negative direction.

8.4.1 Brain connectivity in networks

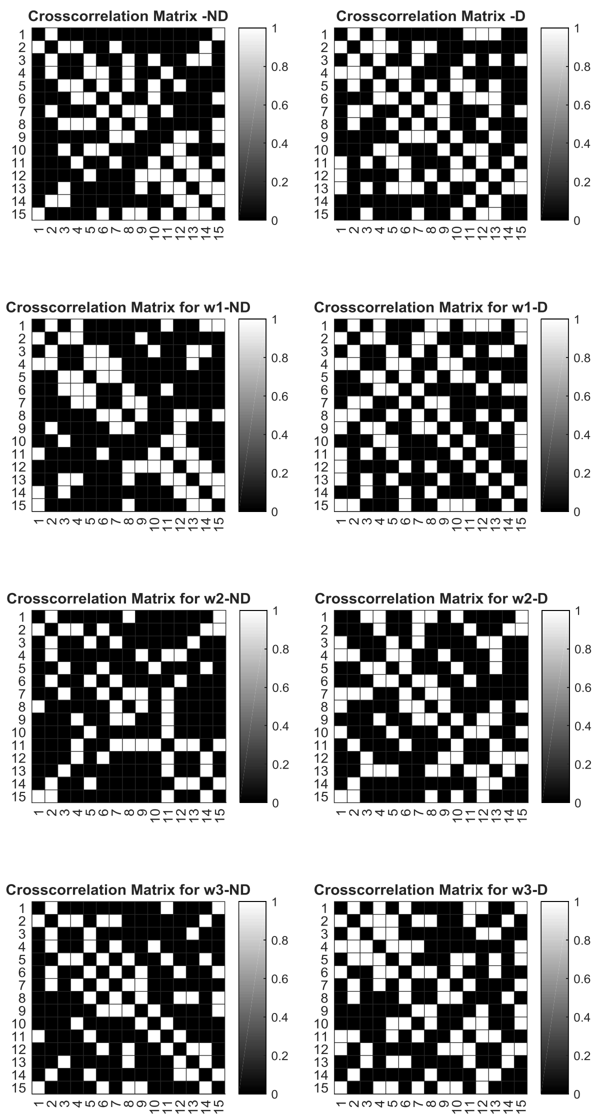
Based on the theory of network analysis, the symmetric correlation matrices are obtained from the partial correlation coefficients of all pairwise combinations of the 15 channels, which illustrates the information transaction between each channel of the montage designed in ***Chapter 7***.

In order to visualise connections between each pair of channels, partial correlation coefficients are given to generate the heatmap of each task period from w1 to d2. Then the percentile distribution of all correlation values is given. It is demonstrated for the selection of rational thresholding value, which will describe the patterns of brain connectivity. Similarly as reported in relevant studies (Friston et al., 1993), an inverse relationship is observed between the parameters and the threshold, i.e. an increase in the threshold decreases the number of existing channels in the network. By looking through matrices from various threshold values, the pattern is observed that the matrices with thresholds 50^{th} and 90^{th} percentiles reveal relatively fewer white squares, which is lack of enough links and information for functional connectivity analysis. Therefore, the threshold below 50^{th} percentile is considered to be explored further to reveal the differences between groups.

Combined with the graph theory in Section 8.3.4, the calculation of density and clustering parameters narrows down the range of threshold selection. It is found that the clustering coefficients in the network become smaller and smaller when the white squares in matrices decrease. It is clear that at 40^{th} percentile, most of the clustering scores are zero, so either 20^{th} or 30^{th} percentile is used in this study. Finally, 20^{th} percentile is selected to reveal brain connectivity in networks.

Based on the procedures of calculating absolute threshold for each participant, the same method is applied for each group. Calculations are conducted to demonstrate and compare brain connectivity between distraction and non-distraction groups, or between experienced and inexperienced groups.

Observed from Figure 8.2, the distraction group shows more white squares overall compared to a non-distraction group, implying that more activation across the network is found for the distraction group overall. Each task period reflects the same phenomenon as well. Specifically, w1 shows an apparently higher density of white squares for the distraction group, which means the reporting mission on board led to activation across the network at the beginning of watchkeeping. Similarly, task periods d1 and d2 are observed to show the difference between the two groups. Participants of the distraction group have to simultaneously decide whether and when to alter the course while reporting the vessel's position, and while answering the navigational questions to the VTS, which brings more activation across the prefrontal cortex than the non-distraction condition.



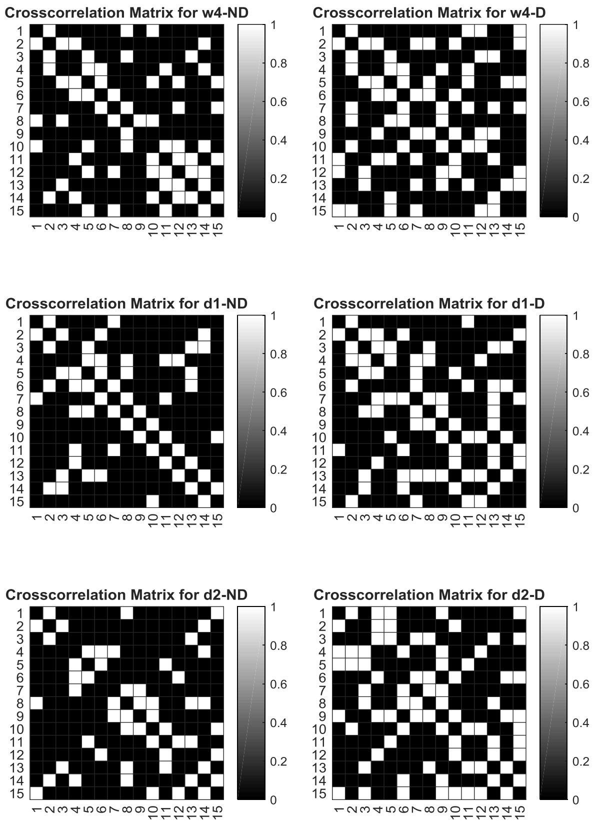
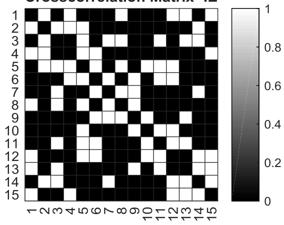
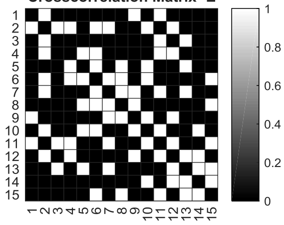


Figure 8.2 Cross-correlation matrix of distraction and non-distraction groups (w1, w2, w3, w4, d1, d2 for the task periods; ND for non-distraction, D for distraction)

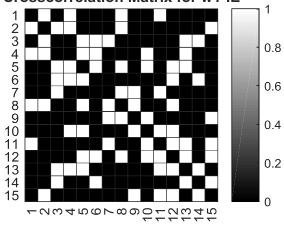
As shown in Figure 8.3, the experienced group shows relatively equal white squares in overall. However, for each task period, they are slightly different. The numbers of white squares reveal a slight difference in w4 task period. It demonstrates more activations in the network for the experienced group than the inexperienced one at the end of the watchkeeping period, which illustrates that inexperienced participants are subject to boredom after a relatively long-time watchkeeping, so as to cause low cognitive demands. Moreover, task period d2 implies decision-making action. The inexperienced group shows more connections than experienced people, which means it costs more activations across the prefrontal cortex for them to decide whether or when to alter the course.



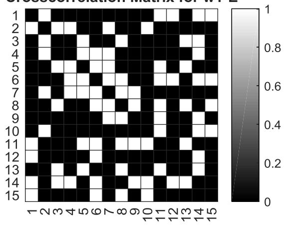
Crosscorrelation Matrix -IE



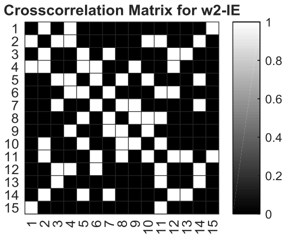
Crosscorrelation Matrix -E



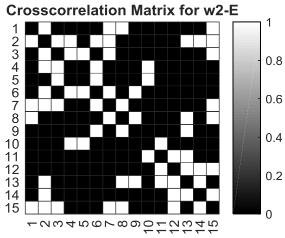
Crosscorrelation Matrix for w1-IE



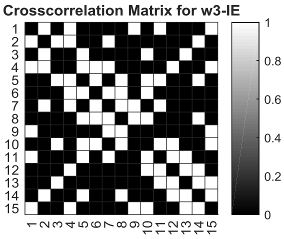
Crosscorrelation Matrix for w1-E



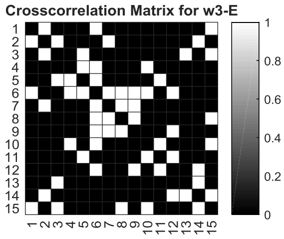
Crosscorrelation Matrix for w2-IE



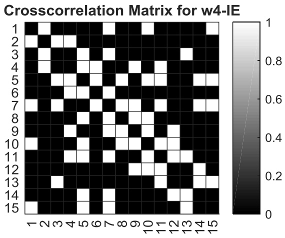
Crosscorrelation Matrix for w2-E



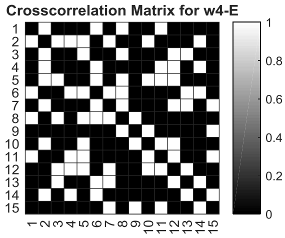
Crosscorrelation Matrix for w3-IE



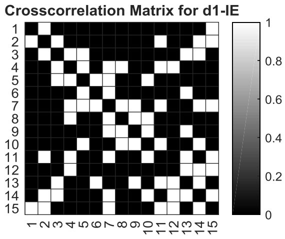
Crosscorrelation Matrix for w3-E



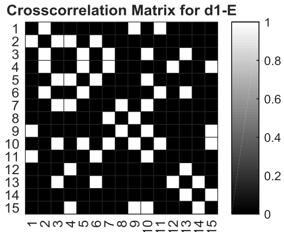
Crosscorrelation Matrix for w4-IE



Crosscorrelation Matrix for w4-E



Crosscorrelation Matrix for d1-IE



Crosscorrelation Matrix for d1-E

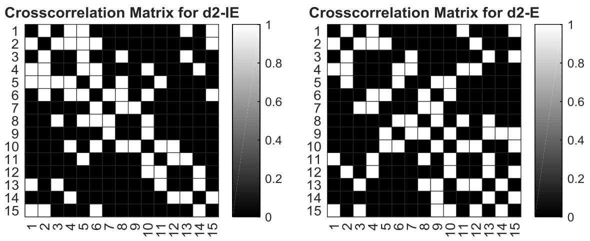


Figure 8.3 Cross-correlation matrix of experienced and inexperienced groups (w1, w2, w3, w4, d1, d2 for the task periods; IE for inexperienced, E for experienced)

8.4.2 Functional connectivity analyses

From the above observations in the squares, it is not statistical to describe the patterns of brain connectivity. In order to illustrate features of the connection network in more detail, calculations of network parameters per each participant across all task periods are conducted in MATLAB software and analysed in SPSS.

However, when partial correlations are calculated based on different thresholds, which provides a unique score of correlation between 2 variables while adjusting for all other correlations, the network is insensitive for the high thresholds. A criterion level of 0.28 was selected in order to remove weak or spurious levels of correlation, this value represents the critical value for a one-tailed test of Pearson's coefficient at $p<.05$ for $N=40$.

A 2 (high/low experience) x 2 (distraction/no distraction) x 6 (task period) ANOVA was conducted on the measure of connection density (D). This model revealed a significant main effect for task period [$F(5, 28) = 15.88$, $p < .01$, $\eta_p^2=0.33$], but no significant effects for either experience level [$F(1, 32) = 0.97$, $p = .33$] or distraction [$F(1, 32) = 0.82$, $p = .37$]. Post-hoc Bonferroni tests revealed a significant decline of D during both decision-making periods of the task compared to the four watch-keeping periods [$p<.01$]. Descriptive statistics for connection density over the six periods of the task are provided in Figure 8.4. There was only one significant interaction effect in the ANOVA model, which indicated an effect between Distraction and Task Period [$F(5, 28) = 3.15$, $p = .03$, $\eta_p^2=0.09$]. This effect is illustrated in Figure 8.5. Post-hoc t-tests revealed a significant increase of D during the fourth period of watchkeeping (w4) for those participants in the no-distraction group compared to the distraction group [t(34)=2.97, p<.01]. In addition, the significant trend over the six periods of the task differed for the distraction group in comparison to the main effect observed in Figure 8.4, i.e. there was no significant difference between w4 and either of the two decision periods (Figure 8.5).

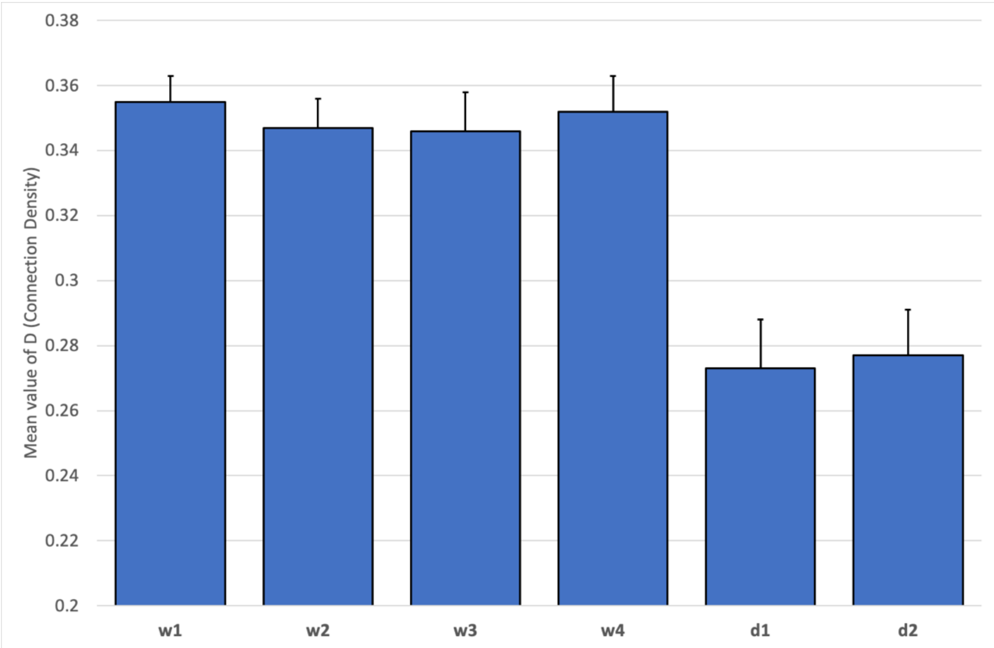


Figure 8.4 Average levels of D (Connection Density) with standard error across all fNIRS channels for six periods of the task (N=36)

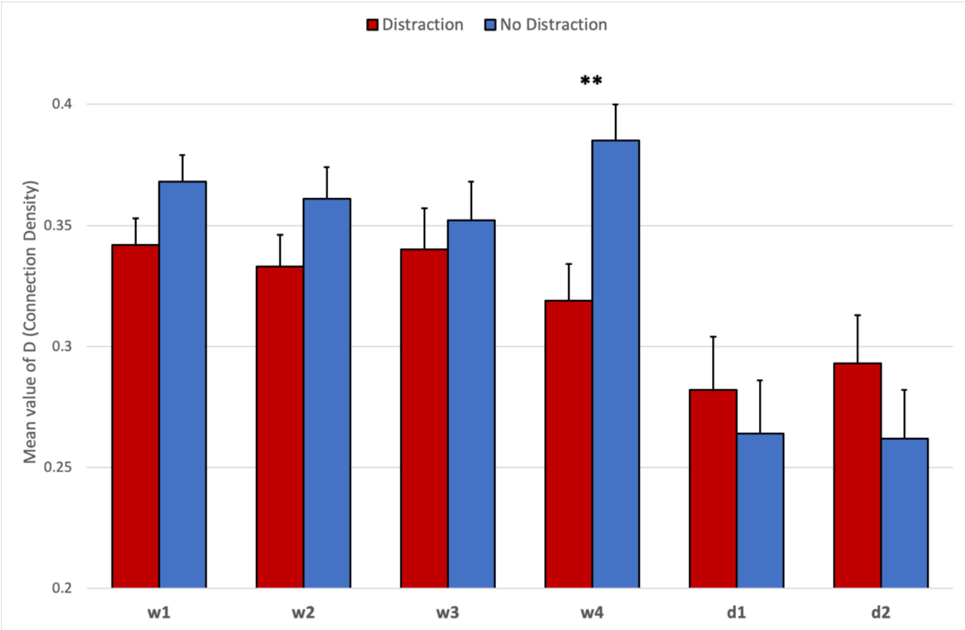


Figure 8.5 Interaction between distraction group x task periods for mean D (connection density) across all fNIRS channels for six periods of the task (N=36). Note: ** = significant difference at p<.01

The same 2 x 2 x 6 ANOVA was conducted on the mean clustering coefficient. There were no significant main effects for either Experience or Distraction, but a significant effect was found with respect to Task Period [$F(5,28) = 2.60$, $p = .05$, $\eta_p^2=0.32$]. Post-hoc Bonferroni tests revealed that: (i) C was significantly higher during decision1 compared to watchkeeping periods w3 and w4 ($p<.01$), (ii) C was significantly higher during decision2 compared to w4 ($p<.01$), and (iii) C was significantly lower during w4 compared to w1 ($p=.05$). Descriptive statistics for C are presented in Figure 8.6.

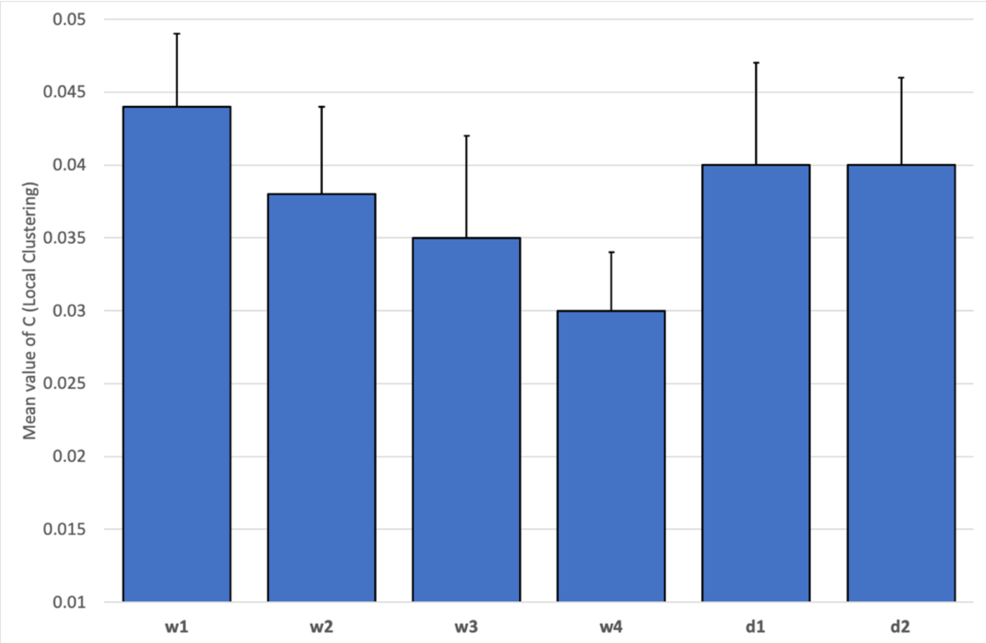


Figure 8.6 Average levels of C (clustering) across all fNIRS channels for six periods of the task (N=36)

It also produced one significant interaction between Distraction and Task Period [$F(5, 28) = 2.79$, $p = .04$, $\eta_p^2=0.34$]. Post-hoc t-tests revealed that the clustering coefficient was significantly lower at w4 compared to w1 [$t(17)=-2.21$, $p=.04$] and d2 [$t(17)=-1.98$, $p=.05$] for the no-distraction group only. This interaction is illustrated in Figure 8.7.

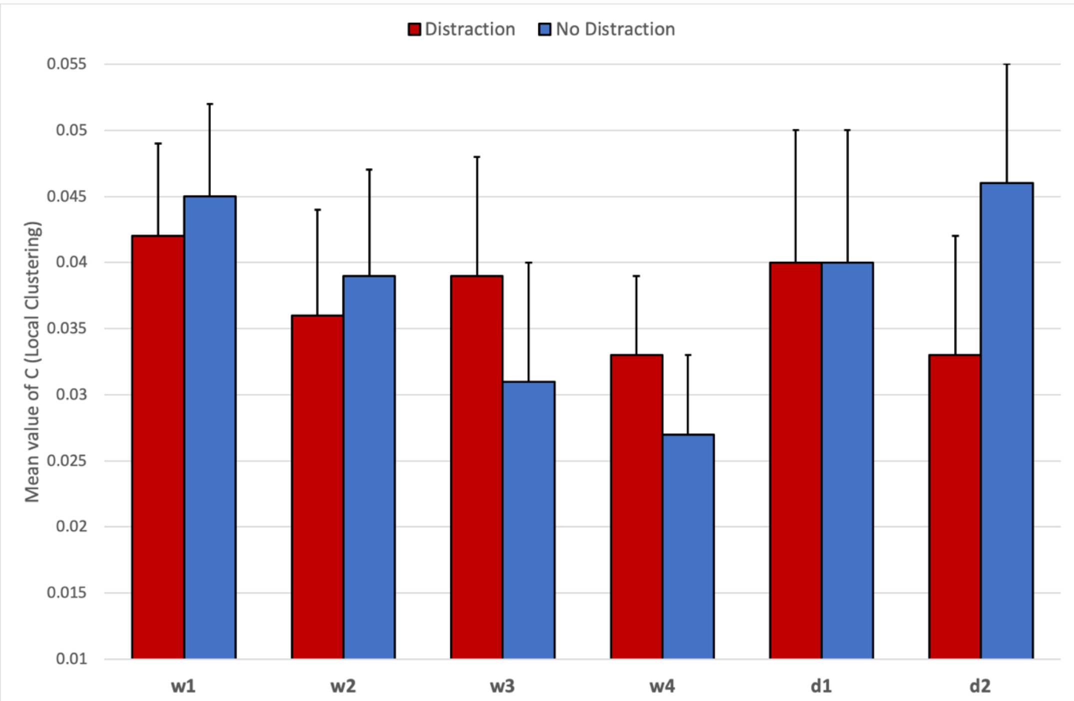
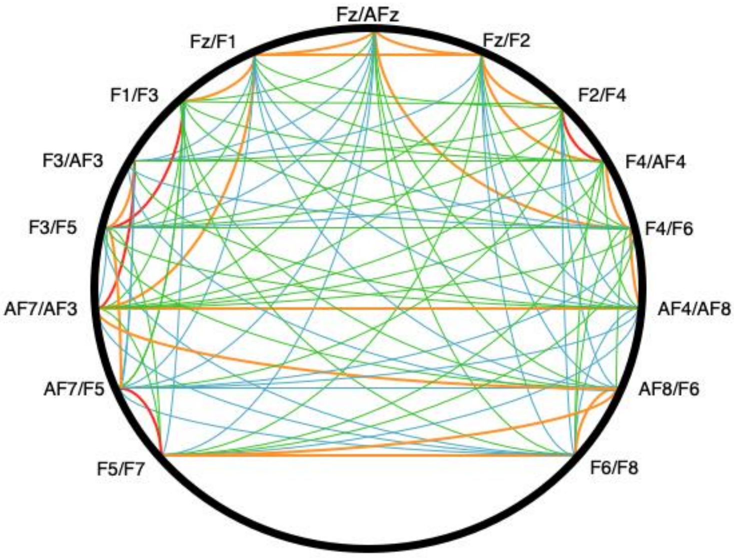


Figure 8.7 Interaction between distraction group x task periods for mean C (clustering) across all fNIRS channels for six periods of the task (N=36)

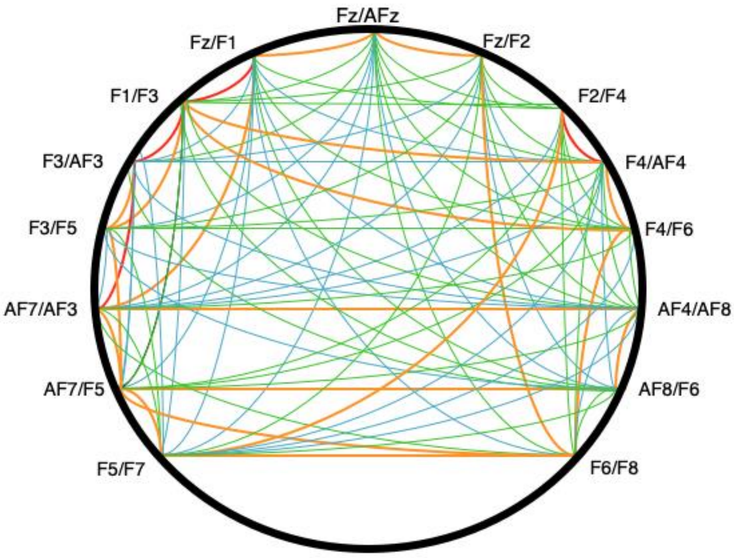
In order to understand the patterns of functional connectivity observed in the graph theoretic analyses, data from the binary adjacent matrices were combined into a visualisation based on the arc diagram (Figure 8.8). The purpose of this visualisation was to indicate the relative frequency of individual connections across the participant group as a whole; specificially, it is to identify which connections and patterns of connections were most prominent across the six periods of the task. In these figures, the colour code represent the number of participants for whom a particular connection passed the threshold of partial r=0.28. A red connection denotes a connection that was observed in 22 of our participants or more, the orange lines indicate the presence of a connection for 17 to 21 of our participants, the green for 13-16 participants and the blue for less than 12 participants. Hence, colours do not correspond to the strength of each connection but rather the relative frequency of that connection within our participant group.

When describing the observed patterns within each period of the task, it focuses on those connections that were most prominent for the group, i.e. red and orange lines. The first period of watchkeeping (w1) indicates a high frequency of local clustering (i.e. red/orange lines between adjacent sites) with a smaller proportion of bilateral connections. This pattern of local clustering persisted into the second period (w2) but the relative frequency of bilateral connections was observed to increase. During w3, the number of adjacent and bilateral connections was observed to decline, particularly with respect to the former. The fourth spell of watchkeeping (w4) represented the period when participants spotted another vessel in the distance; this episode was characterized by an increased frequency of bilateral connections. During the first period of the decision-making phase of the task (d1), a general decrease of frequent connections is observed; there is local clustering at the lateral areas of the frontal cortex on both left (F5/F7-AF7/F5, F6/F8-AF8/F8) and in the fronto-central as well as a small number of bilateral connections (AF7/AF3-AF4/AF8). The final part of the task (d2) represents the period immediately prior to the participants' performance of an evasive manoeuvre. During this period, the most frequent connections within the group were clustered around the fronto-central region (Fz, F1, F2, F3, F4) with a small number of bilateral connections at the left/right edges of the montage, e.g. AF7, F7, AF8, F8.

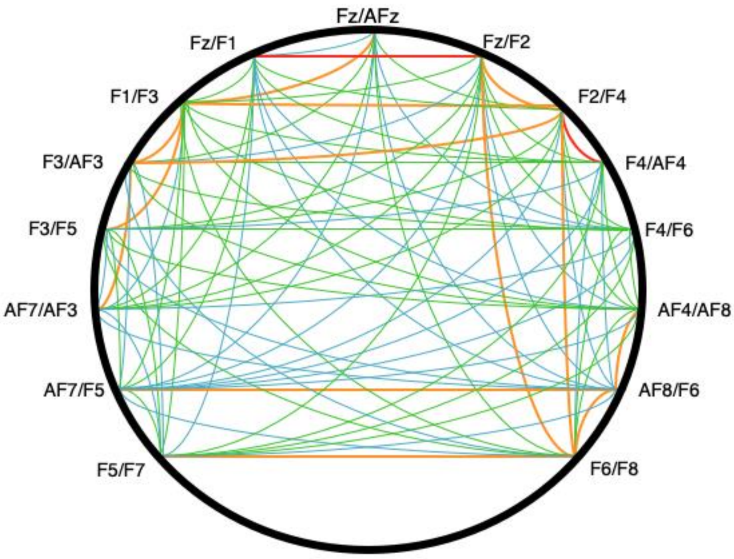
(a) Watch 1



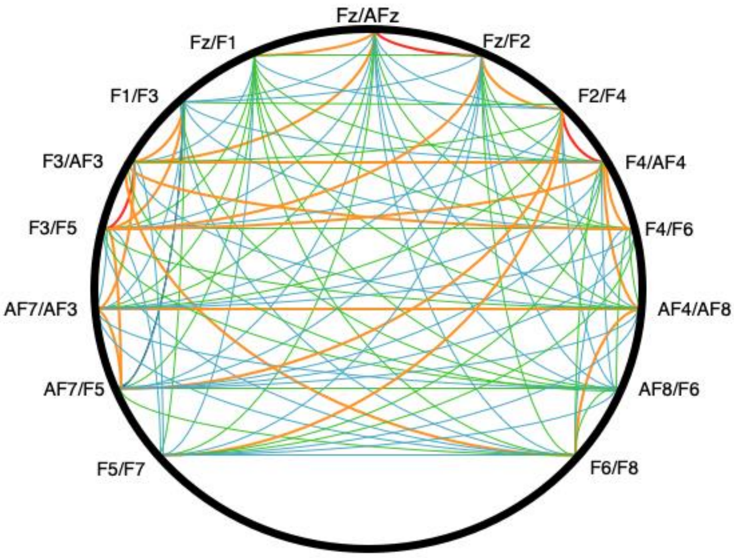
(b) Watch 2



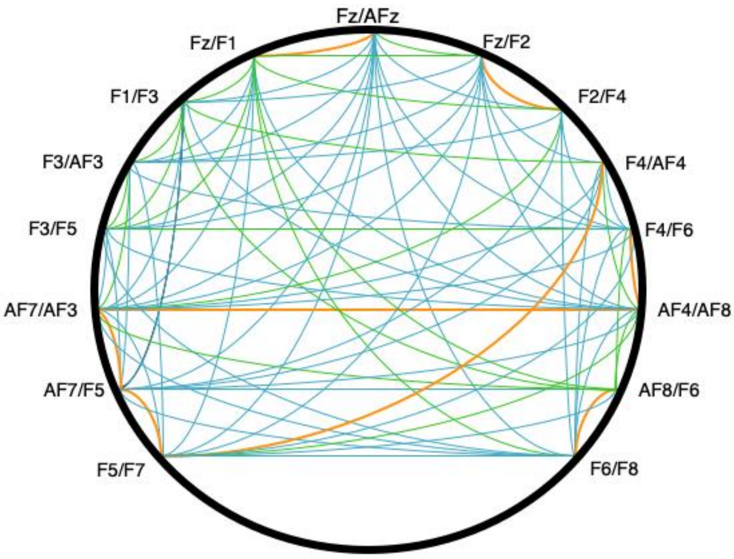
(c) Watch 3



(d) Watch 4



(e) Decision 1



(f) Decision 2

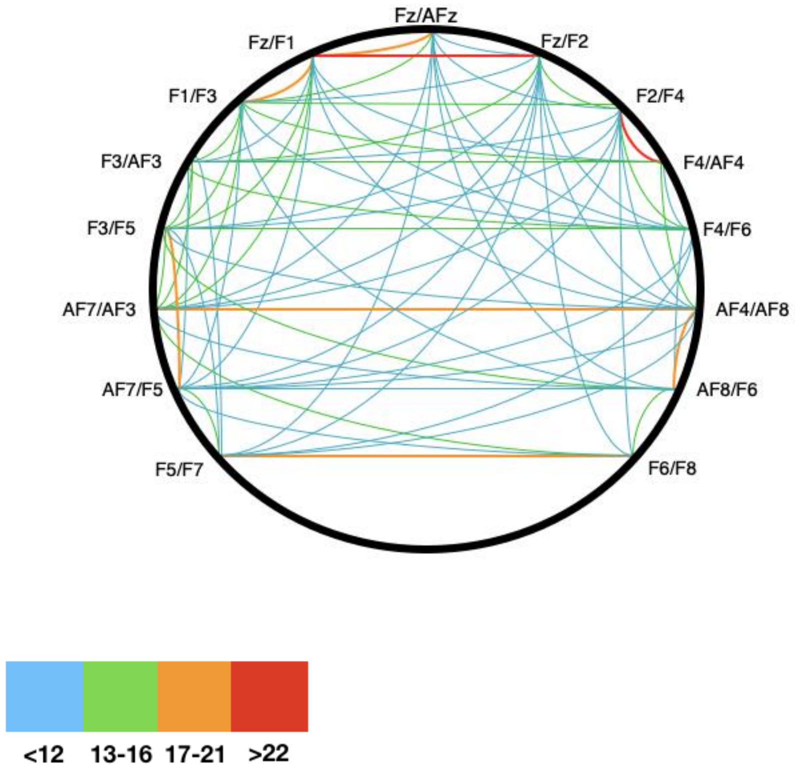


Figure 8.8 Data visualisation showing relative frequency of significant connections observed in the adjacency matrices across all six task periods (N=36). Labels correspond to 10-20 locations of the fNIRS channels. Colour key indicates the number of participants who exhibited a significant partial correlation coefficient for this connection, i.e. red = 22 participants or more, orange = 17-21 participants etc

8.4.3 Relationship between functional connectivity and behaviours

A regression analysis was conducted to explore whether behavioural data could be predicted on the basis of functional connectivity metrics, e.g. density, clustering. Behavioural data were obtained from two period of the task: w4 (i.e. distance at which target vessel was spotted) and d2 (i.e. distance from the target vessel when course was changed). Two linear regression models were created, one for w4 and another for d2, each using distance as a dependent variable with density (D) and clustering (C) as independent variables.

The regression analysis conducted on data from w4 revealed a R^2 of 0.29 (Adj $R^2 = 0.25$), which was a significant model [$F(2,34)=6.79$, $p<.01$]. Detailed inspection of the model (Table 8.1) revealed that increased density and clustering were both associated with the target vessel being spotted at greater distance from participant's ship. From the model, it appeared that density was the stronger predictor of distance relative to clustering (Table 8.1). The same model was applied to equivalent data from d2; this model also reached statistical significance [$F(2,34)=8.07$, $p<.01$] with a R^2 value of 0.33 (Adj $R^2 = 0.29$). The model revealed an inverse relationship between density and distance to the target vessel (Table 8.1).

Table 8.1 Results of the linear regression models with distance to Target Vessel as the dependent variable

	Watch 4 (w4) model				**Decision 2 (d2) model**			
	t	**Std. ß**	**partial r**	**Sig**	**t**	**Std. ß**	**partial r**	**Sig**
Density	3.56	0.54	0.53	<.01	-3.47	-0.50	-0.52	<.01
Clustering	1.94	0.30	0.32	.06	1.37	0.20	0.23	0.18

8.5 Discussion

This chapter was done with simulated watchkeeping tasks in a maritime bridge simulator and fNIRS technology to measure neurophysiological activation. Besides the mental workload analyses in ***Chapter 7***, this chapter further conducts the functional connectivity analysis for seafarers using bridge simulation.

Density falls at d1 (task period 5) when participants are preparing to make the manoeuvre. As the density is the ratio of actual connections to possible connections, hence the network seems to focus communication between a smaller group of nodes during d1 than it did during w1-w4. This explains that the network becomes more efficient during decision-making. There is an interaction between distraction and task period. It indicates increase of density during the fourth period of watchkeeping (w4) for those participants in the no-distraction group compared to the distraction group.

For local clustering, there is a decrease of clustering (which refers to connections between neighbouring nodes) during w4 compared to w1, which may indicate boredom. This is followed by a sudden increase from w4 to d1 when cognitive decision making begins. There is also an interaction between distraction and period. It indicates that the pattern described before only occurs for non-distracted participants; distracted participants do not show a decline of clustering from w1 to w4, possibly because they are alerted by the distraction task. They also do not show a substantial increase at d1, possibly because they are distracted from decision-making by the other task.

With respect to the patterns of functional connectivity observed in Figures 8.4 and 8.6, the main distinction between w4 and d1 was an observable decrease in the overall frequency of connections, i.e. fewer orange and red connections appear in d1 and d2 compared to w1-4 (Figure 8.8). This decline was particularly pronounced for bilateral connections as participants transitioned from w4 to d1 (Figure 8.8). Close inspection of Figure 8.8 indicated that the process of action selection in d1 and d2 was associated with a small number of frequent localized connections at left lateral channels, e.g. F5/F7-AF7/F5 (BA46, BA47), right lateral channels, e.g. AF8/F6-AF4/AF8 (BA46, BA45), and fronto-central channels, e.g. Fz/F1-Fz/AFz (BA8, BA9). In addition, a small number of bilateral connections were frequently present during d1 and d2, e.g. AF7/AF3-AF4/AF8 (BA9-BA9), F5/F7-F6/F8 (BA46-BA46). This pattern of bilateral activation at BA46 has been associated with Episodic control over action selection. The pattern of persistent connectivity and increased activity in the DLPFC may represent a trade-off between exploitation of previous experience and exploration of the immediate context as participants assessed the approach of a target vessel and formulated an evasive manoeuvre.

The purpose of the regression analyses was to explore a relationship between measures of functional connectivity and behavioural outcomes measured during the task simulation. Two linear regression models were constructed to predict distance from the target vessel when it was (1) spotted and (2) when participants performed an evasive manoeuvre (Table 8.1). Both models were statistically significant as functional connectivity metrics accounted for approximately a third of variance observed in the performance data, a figure that was substantially higher than anticipated. The w4 model revealed that density and local clustering were both positively associated with distance to target vessel when spotted; however, this relationship was strongest for connection density (Table 8.1). By contrast, there was an inverse relationship between connection density and the safety margin in the d2 model (Table 8.1), i.e. reduced density was associated with greater distance to target vessel when the evasive manoeuvre was performed. The clustering coefficient measure did not make a significant relationship to the d2 model. Both models reinforce the trends that were observed in Figure 8.4 of increased connection density during vigilance and a significant decline of density during the process of action selection. The regression models confirm an association between measures of functional connectivity in the PFC and performance outcomes in an applied, safety-critical scenario.

To conclude, the current study measured neurovascular activation and functional connectivity in the context of ship bridge operations. Increased activation of the right DLPFC, reduced connection density and a higher level of local clustering across a frontal montage of 15 channels was associated with action selection in comparison to the earlier watchkeeping period of vigilant attention. Activity in the right DLPFC and the level of local clustering declined across the watchkeeping period for participants. It also demonstrated a significant association between metrics of frontal connectivity (i.e. connection density) and behavioural responses to a safety-critical scenario.

8.6 Ethics statement

This study was carried out in accordance with the recommendations of Liverpool John

Moores University with written informed consent from all subjects. All subjects gave written informed consent in accordance with the Declaration of Helsinki. The protocol was approved by Liverpool John Moores University. See appendix A, B.

8.7 Concluding remarks

The following are the most significant remarks comprised in the chapter, and emphasised in the form of bullet points for the reader's ease:

- Density falls at d1 (task period 5) when participants are preparing to make the manoeuvre. It indicates increase of density during the fourth period of watchkeeping (w4) for those participants in the no-distraction group

- There is a decrease of clustering during w4 compared to w1, followed by a sudden increase from w4 to d1 when cognitive decision making begins. It indicates that the pattern only occurs for non-distracted participants.

- The main distinction between w4 and d1 was an observable decrease in the overall frequency of connections. This decline was particularly pronounced for bilateral connections as participants transitioned from w4 to d1.

- The pattern of persistent connectivity and increased activity in the DLPFC may represent a trade-off between exploitation of previous experience and exploration of the immediate context as participants assessed the approach of a target vessel and formulated an evasive manoeuvre.

- Two regression models confirm an association between measures of functional connectivity in the PFC and performance outcomes in an applied, safety-critical scenario.

Chapter 9 Discussion and conclusion

9.1 Contributions to the field

The human reliability methodology has been developed as a quantification tool for human factors in maritime transportation accidents while neurophysiological methodology has been put forward as an experimental indicator for seafarers on board. Moreover, it has been documented that the abovementioned methodology maintains a systematic framework, which continues to develop and improve by wide application in the maritime field. Moreover, the methodology derived from the road traffic and aviation fields, although it has not been used in maritime scenarios, is evident to be one of the promising directions of multi-discipline research related to human factors.

Human factors in maritime safety comprise several aspects such as procedure factors, individual factors, vessel factors, environmental factors, and regulation and management factors, which are common factors contributing to human errors in maritime accidents. Compared to previous studies in the relevant literature, it reveals new primary data directly derived from maritime accident records in two major databanks MAIB and TSB, and quantification of the extent to which different combinations of the factors influence each accident type.

The network modelling the interdependency among the risk factors is constructed by using NBN, which demonstrates general risk factors in maritime accidents. Scenario analyses are conducted to predict the occurrence likelihood of different types of accidents under various situations, which provides transport authorities and ship owners with useful insights for maritime accident prevention. Its novelties consist of manual collection and analysis of the primary data representing frequencies of risk factors directly derived from maritime accident reports, causational risk analyses with respect to different maritime accident types, and modelling by a historical accident data-driven approach, to generate new insights on critical factors contributing to different types of accidents.

The modelling of the interdependency among the risk influencing factors is structured by TAN, and validated by sensitivity analyses. The findings reveal that the critical risk factors for all accident types are ship age, ship operation, voyage segment, information, and vessel condition. More importantly, the findings also present the differentiation among the vital human factors against different types of accidents. It also provides a specific scenario in which the beliefs are upheld, observing the most probable configuration. The work pioneers the analyses of various impacts of human factors on different maritime accident types, which helps provide specific recommendations for the prevention of a particular type of accidents involving human errors.

The advantages of the above research are revealed. However, there is a gap for reflecting mental workload associated with tasks on board. The fNIRS experimental study investigates the role of the prefrontal cortex in watchkeeping and decision-making mental workload analysis of deck officers on a ship bridge using fNIRS, which fills the blank space of application of the fNIRS technique in maritime transportation. Behavioural data indicated that experienced deck officers made the decision to successfully change course (to avoid collision) at a greater distance from the potential hazard compared to inexperienced officers. It illustrates that participants under distraction were considered to require more temporal demand than participants without distraction. Also, it demonstrates that the developed scenarios distracted the ship officers by reporting vessel position at certain points, which is the common task requiring temporal mental workload in the real world. In this way, it helps the maritime organisations to understand the workload faced by seafarers of different qualification levels, as well as better guidelines to improve seafarers' certificate training.

Moreover, in terms of fNIRS data, the right ROI showed increased oxygenation during the decision phase of the task, due to greater mental workload/decision-making. There is some evidence for decreased oxygenation during the late phase of watchkeeping due to boredom. Greater oxygenation is found during decision time for participants with distraction, because of higher workload when simultaneously performing the distraction task and making the decision to change course. Higher oxygenation at right DLPFC is observed for experienced participants, but only when the ship was spotted due to considerably more attention being focused on the decision - which may have contributed to superior performance. Concerning this, it benefits maritime authorities to conduct scientific training so as to lead to the superior performance of seafarers.

With respect to functional connectivity, reduced connection density and a higher level of local clustering across a frontal montage of 15 channels was associated with action selection in comparison to the earlier watchkeeping period of vigilant attention. Density and local clustering were both positively associated with distance to target vessel when spotted; however, this relationship was strongest for connection density. By contrast, reduced density was associated with greater distance to target vessel when the evasive manoeuvre was performed. The regression models confirm an association between measures of functional connectivity in the PFC and performance outcomes in an applied, safety-critical scenario.

From the perspective of scenarios designed in the bridge simulator, complicated or combined tasks such as introducing weather forecast or communication during watch-keeping could be used to manipulate mental workload in a naturalistic navigation task. There is a diverse database for the scenarios to be manipulated. It provides a clue to allocate a sufficient or adequate group to deal with different situations. Also, the development of the ergonomic design of the ship bridge would help the designer construct a better workplace for seafarers, so as to generate the workload appropriate to them.

It is also relevant to note that fNIRS utilises changes of haemoglobin concentrations to illustrate neurophysiological activations to describe the mental workload of seafarers, as directly as the NASA-TLX questionnaire does. Underlining the already emphasised advantages of being able to generate values of the haemodynamic response, the implementation of fNIRS could be considered as a potential aid for mental workload and performance predictors. The fNIRS technique could serve to monitor and report human performance with a widely accepted methodology during the maritime transportation, capable of consistent application across not only shipping divisions, but additionally across industry sectors as a standard performance metric.

9.2 Research objectives achieved

The primary purposes of this research are to investigate how human factors combined with common risk factors affect the safety of maritime transportation, and how individual physiological factor - mental workload - influences neurophysiological activation, and decision making of experienced and inexperienced seafarers.

In order to achieve the research aims, the objectives addressed are fulfilled as follows.

- To obtain the primary data representing frequencies of risk factors directly derived from maritime accident reports.

  Manual case by case analysis of recorded maritime accidents from MAIB and TSB that occurred from 2012 to 2017 is undertaken to develop a primary database to support this study. Accidents related to human errors in the process of navigation and sailing, integrated with literature, are analysed to identify risk factors in maritime accidents from different views. It provides a general demonstration of maritime accidents and rational classification of related risk factors as procedure factors, individual factors, vessel factors, environmental factors, regulation and management factors.

- To analyse the risk factors in maritime accidents.

  This work proposes a Bayesian Network-based risk analysis approach to analyse the risk factors influencing maritime transport accidents. It reveals new features including new primary data derived from maritime accident records; also, the quantification of the extent to which different combinations of the factors influence each accident type. The network modelling the interdependency among the risk factors is constructed by using NBN and validated by sensitivity analysis. Scenario analyses are conducted to predict the occurrence likelihood of different types of accidents under various situations.

- To incorporate human factors into causational analyses to maritime accident types.

  In order to include more human factors into the model, another data-driven Bayesian Network is used to investigate the effect of human factors on marine safety in maritime accident analyses. It incorporate human factors into causational analysis concerning different maritime accident types and generates new insights on critical human factors contributing to different types of accidents. The modelling of the interdependency among the risk influencing factors is structured by TAN and validated by sensitivity analysis. More importantly, the findings present the differentiation among the vital human factors against different types of accidents. MPE is used to provide a specific scenario in which the beliefs are upheld, observing the most probable configuration.

- To develop a historical accident data-driven approach to train prior probabilities in the risk-based BN.

  After manual collection of the raw data derived from maritime accident reports, the network modelling the interdependency among the risk factors is constructed by data-driven approaches, NBN and TAN, respectively. Both of them train prior probabilities in the risk-based BN and are validated by sensitivity analysis.

- To conduct an empirical study to provide insights for the prevention of a particular type of accidents involving human errors.

Sensitivity analysis helps provide patterns of influencing risk factors. And an empirical study is conducted by scenario analysis and MPE to predict the occurrence likelihood of different types of accidents under various situations, or a specific scenario in which the beliefs are upheld observing the most probable configuration. In this way, it provides insights for the accident prevention involving human errors.

- To design and conduct the experimental study aiming to study the mental workload of seafarers and the behavioural performance using fNIRS technology.

  It is done with simulated watchkeeping tasks in the maritime bridge simulator, and using fNIRS technology to measure neurophysiological activation. The developed scenarios distract the ship officers by reporting vessel position and answering questions at specific points, which is the common task requiring temporal mental workload in the real world. The results show that experienced participants were considered to believe they have better performance than inexperienced people. It also illustrates better performance for experienced seafarers because they made decisions earlier, which leads to successful collision avoidance. Participants under distraction were considered to require more temporal demand than those without distraction. In terms of fNIRS data, it shows significant differences in the right DLPFC of the brain.

- To explore the patterns of functional connectivity in the dorsolateral prefrontal cortex (DLPFC) of experienced and inexperienced seafarers.

  It is done further with functional connectivity analyses for seafarers with bridge simulation. The current study measures neurovascular activation and functional connectivity in the context of ship bridge operations. Increased activation of the right DLPFC, reduced connection density and a higher level of local clustering across a frontal montage of 15 channels is associated with action selection in comparison to the earlier watchkeeping period of vigilant attention. Activity in the right DLPFC and the level of local clustering decline across the watchkeeping period for participants.

There is a significant association between metrics of frontal connectivity (i.e. connection density) and behavioural responses to a safety-critical scenario.

9.3 Recommendations for future research

9.3.1 Inclusion of a wide range of human factors

The TAN modelling chapters brought forward some issues that are worthy of note for further lines of investigation. For example, the TAN model accounts for the limited number of risk factors according to the frequencies of factors, especially for individual factors. It is rational but could be considered further, as some factors have relatively low frequencies of being blamed but actually take primary responsibility. That is to say, even factors with low frequencies are significant factors for the maritime accidents. This research only accounts for the frequency rather than severity. It would be interesting to gather more data concerning the severity of maritime accidents, as well as related risk factors, to conduct the analyses for the risk of certain accident types.

Moreover, future work could encompass more maritime accident reports with the original description of the process of accidents to enrich the data source to this research. It will illustrate the features of modern maritime accidents, and fulfil the database of human factors which could be further served by other researchers and transport authorities for better improvement of management.

Also, while out of the scope of the work herein, it would be interesting to integrate the human reliability research with an experimental neurophysiological study. For example, the findings of the fNIRS experimental study illustrate some patterns of human performance with perspectives of mental workload. However, some clues can also be found in BN modelling obtained from the maritime accident reports. There is a possibility to integrate them from both subjective and objective views. This type of retrofit could entail a comprehensive benefit with the inclusion of data gathering of individual factors, which was previously not demonstrated in the maritime accident reports. It will introduce a novel way of human factors' study in the maritime field.

9.3.2 Insights for human factors in ship autonomy

There are plenty of projects or research related to ship autonomy from various countries, e.g. MUNIN project in EU (Man et al., 2014), AAWA project in Finland (Wahlstrom et al., 2015), small military boats unmanned solutions in U.S. Navy, Supporting Voice Communication in the UK (Brodje et al., 2015). Another future work could be surrounded by human factors with ship autonomy.

The first impression of human factors in USV could be based on autopilot and shore-based pilot. It could be demonstrated that the idea of unmanned ship operation derives from shore-based pilotage. Shore-based pilotage is defined by the European Maritime Pilots Association (EMPA), and the International Maritime Pilot's Association (IMPA) as 'an act of pilotage carried out in a designated area by a pilot licensed for that area from a position other than aboard the vessel concerned, to conduct the safe navigation of that vessel'. Since COST301 (1987–91), there has been considerable interest in remote pilotage in the EU, and this has benefited and promoted the TAIE project (1991–4). TAIE's objectives include determining the suitability of VTS for remote pilotage. In addition, pilotage organisations were pressured to provide remote pilotage to a port or face elimination of these pilotage services in Germany and the Netherlands (Hadley, 1999). The most prominent concern of remote pilotage is the importance the pilots attribute to establishing good contact with the regular crew of the ship (Bruno and Lutzhoft, 2009). The costs and benefits of remote pilotage (Hadley, 1999) are: (i) Well planned and smoothly implemented vessel movements in all weathers; (ii) Perceived efficiency in a competing port; (iii) Savings to ship owners, charterers and receivers from reduced time wastage; (iv) Enhanced safety of navigation, reducing risks.

As the idea of remote pilotage passed by, the concept of autonomous control of ships emerges. E-Navigation Test Bed of ACCessibility for Shipping, Efficiency Advantages and Sustainability (ACCSEAS) in EU implement and demonstrate e-Navigation systems to alleviate North Sea Region navigation risks (Bransby et al., 2012). Also, 'route suggestions' has also been developed for shore stations, such as VTS, to transmit route segments from several areas of responsibility to individual vessels (Brodje et al., 2015). It served as a graphical means of supporting service within voice communication between navigator and VTS Operator. With the research trends on unmanned surface vehicles, unmanned ships projects become an essential aspect for four reasons. These are working environment and larbour shortage aboard, reducing cost on waterborne transportation, reducing emissions of vessels, and increasing safety in shipping (Porathe et al., 2014).

It seems that the human factor emerging in unmanned ships is quite different from in traditional ships. The EU project Maritime Unmanned Ship through Intelligence in Networks (MUNIN) provides the context to conduct the human factors research by the interview of experienced participants (Man et al., 2014). However, the unmanned ship does not indicate there is no crew manoeuvring the ship. Contrary to its name, it is impossible that nobody is responsible for the ships. Humans will still work on monitoring, remote control, and maintenance, especially on the high seas unmanned ships where it has to coexist with manned ship systems (Porathe et al., 2014).

Several generations of vessels have been launched since World War II. These advances in automation and reallocation of crew responsibility, as well as shore-based equipment and onboard devices, have permitted reductions in crew size (Council, 1990). In the late 1980s, European and Japanese governments supported even greater automation, centralizing navigation, engine control, communications, and administrative functions on the bridge to build the 'ship operation centre', as well as throughout the vessel. From this perspective, the fast pace of innovation and development in shipping is continuing worldwide. Unmanned ships allow fewer crew on board. Meanwhile, several parts of the crews or part of the crew responsibility are going to be allocated ashore. It should be noted that semi-autonomy is highly typical of unmanned vehicles, and in the past, this has been favoured over full autonomy due to the diverse shifts of missions (Campbell et al., 2012).

Obviously, it is demonstrated that the human is still one of the most important contributions to shipping. In addition, the feasibility of unmanned, autonomous merchant vessels is investigated by the EU project MUNIN (Porathe et al., 2014). In the study, the ships are manned while departing and entering port and unmanned during the voyage. When on ocean-passage, it is controlled by an automatic system within on-board sensors allowing the ship to make collision avoidance manoeuvres according to international regulation. It is also continuously monitored by a remote shore centre able to take remote control should the automatic systems break.

It can be seen that if decisions from the operator on board, where stress, mental workload and fatigue play a vital role, are moved to a less dominant work environment, some safety benefits might be achieved.

The unmanned ship does not mean the resolution of all the problems from human errors; on the contrary, it brings more challenges related to human factors in the Shore Control Centre (SCC) (Man et al., 2014). People need to be able to take full control over the ship at any time or several ships simultaneously. Without ship sense or situation awareness from the feeling of the ship’s movement and navigation environment, operators do not find it easy to manoeuvre ships remotely. There will be no physical connection between the people and the vessel environment. Specifically, the visual and vestibular sense of the environment, a tactile sense in ship handling for bridge officers, will be missing.

With this background, human factors ashore may encounter different issues compared to human factors on board. Firstly, there will be no physical connection between the human and the ship, and no directly perceived information from the ship’s environment. Secondly, the traditional methods used to prioritise information for humans do not generate sufficient situation awareness. Otherwise, they will become blind to the environment.

Thirdly, situation awareness is an accumulated factor continually developing with a high risk of information overloading. Maintaining situation awareness becomes more challenging than creating situation awareness to keep track of the dynamic situation.

Although unmanned commercial shipping does not exist yet, it is worth considering these prominent issues (Wahlstrom et al., 2015). Without the bridge and the systems supporting the crew, the ships could be lighter and carry more cargo – this would increase revenues and fuel efficiency. The most well known problem of automation is to retain adequate situation awareness through remote sensing (Porathe et al., 2014). Man invited ten master mariner program students with experience at sea to participate in the focus group interview (Man et al., 2014), discussing the different actions taken on board and ashore. The results highlight ship sense and situation awareness existed ashore. In addition, compensating and mimicking ship sense by the simulator as the human-machine interface is the purpose of obtaining situation awareness.

The most considerable issues also include information overload, boredom, mishaps during changeovers and handoffs, lack of feel of the vessel, constant reorientation to new tasks, delays in control and monitoring, and the need for human understanding in local knowledge and object differentiation (e.g., in differentiating between help-seekers and pirates) (Wahlstrom et al., 2015). It is shown that positive aspects include lack of seasickness and physical damage to the crew in harsh weather conditions. This implies that the unmanned ships should be designed with agile command and control, considering human-machine interaction and to communicate with the manned vessels and the authorities proactively.

With greater emphasis being placed on the use of automatic devices and displays, it requires training of simulators to use a two-dimensional screen instead of using their standard three-dimensional view. This is likely to add to the cost of unmanned ship's training service. However, it should be stated that, with technological development, an operator may be working hard just to remain familiar with equipment rather than making himself an expert in use. Hansen integrated a system within a 40-foot laboratory boat, advanced onboard control, sensing, data fusion, physical plant and payload monitoring and management to replace traditional human crew functions (Hansen et al., 2006). It discussed a path proposed during Intelligent Autonomy (IA) NIST workshops to specify a quantifiable measure of full USV autonomy equipped with skills. Moreover, the USV Skill Set Architecture (SSA) is proposed.

Man redefined the crew structure in the SCC, operator, supervisor, captain, engineer; 5 scenarios in the two-day period were conducted (Man et al., 2015) to explain the situation awareness in unmanned ships. It was demonstrated that the onboard thresholds of the alarms are not necessarily suitable for the situation of remote monitoring. The alarm shall be related to the "tendency" of the event to facilitate the operator's SA efficiently. More types of information (e.g. visual/audio) should be available in the SCC to actively support people for decision-making. From this point of view, the design of the SCC shall not be a mimic of the bridge design. Redefining the human factors and human errors contributing to maritime accidents is necessary, especially for situation awareness. Porathe et al. (2014) stated that human errors will continue to be the biggest challenge and must be addressed carefully and meticulously.

9.4 Concluding remarks

The work presented herein has initially documented a literature review underlining human reliability and risk assessment in the maritime system, specifically emphasising human factors in maritime accidents through accident investigation reports. Additionally, the application of functional Near-Infrared Spectroscopy was demonstrated to imply how it can be utilised for the maritime transportation field.

More importantly, research challenges on the evaluation of common factors contributing to human errors in the maritime industry, and how to control measures of human errors to reduce the risk in maritime transport remain to be solved. Therefore, human factors research is expected to be extended and explored by redefining risk factors, incorporating quantitative methods into human errors assessment and integrating neurophysiological methods, in order to improve the safety level of maritime transportation and mitigate the risk for seafarers on board.

Human reliability methods are applied for the identification of risk factors contributing to human errors in maritime accidents. Combined with Bayesian networks, contributory factors and the inter-relations among them can be modelled to illustrate causations and quantitative analyses among risk factors. Moreover, the application of the fNIRS technique and NASA-TLX derived from the neuroscience field is the supplement of multi-discipline knowledge. It explores the role of the prefrontal cortex in watchkeeping and decision-making mental workload analysis of deck officers on a ship bridge, and proposes an effective experimental method to understand the functional connectivity of brains, as well as the differences of decision-making by experienced and inexperienced officers.

The above modelling and experimental study are intended to recommend the possible countermeasures for mitigating human errors to reduce the risks of accidents, and demonstrate the patterns of seafarers' decision-making which is beneficial for better performance of seafarers and provides new insights for the training of ship officers and seafarers' certification.

Finally, the inclusion of a broader range of human factors in maritime transportation and the experimental neurophysiological methods would be future explored for the potential human reliability research. Moreover, the remote human-centred design of novel vessels and the development of unmanned ships navigating with traditional ships introduces new scenarios for the human factors' research in the maritime field, which shows promise by associating neurophysiological experiment in the maritime section.

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Publications

Finally, this part lists some of the author's publications and submitted or in-pipeline works, which are related to the work presented herein.

Journal papers

1. Fan, S., Fairclough, S., Blanco-Davis, E., Zhang, J., Bury A., Warren J., Yang Z., Yan, X., Wang J.. The Role of the Prefrontal Cortex & Functional Connectivity in Watchkeeping and Collision Avoidance during Maritime Operations: An fNIRS study. Brain and Behavior, under review.

2. Fan, S., Blanco-Davis, E., Yang, Z., Zhang, J., & Yan, X.(2020). Incorporation of human factors into maritime accident analysis using a data-driven Bayesian network. Reliability Engineering & System Safety, accepted.

3. Fan, S., Zhang, J., Blanco-Davis, E., Yang, Z., & Yan, X.(2020). Maritime accident prevention strategy formulation from a human factor perspective using Bayesian Networks and TOPSIS. Ocean Engineering, accepted.

4. Fan, S., Yang, Z., Blanco-Davis, E., Zhang, J., & Yan, X. (2020). Analysis of maritime transport accidents using Bayesian networks. Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability, 234(3), 439-454.

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

Conference papers

6. Fan, S., Zhang, J., Blanco-Davis, E., Yang, Z., Wang, J., & Yan, X. (2018). Study on

seafarers' emotion identification during watch-keeping using bridge simulation. In Safety and Reliability-Safe Societies in a Changing World-Proceedings of the 28th International European Safety and Reliability Conference, ESREL 2018 (pp. 347-354). Taylor & Francis.

7. Fan S., Yan X., Zhang J., Wang J. (2017). A Review on Human Factors in Maritime Transportation Using Seafarers' Physiological Data. Proceedings of the 4th International Conference on Transportation Information and Safety (ICTIS). August 8 - August 10, 2017, Banff, Alberta, Canada.

Appendices

Appendix A NASA-TLX Questionnaire

NASA-TLX

Number: **Age:** **Gender:** **Experience/qualification:**

Please rate the MENTAL DEMAND of the task: How much mental and perceptual activity was required

Low High

1 2 3 4 5 6 7 8 9 10

Enter a number between 1 and 10 here for MENTAL DEMAND

Please rate the PHYSICAL DEMAND of the task: How much physical activity was required?

Low High

1 2 3 4 5 6 7 8 9 10

Enter a number between 1 and 10 here for PHYSICAL DEMAND

Please rate the TEMPORAL DEMAND of the task: How much time pressure did you feel due to the pace at which task elements occurred?

Low High

1 2 3 4 5 6 7 8 9 10

Enter a number between 1 and 10 here for TEMPORAL DEMAND

Please rate your own PERFORMANCE: How successful do you think you were in completing the goals of the task?

Low High

1 2 3 4 5 6 7 8 9 10

Enter a number between 1 and 10 here for PERFORMANCE

Please rate your EFFORT: How hard did you have to work (mentally and physically) to accomplish your level of performance?

Low High

1 2 3 4 5 6 7 8 9 10

Enter a number between 1 and 10 here for EFFORT

Please rate your FRUSTRATION: How discouraged, irritated, stressed and annoyed did you feel during the task?

Low High

1 2 3 4 5 6 7 8 9 10

Enter a number between 1 and 10 here for FRUSTRATION

☐ *I have read the information sheet provided and I am happy to participate. I understand that by completing and returning this questionnaire I am consenting to be part of the research study and for my data to be used as described.*

Appendix B Participant Information Sheet

LIVERPOOL JOHN MOORES UNIVERSITY
Participant Information Sheet
LJMU's Research Ethics Committee Approval Reference:
YOU WILL BE GIVEN A COPY OF THIS INFORMATION SHEET
Title of Study: Human error assessment for seafarers in ship bridge: an experimental study
School/Faculty: School of Maritime and Mechanical Engineering
Name and Contact Details and status of the Principal Investigator:
Shiqi Fan, S.Fan@2017.ljmu.ac.uk, PhD student
Name and Contact Details of the Investigators:
Dr Eduardo Blanco Davis, E.E.BlancoDavis@ljmu.ac.uk
Prof Stephen Fairclough, S.Fairclough@ljmu.ac.uk

You are being invited to take part in a research study. Before you decide it is important for you to understand why the study us being done and what participation will involve. Please take time to read the following information carefully and discuss it with others if you wish. Ask us if there is anything that is not clear or if you would like more information. Take time to decide whether or not you wish to take part. Thank you for reading this.

1. What is the purpose of the study?

The purpose of this study is to evaluate the root causes that contribute to human error within the bridge room of a vessel. Statistics indicates that 75% -96% of water traffic accidents are caused by the human and organisational factors. This study will give us in depth knowledge of the risks associated with the bridge room of a vessel and in turn allow us to implement further risk control options or training for seafarers.

2. Why have I been invited to participate?

You have been invited because you are aged 18 years old or older. In addition, you are qualified experienced or novice seafarers, or have education experience in navigation technology.

The exclusion / inclusion criteria are head injury conditions or suffering with high blood pressure, since this may affect the results from experiment equipment - fNIRS. Blood pressure data will be collected prior to testing. Any person suffering from anxiety condition and/or receiving medication for anxiety condition is excluded neither.

3. Do I have to take part?

No. It is up to you to decide whether or not to take part. If you do decide to take part you will be given this information sheet to keep and be asked to sign a consent form. You can discontinue the study for any reason without any explanation and without it affecting your rights/any future treatment/service you receive. And the data will not be withdrawn as it will be unidentifiable.

4. What will happen to me if I take part?

We will talk you through the study procedures and give you the chance to ask any questions. The experiment will take place at bridge simulator in ground floor at James Parsons Building, Byrom Street, L3 3AF, Liverpool. Participants will undergo the following process in ship bridge simulator.

Firstly, we will ask you to take a blood pressure test to confirm that you do not have high blood pressure which is not suitable for the experiment. However we are not qualified to make judgements on participants' health, you would be advised to visit your GP for your blood pressure. After reading this information and giving your written consent you will be asked to partake in some basic training in the bridge simulator. This will involve familiarising you with the simulator software, how certain selected systems work and how you can change systems to solve problems. The training exercise will last average 30 minutes for subjects. Participants will be allocated into experienced group and inexperienced group, depending on whether you complete a number of hours in the bridge simulator as part of your existing training, e.g. a specific course NAEST in LJMU. Once training is completed you will be placed with a skull cap containing 8 sensors and 8 detectors required to measure the blood flow in your pre-frontal cortex via the use of infra-red light, seen as below.


Then you will be asked to complete a task in bridge simulator. Your task will be a Collision Regulation exercise set in open water, and you need to alter the course under the Rules to avoid a collision with other ships, as you are in real life. The tasks on average will take around 20 minutes. After tasks, the participant is supposed to finish the questionnaire about the subjective workload.

5. **Will I be recorded and how will the recorded media be used?**

No, your action will not be recorded. Age, gender, maritime experience/qualification of you made during this study will be used only for data analysis and result illustration. No other use will be made of them without your written permission, and no one outside the project will be allowed access to the original data.

6. **What are the possible disadvantages and risks of taking part?**

There are no anticipated risks involved with this study. You may feel a slight discomfort from wearing the head cap for the duration of the test and in the rare case that the discomfort gets too much then you can stop the task as anytime and re-adjust the head cap or discontinue the study. You will be asked if you are experiencing any nausea during the training session and will be withdrawn if nausea is an issue for you in the simulator. Some of the tasks, with them being time dependant may cause varying degrees of stress and mental fatigue.

7. **What are the possible benefits of taking part?**

The benefits of taking part are useful learning experience for bridge simulator. Whilst will be £10 voucher to you for taking part in the study, it is hoped that this work will enhance your professional.

8. **What will happen to the data provided and how will my taking part in this project be kept confidential?**

The information you provide as part of the study is the **research study data**. Any research study data from which you can be identified (e.g. audio and/or video recordings), is known as **personal data**.

Personal data does not include data that cannot be identified to an individual (e.g. data collected anonymously or where identifiers have been removed).

If necessary, personal data will be stored confidentially for 5 years after the study has finished. Personal data will be accessible to the research team. Personal identifiable data/information/tissue will not be transferred outside of the European Economic Area.

You will not be identifiable in any ensuing reports or publications. Anonymous information which is not identifiable will be stored in locked cabinets and only the researcher and supervisor will have access to the data. fNIRS devices will be only accessible to the researchers, and the data/information be deleted from the device once transferred to storage.

Anonymised data might be used for additional or subsequent research studies and we might share anonymised data with other investigators (e.g. in online databases). All personal information that could identify you will be removed or changed before information is shared with other researchers or results are made public. The data provided will not be withdrawn as it will be unidentifiable.

9. What will happen to the results of the research project?

The investigator intends to complete a dissertation to satisfy their degree programme, publish the results in a PhD thesis, journal articles, or conference papers.

10. Who is organising and funding/commissioning the study?

This study is organised by Liverpool John Moores University and has no conflict of interest.

11. Who has reviewed this study?

This study has been reviewed by, and received ethics clearance through, the Liverpool John Moores University Research Ethics Committee (Reference number: 18/ERI/021).

12. What if something goes wrong?

If you have a concern about any aspect of this study, please contact the relevant investigator who will do their best to answer your query. The researcher should acknowledge your concern within 10 working days and give you an indication of how they intend to deal with it. If you wish to make a complaint, please contact the chair of the Liverpool John Moores University Research Ethics Committee (researchethics@ljmu.ac.uk) and your communication will be re-directed to an independent person as appropriate.

13. Data Protection Notice

The data controller for this study will be Liverpool John Moores University (LJMU). The LJMU Data Protection Office provides oversight of LJMU activities involving the processing of personal data, and can be contacted at secretariat@ljmu.ac.uk. This means that we are responsible for looking after your information and using it properly. LJMU's Data Protection Officer can also be contacted at secretariat@ljmu.ac.uk. The University will process your personal data for the purpose of research. Research is a task that we perform in the public interest.

Your rights to access, change or move your information are limited, as we need to manage your information in specific ways in order for the research to be reliable and accurate. If you withdraw from the study, we will keep the information about you that we have already obtained.

You can find out more about how we use your information by contacting secretariat@ljmu.ac.uk.

If you are concerned about how your personal data is being processed, please contact LJMU in the first instance at secretariat@ljmu.ac.uk. If you remain unsatisfied, you may wish to contact the Information Commissioner's Office (ICO). Contact details, and details of data subject rights, are available on the ICO website at: https://ico.org.uk/for-organisations/data-protection-reform/overview-of-the-gdpr/individuals-rights/

16. Contact for further information

Shiqi Fan, 1st Floor research suite, GERI building, S.Fan@2017.ljmu.ac.uk

Thank you for reading this information sheet and for considering to take part in this study.

Note: A copy of the participant information sheet should be retained by the participant with a copy of the signed consent form.

Appendix C Contributions to journals

- The work in ***Chapter 4*** has contributed to the following papers:

1. Fan, S., Yang, Z., Blanco-Davis, E., Zhang, J., & Yan, X. (2020). Analysis of maritime transport accidents using Bayesian networks. Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability, 234(3), 439-454.

2. Fan, S., Blanco-Davis, E., Yang, Z., Zhang, J., & Yan, X.(2020). Incorporation of human factors into maritime accident analysis using a data-driven Bayesian network. Reliability Engineering & System Safety, accepted.

3. Fan, S., Zhang, J., Blanco-Davis, E., Yang, Z., & Yan, X. (2020). Maritime accident prevention strategy formulation from a human factor perspective using Bayesian Networks and TOPSIS. Ocean Engineering, accepted.

4. Fan, S., Zhang, J., Blanco-Davis, E., Yang, Z., Wang, J., & Yan, X. (2018). Study on seafarers' emotion identification during watch-keeping using bridge simulation. In Safety and Reliability-Safe Societies in a Changing World-Proceedings of the 28th International European Safety and Reliability Conference, ESREL 2018 (pp. 347-354). Taylor & Francis.

5. Fan S., Yan X., Zhang J., Wang J.(2017). A Review on Human Factors in Maritime Transportation Using Seafarers' Physiological Data. Proceedings of the 4th International Conference on Transportation Information and Safety (ICTIS). August 8 - August 10, 2017, Banff, Alberta, Canada.

- The work in ***Chapter 5*** has contributed to the following papers:

1. Fan, S., Yang, Z., Blanco-Davis, E., Zhang, J., & Yan, X. (2020). Analysis of maritime transport accidents using Bayesian networks. Proceedings of the Institution

of Mechanical Engineers, Part O: Journal of Risk and Reliability, 234(3), 439-454.

2. Fan, S., Blanco-Davis, E., Yang, Z., Zhang, J., & Yan, X.(2020). Incorporation of human factors into maritime accident analysis using a data-driven Bayesian network. Reliability Engineering & System Safety, accepted.

- The work in ***Chapter 6*** has contributed to the following papers:

1. Fan, S., Blanco-Davis, E., Yang, Z., Zhang, J., & Yan, X.(2020). Incorporation of human factors into maritime accident analysis using a data-driven Bayesian network. Reliability Engineering & System Safety, accepted.

2. Fan, S., Zhang, J., Blanco-Davis, E., Yang, Z., & Yan, X. (2020). Maritime accident prevention strategy formulation from a human factor perspective using Bayesian Networks and TOPSIS. Ocean Engineering, accepted.

- The work in ***Chapter 7*** and ***Chapter 8*** has contributed to the following paper:

Fan, S., Blanco-Davis, E., Zhang, J., Bury A., Warren J., Yang Z., Yan, X., Wang J., Fairclough, S.. The Role of the Prefrontal Cortex & Functional Connectivity in Watchkeeping and Collision Avoidance during Maritime Operations: An fNIRS study. Brain and Behavior, under peer review.