

**NANYANG  
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**SINGAPORE**

DATA-DRIVEN, CONTEXT-AWARE HUMAN  
FATIGUE MANAGEMENT IN TRAFFIC CONTROL  
CENTERS

LI FAN

SCHOOL OF MECHANICAL & AEROSPACE

ENGINEERING

2020



**DATA-DRIVEN, CONTEXT-AWARE HUMAN  
FATIGUE MANAGEMENT IN TRAFFIC CONTROL  
CENTERS**

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**School of Mechanical and Aerospace Engineering**

**A thesis submitted to the Nanyang Technological University  
in partial fulfillment of the requirement for the degree of Doctor  
of Philosophy**

**2020**



## Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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## Authorship Attribution Statement

This thesis contains material from 4 papers published in the following peer-reviewed journals and from 4 papers accepted at conferences in which I am listed as an author.

Chapter 3 contains material from **Li, F.**, Chen, C. H., & Khoo, L. P. (2016). Information Requirements for Vessel Traffic Service Operations. *World Academy of Science, Engineering and Technology, International Journal of Computer, Electrical, Automation, Control and Information Engineering*, 10(5), 915-919; **Li, F.**, Lee, Y. C., Xu, G., Chen, C. H., & Khoo, L. P. (2017). Identifying causal factors of human fatigue in vessel traffic system. *Applied Human Factors and Ergonomics*. Springer, Cham (Abstract).

The contributions of the co-authors are as follows:

- Prof Chen and Prof Khoo provided the initial project direction and edited the manuscript drafts.
- I prepared the manuscript drafts. The manuscript was revised by Dr. Lee Yu-Chi and Dr. Xu Gangyan.

Chapter 4 contains material from Renata, V., **Li, F.**, Chen, C. H., & Khoo, L. P. (2018, Oct). Investigation on the Correlation between Eye Movement and Reaction Time under Mental Fatigue, In *Cyberworlds (CW), 2018 International Conference on*. IEEE; **Li, F.**, Chen, C. H., Xu, G., Khoo, L. P., & Liu, Y. (2019). Proactive mental fatigue detection of traffic control operators using bagged trees and gaze-bin analysis. *Advanced Engineering Informatics*, 42, 100987

The contributions of the co-authors are as follows:

- Prof Chen and Prof Khoo provided the initial project direction and edited the manuscript drafts.
- I prepared the manuscript drafts. The manuscript was revised by Dr Lee Ching-Hung and Dr Liu Yisi.

- Miss Renata conducted the experiments under my instructions.

Chapter 5 is published as **Li, F.**, Chen, C. H., Khoo, L. P., & Xu. G. (2018, Dec), Contextual Information-based Human Fatigue Prediction for Integrated Traffic Control, *In the 48th International Conference on Computers and Industrial Engineering (CIE 48)*, and **Li, F.**, Chen, C. H., Zheng, P., Feng, S., Xu, G., & Khoo, L. P. (2020). An explorative context-aware machine learning approach to reducing human fatigue risk of traffic control operators. *Safety Science*, 125, 104655.

The contributions of the co-authors are as follows:

- Prof Chen and Prof Khoo provided the initial project direction and edited the manuscript drafts.
- I wrote the drafts of the manuscript. The manuscript was revised together with Dr. Xu Gangyan and Dr. Zheng Pai.

Chapter 6 contains materials from **Li, F.**, Chen, C. H., Lee, C. H.\*, & Khoo, L. P. (2020), A User Requirement-driven Approach Incorporating TRIZ and QFD for Designing Smart Vessel Alarm System to Reduce Alarm Fatigue. *Journal of Navigation*, 1-21; **Li, F.**, Lee, C. H.\*, Chen, C. H., & Khoo, L. P. (2020), Hybrid data-driven vigilance model in traffic control center using eye-tracking data and context data. *Advanced Engineering Informatics*, 42, 100940.

The contributions of the co-authors are as follows:

- Prof Chen and Prof Khoo provided the initial project direction and edited the manuscript drafts.
- I prepared the manuscript drafts. The manuscript was revised by Dr Lee Ching-Hung.

5 / 3 / 2020

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## Abstract

Traffic control operators (TCOs) are at risk of human fatigue due to their heavy workload, their monotonous work, and the long duration of their shift work. Human fatigue can result in inefficiency, impaired alertness, and even a high probability of human error, and it has been identified as the primary cause of many traffic accidents. Thus, much research has focused on the management of human fatigue in transportation. However, strategies for managing human fatigue in transportation mainly focus on a single aspect of human fatigue, such as mental fatigue or physical fatigue. In addition, the existing strategies primarily center on prescriptive hours-of-work regulations. However, such regulations lack flexibility and fail to consider factors such as individual differences and the dynamic working conditions involved in traffic control. To fill this research gap, this study aims to develop context-aware human fatigue management strategies based on dynamic interactions between the contextual factors of human fatigue other than hours of work.

In this study, data-driven approaches are proposed to prevent and mitigate human fatigue across traffic control centers (TCCs) and to develop context-aware fatigue management, which consists of four parts: task-driven causal factor analysis (TCFA), eye movement-based fatigue detection (EMFD), context-aware human fatigue prediction (CHFP) and data-driven intervention design (DID). Specifically, TCFA identifies and evaluates direct and indirect causal factors using a fatigue causal network that considers the multidimensional aspects of human fatigue. EMFD enables an objective and unobtrusive assessment of human fatigue by conducting gaze-bin analysis to

obtain inputs for semisupervised bagged trees. EMFD paves the way for an alternative means of detecting human fatigue and enables the application of a low sampling rate eye tracker in TCCs. CHFP adopts a novel fatigue causal network and bagged tree techniques to predict human fatigue based on complex and interacting context data. Both dynamic work conditions and individual differences are considered in CHFP. To lower the occurrence of fatigue, a novel scheduling algorithm and a user requirement (UR)-driven framework for the redesign of traffic alarm systems are developed to achieve DID, which adaptively arranges work for operators by considering individual differences and work types and provides recommendations for reducing alarm fatigue.

Several case studies were conducted in vessel traffic service centers to demonstrate and test the efficiency of the proposed context-aware human fatigue management approach. TCFA enabled both direct and indirect causal factor analysis. EMFD achieved an excellent accuracy of 89%, outperforming other classical methods, while CHFP achieved a high accuracy of 89%. Furthermore, DID, which adaptively arranges work for operators by considering individual differences and work types, showed that 27% of operators could be rearranged to reduce the possibility of human fatigue.

In conclusion, this research develops a novel context-aware system for human fatigue management that advances the applications of artificial intelligence (AI) in human factor studies, provides insightful guidance for safety managers regarding the mitigation of human fatigue, and lays the foundation for further explorations of context-aware safety management.

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## List of Publications

### International Journals

**Li, F.,** Chen, C. H., Lee, C. H.\*, & Khoo, L. P., A User Requirement-driven Approach Incorporating TRIZ and QFD for Designing Smart Vessel Alarm System to Reduce Alarm Fatigue. *Journal of Navigation*, 1-21.

**Li, F.,** Lee, C. H.\*, Chen, C. H., & Khoo, L. P., Hybrid data-driven vigilance model in traffic control center using eye-tracking data and context data. *Advanced Engineering Informatics*, 42, 100940.

**Li, F.,** Chen, C. H., Khoo, L. P., & Xu. G.\*, Proactively Detection of Human Fatigue in Traffic Control Center using the Bagged Trees and Gaze-bin Analysis, *Advanced Informatics Engineering*, 42, 100987.

**Li, F.,** Chen, C. H., Zheng, P., Feng, S., Xu, G., & Khoo, L. P. (2020). An explorative context-aware machine learning approach to reducing human fatigue risk of traffic control operators. *Safety Science*, 125, 104655.

**Li, F.,** Chen, C. H., Xu. G., Khoo, L. P., & Chang, D.\*, Key Causal Factors of Human Fatigue in Vessel Traffic Service: A Task-drive Approach, *Journal of Navigation*. (Minor revision)

**Li, F.,** Chen, C. H., Khoo, L. P. & Xu. G.\*, Hierarchical Interpolation-based Eye-tracking Data Analysis for Human Fatigue Detection in Traffic Control Center, *IEEE Transactions on Human Machine System*. (Minor revision)

**International Conferences**

**Li, F.**, Chen, C. H., & Khoo, L. P. (2016). Information Requirements for Vessel Traffic Service Operations. *World Academy of Science, Engineering and Technology, International Journal of Computer, Electrical, Automation, Control and Information Engineering*, 10(5), 915-919.

**Li, F.**, Chen, C. H., Khoo, L. P., & Xu, G. (2018, Dec), Contextual Information-based Human Fatigue Prediction for Integrated Traffic Control, *In the 48th International Conference on Computers and Industrial Engineering (CIE 48)*.

**Li, F.**, Lee, C. H., Xu, G., Chen, C. H., & Khoo, L. P. (2017). A QFD-Enabled Conceptualization for Reducing Alarm Fatigue in Vessel Traffic Service Centre. *Transdisciplinary Engineering: A Paradigm Shift: Proceedings of the 24th ISPE Inc. International Conference on Transdisciplinary Engineering, July 10-14 2017 (Vol. 5)*. IOS Press.

**Li, F.**, Lee, Y. C., Xu, G., Chen, C. H., & Khoo, L. P. (2017). Identifying causal factors of human fatigue in vessel traffic system. *In International Conference on Applied Human Factors and Ergonomics. Springer, Cham* (Abstract).

Renata, V., **Li, F.**, Chen, C. H., & Khoo, L. P. (2018, Oct). Investigation on the Correlation between Eye Movement and Reaction Time under Mental Fatigue, *In Cyberworlds (CW), 2018 International Conference on*. IEEE.

Xu, G., **Li, F.**, & Chen, C. H. (2017, August). Local AIS data analytics for efficient operation management in Vessel Traffic Service. *In Automation*

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*Science and Engineering (CASE), 2017 13th IEEE Conference on (pp. 1668-1672). IEEE.*

Li, Q. Y., Lee, C. H., Chen, C. H., Lee, Y. C., & **Li, F.** (2017). Dynamic Enhancement for Customer Experience by Incorporating Customer Experience Journey Map and Service Assembly Concept. *In Proceedings of the 24 th ISPE Inc. International Conference on Transdisciplinary Engineering: A Paradigm Shift (Vol. 5, pp. 860-867).*

Xu, G., **Li, F.**, Chen, C. H., Lee, C. H., & Lee, Y. C. (2015). Toward Resilient Vessel Traffic Service: A Sociotechnical Perspective. *Transdisciplinary Engineering: A Paradigm Shift*, 829.

## Acknowledgments

I attribute the completion of this thesis to the support and encouragement of many people.

First and foremost, I would like to extend my heartfelt gratitude to my supervisor, Associate Professor Chen Chun-Hsein, and Cosupervisor, Professor Khoo Li Pheng, whose patient guidance, valuable suggestions and constant encouragement allowed me to successfully complete this thesis. Their conscientious academic spirit and modest, open-minded personalities inspire me both in my academic career and in my everyday life. They gave me extensive help and advice during the whole writing process, making my accomplishments possible.

Additionally, I would like to express my sincere gratitude to my advisors, Dr. Xu Gangyan, Dr. Song Jia Hong, and Dr. Zheng Pai, who directly instructed me in reviewing papers, conducting studies, and writing academic papers. Their instructions helped broaden my horizon and provided me with a clear direction by which to complete this paper. Their guidance will always be of great value and will continue to be important in my future academic research.

My thanks also go to my friends whose companionship and assistance have brightened my everyday life throughout the years of my postgraduate studies.

Last but not least, I would like to express my special thanks to my family, my parents and my older brother, whose care and support have motivated me to move forward and make me want to be a better person.

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## List of Abbreviations

<b>Abbreviations</b>	<b>Full title or explanation</b>
<b>AAR</b>	Alarm assignment rules
<b>AH</b>	Alarm handling
<b>AI</b>	Artificial intelligence
<b>AIS</b>	Artificial immune system
<b>AIS-XGBFP</b>	Artificial immune system-extreme gradient boosting-enabled fatigue prediction
<b>ANOVA</b>	Analysis of variance
<b>AP</b>	Alarm presentation
<b>AS</b>	Alarm shelving
<b>ATA</b>	Alarm trigger algorithm
<b>AuIS</b>	Automated identification system
<b>BA</b>	Blink amplitude
<b>BP</b>	Blood pressure
<b>CART</b>	Classification and regression tree algorithm
<b>CBR</b>	Case-based reasoning
<b>CCTV</b>	Closed-circuit television
<b>CF</b>	Causal factor
<b>CR</b>	Circadian rhythms
<b>DCPA</b>	Distance to closest point of approach
<b>DEFS</b>	Dutch exertion fatigue scale
<b>DFS</b>	Dutch fatigue scale
<b>D-FS</b>	Depth-first search algorithm
<b>DI</b>	Demographic information
<b>DID</b>	Data-driven intervention design
<b>DR</b>	Design requirement
<b>DTR</b>	Decision tree regression
<b>DV</b>	Demographic variables
<b>EDR</b>	Electrodermal response
<b>EEG</b>	Electroencephalogram
<b>EEUMA</b>	Engineering equipment and materials users association
<b>EMFD</b>	Eye movement-based fatigue detection
<b>FAID</b>	Fatigue audit inter dyne
<b>FSS</b>	Fatigue severity scale
<b>HoQ</b>	House of quality
<b>HRV</b>	Heart rate variability
<b>HTA</b>	Hierarchy task analysis
<b>ICT</b>	Information and communication technology
<b>INS</b>	Information service
<b>IoT</b>	Internet of things
<b>ISO</b>	International organization for standardization
<b>LCR</b>	Long closure rate
<b>LR</b>	Linear regression
<b>NASA-TLX</b>	NASA task load index

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<b>NHTSA</b>	National highway traffic safety administration
<b>PC</b>	Physical conditions
<b>PF</b>	Personality factors
<b>PERCLOS</b>	Percentage of eyelid closure over time
<b>PI</b>	Personality information
<b>PQT</b>	UR-driven design framework
<b>PTMS</b>	Port traffic management system
<b>QFD</b>	Quality function deployment
<b>RESEFNN</b>	Recurrent self-evolving fuzzy neural network
<b>RFR</b>	Random forest regression
<b>RR</b>	Respiration rate
<b>SAFE</b>	System for aircrew fatigue evaluation
<b>SAFTE</b>	Sleep, activity, fatigue, and task effectiveness
<b>SCM</b>	Swiss cheese model
<b>SF</b>	Signal filter
<b>SOLAS</b>	Safety of life at sea
<b>SOP</b>	Standard operating procedure
<b>SVM</b>	Support vector machine
<b>TCCs</b>	Traffic control centers
<b>TCFA</b>	Task-driven causal factor analysis
<b>TCOs</b>	Traffic control operators
<b>TCPA</b>	Time to closest point of approach
<b>TRIZ</b>	Theory of inventive problem solving
<b>UR</b>	User requirement
<b>VTM</b>	Vessel traffic management
<b>VTS</b>	Vessel traffic service
<b>VTSO</b>	Vessel traffic service operators
<b>WC</b>	Working conditions
<b>XGBoost</b>	Extreme gradient boosting

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## **Chapter 1 Introduction**

This chapter consists of five sections. The research background is presented in Section 1.1, in which the importance of human fatigue management and the necessity of context-aware management are highlighted. Based on the research background, the objectives of this study are stated in Section 1.2, followed by the scope of this research in Section 1.3. Subsequently, the significance of this research is elucidated in Section 1.4. The introductory conclusion, with an outline of the organization of this thesis, is given in Section 1.5.

### **1.1 Background**

Traffic control centers (TCCs) provide services to traffic operators (e.g., drivers, pilots, and masters) to maintain the flow and safety of traffic and to decrease environmental impacts while improving economic efficiency. TCCs are implemented for all modes of transport, including vessel traffic service, air traffic management, freeway traffic management and rail traffic control [1-3]. Unlike traffic operators, the work of traffic control operators (TCOs) includes intense information processing and passive monitoring instead of active control [4]. In addition, they work around the clock in shifts to guarantee smooth traffic, mitigate delays and improve the safety of the traffic network. Shift work has been found to be a major cause of human fatigue in transportation [5], as it interrupts the sleep-wake cycle and degrades the sleep conditions. As a result, TCOs usually face a higher probability of human fatigue [6] than traffic operators, inducing higher chances of disastrous outcomes for public safety [7, 8].

Human fatigue can lead to a delay in response time, undermine the capacity for information integration, and even reduce situational awareness. Fatigue is increasingly considered to be the primary cause of most traffic accidents [9], and the National Highway Traffic Safety Administration (NHTSA) reported that drowsy drivers cause nearly 100,000 crashes per year in the United States of America [7]. A survey of 1488 pilots found that 71% of them suffered from fatigue [10]. In rail transport, “an operator falling asleep” has been frequently reported as a contributing factor in critical accidents [11]. Hence, it is imperative and vital to manage and address human fatigue in TCCs.

Recently, organizations and researchers have advocated improving work schedules as the main solution to reduce the risk of human fatigue [12]. Such organizations and researchers increasingly rely on biomathematical fatigue models to assess the likelihood of human fatigue under a given work schedule and to manage the impact of shift design [13, 14]. It is important to assess the human fatigue of TCOs associated with a given work schedule. Nevertheless, emerging fatigue models in other fields are not adequate for traffic control due to the following challenges. First, existing models focus on time effects [15] and pay insufficient attention to dynamic working conditions. The working conditions of TCOs vary with vehicle type, traffic density and weather conditions and usually impose a dynamic workload on TCOs [16]. Nevertheless, the existing fatigue models assume that operators have a stable workload. Second, few current models consider individual differences in response to fatigue-inducing factors. In general, there are dramatic individual differences in the experience of human fatigue [14]. Depending on factors such

as personality, age, and experience, the degree of human fatigue varies significantly for different TCOs under the same working conditions [17, 18].

Considering these two limitations, context-aware management may be adopted to reduce the risk of human fatigue. The goal of context-aware management is to acquire and utilize contextual information to provide appropriate services to a particular type of people at a specific time [19]. In this study, context-aware management will provide a foundation for adaptive fatigue prediction and work arrangement. In general, context includes information about the present status of any entity in the environment [19]. Specifically, the context of human fatigue includes fatigue-inducing factors and the effects of human fatigue on psychophysiological behaviors. According to recent studies, considering more related factors would be beneficial for managing human fatigue [7, 12, 20].

In summary, the complex interactions among fatigue-inducing factors highlight the necessity of context-aware fatigue management. Nevertheless, context-aware management is a relatively new field of research. Applying this approach to human fatigue management in TCCs involves several challenges:

- 1) Human fatigue is usually confused with tiredness and drowsiness [21]; in some studies, human fatigue, tiredness, and drowsiness are synonymous [6]. Nevertheless, some researchers have suggested that there are significant differences between drowsiness and human fatigue [22]. Wolf et al. [23] found correlations and differences in reported sleep and perceived fatigue. Hence, it is necessary to clearly define “human fatigue” before identifying its causal factors.

- 2) There is an inordinate number of interacting factors that induce human fatigue [24]. Considering their complex interrelationships, it is very challenging to determine the key causal factors of human fatigue, and it is difficult to objectively assess the importance of such causal factors due to the limited number of accident reports related to human fatigue. In general, the objective measurement of such factors hinges on statistical data derived from incidents and accidents [25]. Nevertheless, human fatigue is usually underestimated, and it is not included in traffic disaster reports [26].
- 3) Measuring human fatigue in any situation is complex, and no effective and direct method is currently available.
- 4) Traffic conditions are dynamic and complex. Since human fatigue is significantly affected by individual differences and working conditions, which vary with vehicle types, traffic density and weather conditions[27], it remains a challenge to predict operators' fatigue and arrange their work schedules accordingly.

This thesis presents a formal study of these four issues. Considering the complex and dynamic challenges involved in these four issues, the proposed study adopts Artificial Intelligence (AI) techniques, such as artificial immune system, support vector machines, and neural networks, etc., to establish a data-driven, context-aware systematic framework for managing human fatigue. These techniques facilitate data analysis and decision making and have been widely employed in context-aware management [28].

## 1.2 Objectives

The overall goal of this thesis is to establish a *data-driven, context-aware systematic* framework for managing human fatigue. Accordingly, this goal is decomposed into several subobjectives to address the following key research issues:

*1) Identify the critical causal factors of human fatigue in TCCs*

Recognizing the causal factors is generally considered the first step in managing human fatigue [7], and understanding these factors can help in developing fatigue countermeasures [29]. Fundamentally, human fatigue-inducing factors differ for varying fields [30]. Different job scopes or tasks may have significantly different causal factors. Hence, the primary goal of this study is to identify the causal factors of human fatigue in TCCs.

*2) Measure human fatigue objectively and unobtrusively in real time*

One way to minimize the risks of human fatigue is to monitor human fatigue and to alert fatigued subjects. Hence, fatigue monitoring in dynamic and safety-critical traffic control tasks has been increasingly recognized for its importance in improving safety. To address this problem, this research intends to develop an objective and unobtrusive approach to the detection of human fatigue using bio signals, which have high time resolution [31]. Given the large quantity of bio signals data, the AI techniques, such as support vector machines and decision trees are used to facilitate data-driven detection of human fatigue.

*3) Predict levels of human fatigue based on context data*

Human fatigue prediction can be used to schedule working time, improve operational flexibility, and guarantee safety [13, 14, 32, 33]. Considering the dynamic work conditions of TCCs, the integration of contextual information for

the purpose of human fatigue prediction must be achieved. Contextual information can be collected by ubiquitous sensors, such as smart phones. The interactions among contextual information are dynamic and complex [28]. Hence, an adaptive and coevolve algorithm of AI techniques, such as an artificial immune system, could be used to handle the contextual information of human fatigue.

*4) Design context-aware interventions to reduce the possibility of human fatigue*

In transportation, the existing strategies for managing human fatigue primarily consist of undertaking prescriptive “hours-of-work” regulations [27]. However, these regulations lack a certain flexibility and fail to consider the dynamic fatigue-inducing factors in context. Hence, this study proposes to design context-aware interventions to manage human fatigue.

### **1.3 Scope**

Concerning the research objectives, this thesis concentrates on issues of human fatigue in TCOs and relies on context data to facilitate human fatigue management. The scope of this research is as follows:

*1) An approach for analyzing the causal factors of human fatigue in TCCs*

This approach identifies and evaluates the causal factors of human fatigue in TCCs. Therefore, a definition of human fatigue in TCCs will be introduced and discussed. Additionally, a novel method will be proposed to guide users to determine the direct and indirect factors that induce human fatigue. Furthermore, an importance estimation strategy will be developed to evaluate the importance of causal factors considering the interrelationships among them.

*2) An objective measurement of human fatigue*

This tool is expected to assess human fatigue objectively and unobtrusively. To fulfill this task, human factor experiments will be conducted to collect eye movement data, which can be obtained unobtrusively. Since eye movement data are typically of low quality, a method will be deployed to clean the eye movement data. Some eye movement-based parameters will be defined, and a novel algorithm will be developed to assess human fatigue.

*3) A context-aware human fatigue predictor*

This model analyzes causal factors that can be derived from contextual information and presents a hybrid approach to the prediction of the human fatigue of TCOs via the causal factors captured. A novel way in which to represent the numerous complex causal factors will be proposed. Based on the novel inputs, an algorithm to predict human fatigue based on context data will be developed. Furthermore, the benefits of integrating working conditions and individual differences in human fatigue prediction will be illustrated with a case study.

*4) Interventions to reduce the risks of human fatigue considering individual differences and working conditions*

Considering the multidimensional aspects of human fatigue, several interventions should be designed. A scheme for assigning operators to appropriate work sectors at a particular time based on context data will be developed, and a novel and systematic platform for context data collection will be established. Moreover, a method will be established to provide recommended arrangements considering individual differences and working conditions. Furthermore, a conceptual framework for reducing other aspects of human fatigue will be developed. It is expected that the interventions will

improve overall performance and reduce the overall risk of human fatigue in TCCs.

#### **1.4 Significance of the research**

The fulfillment of the research objective will contribute to the following research areas.

*1) Exploratory research on context data in human fatigue management in TCCs*

While practitioners have gradually realized the importance of considering the context in managing human fatigue, to date, especially in the traffic control fields, this aspect has not been exploited. This research is positioned to make a pioneering contribution by elucidating the prospect of context data in fatigue management on a theoretical level and by supporting adaptive work arrangement on a practical level, which will benefit both TCOs and safety managers.

*2) Development of a context-aware scheme for human fatigue management*

This scheme involves a careful study of the definition of human fatigue in TCCs and the specific research problems caused by integrating context data in each fatigue management phase and the development of novel or advanced methods and approaches to tackle these research problems. Hence, academic contributions to the realization of such systematic, context-aware fatigue management are expected.

These two areas cover the significance of this study in general. In Chapter 7 of the thesis, the distinct contributions that fall within these two areas are stated.

### 1.5 Organization of the thesis

As shown in Figure 1.1, this thesis is organized as follows.

Chapter 1 introduces the background, objectives, scope, significance, and overall architecture of this research.

Chapter 2 presents a comprehensive review of the extant literature. An investigation into the critical components of human fatigue management is performed, indicating the importance of the fatigue model for managing human fatigue. After a thorough analysis of human fatigue management, the potential of integrating context data in human fatigue management is explained. Subsequently, studies related to context data on human fatigue are carefully reviewed. The challenges of and necessity for a study on context-aware human fatigue management are discussed, and the previous studies on context-aware techniques are also reviewed. As a result, the directional orientation and grounding of this research are established at the end of this chapter.

Chapter 3 provides a novel definition of human fatigue and explains the task-driven causal factor analysis (TCFA) of human fatigue in TCCs. A task-driven approach for the identification of causal factors and a causal network-based approach for the selection of key causal factors are described. To demonstrate the effectiveness of the proposed approach, a case study of a local vessel traffic service center is presented.

Chapter 4 introduces eye movement-based fatigue detection (EMFD). In this chapter, eye movements are examined to reveal several novel fatigue indicators. An innovative method that involves gaze-bin analysis and semisupervised bagged trees is proposed. A lab-based experiment is then conducted to test the effectiveness of the proposed method.

Chapter 5 describes a hybrid approach to making a proactive prediction of human fatigue based on the contextual information of dynamic working conditions and individual differences. The fatigue causal network developed in substudy 1 is adopted to efficiently represent the context factors and their interactions. The artificial immune system (AIS) concept is adopted for context-aware fatigue management. Specifically, a novel method referred to as artificial immune system-extreme gradient boosting-enabled fatigue prediction (AIS-XGBFP) is proposed to establish a fatigue prediction model.

Chapter 6 provides two interventions for reducing the risks of human fatigue in TCCs. One intervention is focused on adaptive work arrangement. Specifically, a framework for the data-driven platform is established. Decentralized data collection is proposed to improve computational efficiency and to maintain model performance in the event of data loss. Based on Chapters 4 and 5, an algorithm is proposed to adaptively arrange work for operators considering individual differences and work types. Considering contextual information, adaptive fatigue management can adapt to the dynamic working conditions and individual resilience of TCOs. The other intervention is a user requirement (UR)-driven conceptual framework for redesigning traffic alarm systems. A method for collecting and analyzing URs based on quality function deployment (QFD) is proposed. In addition, to generate innovative ideas, the theory of inventive problem solving (TRIZ) is extended to traffic alarm system design.

Chapter 7 concludes the thesis with a summary of the research findings, discussion, and directions for future research.

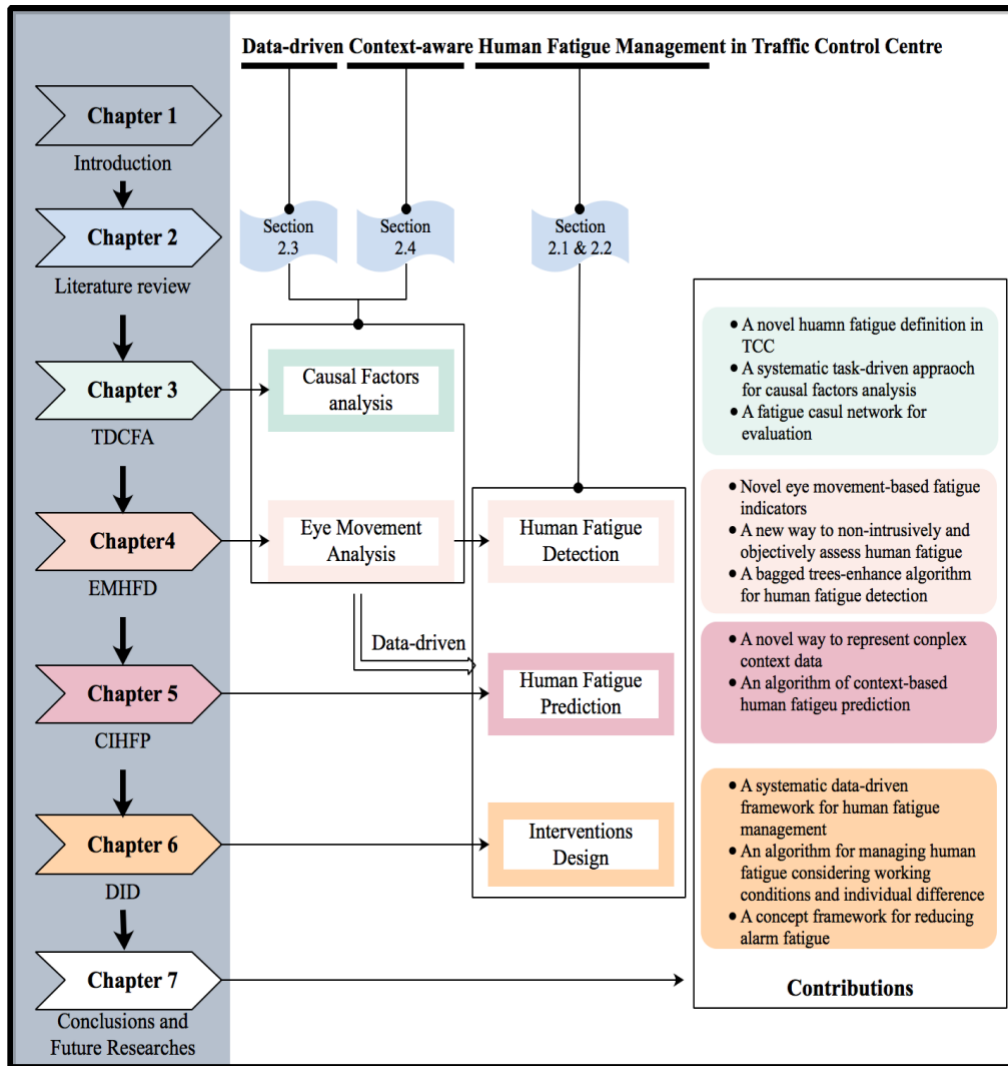


Figure 1.1 Organization of the thesis

## Chapter 2 Literature Review

This chapter presents the detailed background of this research and establishes the context of this thesis. First, Section 2.1 introduces the definition of human fatigue. Then, the importance and critical components of human fatigue management are presented in Section 2.2. Section 2.3 explores the complex data that describe the context and characteristics of human fatigue. Section 2.4 summarizes context-aware management in various fields. The considerable potential and uniqueness of context-aware techniques in managing human fatigue are identified; these findings inspired this study and encourage further efforts to leverage context awareness with regard to human fatigue management. The research gaps are specified in Section 2.5.

### 2.1 The concept of human fatigue

Human fatigue is generally defined as a state/condition caused by something. Hence, the definitions of fatigued conditions are first reviewed, followed by the causes of fatigue.

*Perceived condition/subjective feelings:* Several definitions describe human fatigue, especially mental fatigue, as a feeling [21, 22]. For example, Shen et al. [34] suggested that fatigue is an overwhelming sense of tiredness, a lack of energy and a feeling of exhaustion. These experiential definitions of human fatigue heavily depend on subjective sense and individual understanding. In addition, the links of perceived fatigue to human performance are not straightforward [22]. Hence, other researchers define human fatigue from the perspective of objective measurements, including psychophysiological depletion and performance decrement.

*Psychophysiological depletion:* Alonso et al. [26] claimed that fatigue is “one of the most dangerous psychophysical conditions”. Hirshkowitz [35] defined fatigue as “a decreased response of cells, tissues, or organs after excessive stimulation, stress or activity”. Although defining fatigue as a psychophysiological state allows fatigue levels to be objectively assessed, the complex psychophysiological mechanisms underpinning fatigue require more study. Phillips [22] even suggested that we might never understand the physiology of human fatigue. Hence, defining fatigue merely as a suboptimal psychophysiological condition provides limited practical benefits when conducting fatigue studies.

*Performance decrement:* Dodge [36] concluded that fatigued people are incapable of receiving sensorial information and sending motor responses. Charbonnier et al. [6] mentioned that mental fatigue is associated with a decrease in vigilance. Defining fatigue in terms of performance makes it possible to measure the levels of fatigue based on behavioral patterns. Hence, many studies use human performance as a fatigue indicator [37, 38].

The studies reviewed above focus on how researchers describe fatigue as a condition without considering the causes of human fatigue. In the following, the roots of fatigue are examined.

*Insufficient rest/sleep/recovery:* Fatigue is generally defined as a condition caused by inadequate rest [39]. This type of definition is used in a limited manner because it can easily be confused with drowsiness.

*Exertion:* Most studies agree that fatigue is caused by demanding physical or mental activities [6, 40]. Nevertheless, both high-demand and low-demand

work can induce human fatigue. In addition to the degree of exertion, the duration of exertion should be emphasized in defining human fatigue. Charbonnier [6] claimed that fatigue is caused by performing activities for an extended period of time.

*Subjective feelings:* Fatigue, especially mental fatigue, is always linked to people's emotions and motivations. Hockey [41] defined mental fatigue as a lack of motivation caused by the feeling that something is increasingly less rewarding over time. Montgomery et al. [42] defined mental fatigue as "the unwillingness of alert, motivated subjects to continue performing a specific mental task". In these definitions, fatigue is caused by subjective feelings such as unwillingness and a bad mood.

*Health:* According to the Oxford English Dictionary, fatigue can result from illness. Although many studies indicate that fatigue is often caused by illness, food intake and habits [24], few definitions in the engineering fields mention these factors [22].

Table 2.1 summarizes all the definitions mentioned above. Most researchers suggest that fatigue is a psychophysiological condition caused by exertion. However, there is still no definition that considers the specific consequences of fatigue and the effects of both exertion and subjective feelings. Phillips [22] claimed that the definition of fatigue should include experiential fatigue as a central aspect. Hence, in this study, a novel definition of human fatigue that accounts for the interactions between subjective feelings and exertion in relation to psychophysiological states is proposed.

Table 2.1 Summary of human fatigue definitions

Source	Cause				Consequence		
	Exertion	Subjective feelings	Rest	Health	Perceived condition	Psychophysiological depletion	Performance decrement
Phillips et al., 2015 [22]	√					√	
Shen et al., 2006 [34]					√		
Trejo et al., 2015 [21]					√	√	
Alonso et al., 2016 [26]	√					√	
Hirshkowitz, 2013 [35]	√					√	
Dodge, 1982 [36]	√						√
Charbonnier et al., 2016 [6]	√						√
Gander, 2001 [27]			√				√
Job and Dalziel, 2001 [43]			√			√	
Van Cutsem et al., 2017 [40]	√					√	
Hockey, 2013 [41]		√			√		
Montgomery et al., 1995 [42]		√					
Oxford dictionaries				√			

## 2.2 Human fatigue management

### 2.2.1 Ideal human fatigue management

Human fatigue management originated from the aviation and military domains and it has received increasing research attention. Human fatigue management continues to evolve [14, 44], as human fatigue has been widely accepted as a major cause of traffic accidents. In general, human fatigue management includes several complementary elements. Khosro and Zohreh [45] found that optimal human fatigue management includes both *fatigue reduction* and *fatigue proofing* strategies. Fatigue reduction means reducing the likelihood that a worker will experience human fatigue. By contrast, fatigue proofing refers to decreasing the probability that a fatigued worker will make errors [46]; for example, complex tasks should be assigned to an alert worker. Different from Sadeghniaat-Haghighi and Yazdi [45], Leman et al. [47] suggested that human fatigue management consists of comprehensive processes for *measuring*,

*mitigating*, and *managing* fatigue risk. In fact, most researchers support the idea that human fatigue management includes at least three elements, and they suggest measuring human fatigue as the first step in managing fatigue in the workplace [45, 48].

Balkin et al. [48] reviewed technological approaches to fatigue management over the past decade and concluded that optimal human fatigue management includes three parts:

- *Human fatigue measurement*: the ability to measure and monitor fatigue/performance online in the operational environment (as a backup and check of the performance prediction model);
- *Human fatigue prediction*: the ability to predict fatigue, based on the factors that produce it, well before operational performance; and
- *Intervention*: the ability to effectively intervene when potential deficits are identified or anticipated. Organizations and researchers have advocated work schedule improvement as the primary solution to reducing the risks of human fatigue [12].

In agreement with [48], this study intends to propose systematic human fatigue management based on these three aspects. In the following sections, the existing literature related to human fatigue measurement, human fatigue prediction, and work arrangement is reviewed.

### **2.2.2 Fatigue measurement**

Fatigue measurement is an indispensable part of human fatigue forecasting [7, 49, 50]. Because measuring human fatigue in any situation is complicated,

no practical methods are currently available. The fatigue measures reported in the current literature can be categorized into performance measures, psychological measures, and subjective measures.

*Performance measures:* Fatigue results in impaired performance and reduces work efficiency [37]. Therefore, the degradation of task performance has been widely utilized as a fatigue indicator [51, 52].

Pimenta et al. [37] employed a neural network to classify fatigue based on human performance, such as key-down time, the time between keys, mouse velocity, and mouse acceleration. Additionally, perceptual functions, performance continuity, and time regularity can be employed to detect human fatigue [51].

*Psychophysiological measures:* Electroencephalogram (EEG) activity, heart activity and eye movements are the most commonly used physiological indicators of human fatigue. Chai et al. [53] used a Bayesian neural network to predict human fatigue levels; the predictions of this neural network resulted in an accuracy of 76% [53]. However, EEG features were differently distributed across different sessions [54]. Thus, accurate recognition of human fatigue requires more research. Lin et al. [55] proposed a generalized EEG-based self-organizing neural fuzzy system to predict the human fatigue level of drivers and found that it was feasible to estimate a subject's reaction times based on 1 second of EEG data. However, this system could only provide assistive warnings to the fatigued driver. Based on the research of Lin et al. [55], Chuang et al. [56] proposed a recurrent self-evolving fuzzy neural network (RESEFNN) to predict driving fatigue based on brain dynamics. Considering the continuous and cumulative process of the human cognitive state, they developed a recurrent

structure to remember past events. Compared with nonrecurrent structures, the RESEFNN exhibited significantly improved performance [56].

Based on the effects of fatigue on heart rate variability (HRV), Patel et al. [57] presented an AI system to detect the early onset of fatigue in drivers. However, some studies found that using HRV as a fatigue indicator was somewhat unreliable [58]. In addition to heart rate variables, other well-known physiological measures exist, such as electrodermal response (EDR), respiration rate (RR) and blood pressure (BP) [58, 59].

The eye movement measurement of human fatigue includes eyelid movement measures and eye fixation measures. Han et al. [60] proposed a method that requires only eyelid movement information to detect driver drowsiness. However, the performance of this method is affected by the limited amount of data.

In addition, some researchers have used multidimensional psychophysiological data to measure human fatigue. Zhao et al. [61] applied dual indicators of the percentage of eyelid closure over time (PERCLOS) and the power ratio of alpha, beta, and theta waveforms to identify whether a driver was in a state of fatigue [60]. Moreover, Ji et al. [62] employed eyelid movement, fixation movement, head movement, and facial expressions to infer robust, accurate and reliable fatigue characterizations. Bergasa et al. [63] combined PERCLOS, eye closure duration, the blink rate, the nodding rate, face position and fixed gaze to predict the level of fatigue of drivers.

*Subjective Measures:* In general, three types of subjective measures have been used to rate subjective human fatigue: the sleepiness scale, the workload scale and the fatigue scale [39]. Both the sleepiness and workload scales are

indirect scales. Samn and Perelli [64, 65] proposed a fatigue scale called the Samn-Perelli Fatigue Scale to record presleep fatigue and postsleep fatigue. In addition to the Samn-Perelli Fatigue Scale, there are other fatigue scales, such as the fatigue severity scale (FSS), the Dutch fatigue scale (DFS), and the Dutch exertion fatigue scale (DEFS) [66]. These scales mainly measure the severity of fatigue and investigate how fatigue affects the activities of subjects in terms of aspects such as motivation and physical functioning. Some visual analogy fatigue scales have also been proposed to measure fatigue [67, 68]. However, most such scales measure fatigue severity and are utilized in the healthcare context.

The subjective measurement of human fatigue has the advantages of effectiveness, efficiency, and low cost. However, participants in subjective assessment must be trained to detect and evaluate their fatigue correctly and efficiently [69]. In addition, the successful monitoring of human fatigue levels depends on the cause and type of fatigue experienced.

### ***2.2.3 Fatigue prediction***

Predicting human fatigue is the most important part of the human fatigue research [7]. To date, some research has been conducted to predict human fatigue based on working time and circadian rhythms. Such studies can be broadly classified into two-process and three-process models.

As early as 1982, Borbély [70] proposed a model of human fatigue that involves two processes: Process S and Process C. Process S presents the effects of sleep and waking time on the level of human fatigue whereas Process C considers the interactions between circadian rhythms and sleep-wake independence. The two-process fatigue model includes the sleep-wake history

as the only input in the prediction of human fatigue. Many efforts have been made to broaden the application of the two-process fatigue model [71].

*System for Aircrew Fatigue Evaluation (SAFE)* [71]: The SAFE implements a two-process model to forecast fatigue in the field of civil aviation. It employs the sleep-wake history as the input and predicts human fatigue directly from sleep-wake data.

*Fatigue Audit Inter Dyne (FAID)* [72]: The FAID model was developed based on the two-process model. Unlike the SAFE, the FAID model takes shift schedules as inputs. Based on shift schedules, the FAID model can infer the average sleep time and then predict the level of human fatigue [15].

Over time, researchers have found that sleep inertia has significant effects on human fatigue [15]. Therefore, the three-process fatigue model includes sleep inertia as the third process. In general, the three-process model produces more accurate prediction results [15].

*Sleep, Activity, Fatigue, and Task Effectiveness (SAFTE)* [73]: The SAFTE model is a three-process model that considers sleep-wake patterns, circadian rhythms, and sleep inertia. This model is especially useful for predicting human performance on a psychomotor vigilance task.

#### ***2.2.4 Intervention design for reducing human fatigue***

Interventions for reducing human fatigue can be divided into two categories: (a) preventive strategies for reducing the possibility of inducing human fatigue and (b) operational strategies for stimulating fatigued operators [45].

*Preventive strategies:* Preventive strategies are generally designed to reduce the possibility of circadian disruption, which has been considered to be

the most important cause of human fatigue. Specifically, preventive strategies include rest guidelines, naps during night shifts, improvements in sleeping habits, and stimulators [45]. For example, aircraft pilots are required to have a minimum 10-hour rest period before going on duty [74]. Scott et al. [75] tested the impacts of educating nurses with regard to the hazards of fatigue and discovered that significant improvements were noted in sleep quality, alertness and education.

*Operational strategies:* In general, operational strategies include alarms, physical activities, and caffeine consumption. Gershon et al. [76] examined and confirmed the effectiveness of energy drinks as fatigue countermeasures. Gershon et al. [77] investigated 190 participants and found that listening to the radio and opening a window are effective operational strategies for coping with human fatigue. In addition to these countermeasures, challenging secondary tasks given to operators and alerts are generally utilized in the transportation field [78]. Operational strategies can temporarily enhance the performance of fatigued operators; however, their effects cannot last because they do not address the underlying mechanism of human fatigue [45].

It is likely that the abovementioned countermeasures do not consider all aspects of human fatigue, and they cannot adapt to dynamic working conditions. Specifically, the existing strategies for managing human fatigue in transportation primarily involve implementing prescriptive “hours-of-work” regulations. However, these regulations lack a certain degree of flexibility and fail to consider dynamic fatigue-inducing factors in context.

## **2.3 Context data on human fatigue**

The context of human fatigue includes fatigue-inducing factors and the effects of human fatigue on psychophysiological behaviors. These factors and effects are reviewed in the following sections.

### ***2.3.1 Causal factors***

There are two widely accepted types of factors that may induce human fatigue: personal fatigue-inducing factors and work-related fatigue-inducing factors. Personal fatigue-inducing factors refer to individual differences in resilience to work-related factors. Work-related fatigue-inducing factors include work environments, the work arrangement, and work attributes [79].

In general, health status, health-related lifestyle factors and sleep patterns are the primary personal fatigue-inducing factors. Health status can increase the risk of fatigue by impairing the central nervous system and directly affecting the brain. Recent evidence shows that medical conditions such as neurodegenerative disease, cardiovascular disease, obesity, and high cholesterol can severely decrease alertness [80, 81]. Similarly, health-related lifestyle factors can influence human fatigue. Smoking, illegal drugs, the excessive use or withdrawal of stimulants and alcohol, and a lack of physical exercise may exacerbate fatigue in both the short and long term [81]. A sedentary lifestyle and unhealthy eating habits, which may result in obesity, can also lead to a high probability of human fatigue [24]. In addition to health status and health-related lifestyle factors, personal sleep patterns and, in particular, the proper timing of sleep have significant effects on human fatigue. Sleep has been established as a contributing factor to the development of human fatigue [82]. Grandjean [83] even suggested that sleep is the best way to recover from fatigue. Factors such

as age, gender, experience, social activities, domestic duties, partner relationship, and cognitive strategies may also interfere with one's resilience to fatigue [84]. A survey conducted by Winwood et al. [79] showed that being part of a family structure may assist full-time nurses in fighting maladaptive fatigue.

In addition to personal factors, many work-related factors can induce human fatigue, including shift work [79]. Shift work disrupts the cycle of sleeping and being awake [4]; thus, it may have a chronic effect on health and even result in cumulative sleep deprivation. Operators working the night shift always suffer from a high probability of human fatigue. Moreover, human fatigue always occurs during early-morning shifts [5]. Workload is another critical work-related factor of human fatigue [85]. A nonmonotonic relationship between workload and fatigue was identified in a routine naval patrol [85]. Grech et al. [85] suggested that the optimal workload level might change over time. Thus, the causal factors related to workload are always indirect causal factors of human fatigue.

There are implicit social and organizational factors in the workplace that affect human fatigue [24], including factors such as safety culture, safety climate, and safety management. Safety culture influences all individual perceptions of safety policies, procedures, practices and behaviors [86]. A pathological safety culture, in which near misses and minor incidents are ignored, almost always leads to deficient organizational systems. A safety climate and safety management can also be considered fatigue-inducing factors as they exert their effects on the safety motivation and workers' knowledge. Advanced technology utilized in the workplace can also be a risk factor for human fatigue. Operators may rely too heavily on technology, such as

automated systems. An automated system can reduce the requirements of maintaining one's alertness, resulting in a monotonous work environment, which is a critical factor in human fatigue [87].

In summary, human fatigue operates at a high level of complexity. Many interactive factors influence fatigue, compounding the challenge of modeling human fatigue [7].

### ***2.3.2 Physiological data***

In general, the total quantity and quality of work performed, task accuracy, response time and speed are the most common predictors of human fatigue [88]. Radüntz [59] found significant differences in accuracy rates among all fatigue levels. The accuracy of controlling vehicles was found to have a sufficient correlation with fatigue level. Heavy-truck drivers were better able to maintain their vehicle speed, steering, and accelerator pedal movements under alert conditions than under fatigued conditions. Fairclough and Graham [89] found that tired drivers made larger steering wheel movements and fewer steering wheel reversals. However, drivers could guarantee their lane position even under fatigued conditions [90].

These changes due to human fatigue allow researchers to measure levels of human fatigue.

Fatigue has adverse effects on human internal states and always results in cognitive lapses [56]. In other words, human fatigue leads to physiological change. Thus, many physiological variables have been studied to detect the level of human fatigue. Brain dynamics are highly associated with mental states. Thus, some research has focused on predicting human fatigue based on EEG measurement technologies [56]. EEG, which monitors brain activity, is

classified into waveform categories such as alpha, beta, and delta based on rhythms. The literature abounds with evidence of the effects of human fatigue on EEG variables [91]. An increasing level of human fatigue results in increasing synchronizations in the delta and alpha bands in certain lobes [92]. Increased fatigue may lead to a proportional increase in high-load EEG segments and an increase in the amplitude of the centrofrontal alpha [59].

HRV has also been investigated to measure fatigue levels [93, 94]. Vicente et al. [95] found that human fatigue has significant effects on some HRV features. Statistical analysis suggested that the heart rate of a non-fatigued person was significantly different from the heart rate of a fatigued person.

In addition to these parameters, eye movement data are an objective and reliable indicator of human fatigue [96, 97]. In general, eyelid movement includes PERCLOS, the number of blinks, the blinking rate, the eye closure time [63, 98], the blink duration, the long closure rate (LCR), and the blink amplitude (BA). In a fatigued state, the eye blink rate, PERCLOS and the LCR increase beyond the average rate [99, 100] while the BA decreases [101].

Eye fixation data include the saccadic speed [97], the number of fixations [63], the saccade rate, the peak saccade velocity, the amplitude and duration of saccades [102], and the latency [103]. Accumulated fatigue will decrease the saccadic speed, the peak saccade velocity and the amplitude of saccades [103, 104] but increase the saccade duration [102]. Specifically, peak velocity was found to be a sensitive indicator of mental fatigue [102]. However, the optimal variations in eye fixation movement depend on the research problem [105].

### *2.3.3 Data-driven approaches for managing human fatigue*

Traditional approaches to human fatigue management are mostly based on questionnaires [37]. Recently, however, various machine learning approaches, including random forests, decision trees [106, 107], AdaBoosted decision trees, and support vector machines [108-110], have been applied in the management of human fatigue. Tango and Botta [109] investigated the performance of the support vector machine (SVM), linear regression (LR), and a neural network in detecting visual distraction based on vehicle dynamics data. They found that the SVM outperformed all other machine learning methods. Kamalian et al. [108] tested the performance of k-nearest neighbors, decision trees and the SVM in developing a fuzzy system to estimate a human user's score. All of these approaches achieved good performance in validation tests.

Among the abovementioned machine learning approaches, the SVM is the one that is most widely used in the existing literature related to human fatigue management. Nevertheless, it cannot effectively address the problem of the great diversity of human factor data [108]. In addition to SVM, the AIS has also been widely used. The AIS is a modeling technique that simulates the biological immune system, which is adaptive and self-organizing [111]. It has many useful features, such as its ability to adapt and to learn from examples and its memorization and generalization capabilities. With these functions, the AIS has been successfully used in various fields, and it has even shown better performance than artificial neural network fuzzy systems and other approaches [112].

## **2.4 Context-aware management**

The complex interactions among fatigue-inducing factors highlight the necessity of context-aware fatigue management other than relying solely on the hours of work. In this section, the development and techniques of context-aware management are presented. In addition, the necessity of context-aware human fatigue management is revealed.

### ***2.4.1 Development of context-aware techniques***

In general, context includes information about the present status of any entity in the environment, and the goal of context-aware management is to acquire and utilize contextual information to provide appropriate services to specific people at a particular time [19, 113-115].

Context-aware management is a relatively new research field. Nevertheless, many techniques have been proposed [19, 116-119], and activities in context-aware systems have increased dramatically in recent years. For instance, Chang et al. [120] predicted taxi demand distributions using contextual information on time, weather and taxi location. Braunhofer et al. [116] developed a context-aware recommender system to generate recommendations based on weather conditions and places of interest.

Although a considerable number of studies have shown that context-aware techniques can improve system performance [19], few studies have investigated the potential of developing context-aware fatigue management, let alone in the transportation field.

### ***2.4.2 The necessity of context-aware fatigue management***

As mentioned in Section 2.1, many factors affect human fatigue in an interacting way. Thus, incorporating other causal factors will be beneficial for

forecasting human fatigue [20, 121]. Jewett and Kronauer [121] found that light exposure has an influence on sleep quality and proposed resetting the oscillators of the three-process fatigue model based on the level of light exposure. Strahan et al. [20] surveyed two government organizations to study the effect of the safety climate and occupational stress on the level of human fatigue. The results of this study confirmed that the organizational safety climate and occupational stress could be adopted to predict work-related driver fatigue. Ji et al. [7] proposed a probabilistic framework to model fatigue generation processes. The framework suggested that contextual information could induce human fatigue. The framework proposed by Ji et al. [7] can incorporate visual parameters and complex contextual information to predict human fatigue; however, the framework is established based on survey data on corporate/executive aviation operations. More research is required to improve the parameterization of this fatigue model.

## 2.5 Specification of the research gaps

The above review focused on the background and strategies of human fatigue management. It covered a broad domain spectrum from the definition of human fatigue to human fatigue management as well as context-aware techniques. Based on the literature reviewed in this chapter, the following issues and gaps must be addressed.

1) *Causal factors of human fatigue in TCCs.* Identifying the causal factors of human fatigue is usually the first step in managing human fatigue. Although many studies have analyzed the causal factors of human fatigue, some

limitations still exist, as discussed in the above sections. The gaps in the research include the following:

- A standard and widely accepted definition of human fatigue is lacking.
- Due to the lack of a systematic approach to identifying causal factors, the potential and indirect causal factors of human fatigue have not been explored.
- Approaches to evaluating the complex and interacting causal factors of human fatigue are scarce.

2) *An objective and unobtrusive human fatigue detector.* Among all the physiological behaviors mentioned in Section 2.2.2, eye movements are the most suitable indicator of human fatigue [122]. On the one hand, some eye parameters cannot be voluntarily controlled; thus, the mental state can be objectively and accurately inferred based on eye movements. On the other hand, eye movements can be measured continuously during extended cognitive tasks. Although eye movements are potential indicators of human fatigue, little research has detected human fatigue using eye movements in real time, resulting in the following gaps:

- Suitable fatigue indicators that could be extracted from short-period recorded eye movement data are lacking.
- The way in which eye movement data can be summarized for machine learning techniques is underresearched.
- Approaches to the linking of eye movement data to levels of human fatigue are scarce due to the high classification noise.

3) *Predicting human fatigue considering context conditions.* To date, some researchers have tried to predict human fatigue based on working time and circadian rhythm models [15]. However, these models are inadequate in predicting human fatigue in TCCs. First, they focus on time effects and fail to consider the dynamic work conditions of TCCs. Second, few such models capture the dramatic differences among individuals. Specifically, to achieve a context-aware prediction of human fatigue, several gaps have yet to be filled:

- A method for capturing contextual information, which includes the characteristics of dynamic work conditions and the individual differences exhibited by TCOs, is lacking.
- A way to represent context data on human fatigue considering their interactions is lacking.
- The effects of working conditions and individual differences on the prediction performance of human fatigue have not been explored.
- A data-mining approach to the predicting human fatigue based on complex context data is lacking.

4) *Intervention design based on context data.* Organizations and researchers have advocated work schedule improvement as the primary solution to reduce the risks of human fatigue [12]. Meanwhile, recent studies have shown the necessity and promising benefits of considering contextual information in work arrangements [7, 20, 79]. Nevertheless, they have been scarcely reported in the area of context-aware fatigue management, and several issues still must be further addressed:

- Limited studies have considered the multidimensional aspects of human fatigue.

- A platform for collecting context data that present the dynamic working conditions and individual differences exhibited by TCOs is lacking.
- An approach to managing the problem of alarm fatigue is lacking.
- An algorithm for generating appropriate work arrangements for particular operators at specific times is lacking.

These gaps provided the motivation to conduct an in-depth study on context-aware human fatigue management. Accordingly, research gaps 1) to 4) are filled in Chapters 3 to 6.

## Chapter 3 Task-driven Causal Factor Analysis for Human

### Fatigue

#### 3.1 Brief

As mentioned in Section 2.3.1, human fatigue can be caused by various causal mechanisms, such as sleep loss, circadian rhythms and workload [123]. Thus, the implementation of fatigue management should take into account the cause and type of human fatigue [123]. In general, defining and identifying causal factors are the first step in mitigating human fatigue and improving human performance [124]. Based on the previous literature, each industry has specific human fatigue-inducing factors. Even within one sector, a particular job task may be significantly associated with different fatigue-related factors compared to other job tasks in the same setting [30]. Hence, a general approach to identifying and analyzing causal factors would be useful. Recognizing causal factors is generally considered the first step in managing human fatigue [7], and it could help in obtaining an understanding of human fatigue and in developing fatigue countermeasures [123]. Although researchers have studied the causal factors of human fatigue in various fields, a systematic method for analyzing the causal factors of human fatigue is still lacking.

The specific aim of this chapter is to determine the key causal factors of human fatigue in TCCs, with a focus on TCC operations and the workspace environment. To achieve this aim, the study addresses the following concerns:

1) *Definition of human fatigue.* There is no clear and widely agreed-upon definition of human fatigue [21]. Fatigue is frequently confused with tiredness

and drowsiness [21]; in some studies, human fatigue, tiredness, and drowsiness are synonymous [6]. Nevertheless, some researchers have suggested that there are significant differences between drowsiness and human fatigue [22, 23]. Hence, it is necessary to clearly define human fatigue before identifying its causal factors.

2) *Identification of causal factors.* Historically, researchers have investigated the causal factors of human fatigue through questionnaires, interviews, task analyses and literature reviews [24, 124]. It is imperative to establish an effective and systematic method to collect the causal factors of human fatigue.

3) *Evaluation of causal factors.* Objective assessment of the importance of the causal factors of human fatigue is difficult due to the limited accident reports related to human fatigue in TCCs. In addition, there are too many interacting factors that induce human fatigue [24]. Considering the complex interrelationships, determining the key causal factors is very challenging.

To achieve the aim of identifying the critical causal factors of human fatigue in TCCs and addressing the abovementioned concerns, the study proposes a novel definition of human fatigue, develops a task-driven approach for causal factor identification and presents a fatigue causal network for evaluation. The remainder of this chapter is organized as follows. A novel definition of human fatigue is presented in Section 3.2. Sections 3.3 and 3.4, respectively, describe the methodology, including task-driven identification and causal network-based evaluation, and they discuss the results of the vital causal

factors and symptoms of human fatigue in a case study of vessel traffic service (VTS). Section 3.5 summarizes the main conclusions reached in this work.

### **3.2 Definition of human fatigue**

To identify the key causal factors of human fatigue, a good definition of human fatigue should meet the following requirements. (1) It indicates that the causes of human fatigue should be work related. The aim of this work is to investigate the work-related causal factors of human fatigue. Hence, the definition of human fatigue should indicate that fatigue is task-induced rather than caused by personal or social factors. (2) It indicates the multidimensional consequences of human fatigue. Defining human fatigue from a single dimension is inadequate as studies have shown that there are dissociations between performance decrement and experienced fatigue [22]. Some researchers have divided fatigue into mental and physical fatigue [21] based on physical or mental exertion. Nevertheless, this study proposes combining mental and physical fatigue because two types of fatigue interact [40]; people can experience mental and physical fatigue simultaneously. (3) It optimizes face validity because it is an experiential and operational definition. To enable causal factors to be identified through subjective methods such as surveys and interviews, everyday language should be used to define human fatigue [22]. In addition, the consequences of fatigue can be assessed by subjective feelings. According to Table 2.1, the existing definitions basically fail to satisfy these criteria. From these requirements and the current definitions, the following novel definition is proposed:

*Fatigue is a suboptimal physical, emotional, motivational, and cognitive condition caused by a prolonged period of exposure to task-related stimuli.*

Instead of using a phrase such as “psychophysiological”, the study explicitly indicates the multidimensions of fatigue using everyday language. Fatigue is generally considered to be a decrement in an individual’s physical and mental conditions. Nevertheless, in some studies, mental condition is confused with cognitive state. MacMahon et al. [125] used the term “cognitive fatigue” instead of “mental fatigue,” as they found that “mental fatigue” was induced by typical cognitive tasks. Analyses of several multidimensional fatigue scales [126, 127] and fatigue definitions have shown that fatigue includes several aspects, including physical, cognitive, emotional, and motivational aspects. This definition implies that people under fatigue may experience performance decrement, a lack of motivation, a bad mood and even impaired cognitive capacity, in line with the definitions put forth by Zuraidi et al. [126] and Van Cutsem et al. [40].

The definition implies that fatigue is to some degree relative to a specific optimal condition for which the optimal state is the average health condition after the individual is fully recovered and rested [22]. Defining fatigue as a relative condition enables people to recognize fatigue states through experience. Additionally, the definition is in line with the idea that fatigue causes a decrement in psychophysiological states [22].

The use of the description “*a prolonged period of exposure to task-related stimuli*” for the cause of human fatigue can be explained in terms of three aspects. First, fatigue is a gradual and cumulative phenomenon [6]; hence, the

definition highlights the time effects of task-related factors. Second, instead of “exertion”, “task-related stimuli” are used as the cause. The term “stimuli” is in line with the definitions of Dodge [36] and Hirshkowitz [35]. According to Phillips’ [22] definition, the term “exertion” emphasizes that people must put forth effort. Nevertheless, people may experience fatigue under low-demand work conditions because such conditions are boring and monotonous. In addition, people may experience emotional fatigue due to psychological factors, such as feeling that something is increasingly less rewarding over time or even being unwilling [41] to continue performing a given task. Hence, the term “stimuli” is used.

### 3.3 Task-driven identification of causal factors

Figure 3.1 shows the framework of the proposed task-driven causal factor identification. Tasks are identified by performing standard operating procedure (SOP) reviews and field observations.

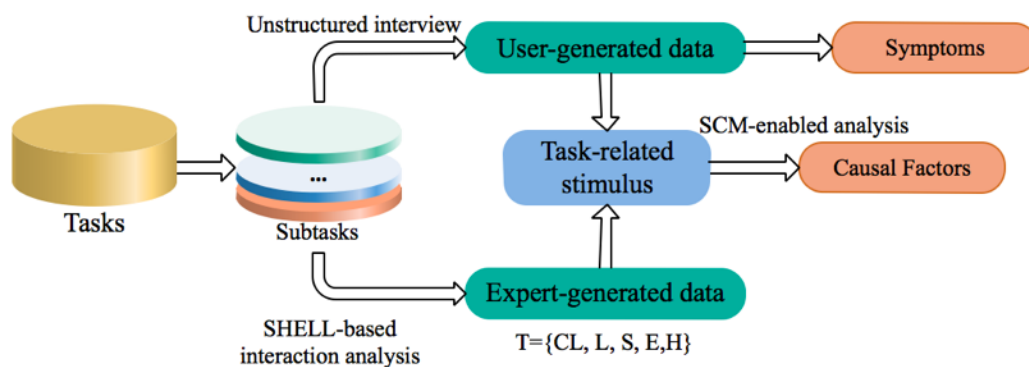


Figure 3.1 Framework of Task-driven Causal Factor Identification

Hierarchy task analysis (HTA) [128] can be employed to hierarchically decompose the main task into subtasks to facilitate a better understanding of an operational process. In this way, the main task  $T$  can be represented as  $\{T_1, T_2, \dots, T_n\}$ , where  $n$  is the number of subtasks.

According to SHELL theory [129, 130], an individual may interact with the environment, hardware, software, and other liveware when he or she performs any task. Hence, any subtask  $T_n$  could be represented as  $T_n \rightarrow \{CL_n, L_n, S_n, E_n, H_n\}$ , as shown in Figure 3.1. CL is the individual who performs the task. L encompasses the human element of the target industry. S refers to the nonphysical and intangible aspects of the target industry that govern how the industry operates and how information within the industry is organized. Software factors such as safety procedures, regulations, and work sector characteristics influence workload and may cause human fatigue. E concerns the context in which tasks are executed. H refers to physical elements such as operating consoles, seats and computers.

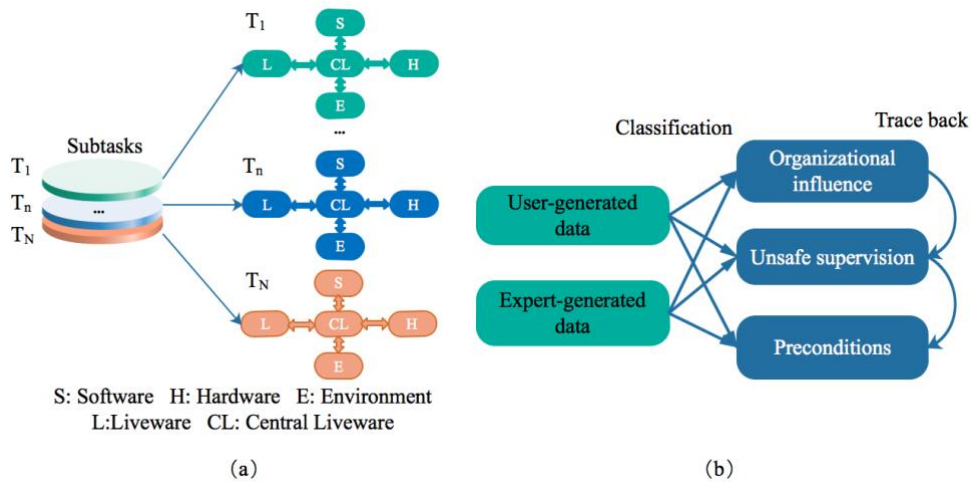


Figure 3.2 Illustration of (a) SHELL-based interaction analysis and (b) SCM-based analysis

The core concept of the Swiss cheese model (SCM) postulates that both direct and indirect factors cause accidents [131]. Following the SCM concept, the data collected in interviews and interaction analysis are classified into three categories: preconditions, unsafe supervision and organizational influences. For the precondition factors, their corresponding indirect factors fall under unsafe

supervision and organizational influences. Figure 3.2 illustrates the process for SCM-enabled causal factor analysis. In general, unsafe supervision includes inappropriately planned operations, the failure to rectify known problems, inadequate supervision, and violations by supervisors. Organizational influences consist of the organizational climate, resource management, and regulatory processes. More specifically, inappropriately planned operations refer to improper crew scheduling and improper operational planning [132]; for example, supervisors may fail to provide correct data or to conduct an adequate briefing. Violations by supervisors refer to situations in which supervisors disregard existing rules, regulations and SOPs [132]. Resource management includes human resource management, such as training and staffing, monetary safety budgets and equipment design. Organizational climate refers to the organizational culture, which includes the values, attitudes, and beliefs of an organization. Organizational process relates to the formal processes, procedures, and oversight within the organization.

### **3.4 Network-based evaluation**

To evaluate the causal factors and their complex interrelationships, in this study, the study established a causal network of human fatigue. The specific steps for realizing the causal network are summarized as follows:

1. Analyze the interrelationships among any two causal factors;
2. Add the necessary virtual nodes;
3. Rate the strength of each node; and
4. Establish a matrix to model the causal network.

There are two types of influence, i.e., direct and indirect, that one causal factor (CF) can have on another. Figure 3.3 shows the interrelationships among the causal factors. As shown in the figure, for the direct influence (A),  $CF_j$  interacts with  $CF_k$  by directly affecting  $CF_i$ . Regarding the indirect influence (B),  $CF_j$  interacts with  $CF_k$  by affecting the interaction between  $CF_i$  and  $CF_k$ . In this study, a matrix is established to present the interrelationships among the causal factors. In general, direct influences can be represented by the entries of the matrix itself; however, representing indirect influences is more challenging [133]. To address this issue, i.e., representing indirect influences, a virtual node ( $V$ ) is introduced to convert an indirect influence into a direct influence. By using the virtual node, the indirect influence can be treated such that  $CF_j$  influences  $CF_k$  indirectly through the virtual element,  $V_j$ . In this manner, the introduction of virtual node  $V_j$  enables the indirect influence of  $CF_i$  on  $CF_k$  to be more clearly illustrated. Hence, the influence of  $CF_i$  on  $CF_k$  can be treated as the cumulative effect of direct and indirect influences. The introduction of the virtual node provides the basis for matrix construction.

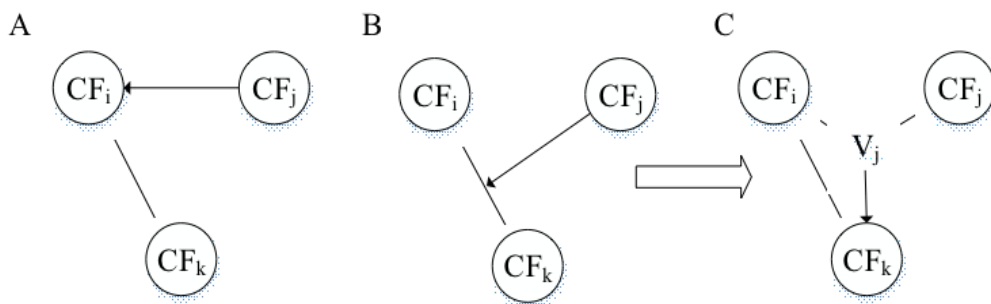


Figure 3.3 Illustration of the interrelationships among causal factors (CFs)

Basically, the causal network utilizes all causal factors, virtual nodes and symptoms of fatigue (SF) as elements. To rate the importance of each element, an ordinal scale, i.e., low, moderate and high, which has been proven to be an

effective way to qualitatively classify causal factors, is adopted. The ordinal scale is subsequently converted into a comparative format where 1 denotes “low”, 3 represents “moderate” and 5 indicates “high”. The following matrix represents the interrelationships of any two elements:

$$C = \begin{bmatrix} c_{11} & \cdots & c_{1n} \\ \vdots & \ddots & \vdots \\ c_{n1} & \cdots & c_{nn} \end{bmatrix} \quad (3.1)$$

$$\text{For } i \neq j, c_{ij} = \begin{cases} 1 & E_j \text{ has effects on } E_i. \\ 0 & E_j \text{ has no effects on } E_i. \end{cases}$$

$$\text{For } i = j, c_{ij} = \begin{cases} 1 & \text{if the rate of } E_i \text{ is low;} \\ 3 & \text{if the rate of } E_i \text{ is moderate;} \\ 5 & \text{if the rate of } E_i \text{ is high.} \end{cases}$$

Each column of  $C$  is a principal eigenvector of the effects of the  $j$ th element on the  $i$ th element. For  $i=j$ ,  $c_{ij}$  refers to the strength of the  $i$ th node.

Table 3.1 Demonstration of item format in the questionnaires

	<b>CF1</b>	<b>CF2</b>	<b>SF1</b>
<b>CF1</b>	Low/moderate/high	0/1	0/1
<b>CF2</b>	0/1	Low/moderate/high	0/1
<b>SF1</b>	0/1	0/1	Low/moderate/high

“*SF*” refers to symptoms of human fatigue in VTS. In general, the importance of a node can be determined by the “degree”, which refers to the number of adjacent nodes. As the direction of edges and the strength of adjacent nodes are important parameters, two new terms are proposed in this study: out-degree and in-degree, which can be expressed using Eqs. (3.2) and (3.3), respectively:

$$kout_i = \sum_{j=1}^n c_{jj} \times c_{ij}, j \neq i \quad (3.2)$$

$$kin_i = \sum_{j=1}^n c_{jj} \times c_{ji}, j \neq i \quad (3.3)$$

where  $kout_i$  refers to the out-degree of the  $i$ th node and  $kin_i$  denotes the in-degree of the  $i$ th node. Based on the out-degree and in-degree, the influence power of the  $i$ th node,  $I_i$ , can be represented by Eq. (3.4) as follows:

$$I_i = c_{ii} + kout_i + kin_i \quad (3.4)$$

Basically, the influence power indicates the impact of a node on its adjacent nodes. To determine the importance of a node, both its influence on its adjacent nodes and the range of influence must be assessed. By considering the general properties of the causal network, the number of paths from the root nodes to the end of the chain node that passes through the  $i$ th node is defined as its influence range ( $Np_i$ ).  $Np_i$ , which is a classical problem in network analysis, can be determined using a depth-first search (D-FS) algorithm.

In this study, multicriteria ranking is employed to evaluate the importance of causal factors. To do so,  $I_i$  and  $Np_i$ , which provide essential information, are preprocessed as follows: (1) Calculate the  $I$  of each  $CF$  and rank all  $CFs$  according to the value obtained. The ranking of  $CF_i$  is denoted by  $a_{i1}$ . (2) Calculate the  $Np$  of each  $CF$  and rank all  $CFs$  according to the value obtained. The ranking of  $CF_i$  is denoted by  $a_{i2}$ . (3) Rank all  $CFs$  according to the value of  $c_{ii}$ . The ranking of  $CF_i$  is denoted by  $a_{i3}$ .

The importance of  $CF_i$  can be expressed by using a vector,  $A_i (a_{i1}, a_{i2}, a_{i3})$ . The causal factors can be ranked by adopting the following rule:

“ $CF_i$  is ranked ahead of  $CF_j$  if Vector  $A_i$  is smaller than Vector  $A_j$ ”.

To compare Vector  $A_i$  and Vector  $A_j$ , their moduli are first calculated. For example, for  $A_i (1,3,5)$  and  $A_j (2,4,2)$ , the modulus of  $A_i$  equals 5.92, and the modulus of  $A_j$  is 4.90. Hence,  $CF_i$  is ranked ahead of  $CF_j$ .

### **3.5 Case study of causal factor analysis**

#### ***3.5.1 Participants and procedures***

A two-month field observation was conducted in VTS centers in Singapore to understand the daily tasks of VTSOs. Field observations were carried out in a naturalistic and passive manner, i.e., with the researcher standing beside an operator without interrupting his or her work. With an understanding of VTS operations, an unstructured interview with eight operators was conducted. The eight participants (male = 7; female = 1) had an average age of 35 years (standard deviation (SD) = 5 years), with an average experience of 8 years.

The operators received a brief introduction about the novel definition of human fatigue before the interview. They were encouraged to ask questions about the definition. The unstructured interviews consisted of three crucial stages: asking open-ended questions, probing for details and seeking to verify unclear points. The open-ended questions were designed based on task analysis. The operators were asked to recall the challenges or problems they face in performing each subtask. Probing questions were generated when an operator mentioned any fatigue patterns. According to the novel definition, fatigue patterns include physical, emotional, motivational, and cognitive decrements. Finally, the interviewer repeated what he or she heard so that the interviewees could confirm the information summarized. To encourage operators to explore

their knowledge and provide more information about fatigue, their identities were kept anonymous throughout the study.

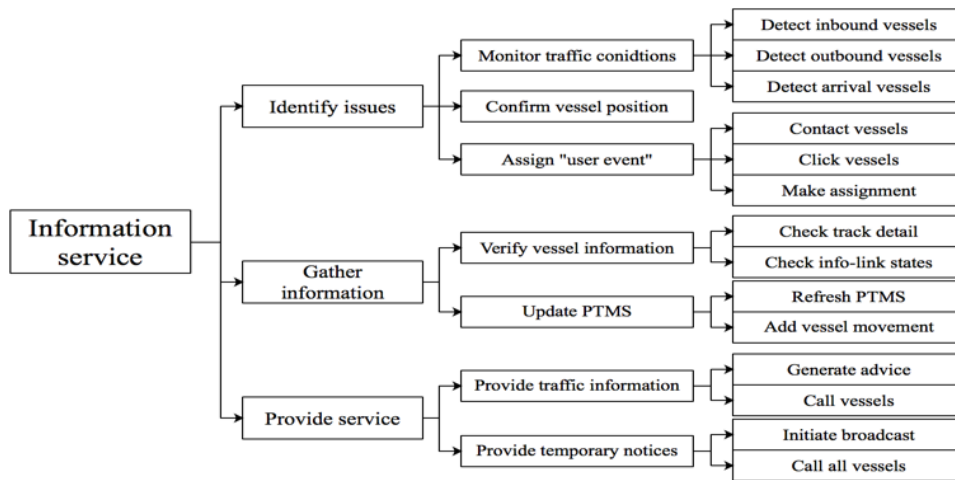
Other causal factors were elicited based on expert knowledge. The details are explained in Section 3.2. With the collected causal factors and fatigue symptoms, questionnaires were designed for factor evaluation. A VTS manager assisted in distributing the questionnaires to VTSOs in Singapore through email. In the questionnaires, no identifying information was required. The participants completed the questionnaires after work and returned them to the VTS manager via email. They were encouraged to ask the VTS manager about the terms used in the questionnaires and to provide written feedback on the questionnaires. The participants were informed of the objectives of this study and of the definition of human fatigue. They were required to sign a consent form for participating in this study, which was approved by the institutional review board.

A total of 60 questionnaires were distributed. In total, questionnaires from 48 licensed VTSOs (male=40, female=8), with an average age of 41 years old and an average experience of 11 years, were collected. The response rate of 80% is acceptable [25].

### ***3.5.2 Task analysis and factor identification***

It was understood that only the information service (INS) was provided by the VTS of Singapore to vessels. First, VTSOs identify potentially unsafe events by monitoring the traffic conditions of vessels and communicating with the masters or pilots. Second, once a possible hazardous event is spotted, VTSOs will gather the basic information and refresh the port traffic

management system (PTMS) to check vessel movements. Finally, based on the information gathered, VTSOs will provide corresponding advice to the vessels, such as the intentions of other ships, the number of ships in the vicinity and the type of ships in the vicinity. At times, VTSOs may broadcast temporary notices to all vessels under special conditions, such as poor visibility. Figure 3.4 depicts the hierarchical analysis of the INS, whose details are presented as follows.



Notes: PTMS - port traffic management system

Figure 3.4 Hierarchical analysis of the INS

Based on the task analysis, 23 task-related factors were identified, as listed in Table 3.2.

Table 3.2 Task-related factors

Operations	Task-related factors
<b>Detect inbound/outbound vessels/ arrival vessels</b>	CF1: Continuous monitoring or tracking CF2: Too many vessel traffic regulations CF3: Too many vessels with the same icons CF4: Overlap of vessel information CF5: Marker or notes left by other operators CF6: The display is too large
<b>Confirm vessel movement/ verify vessel information/ update information</b>	CF7: A large amount of information CF8: Key information masked CF9: Information updated by the AuIS is not complete/ consistent CF10: Sensing information affected by light reflection CF11: Slow feedback of hardware system CF12: Demand to memorize information
<b>Provide temporary notices</b>	CF13: No or slow feedback CF14: Work interrupted by assignments from manager CF15: Need to collect information from different systems and masters/pilots
<b>Provide traffic information</b>	CF16: Inefficient communication due to a language barrier CF17: Communication is interrupted by other pilots

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<b>Assign user event (UE)</b>	CF18: Too many unnecessary alarms CF19: Ambiguous alarms CF20: Time pressure in providing information CF16: Inefficient communication due to language barrier CF21: Too many steps to make assignments CF22: Lack of experience CF23: Difficulties in clicking vessels using the mouse
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In addition to these task-related factors, 24 factors were collected by SCM-based analysis, as listed in Table 3.3.

Table 3.3 The causal factors identified by SCM-based analysis

<b>Organizational influence</b>	<b>Unsafe supervision</b>	<b>Preconditions</b>
<b>CF24: Safety culture</b>	CF28: Work arrangement	CF37: Information management system
<b>CF25: Organizational rules</b>	CF29: Revision of SOP	CF38: Night shift
<b>CF26: Organizational structure</b>	CF30: Staffing levels	CF39: Recovery/ rest
<b>CF27: Organizational policies</b>	CF31: Team interaction	CF40: Individual capacity
	CF32: Training	CF41: Health and wellness condition
	CF33: Safety management system	CF42: Subjective feelings
	CF34: Update equipment	CF43: Interface design
	CF35: Recruitment policies	CF44: Environment
	CF36: Work sector division	CF45: Usability of equipment
		CF46: Time on task
		CF47: Workload

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### 3.5.3 Symptoms of human fatigue in VTS

Table 3.4 shows the results related to the top ten fatigue symptoms in VTS. The mean value listed in the third column indicates the impact of fatigue symptoms. VTSOs suffer from multidimensional fatigue. In addition, physical fatigue seems to be more severe than cognitive fatigue in VTS. There are six physical symptoms ranked in the top ten, whereas there are only two cognitive symptoms in Table 3.4. In addition to physical and cognitive symptoms, symptoms related to motivation and emotion can be found in Table 3.4. The top-ranking symptom of human fatigue is “eyes feel strained”. In addition, SD

is ranked lower than most other human fatigue symptoms. This result means that most VTSOs suffer from a high level of “eyes feel strained”. In VTS, the decrement in cognitive states does not seem to be serious, as cognition-related fatigue symptoms have a low ranking. Moreover, the symptom “cannot sense information” has the highest SD. It can be deduced that some operators suffer from impaired cognitive capacities while others can maintain their information-processing capacity.

Table 3.4 Top 10 symptoms of human fatigue in VTS

Category	Descriptions	Mean	SD
Physical	SF1: Eyes feel strained	4.18	0.38
Physical	SF2: Feel tired in the whole body	3.47	0.49
Physical	SF3: Feel stiff in the neck and shoulder	3.37	1.30
Physical	SF4: Flickering in eyes	3.06	1.19
Motivational	SF5: Lack of motivation, would rather be doing something else	3.06	1.30
Emotional	SF6: Bad mood, fed up with the task	2.96	1.05
Physical	SF7: Hearing ability reduced	2.65	1.19
Cognitive	SF8: Increased response time	2.65	0.32
Emotional	SF9: Find the task monotonous	2.55	0.97
Cognitive	SF10: Cannot sense information	1.94	2.87

### 3.5.4 Key causal factors of human fatigue in VTS

All causal factors were evaluated using the causal network. Figure 3.5 illustrates the fatigue causal network.

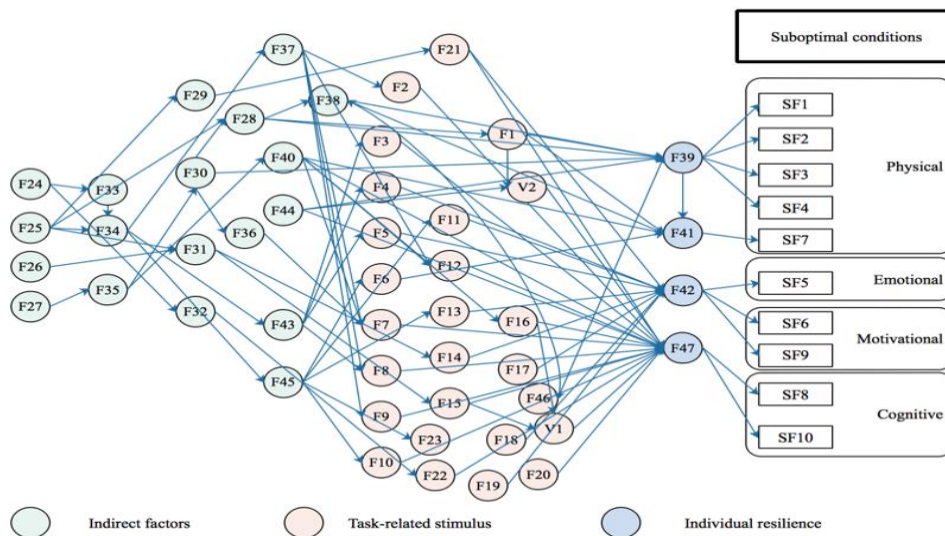


Figure 3.5 Illustration of the fatigue causal network

In this study, the factors ranked in the top 25% were identified as key causal factors, and they are analyzed below. Table 3.5 shows the key causal factors and their rankings in three dimensions: (1)  $a1$  is the rank of the influence power ( $I$ ) of each causal factor; (2)  $a2$  is the rank of the influence range ( $Np$ ) of each causal factor; and (3)  $a3$  is the rank of the impact of the causal factor.

Table 3.5 Key causal factors of human fatigue in VTS

Causal factors	$a1$	$a2$	$a3$	Final Rank
Safety culture	6	4	16	4
Organizational rules	10	5	18	6
Workload	1	1	10	2
Rest/recovery	2	8	1	1
Subjective feelings	9	21	22	8
Health and wellness condition	5	7	15	3
Language barrier	25	27	4	11
Marker or notes	20	26	5	9
Overlap of vessel information	12	26	8	7
Unnecessary alarms	24	30	6	12
Amount of information	11	14	2	5
Continuous monitoring	22	29	3	10

“Safety culture” and “organizational rules” were classified as root causes; they have high rankings in both influence power and influence range. The results indicate that “safety culture” and “organizational rules” have significant effects on the entire fatigue causal network.

“Workload”, “recovery”, “subjective feelings” and “health and wellness condition” are impact factors that can be considered preconditions of human fatigue. Table 3.5 shows that all of them except “subjective feelings” are highly ranked in the three dimensions. Considering the three dimensions, “rest” ranked first. Hence, the “work/rest arrangement” of VTS requires more development. VTSOs perform shift work; hence, they always suffer from the problem of ensuring adequate rest and recovery. “Workload” ranked second; its  $a3$  ranking

is much lower than that of “rest”. a3 shows the subjective feelings of the VTSOs. It can be concluded that the operators felt the problem of “rest” to be more serious than the problem of “workload”. The VTSOs did not work close to the limits of their capacity. Nevertheless, they felt a lack of motivation to continue their work.

Other key factors include “language barrier”, “amount of information”, “marker or notes”, “unnecessary alarms”, “overlap of vessel information”, and “continuous monitoring”. These are the task-related stimuli and direct causal factors of human fatigue in VTS as they have a high ranking in a3. A factor with a high ranking in a3 means that the operators encountered the factor very frequently and perceived the factor to be critical. These task-related stimuli are discussed below:

*Language barrier:* From the task decomposition, it appears that VTSOs frequently communicate with the pilots of vessels coming from different countries. Nevertheless, communication can be interrupted by the “language barrier”, as the pilots of vessels may be not proficient in English. During the unstructured interview, the VTSOs mentioned that pilots might ignore advice or even insist on speaking their language during communication. This factor obtains a high ranking in a3 as the operators stated that it dramatically affects their work. However, “language barrier” obtains low rankings in a1 and a2. Hence, it does not have a significant influence on other factors.

*Amount of information:* From the task analysis of VTS operations, VTSOs frequently work close to the limits of their information-processing capacity. They must handle numerous warnings, calls from vessels, and traffic

information. The effort required to process high-density information and simultaneously make adequate decisions can be daunting and may potentially induce a high workload. Due to its direct effect on workload, this factor ranks high in both a1 and a2. Although the operators felt that their workload was acceptable, they also stated that the amount of information should be reduced.

*Overlap of vessel information:* The identification information of a vessel, including its name, call number, and type, is displayed next to its icon. Nevertheless, when a vessel is close to another vessel, their information always overlaps, as shown in Figure 3.6. At such times, VTSOs must drag the information labels manually. According to the field observation, the VTSOs spend most of their time managing overlapping information.



Figure 3.6 Information overlap

*Unnecessary alarms:* The integrated VTS alarm system was developed to assist in identifying potential unsafe issues. However, the operators mentioned that most of these alarms are unnecessary. Examples include “I receive

*hundreds of warnings per day, but I ignore most of them. I think they are unhelpful and useless*"; *"I detect abnormal situations before the alarm system. I rarely use it"*; and *"The voice alarms interrupt my communication"*. These unnecessary alarms induce distrust in systems, resulting in a slow response to the alarm system.

*Markers or notes*: VTSOs used "markers or notes" to mark the vessels that require their attention, as shown in Figure 3.7. However, there is no standard in making markers. As a result, the operators make markers according to their own preferences and working habits. They may be confused by the markers or notes left by the other operators. Similar to the "language barrier", this factor does not have a great influence on other causal factors; however, it was rated as "very important" by the operators.

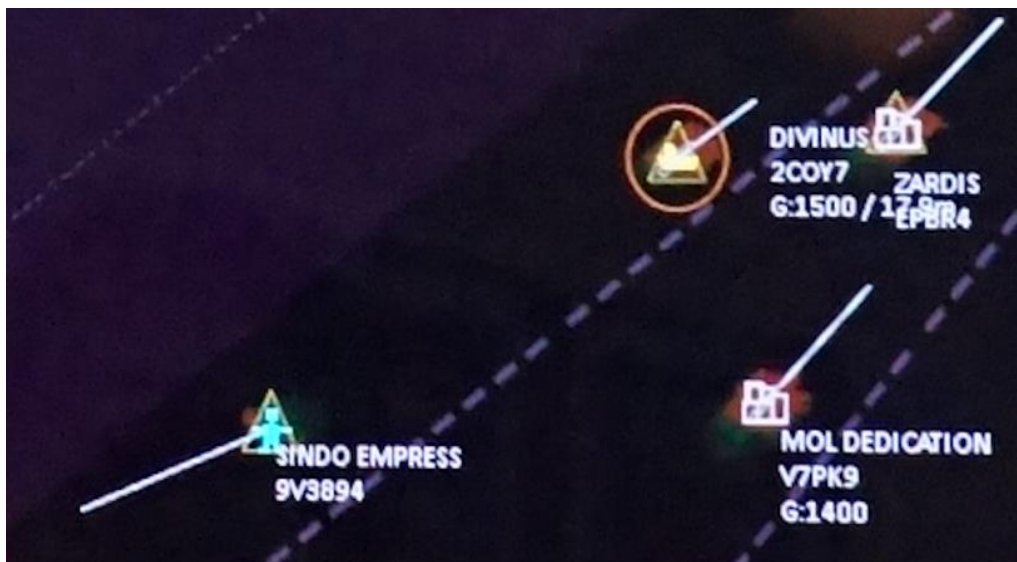


Figure 3.7 Markers and notes

*Continuous monitoring*: With the increase in automation technology in VTS, the role of the VTSO tends to change from that of a controller to that of a monitor whose main task is monitoring tasks. Thousands of laboratory experiments have demonstrated that human vigilance will easily be interrupted

when people are working on monitoring tasks [134]. In addition, the operators mentioned that their eyes felt strained after continuous monitoring. This factor was ranked just after “rest” and “amount of information” in a3.

In summary, the causal network-based evaluation provides a comprehensive assessment of three aspects: the influence range, influence impact, and subjective rate of importance. In general, operators could identify direct task-related stimuli according to their experience. Nevertheless, the importance of indirect causal factors could not be determined by subjective feelings. The proposed network can well fill this gap.

The evaluation approach meets the criteria of a well-designed measurement as suggested by Liu et al. [25]: (1) it assesses a considerable number of factors; (2) it evaluates the importance of factors from several dimensions; and (3) it aggregates various judgments.

### **3.6 Summary**

It is desirable to identify the task-related causal factors of human fatigue and to subsequently design corresponding preventive interventions for its management. Based on this understanding, this study was conducted to determine the key causal factors of human fatigue in TCCs.

As the causal factors of human fatigue are associated with specific job domains, this study employed TCFA. This analysis provides the basis for human fatigue management, the identification of specific causal factors of human fatigue and an objective, holistic and quantitative evaluation of causal

factors. A case study was conducted in VTS in Singapore, and several critical causal factors and symptoms in VTS were identified.

Unexpectedly, the physical fatigue suffered by VTSOs was greater and more serious than their cognitive fatigue. The results provide directions for future fatigue management.

## **Chapter 4 Proactive Human Fatigue Detection based on Bagged Decision Trees and Gaze-bin Analysis**

### **4.1 Brief of human fatigue detection**

Among all the physiological behaviors mentioned in Section 2.2.2, eye movements have been shown to be the most suitable indicator of human fatigue [122]. With technological improvement, eye movements can be remotely tracked using contactless eye trackers [135, 136]. Hence, eye movements can be measured unobtrusively and continually during extended cognitive tasks. In addition, changes in eye movements can be promptly captured to identify and understand the interactions between users and human interface devices. Consequently, eye movement-based fatigue detectors have recently received great attention [122, 137-139].

The existing methods in EMFD have focused on using eye movements recorded over an extended period to generate descriptive fatigue indicators, such as the mean, SD and median of fixations and saccades [140]. However, these indicators impede the ability to warn fatigued subjects in a timely manner, and they heavily depend on the selection of parsing methods and the quality of the eye-tracking data [141]. These factors have given rise to many contradictory results in studies of eye movement-based mental fatigue detection. For example, although many studies have suggested that saccadic parameters vary with the fatigue level [97, 103, 105], Saito [142] did not find any significant quantitative changes in saccadic eye movement in five hours of eye-tracking tasks.

Therefore, instead of focusing on fixations and saccades, it would be better to capture dynamic information from eye-tracking data recorded over a short period of time, which poses several challenges. First, splitting eye-tracking data recorded over a long period into short-period data will introduce overlapping data, which can affect the accuracy of the fatigue detection model. Second, labeling eye-tracking data recorded over a short period is labor intensive. Third, it is difficult to determine the period of the time window. It is believed that the time window period will significantly affect the performance of human fatigue models, such as their detection accuracy and time delays [143]; however, little attention has been paid to determining the appropriate time window.

To address these challenges and achieve the aim of proactively and noninvasively monitoring the human fatigue of TCOs, a method that involves extending bagged decision trees with semisupervised training to gaze-bin analysis is proposed. Bin analysis, which refers to counting how many values fall into a specific interval, can accurately present the distribution of numerical data and capture dynamic features from short-period data. The bagged decision tree method adopts the concept of assembling multiple decision trees, and it performs well in analyzing data with substantial classification noise [144]. Semisupervised training enables both labeled and unlabeled training data to be used.

This chapter is organized as follows. In Section 4.2, the novel problem of using gaze-bin analysis to discriminate human fatigue is stated. Section 4.3 describes the innovative approach suggested for detecting human fatigue using gaze-bin analysis. The case study in VTS and the performance of the proposed approach are presented in Section 4.4; in addition, Section 4.4 presents the

effects of the model characteristics and the comparison results of the proposed method in relation to other classical methods. Section 4.5 summarizes the contributions and limitations of this work.

## 4.2 Gaze-bin analysis-based indicators of human fatigue

### 4.2.1 Gaze-bin analysis

Figure 4.1 (a) shows the basic concept of the existing parameters. The previous studies generally focused on first identifying fixations and saccades and then generating statistical parameters. Different from existing studies, a novel research problem, gaze-bin analysis, is investigated. Basically, there are eye-tracking data  $E = \{X, Y, T\}$ , where  $X, Y$  refers to the set of  $x$  and  $y$  coordinates of the gaze points and  $T$  is the set of timestamps. The gaze velocity of each gaze point can be calculated by determining the difference between the center of two points and multiplying by the sampling frequency ( $f$ ) of the eye tracker.

$$v_t = f \times \sqrt{(x_t - x_{t-1})^2 + (y_t - y_{t-1})^2} \quad (4.1)$$

$$t \in T, x \in X, y \in Y$$

Hence, the eye-tracking data are represented as  $E = \{V, T\}$ , where  $V$  is the set of gaze velocity data.

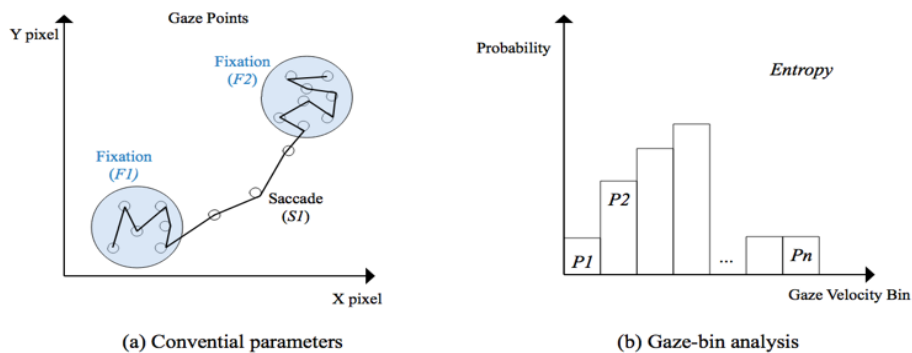


Figure 4.1 Representation of eye-tracking data

First, the eye-tracking data were split into short-period data packets, and then, bin analysis was conducted. The time series data on eye movements were split into  $N$  packets based on the time window and shift window. The time window ( $T_w$ ) denotes the period of each packet. The shift window ( $S_w$ ) refers to the length that the time window moves forward.  $T$  refers to the length of the eye-tracking data recording time.

$$N = \left\lfloor \frac{T}{S_w} \right\rfloor - \left\lfloor \frac{T_w}{S_w} \right\rfloor + 1 \quad (4.2)$$

$$M = T_w \times f \quad (4.3)$$

In this way, eye-tracking data  $E = \{V, T\}$  are presented as  $E = \{D_1, D_2, \dots, D_N\}$ .  $M$  refers to the number of gaze points belonging to a data packet, while  $f$  is the sampling rate frequency of the eye tracker.

The basic idea of gaze-bin analysis is shown in Figure 4.1 (b). Eye-tracking data  $E = \{D_1, D_2, \dots, D_N\}$  can be represented as  $E = \{P\} = \{p_1, p_2, \dots, p_N\}$ , where  $P$  is the set of gaze velocity probability vectors.

The bin analysis was extended to gaze velocity analysis by describing each data packet as a histogram of all velocities at which the eye travelled during the time window ( $T_w$ ). The gaze velocity data belonging to the data packet are transformed into a discrete probability mass function and entropy,  $p=(p(v_1), p(v_2), \dots, p(v_B), e)$ :

$$v_b = b \times \frac{V_{max}}{B - 1} \quad (4.4)$$

$$e = \sum_{b=1}^B p(v_b) \times \log(p(v_b)) \quad (4.5)$$

$p(v_b)$  is the probability that the gaze velocity is larger than  $v_{b-1}$  and smaller than  $v_b$ .  $V_{max}$  is the maximum velocity of the fixation,  $B$  is the number of bins, and  $e$  is the entropy of the gaze velocities belonging to the time window.

Because the velocities of the saccades are much faster than the velocities of the fixations and the amount of time spent on saccades is substantially shorter than that spent on fixations, just one bin (bin  $B$ ) was set for the saccades.

#### 4.2.2 Problem statement

This study proposes a novel analysis of short-period eye-tracking data instead of statistical analysis of fixations and saccades, which can be conducted using only long-period recorded eye-tracking data. In this way, a new problem of using gaze-bin analysis to discriminate human fatigue in TCCs is introduced. The problem is stated as follows: given a set of eye-tracking data  $P = \{p_1, \dots, p_m\}$  and a set of fatigue levels  $FL = \{fl_1, \dots, fl_j\}$ , the aim is to (1) train a fatigue model  $\{P, FL\} \rightarrow FM$  and (2) predict the human fatigue level using short-period eye-tracking data  $fl \stackrel{FM}{\leftarrow} \{p\}$ . This problem is based on the following assumptions:

*Assumption 1:* The dimension of  $FL$  is much smaller than the number of data packets belonging to  $P$ . In other words,  $j \ll m$ .

*Assumption 2:* Eye-tracking data collected from the same participants are subject to the same distribution.

*Assumption 3:* There are some overlaps among data packets,  $p_d \cap p_{d+1} \neq \emptyset$ , where  $\{p_d, p_{d+1}\} \in P$ .

Compared with existing human fatigue detection studies, which focus on fixations and saccades from eye-tracking data recorded over an extended period, the proposed solution of using gaze-bin analysis is expected to capture dynamic features from short-period eye-tracking data. Moreover, the gaze-bin analysis is independent of event detection methods and eye trackers. Hence, the gaze-bin

analysis is expected to reduce the contradictory results caused by eye trackers and event detection methods.

### **4.3 Semisupervised bagged trees for human fatigue detection**

This section presents an innovative method to address the challenges summarized in Section 4.1 for gaze-bin analysis-based human fatigue detection. In general, the training data and test data were randomly selected. Nevertheless, a simple selection is not applicable in this study due to the overlapping data packets. Hence, the proactive selection of training and testing data is introduced first. Then, a semisupervised bagged tree method for training the fatigue model using labeled and unlabeled data is discussed. Lastly, the procedures of human fatigue detection are stated.

#### ***4.3.1 Proactive selection of training and testing data***

In total,  $N$  data packets were utilized for training and testing the bagged tree model. First, 80% of the data packets were randomly selected for training, and the remaining data packets were used for testing. To avoid overfitting caused by overlapping data packets, the training data and testing data were split before training. The overlapping data packets were deleted, as shown in Figure 4.2. A random number  $s$  was generated using MATLAB R2018a. To prevent  $s$  from being outside of the index,  $s$  was set to be larger than  $N_o$  and smaller than  $0.8N - N_o - 1$ . The data packets numbered  $s$  to  $s + 0.2N$  were utilized as testing data, while the data packets whose numbers ranged from  $s - 0.5N_o$  to  $s + 0.2N + 0.5N_o$  were deleted. After deleting the overlapping data, the remaining data were used to train the model.

$$N_o = 2 * \left( \left\lfloor \frac{T_w}{S_w} \right\rfloor - 1 \right) \quad (4.6)$$

where  $N_o$  is the number of overlapping data packets.

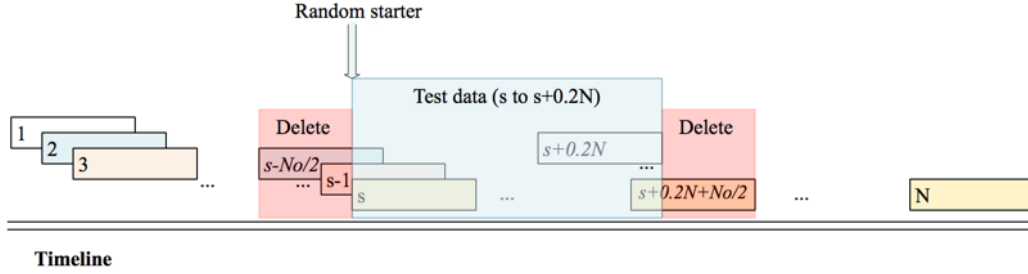


Figure 4.2 Generating data for training and testing

In this way, the training data set  $Tr = \{D_1, \dots, D_{s-N_o-1}, D_{s+0.2N+N_o+1}, \dots, D_N\}$  and the testing data set  $Ts = \{D_s, \dots, D_{s+0.2N}\}$  were obtained.

#### 4.3.2 Semisupervised training with decision trees

Given a set of eye-tracking data  $Tr = \{D_1, \dots, D_{s-N_o-1}, D_{s+0.2N+N_o+1}, \dots, D_N\}$  and a set of fatigue levels  $FL$ , the number of data packets in  $Tr$  is much larger than the dimension of  $FL$ .  $\{Tr, FL\}$  can be presented as  $\{D^l, D^u\}$ , where  $D^l$  denotes the set of labeled eye-tracking data and  $D^u$  denotes the set of unlabeled eye-tracking data. Essentially,  $\{D^l, D^u\} = \{d_1^l, d_2^l, \dots, d_j^l, d_{j+1}^u, \dots, d_m^u\}$ ,  $d^l = \{p, fl\}$ , and  $d^u = \{p\}$ . Hence, a labeling vector  $FL^* = (fl_{j+1}^*, \dots, fl_m^*)^T$  is generated for the unlabeled data set.

First, a decision tree using the labeled data set  $D^l$  was generated, and then, the decision tree was used to generate a labeling vector  $FL^* = (fl_{j+1}^*, \dots, fl_m^*)^T$  for the unlabeled data set. A subset  $fl_{sub}^*$  with high classification confidence of  $FL^*$  was selected to label  $D_{sub}^u$ . Then, the decision tree was trained using the data set  $\{D^l, D_{sub}^u\}$ , and a subset of data was

reselected from the unlabeled data set. The procedure was repeated until it reached a stopping condition. The C4.5 algorithm was used to build decision trees because it is the most well-known algorithm for building decision trees, and it has been successfully used in many fields [145]. Algorithm 4.1 presents the main structure of the semisupervised training algorithm. The output training data set can be represented as  $Tr = \{d_1^l, \dots, d_m^l\}$ . The time complexity of Algorithm 1 is  $O(T \cdot B \cdot |D^l|^2)$ , as the time complexity of C4.5 is  $O(B \cdot |D^l|^2)$ .

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**Algorithm 4.1: Semisupervised training algorithm**


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T: number of iterations. C: prediction confidence threshold

t=1

while t < T

Dt  $\leftarrow$  Decision tree ( $D^l$ )

$FL^* = Bt(D^u)$

select  $D_{sub}^u$  whose  $p(FL_{sub}^*) > C$

$FL \leftarrow \{FL + FL_{sub}^*\}$

$D^l \leftarrow \{D^l + D_{sub}^u\}$

$D^u \leftarrow \{D^u - D_{sub}^u\}$

t = t + 1

end

Output: generate final training data set  $D^l$  and a labeling vector  $FL^*$

---

### 4.3.3 Bagged tree-enabled human fatigue detection

To build  $A$  trees for bagging,  $A$  copies of data set  $BT = \{BT_1, BT_2, \dots, BT_A\}$  were generated from the training data set  $Tr$  using sampling with replacement. Based on each data set  $BT_a$ , a decision tree  $F^{*a}$  could be built using the classification and regression tree (CART) algorithm.

Given the training data set  $BT_a = \{(p_1^a, fl_1^a), \dots, (p_m^a, fl_m^a)\}$ , where  $p^a \in P, fl^a \in FL$ , the decision tree  $F^{*a}$  divides  $P$  into  $K$  feature subspaces. On each subspace, the same prediction is made for all data packets belonging to the subspace. The  $Pro_{kF}$ , estimated probability of class  $F$  on the  $k$  subspace is the proportion of training observations in the  $k$ th subspace that are from the  $F$ th

class. The method aims to find  $F^{*a}$ , which can achieve a minimized Gini index [146]:

$$Gini = \sum_{F=0}^1 Pro_{kF}(1 - Pro_{kF}) \quad (4.8)$$

The final prediction for a given observation  $p$  is calculated using Eq. (4.9) [147].

$$F_{bag}(p) = \left\lfloor \frac{1}{2A} \sum_{a=1}^A F^{*a}(p) \right\rfloor \quad (4.9)$$

Out-of-bag errors are typically used to evaluate the bagged model. Although the out-of-bag error estimation is particularly convenient, it is not suitable for this study due to the overlapping data packets. As illustrated in Figure 4.2, each data packet overlaps with several other data packets, making out-of-bag observation too complex. Hence, in this study, a k-fold cross-validation method was extended. The aforementioned testing data set  $T_s = \{D_s, \dots, D_{s+0.2N}\}$ , where  $D_s = (P_s, FL_s)$ , was used to test the bagged model. For each fold  $l$ , the  $Accuracy_l$  can be obtained based on Eq. (4.10).

$$Accuracy_l = 1 - \frac{1}{0.2N} \sum_{r=s}^{s+0.2N} |(FL_r - F_{bag}(P_r))| \quad (4.10)$$

In addition to accuracy, sensitivity and specificity were tested. Accuracy measures the percentage of correctly classified observations, while sensitivity, which is also known as the true positive rate, determines the proportion of actual positives that are correctly identified as positives. In contrast, specificity measures the proportion of actual negatives that are correctly identified as negative. In this study, “alert” is defined as positive, and “fatigue” is defined as negative. The time complexity of the bagged trees is  $O(A \cdot B \cdot m \cdot \log(m)^2)$ .

## 4.4 Field-based experiments

This section describes the data collection and the performance of the proposed method. The effects of the model characteristics, including the time window, bin number, and input features, are examined and presented, and the proposed method is compared with other commonly used methods, such as decision tree, LR and SVM methods.

### 4.4.1 Data collection and experiment settings

Eight VTSOs consisting of seven males and one female with normal vision were recruited for this study. Their ages ranged from 30 to 50, with an average age of 42 years. All of them worked in the morning shift, which runs from 7:30 a.m. to 15:30 p.m. None of them suffered from sleep disorders.

The data collection phase consisted of four sessions (Figure 4.3). The participants were asked to conduct their daily work and to complete a 5-minute Mackworth clock test after every two hours of work. The Mackworth clock test requires participants to monitor a dot moving around and to press the space bar immediately when the dot jumps more than usual. The participants were further instructed to complete the Samn-Perelli Fatigue Scale before and after the Mackworth clock test. Their eye movements were recorded using Tobii X3-120 with a sampling frequency of 120 Hz. A 14-inch Lenovo laptop with a 768\*1024 resolution monitor was used to display the vigilance test. The participants were required to sit 50 cm away from the laptop and were required to sit still during the experiments. The illumination of the test room was maintained at approximately 400 lx.

Tobii X3-120 can track eye movements in an unconstrained and natural way by placing it in front of the participants. However, applying it in TCCs would still be challenging [28]. On the one hand, due to the natural movement of TCOs when working, it is difficult to collect high-quality eye-tracking data. On the other hand, the illumination and reflection of the visual display may decrease the performance of eye trackers due to the large amount of noise collected [148, 149].

A total of 160 minutes (8 participants  $\times$  5 minutes  $\times$  4 sessions) of eye movement data from eight VTSOs were collected. The human fatigue data were summarized from the results of the Samn-Perelli Fatigue Scale and the Mackworth clock test.

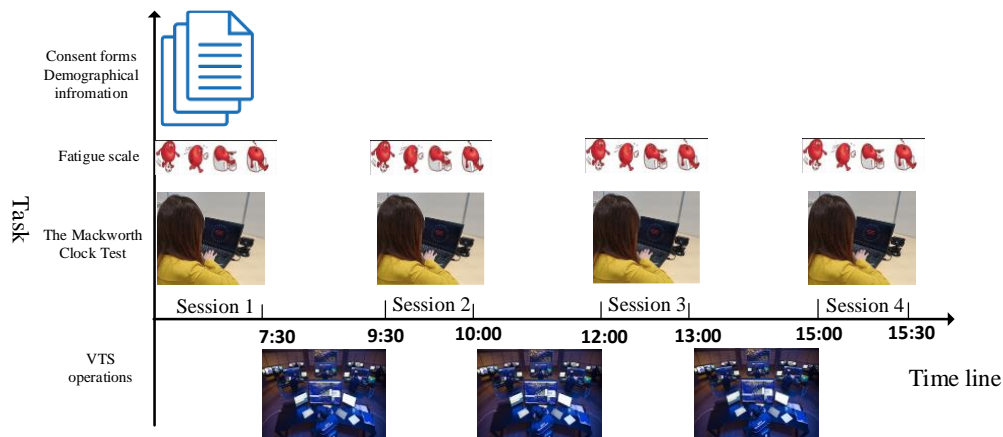


Figure 4.3 Data collection procedures

The time window ranges from 4 to 10 seconds. The shift window was set to a quarter of the time window. According to Eq. (4.6), the number of overlapping data packets is 6. The number of data packets  $N$  varies with the length of the time window, as shown in Table 4.1. In addition to the time window, the value of the bin number ( $b$ ) required more investigation because it can affect the performance of the human fatigue detection model. In this study,  $b$  was set to 6, 8, 10, 12, 14, and 16.

Table 4.1 The number of data packets with different time windows (for each participant)

<b>Time window (seconds)</b>	<b>N</b>	<b>Np</b>	<b>N test</b>
<b>4</b>	1196	6	1199
<b>6</b>	796	6	159
<b>8</b>	596	6	119
<b>10</b>	476	6	95

A within-subject design was adopted to investigate the effects of the variables on model performance in terms of three aspects, specifically, accuracy, sensitivity and specificity. For each model, 10 observations were obtained from a 10-fold cross-validation. A repeated-measures analysis of variance (ANOVA) was conducted to test the differences in observation of all the models. For factors that did not satisfy Mauchly's test of sphericity before the repeated-measures ANOVA, a Greenhouse-Geisser correction was applied. The significance level in this study is 0.05.

#### ***4.4.2 Performance of the human fatigue detection models***

This section presents the effects of the two main variables: bin numbers (6)  $\times$  time windows (4), on bagged tree model performance in terms of three aspects, specifically, accuracy, sensitivity and specificity. MATLAB 2017a was used to generate the fatigue models. Bayesian optimization was used to preliminarily select the optimal hyperparameters for the bagged tree models. After a preliminary study, the number of trees was set to 1500, and the minimum leaf size was set to 1.

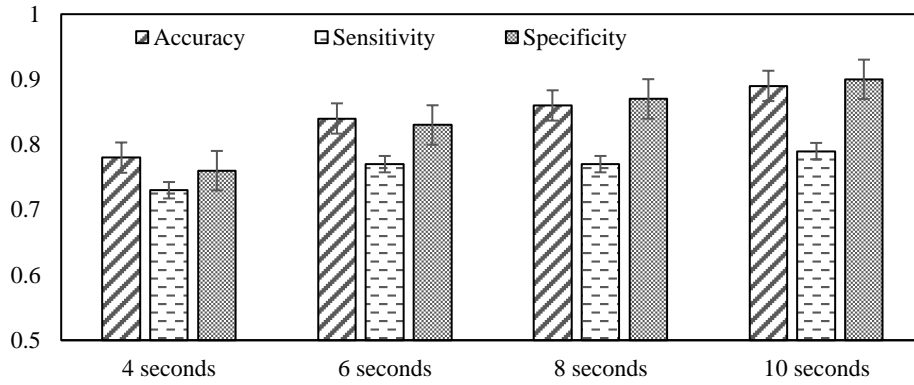


Figure 4.4 Model performance versus the time window

Figure 4.4 shows the performance of the human fatigue detection models across different time windows. The results show that the time window had a significant effect on the accuracy ( $F_{1.452, 10.161} = 13.262, p = 0.002 < 0.05$ ) and specificity ( $F_{3, 21} = 22.9, p = 0.002 < 0.05$ ) of the human fatigue detection models but not on their sensitivity ( $F_{1.222, 8.56} = 0.799, p = 0.519 > 0.05$ ). Therefore, the time window has no significant effects on detecting the “alert” state, while it has significant effects on detecting the “fatigue” state. In other words, using longer periods to summarize the data made the fatigue state easier to detect. With an increase in the time window, the human fatigue detection models can detect a “fatigue” state with higher accuracy and more sensitivity. However, the main effects of the bin number on model performance are not significant (accuracy:  $F_{2.149, 15.046} = 0.206, p = 0.958 > 0.05$ ; sensitivity:  $F_{2.371, 16.597} = 0.589, p = 0.708 > 0.05$ ; specificity:  $F_{3, 21} = 0.507, p = 0.769 > 0.05$ ). Hence, the performance of a human fatigue detection model is not sensitive to the bin number.

Figure 4.5 shows the line graph of model performance across different bin numbers. The best performance (accuracy = 0.90; sensitivity = 0.81; specificity = 0.90) was achieved when the time window was set to 10 seconds and the bin number was set to 8.

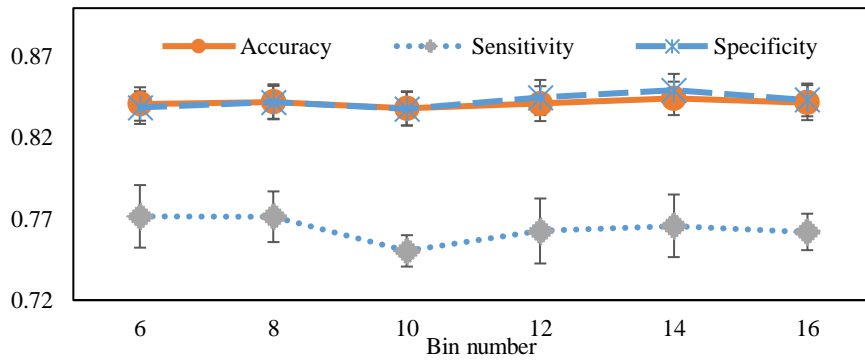


Figure 4.5 Model performance versus bin number

Figure 4.6 shows the cloud graph of human fatigue detection accuracy with different bin numbers and time windows. As shown in Figure 4.6, a longer time window can yield better performance; however, a larger bin number shows no significant improvement. The interaction effect of bin number and time window appeared to be nonsignificant ( $F_{15,105} = 1.097$ ,  $p = 0.368$ ; sensitivity:  $F_{15,105} = 1.178$ ,  $p = 0.301$ ; specificity:  $F_{15,105} = 0.989$ ,  $p = 0.472$ ). In the following sections, the bin number is fixed at 8.

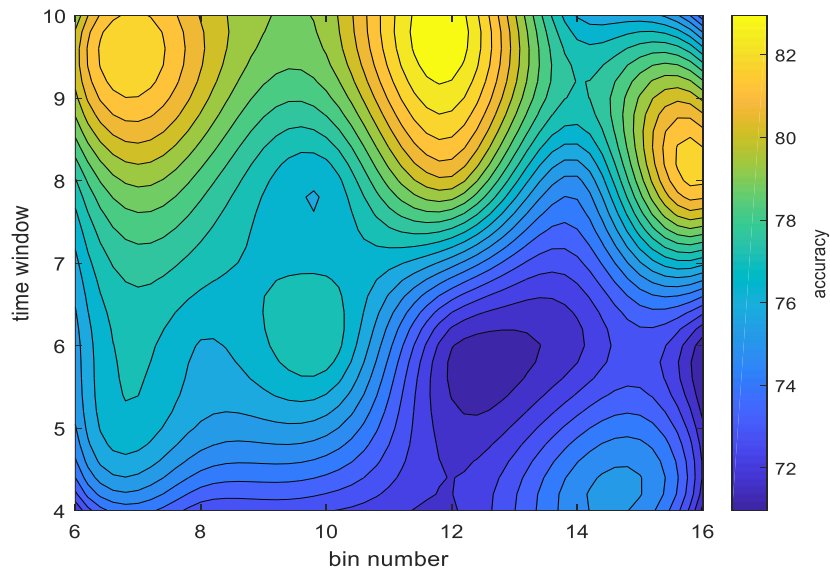


Figure 4.6 Effects of the bin number and time window on detection accuracy

#### 4.4.3 Comparison with other common fatigue indicators

This section compares the performance of four types of feature combinations: gaze-bin analysis, fixations, saccades and combination data.

Table 4.2 shows their parameters. Specifically, gaze-bin analysis includes two types of parameters: the velocity probability of each bin and entropy. For fixations and saccades, many statistical parameters can be generated from the raw eye movement data. Thus, several frequently used fixation parameters and saccade parameters were selected based on a review of the extant literature.

Table 4.2 Feature combinations used as model inputs

Eye movement parameters	Gaze-bin analysis (G)	Feature combination		
		Fixation data (F)	Saccade data (S)	Combination data I
Mean fixation duration		✓		✓
Mean fixation velocity		✓		✓
Mean fixation stability		✓		✓
Fixation count		✓		✓
Saccade count			✓	✓
Mean saccade peak velocity			✓	✓
Mean saccade velocity			✓	✓
Mean saccade amplitude			✓	✓
Mean saccade duration			✓	✓
Gaze velocity probability	✓			
Entropy	✓			

Table 4.3 shows the performance of the fatigue models with the four types of feature combinations. The results show that the feature combinations had a significant effect on the performance of human fatigue detection (accuracy:  $F_{(3, 21)} = 5.806, p = 0.005 < 0.05$ ; specificity:  $F_{(3, 21)} = 3.677, p = 0.028 < 0.05$ ) but not on sensitivity ( $F_{1.346, 9.422} = 2.662, p = 0.131 > 0.05$ ). Multiple comparisons show that the gaze-bin analysis could achieve a higher accuracy in human fatigue detection than other inputs. There is no significant difference in model performance between fixation data, saccade data and combination data. The results suggest that fixation data can contribute to human fatigue detection. Furthermore, the results show that the combination of fixation data with saccade data cannot greatly improve the accuracy of human fatigue detection. This finding can be explained based on two aspects. First, the combination of

fixation and saccade data introduces too many input features and impairs the performance of the bagged tree. Second, there should be some relationships between fixations and saccades.

Table 4.3 Model performance (bin number = 8)

Performance	Gaze-bin analysis	Fixation data	Saccade data	Combination data
Accuracy	0.84	0.77	0.79	0.81
Sensitivity	0.77	0.71	0.67	0.75
Specificity	0.85	0.75	0.78	0.79

There was no interaction effect of time window and feature combinations (accuracy:  $F_{9, 63} = 1.782$ ,  $p = 0.89$ ; sensitivity:  $F_{9, 63} = 0.820$ ,  $p = 0.600$ ; specificity: accuracy:  $F_{9, 63} = 0.665$ ,  $p = 0.737$ ). For all types of inputs, model performance increased with the time window, as shown in Figure 4.7.

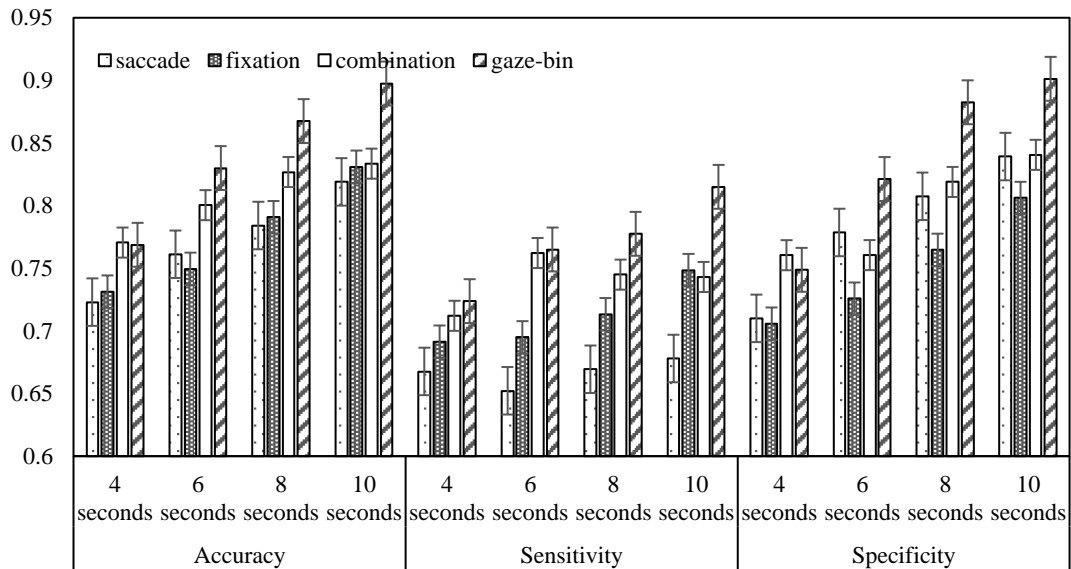


Figure 4.7 Effects of feature combinations and the time window on the performance of human fatigue detection

#### 4.4.4 Comparison with other methods

The proposed approach was compared with other classical methods, specifically, LR, decision trees, and the SVM. For the three types of performance, neither the method nor time window satisfied Mauchly's test of

sphericity. Hence, Greenhouse-Geisser correction was applied to all results of the main effects test. Table 4.4 shows the accuracy of the different methods using gaze-bin analysis as inputs. Figure 4.8 shows the accuracy, specificity, and sensitivity of the different methods using gaze-bin analysis as inputs. The methods used to detect human fatigue had significant effects on accuracy (accuracy:  $F_{1.210, 8.473} = 19.004, p = 0.002 < 0.001$ ). Multiple comparisons show that bagged trees outperformed the other three methods in terms of accuracy. Moreover, decision trees achieved significantly higher accuracy than LR and the SVM. No significant effects on sensitivity and specificity (sensitivity:  $F_{1.023, 7.160} = 3.369, p = 0.108 > 0.05$ ; specificity:  $F_{1.058, 7.403} = 0.471, p = 0.705$ ) were found. Therefore, bagged trees cannot significantly improve efficiency in detecting a “fatigue” state or an “alert” state. The time window affected specificity ( $F_{1.39, 9.733} = 11.3, p = 0.005 < 0.05$ ) but not accuracy ( $F_{1.139, 7.795} = 1.569, p = 0.251 > 0.05$ ) or sensitivity ( $F_{1.118, 7.286} = 1.941, p = 0.154 > 0.05$ ). The model’s specificity increased with the time window size, suggesting that using longer periods of eye movement data can improve the model’s ability to detect a fatigued state. The interaction effects of time window and methods on accuracy ( $F_{9, 63} = 2.329, p = 0.025 < 0.05$ ) and sensitivity ( $F_{9, 63} = 2.691, p = 0.010 < 0.005$ ) were significant; however, the interaction effect on specificity was not significant ( $F_{9, 63} = 0.755, p = 0.64$ ). Compared with the results of Section 4.4.2, the time effects on bagged trees are more significant than those on the other three methods. Therefore, no main effect of time window on accuracy was found in this section.

Table 4.4 Model performance (bin number = 12)

Performance	Decision tree	Linear regression	Support machine vector	Bagged trees
Accuracy	0.76	0.71	0.70	0.84
Sensitivity	0.65	0.63	0.68	0.75
Specificity	0.82	0.81	0.81	0.85

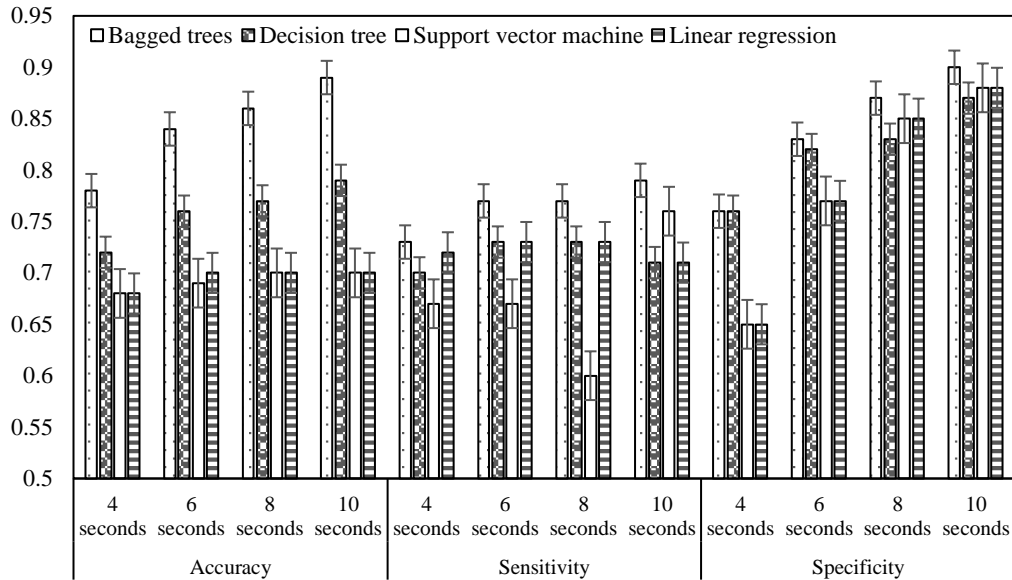


Figure 4.8 Effects of the methods and time window on the performance of human fatigue detection

#### 4.5 Summary

The performance of TCOs is usually impaired by mental fatigue, resulting in considerable threats to public safety. To minimize these risks, an innovative approach to noninvasively detect human fatigue in TCOs using gaze-bin analysis was proposed. A case study was conducted to test the effectiveness and performance of the proposed approach.

We run Algorithm 1 and the bagged trees on ThinkPad X1 Carbon with 8th Gen Intel Core™. The processing time for both Algorithm 1 and the bagged trees was shorter than 1 second. Hence, the proposed method can provide fatigue detection timely. The results in Sections 4.4.2, 4.4.3, and 4.4.4 confirmed that the proposed method could provide better performance than existing methods in this case study. It is expected that the results can be

extended to TCC operations. Specifically, the study collected eye-tracking data from the Mackworth clock test, which is a monitoring task. Monitoring tasks are the most frequent operations of TCOs. Moreover, the eye-tracking pattern related to gaze velocity is relatively task independent. As mentioned in Section 1, fixations and saccades are highly related to tasks and interface design whereas gaze velocity is relatively uncontrollable. With regard to these two aspects, gaze-bin analysis is expected to be a task-independent fatigue indicator and can be applied in other operations.

## **Chapter 5 A Context-aware Machine Learning Approach to Predicting Human Fatigue**

### **5.1 Brief of human fatigue prediction**

In recent years, organizations and regulators have advocated several fatigue models that aim to predict human fatigue to effectively schedule working time, improve operational flexibility, and guarantee safety [13, 14, 150]. Some researchers have tried to predict human fatigue based on working time and circadian rhythm models [15, 71]. However, these models are inadequate for predicting human fatigue in TCCs. First, they focus on time effects and fail to consider the dynamic work conditions in TCCs. The workload of TCOs varies with traffic density and weather conditions [16]; however, existing human fatigue models assume that operators have a stable workload. Second, TCOs exhibit dramatic individual differences in human fatigue [14], and few of these models capture such differences.

To address the problems resulting from dynamic work conditions and individual differences, in recent years, some researchers have proposed integrating contextual information for human fatigue prediction [7, 20]. Contemporary studies have claimed that integrating causal factors with circadian rhythm models would be beneficial for managing human fatigue [7, 12, 20]. For example, Strahan et al. [20] recommended that companies should predict human fatigue based on organizational influence and occupational stress. Ji et al. [7] suggested investigating the dynamic aspects of human fatigue by considering various causal factors.

Nevertheless, it has been established that thorough and systematic methods for predicting human fatigue based on contextual information are scarce, and several issues must be addressed. Specifically, research must determine (1) how to capture contextual information, which includes the characteristics of dynamic work conditions and the individual differences exhibited by TCOs; (2) how to address the numerous interrelated factors involved in contextual information; and (3) how working conditions and individual differences affect the performance or accuracy of human fatigue prediction.

To address the above issues, this study analyzes the causal factors contained in contextual information and presents a hybrid approach that combines an AIS and the extreme gradient boosting (XGBoost) algorithm to predict human fatigue in TCOs using the causal factors captured.

The AIS technique simulates the biological immune system, which is adaptive and self-organizing [151, 152]. The biological immune system is a defense system comprising many structures that protects against pathogens such as bacteria and viruses. The pathogen surface includes many antigens that can induce an immune response. When an antigen enters the body, the immune system produces antibodies against it. Antibodies can recognize the antigen and then wipe out it. When an antibody is first activated by an antigen, memory cells develop. This process is termed the primary response. Memory cells can induce a stronger response to a smaller amount of antigen when the same antigen is encounter again. This process is known as the secondary response. Compared with the primary response, the secondary response has a shorter lag time and a larger number of antibodies. Thus, a vaccine, which is an antigenic

material, is used to induce the primary response and provide active acquired immunity to a particular disease.

The proposed approach consists of three phases: the data preprocessing phase, training phase, and testing phase. In this study, AIS is used to preprocess the causal factors and provide structured inputs for a XGBoost model. Furthermore, the benefits of integrating working conditions and individual differences in human fatigue prediction are illustrated using a case study on vessel traffic management based on the information obtained by a questionnaire-based survey.

This chapter is organized as follows. Section 5.2 describes the causal factors of human fatigue captured in contextual information and a novel way to represent these factors. A framework and the detailed algorithm of the proposed approach are reported in Section 5.3. Section 5.4 presents a case study to illustrate the proposed approach; it also includes a comparative study of the proposed approach and other approaches. Section 5.5 summarizes the main conclusions reached in this chapter.

## 5.2 Contextual information of human fatigue

Four main fatigue-inducing factors have been identified: *environmental factors*, *working conditions*, *circadian rhythms* and *individual resilience* (Figure 5.1). Hence, the causal factors of human fatigue can be represented as  $\{E, W, C, I\}$ .  $E$  is a group of environmental factors, including the factors that shape the environment whereas  $W$  is a group of working condition factors that are involved in the specific task.  $C$  includes the factors that affect circadian rhythms, and  $I$  refers to the factors that affect a person's response to the other

three factors. The details about how to quantify these causal factors of human fatigue in TCCs are discussed in Sections 5.2.1-5.2.4.

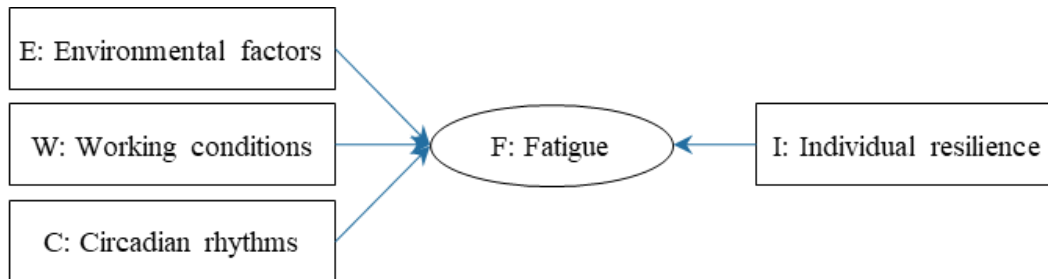


Figure 5.1 The causal factors of human fatigue

### 5.2.1 Work environment

The work environment includes the factors involved in creating the environment. For example, dim lighting causes eye strain, and insufficient lighting can promote sleep [18]. A higher core body temperature can create sleep onset difficulties [19] whereas environmental and occupational noise can increase the level of work-related fatigue [20]. In this study, the work environment was characterized by factors that included lighting levels, noise, air pressure, and temperature.

### 5.2.2 Working conditions

As shown in Figure 5.1, the intensity and length of work are critical work-related factors that contribute to human fatigue. Essentially, the length of work (WL) is suggested by working hours, and the intensity of work (WI) is assessed using the NASA task load index (NASA-TLX) scale, a subjective, multidimensional assessment tool. The NASA-TLX scale assesses workload based on six aspects: mental demand, physical demand, temporal demand, performance, effort, and frustration.

#### ***5.2.4 Circadian rhythms***

TCCs generally adopt shift work to provide 24-hour service. Shift work can directly lead to work-related fatigue [79] as it disrupts the cycle of sleep and wakefulness [153]. Accordingly, shift work may chronically affect health and even result in cumulative sleep deprivation [88]. However, some researchers [15, 71, 72] have focused on investigating the effects of circadian rhythms (CR) and the effect of time on task. In practice, these two factors induce human fatigue interactively. Thus, shift work and time on task are studied to indicate the level of disruption of circadian rhythms.

#### ***5.2.3 Individual resilience***

There are large individual differences in people's susceptibility to becoming drowsy [154]: some people are greatly affected by work conditions, while others are not. Individual differences mainly refer to demographic variables (DV), physical conditions (PC) and personality factors (PF). In general, demographic variables include age, gender, nationality, and experience. In this study, physical conditions were measured by the FSS. The FSS (Appendix A.1) is a 9-item self-report questionnaire scale that contains nine statements related to topics such as motivation and physical functions. Physical conditions involve many aspects including various diseases, eating habits, and drug consumption. It is almost impossible to collect all the information pertaining to physical conditions. Thus, fatigue severity, which is a type of observable pattern of physical conditions, has been adopted as one type of contextual information. Personality factors, such as extraversion and sensation seeking, can be mediating precursors of human fatigue [154, 155], and they can

be assessed using the Bortner Type A scale, which is a simple self-report scale [155]. The Bortner Type A scale (Appendix A.2) covers 14 aspects, such as extremes of ambition, competitiveness, and punctuality [155].

### 5.2.5 Fatigue causal network representation

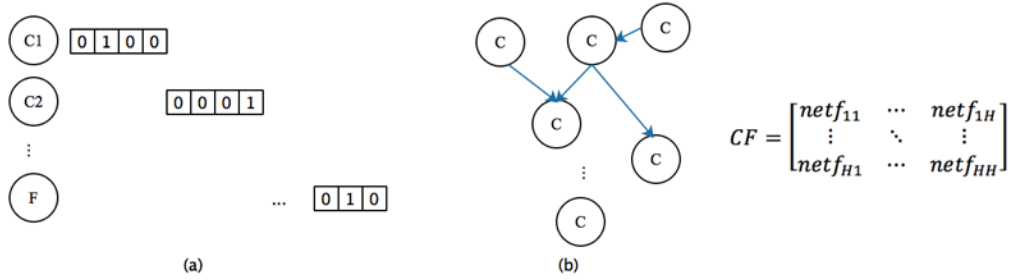


Figure 5.2 Causal factor representation: (a) conventional causal factor representation; (b) fatigue causal network representation

Conventionally,  $\{E, W, C, I\}$  can be represented as  $CF = \{C_1, \dots, C_H\}$ , where  $CF$  refers to all the causal factors of human fatigue. Nevertheless, this type of representation fails to consider the interrelationships among causal factors. It has long been found that there are significant correlations among fatigue-inducing factors [85].

Causal networks, which have been used to manage problems in different domains, such as philosophy, health and the environment, and tourism [133], can be used to express the interrelationships among causal factors. Hence, instead of using a conventional representation of causal factors, in this work, a novel fatigue causal network representation is proposed, and Figure 5.2 illustrates these two types of representation:

$$CF = \begin{bmatrix} netf_{11} & \cdots & netf_{1H} \\ \vdots & \ddots & \vdots \\ netf_{H1} & \cdots & netf_{HH} \end{bmatrix} \quad (5.1)$$

$$\text{For } h \neq j, netf_{jh} = \begin{cases} 1 & netf_j \text{ has effects on } netf_h. \\ 0 & netf_j \text{ has no effects on } netf_h. \end{cases} \quad h, j \in [1, H]$$

For  $h = j, netf_{hj} = C_h$

Each column of  $CF$  is a principal eigenvector of the effects of the  $j$ th element on the  $h$ th element. For  $h = j, netf_{hj}$  refers to the value of the  $h$ th node.

By representing causal factors using the network, the problem of  $F \leftarrow \{C_1, \dots, C_H\}$  is transformed into the following:

$$F \leftarrow \begin{bmatrix} netf_{11} & \cdots & netf_{1H} \\ \vdots & \ddots & \vdots \\ netf_{H1} & \cdots & netf_{HH} \end{bmatrix}$$

where the transformation faces several challenges in modeling human fatigue. First, the causal network induces a high dimensional sparse matrix. It enlarges the dimension from  $N$  to  $N \times N$ , and this high dimension will result in increased computing time. In addition, using the high dimensional matrix as an input for a fatigue prediction model will require a large amount of training data. Second, the heterogeneity of causal factors, including both qualitative variables and quantitative variables, should also be addressed.

### 5.3 AIS and XGBoost-enabled fatigue prediction

Generally, in the artificial immune system, antigens refer to problems waiting to be solved, antibodies refer to solutions, and vaccines refer to problem and corresponding solutions. In this study, causal factors are treated as antigens, grouped causal factors are treated as antibodies, and a vaccine refers to a set of causal factors and their corresponding fatigue levels.

The proposed AIS-XGBFP has three phases: data preprocessing, training, and predicting. In the first phase, a vaccine with causal factors and corresponding fatigue levels is generated. In the second phase, the fatigue causal network and vaccine are integrated to generate antibodies and memory

cells, and a fatigue model is trained based on the memory cells. In the third phase, the fatigue level is predicted by comparing the antigens and the memory cells.

### ***5.3.2 Phase 1: Data preprocessing***

The notation and terminology used in this phase are as follows: the raw data are preprocessed to generate a vaccine,  $Va = \{Va_1, Va_2, \dots, Va_i\}$ . Each  $Va_i$  is denoted by  $Va_i = \langle CF_i, F_i \rangle$ .  $CF$  is the set of fatigue causal factors, while  $F$  refers to the subjective fatigue level.

There are two steps in the preprocessing of raw data. The first step is to delete noisy data. Certain populations may be less likely to participate in a survey even if invited (e.g., elderly operators). Moreover, some participants may be unwilling to answer certain questions (e.g., related to personality or workload). During a questionnaire survey, these challenges can result in incomplete information or missing data. Thus, questionnaires containing nonresponse items were ignored in this research. The second step is normalization. The data collected from questionnaires include categorical variables and numerical variables. The data related to categorical variables are encoded as numerical vectors using one-hot encoding, which performs “binarization” of the category [156]. Numerical variables are first normalized and then scaled from 0 to 1; thus, the values of the causal factors in the vaccine range from 0 to 1.

### ***5.3.2 Phase 2: Training***

In this phase, the vaccine generated from the first phase is treated as training data. Antibodies and memory cells are generated based on the fatigue

causal network and training data. Figure 5.3 depicts the procedures of the training phase.

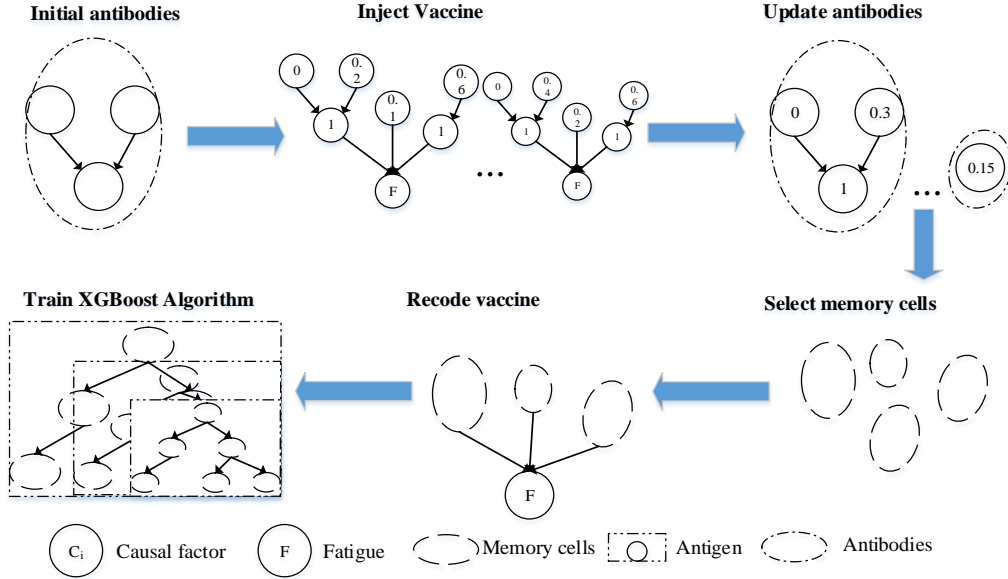


Figure 5.3 Procedures of the training phase

The training phase can be summarized in six steps:

*Step 1: Initialize antibodies ( $Ab$ ).* A set of  $Ab$  is generated based on the fatigue causal network. Causal factors with interrelationships are grouped into one  $Ab$ . The interrelationships among any  $C_k$  and  $C_l$  are defined as  $netf_{k,l}$ . The value of  $netf_{k,l}$  can be obtained from the fatigue causal network, as set forth in Eq. (5.1).

$$Ab_n = \langle C_1, C_2, \dots, C_K \rangle, \text{ if } \prod_{k=1}^L (\sum_{l=1}^L netf_{k,l}) > 0, 1 \leq L \leq K. \quad (5.2)$$

*Step 2: Inject vaccine ( $Va$ ).* The vaccine is a set of causal factor data labeled with the subject fatigue level,  $Va_i = \langle C_1, C_2, \dots, C_H, F_i \rangle$ .

*Step 3: Update antibody.* Each introduced  $Va_i$  is presented to the initial  $Ab$ . The distance function  $D$ , which quantifies the similarity between  $Va_i$  and  $Ab_n$ , is adopted to calculate the affinity  $A$ .

$$D_i(Va_i, Ab_n) = \sum_{k=1}^K |Ab_{n,k} - Va_{i,k}|, \quad (5.3)$$

$$A_i = 1 - \frac{D_i}{L} \quad (5.4)$$

For each  $Va_i$ , determine the  $Ab_n$  that has the highest affinity with it. If the affinity between  $Va_i$  and  $Ab_n$  is larger than the predetermined  $\alpha$ , add the  $Va_i$  to the recognition pool of  $Ab_n$ . Constructed by higher-similarity vaccines, the recognition pool of  $Ab_n$  is denoted by  $Rp\_Ab_n = \langle Va_1, Va_2, \dots, Va_s \rangle$ . If the affinity between  $Va_i$  and  $Ab_n$  is smaller than the predetermined  $\alpha$ , add a new  $Ab$  by reproducing the  $Va_i$ . The value of  $Ab_n$  is updated as the mean value of  $Va$  in the recognition pool of  $Ab_n$ .

*Step 4: Memory cell selection.* The recognition size ( $RS\_Ab$ ) of an  $Ab$  refers to the number of  $Va$  within its recognition pool divided by the amount of injected  $Va$ . If the recognition size of an  $Ab$  is larger than the predetermined  $\beta$ , it is selected as a memory cell. Hence, the memory cell ( $Mc$ ) refers to the selected antibodies that have a large recognition pool.

$$RS\_Ab_n = \frac{S}{I} \quad (5.5)$$

*Step 5: Vaccine recoding.* The recoding of vaccines uses binary code to produce inputs for XGBoost training.  $Va_i = \langle Tr_1, Tr_2, Tr_3, \dots, Tr_G, F_i \rangle = \langle Tr, F_i \rangle$ .  $G$  is the number of memory cells. If the affinity between  $V_n$  and  $Mc_g$  is larger than the predetermined  $\alpha$ , the value of  $Tr_g$  will be set to 1.

$$\begin{cases} Tr_g = 0, \text{ if } D_g(Va_i, Mc_g) \geq \alpha, & g = 1, 2, 3, \dots, G. \\ Tr_g = 1, \text{ if } D_g(Va_i, Mc_g) < \alpha, & g = 1, 2, 3, \dots, G. \end{cases} \quad (5.6)$$

*Step 6: XGBoost training.* The latest available set of  $Va$  is utilized to train the XGBoost algorithm, which is implemented using Python libraries. The XGBoost algorithm is trained to predict  $F_i$  based on  $Va = \langle Va_1, Va_2, Va_3, \dots, Va_i \rangle$ ; each  $Va$  is denoted by  $Va_i = \langle Tr, F_i \rangle$ . In the training phase, T-boosted trees are generated to optimize the following objective functions:

$$obj = \sum_{i=1}^I l(F_i, \hat{F}_i^{(t)}) + \sum_{t=1}^T \Omega(f_t) \quad (5.7)$$

$$\hat{F}_i = \sum_{t=1}^T f_t(Tr) \quad (5.8)$$

where  $l$  is the training loss function and  $\Omega$  is the regularization term. In this study, the logistic loss function is adopted as  $l$ . The regularization term was calculated following [157], where the number of terminal nodes and the depth of the boosted tree are considered. When the regularization parameter is set to zero, the objective falls back to the traditional gradient tree boosting.  $T$  is the number of boosted trees, and  $f$  is the function of the boosted trees. Normally it is impossible to enumerate all possible tree structures. A greedy algorithm that starts from a single leaf and iteratively adds branches to the tree is used instead. The tree ensemble model in Eq. (5.7) includes functions as parameters and cannot be optimized using traditional optimization methods in Euclidean space. Instead, the model is trained in an additive manner. Thus, to achieve the objective, the XGBoost algorithm greedily add the tree that most improve the model.

### 5.3.3 Phase 3: Testing

A set of causal factors, treated as the antigen ( $Ag$ ), was utilized to test the proposed method. The antigen, which is denoted by  $Ag = \langle C_1, C_2, \dots, C_H \rangle$ , is the vector of causal factors. A threshold  $\alpha$  is applied to determine whether the  $Mc$  is similar to the  $Ag$ .

The testing phase involves finding a set of memory cells that have a high level of affinity with the antigen and then predicting the level of human fatigue.

The procedures are summarized as follows:

*Step 1:* For each  $Mc_g$ , compute the affinity between the  $Ag$  and  $Mc$ .

*Step 2:* If the affinity is larger than the predefined threshold  $\alpha$ , set  $Tr_g$  to 1.

If the affinity is smaller than the predefined threshold  $\alpha$ , set  $Tr_g$  to 0.

*Step 3:* Repeat steps 1 to 2 until all memory cells have been tested.

*Step 4:* Predict the fatigue level by using  $Tr$  as the input of the XGBoost algorithm. The fatigue level can be predicted by reassembling the boosted trees (Eq. (5.8)).

## 5.4 Case study in fatigue prediction

VTS is a marine shore-side monitoring service designed to guarantee the safe and efficient navigation of vessels in a port and coastal area [158]. During the field studies, it was found that VTSOs are at risk of suffering from human fatigue. Hence, this case study was performed at a VTS in Singapore to validate the effectiveness of the proposed context-aware fatigue management system.

### 5.4.1 Fatigue model

The data on human fatigue and causal factors were extracted from a questionnaire-based survey. A total of 132 VTSOs from the port authority participated in this survey. Their ages ranged from 25 to 55 years old. The sample group consisted of 119 males and 13 females, with an average working experience of 11 years. All participants were initially screened during a

telephone interview to eliminate those with sleep disorders, and they were asked to refrain from consuming drugs and coffee before the survey.

Information about individual differences, working conditions, the environment and circadian rhythms was collected. Thirty-three (33) variables were gathered (as shown in Figure 5.4). Accordingly, a fatigue causal network (Figure 5.4) was constructed, and the values of the 33 variables were measured by the methods discussed in Li et al. [159].

In terms of human fatigue, the 7-point Samn-Perelli fatigue scale [160] was adopted to evaluate the subjective fatigue level where 1 denotes alert and 7 denotes fatigued. The researcher collected 705 records of human fatigue, 10 records of which were discarded due to item nonresponse. The remaining fatigue records were utilized to train and test the proposed method. Each fatigue record includes 33 causal factors and a corresponding subjective human fatigue level.

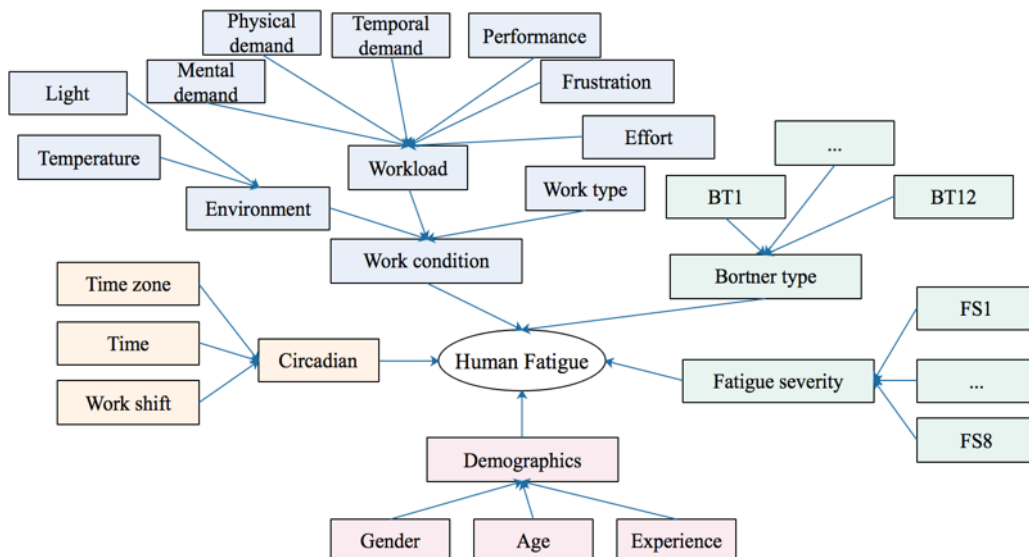


Figure 5.4 The fatigue causal network of VTS [159]  
(FS: The elements of fatigue severity are listed in Appendix A.1; BT: The elements of the Bortner Type A are listed in Appendix A.2).

### 5.4.2 A comparative study of fatigue prediction

As mentioned in Sections 5.3.2 and 5.3.3, it is necessary to determine four parameters: the affinity threshold, the recognition pool size threshold, the number of boosted trees and the maximum depth of the boosted trees. According to Lu et al. [161], the affinity threshold should be set to 0.7, and the recognition size threshold should be set to 0.2 to guarantee accuracy and to limit the number of memory cells. For the other two parameters, a greedy approach was applied to determine their values. In general, the number of boosted trees is set with lower and upper limits in the hundreds and thousands. To reduce model complexity, the maximum depth of a tree was set to 4 to 6. In this study, the number of boosted trees was decided according to the experimental results by setting the value to 500, 1000 and 1500. Similarly, the maximum depth of a tree was decided according to the experimental results by setting the value to 3, 4, and 5. It was found that 1000 boosted trees with a depth of 4 can achieve the best performance. Thus, the four parameters were set to the particular values shown in Table 5.1.

Table 5.1 Parameters of AIS-XGBFF

<b>Parameters</b>	<b>Value</b>
<b>Affinity threshold <math>\alpha</math></b>	0.7
<b>Recognition pool size threshold <math>\beta</math></b>	0.2
<b>Number of boosted trees</b>	1000
<b>Maximum depth</b>	4

A 10-fold cross-validation was conducted to verify the proposed approach. The fatigue records from the port authority were split into 10 parts, with nine forming the training data set and the other forming the testing data set. The training data set serves as the vaccine to generate memory cells and to train the boosted trees; the testing data set is the antigen used to test the performance of

the proposed approach. This research adopts *accuracy* and *deviation* to measure the performance of the proposed approach. *Accuracy* refers to the proportion of true results while deviation is suggested by the average of the squares of the errors, that is, the difference between the estimator and what is estimated.

According to the literature review in Section 2.3.3, decision tree regression (DTR), random forest regression (RFR), the SVM, and LR are commonly used machine learning approaches in human fatigue management. Hence, the proposed AIS-XGBFP approach was compared with these well-known methods. The parameters of DTR, LR, the SVM, and RFR were determined using the built-in hyperparameter optimization function of MATLAB R2018a. Table 5.2 shows the performance of all these methods in predicting human fatigue. Detailed results are shown in Appendix A.3. AIS-XGBFP showed the highest accuracy and lowest deviation.

Table 5.2 The results of 10-fold cross validation

<b>Methods</b>	<b>AIS-XGBFP</b>	<b>LR</b>	<b>SVR</b>	<b>DTR</b>	<b>RFR</b>
<b>Accuracy</b>	0.89	0.88	0.82	0.84	0.85
<b>Deviation</b>	0.09	0.26	0.16	0.12	0.10

To test the performance differences between the proposed approach and the other four methods, ANOVA was conducted in the SPSS (version 19) software environment. The significance level of 5% was adopted in all tests, and the results are shown in Table 5.3. The ANOVA results revealed that AIS-XGBFP had significantly higher accuracy ( $p < 0.05$ ) than the other four methods. Furthermore, compared with the SVM and LR, AIS-XGBFP also showed a significantly lower deviation ( $p < 0.05$ ). It is clear that the stability and accuracy of the proposed method are significantly better than those of the other methods.

Table 5.3 Comparison of prediction performance between AIS-XGBFP and the other methods

<b>Algorithm</b>	<b>Algorithm</b>	<b>Sig. (Accuracy)</b>	<b>Sig. (deviation)</b>
<b>AIS-XGBFP</b>	DTR	.000	.182
	LR	.001	.003
	RFR	.000	.464
	SVR	.000	.000

Next, an experiment was designed to investigate the effects of contextual information on human fatigue prediction. The contextual information was classified into three subsets: contextual information without personality information (No PI), contextual information without demographic information (No DI), and contextual information without working conditions (No WC). The details of the classification can be found in Figure 5.4. Table 5.4 shows that without personality information as input, the predictive performance of the proposed approach significantly degrades. Furthermore, all three subsets result in low accuracy and high deviation. The details can be found in Appendix A.4. In other words, integrating all information can greatly improve the performance of human fatigue prediction.

Table 5.4 The results of 10-fold cross validation

<b>Subset</b>	<b>No PI</b>	<b>No DI</b>	<b>No WC</b>
<b>Accuracy</b>	0.81	0.87	0.85
<b>Deviation</b>	0.14	0.10	0.11

The experimental results show that the proposed algorithm can significantly increase the accuracy of human fatigue prediction. Moreover, with more contextual information as input, a higher accuracy of the prediction results can be achieved. The case study shows that personality information plays the most important role in predicting human fatigue. Without personality information as input, even the proposed algorithm can achieve an accuracy of only 0.81.

## 5.6 Summary

In this chapter, a hybrid approach to predicting human fatigue based on contextual information, called AIS-XGBFP, is proposed. This approach allows users to systematically represent various factors related to fatigue and to account for the inherent uncertainties associated with these factors. Since human fatigue is a common phenomenon in various work settings, this approach can be extended and used in these work settings to reduce the risk of human fatigue. The experimental results obtained from the case study demonstrate the validity of the proposed approach. The statistical tests suggest that the approach can achieve better performance than traditional methods, such as the SVM, random tree forests, and LR. An experiment was conducted to confirm the importance of integrating individual differences and working conditions in the prediction of human fatigue. Large individual differences were found in the susceptibility to becoming fatigued.

## **Chapter 6 Hybrid Data-driven Intervention Design for Mitigating Human Fatigue**

### **6.1 Background of human fatigue intervention design**

According to the review in Section 2.2.4, interventions for mitigating human fatigue mainly include preventive strategies and operational strategies [137]. Preventive strategies reduce the possibility that errors will occur because of human fatigue and decrease the likelihood of human fatigue itself. These strategies include using a second operator as a second set of eyes, developing explicit procedures for monitoring operators, and increasing vigilance with vertical vibration [162, 163]. In addition to preventive methods, extensive studies have been conducted to monitor or detect human fatigue in real time [18, 28]. These studies have given rise to operational strategies that alert operators once human fatigue occurs.

Chapter 4 presents an operational method for detecting fatigued operators. Thus, this chapter focuses on preventive strategies. According to the research in Chapters 3 and 5, the existing preventive strategies cannot fully address the problem of human fatigue in TCCs because preventive strategies (1) focus on time-induced human fatigue and pay limited attention to other dimensions of human fatigue. Moreover, based on Chapter 3, TCOs always suffer from the problem of alarm fatigue, which is the phenomenon of distrusting or neglecting alarms. Alarm fatigue has been identified as the top risk factor in the safety and security industry [164]; nevertheless, limited studies have focused on reducing alarm fatigue. (2) The existing strategies for managing human fatigue in

transportation primarily involve prescriptive “hours-of-work” regulations; however, these regulations lack a certain flexibility and fail to consider dynamic fatigue-inducing factors in the workplace context.

With the development of advanced information and communication technology (ICT), the internet of things (IoT), and AI, data on human states and working conditions can easily be collected and analyzed to proactively support human decision-making, learning, and action. For example, Akhavian and Behzadan [165] successfully used mobile sensors and machine learning classifiers to recognize construction equipment activities in a working environment. Based on the above knowledge and research gaps, the objective of this chapter is to develop a hybrid data-driven framework to reduce fatigue from the preventive perspective. This novel framework can make it possible to fulfill the objectives of developing adaptive work arrangements and redesigning alarm systems to reduce alarm fatigue.

This chapter is organized as follows. Section 6.2 introduces the overall structure of the proposed interventions. Section 6.3 describes the data-driven platform, which provides warnings and recommendations for effective work arrangements. The conceptual framework for redesigning alarm systems is proposed in Section 6.4. The study concludes with a discussion of the potential industrial applications, contributions, limitations, and future development of this research in Section 6.5.

## 6.2 Overall structure of intervention design

This chapter provides two preventive interventions for reducing the possibility of human fatigue: recommendations for work arrangements and recommendations for alarm system design (as shown in Figure 6.1).

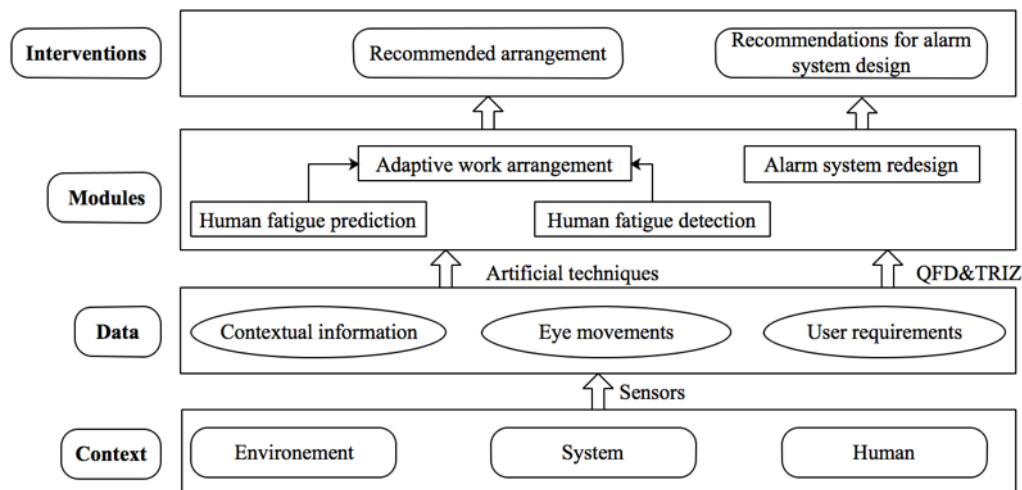


Figure 6.1 Overall structure of intervention design

### 6.2.1 Work arrangements

In this chapter, adaptive work arrangements are proposed to identify an optimized work arrangement based on working conditions and individual conditions to mitigate the risk of human fatigue. As described in Chapter 4, individual conditions were measured using eye movements and bagged trees. The proposed human fatigue detection model monitors the cognitive states of operators in real time and can provide alarms if operators are fatigued. In addition, it sends operators' information to an adaptive work arrangement module. As mentioned in Chapter 5, AIS-XGBFP is used to predict the effects of working conditions on human fatigue. The human fatigue prediction model can predict fatigue levels considering dynamic working conditions and individual differences. Based on this model, a long-term plan can be formulated.

For example, if the model predicts that all operators will be fatigued after 6 hours of work under working condition A, the duration of shifts under working condition A should not be more than 6 hours. In addition, the model can provide prediction results for adaptive work arrangements.

### ***6.2.2 Alarm system design***

A UR-driven design that considers human limitations and URs is proposed to reduce alarm fatigue. URs have been widely accepted as an important source of information from which to derive design metrics and specifications in the early stages of product concept design [166, 167]. The alarm system design guidebook released by the Engineering Equipment and Material Users Association (EEUMA) [168] pointed out that alarm systems should be “context-sensitive” and that designers should account for human limitations during the design phase [169]. Moreover, a study conducted in three VTS centers found that it is critical to provide the right information according to user needs [170]. Therefore, in this chapter, an integrated UR-driven framework for improving alarm systems is introduced.

## **6.3 Context data-driven work arrangements**

### ***6.3.1 Platform establishment***

The platform for establishing context data-driven work arrangements is illustrated in Figure 6.2. The data were collected with connected objects, including an eye tracker, a smart phone and a computer. These objects could collect three types of information: eye movements, human-computer interactions, and user sensing data. Regular commercial eye trackers provide

gaze or eyelid movements with timestamps. Fixation, saccade, and blink events were extracted from the raw eye-tracking data using dispersion-based threshold algorithms or velocity threshold algorithms [148]. The computer recorded data on human-computer interaction, such as the inputs of keyboard and mouse movements. Hence, a set of behavioral data could be generated. In addition to product-generated data, user sensing data, including online feedback, subjective feelings and complaints, were collected.

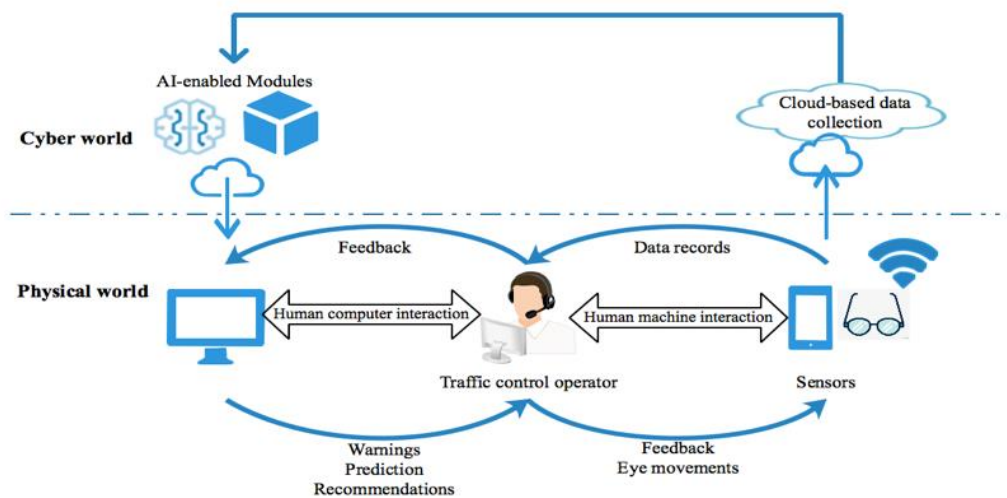


Figure 6.2 Data-driven platform for interventions

All collected data were uploaded to the cloud for data analysis. Due to the large amount of data, machine learning techniques were adopted to generate a human fatigue model. In the following sections, the details of the cloud-based data collection and model generation are discussed.

### 6.3.2 Decentralized data collection

Sensor-generated data were preprocessed separately and then uploaded to the cloud, as shown in Figure 6.3. Thus, feature extraction occurred locally on each sensor. An extracted feature is represented as  $F_k = \{f, s\}$ , where  $f$  is the value of the feature and  $s$  is the sensor label. The sensor label depends on the

information collected from the specific sensor. In this study, three types of information were collected: eye movements, working conditions, and system information. This method benefits from local observations and reduces the cloud computation time. Furthermore, the key advantage of decentralized feature extraction is that it is survivable with regard to the loss of sensing nodes. In the eye movement-based system, the eye trackers always lose track due to light exposure and subjects' nature movements. If the eye tracker loses track of the eye, a part of the eye movement data will be lost. Hence, decentralized feature extraction is developed to minimize the effects of data loss on extracting other features.

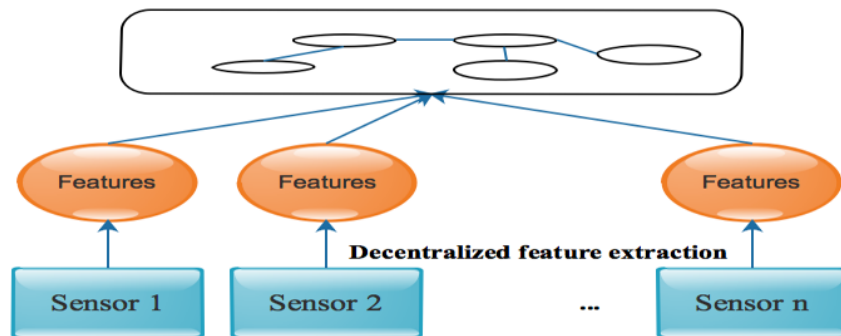


Figure 6.3 Illustration of decentralized data collection

### 6.3.3 Algorithm for work arrangements

To further assist with human fatigue reduction, in this subsection, an adaptive work arrangement approach is introduced. Given a series of tasks  $W = \{W_1, \dots, W_Z\}$  and a group of people  $I = \{I_1, \dots, I_Z\}$ , there are  $Z!$  ways to arrange operators. The objective of adaptive work arrangements is to identify optimized work arrangements based on working conditions and individual differences to mitigate the risk of human fatigue. The problem can be denoted as follows:

$$\begin{aligned} \min. F_{sum} &= \sum_{b=1}^Z xgb\{E, W_b, C, I_b\}, & (6.1) \\ \text{for any } b \text{ and } a &\in [1, Z], W_b \neq W_a, I_b \neq I_a \\ \text{for } b \in [1, Z], &F_b = xgb\{E, W_b, C, I_b\} < F_{threshold} \end{aligned}$$

The fatigue level of every person should not be higher than the threshold. To reduce the complexity of working arrangements, tasks are divided into several groups, and then an analysis of work arrangements is conducted. The values of working condition were transformed into 0 or 1 by one-hot coding [156]. Given two tasks  $W_b = \{w_{b1}, w_{b2}, \dots, w_{bR}\}$  and  $W_a = \{w_{a1}, w_{a2}, \dots, w_{aR}\}$ , where  $R$  is the length of working conditions variables, their similarity is calculated based on Eq. (6.2):

$$S_{ba} = 1 - \sum_{r=1}^R |w_{br} - w_{ar}| / R \quad (6.2)$$

Tasks are classified into the same group ( $GW$ ) if their similarity is higher than a defined threshold  $\alpha$ . In this way, a series of tasks  $W = \{W_1, \dots, W_Z\}$  is grouped as  $W = \{GW_1, \dots, GW_Q\}$ ,  $Q \leq Z$ . Then, the number of combinations ( $NC$ ) can be obtained using Eq. (6.3).

$$NC = C_Z^{Size_1} \times C_{Z-Size_1}^{Size_2} \times \dots \times C_{Z-\sum_{q=1}^{Q-1} Size_q}^{Size_Q} \quad (6.3)$$

$Size_q$  refers to the number of tasks belonging to  $GW_q$ . MATLAB can be used to generate all possible combinations of the elements of vector  $I = \{I_1, \dots, I_Z\}$  for the work groups, and AIS-XGBFP can be used to estimate the fatigue score of each combination. The combination with the lowest fatigue score should be selected. Algorithm 6.1 below shows how to obtain the recommended work arrangement.

**Algorithm 6.1: Context-aware work arrangements**


---

**Inputs:** I: the set of workers  $\{I_1, \dots, I_z\}$   
W: the set of grouped tasks  $\{GW_1, \dots, GW_Q\}$

---

```

1    $Size_q$ : the number of slots belonging to  $GW_q$ 
2   CP: the set of workers whose task should be rearranged
3   For all  $I_z \in I, GW_q \in W$ 
4        $F_z = \{F_{z1}, \dots, F_{zq}, \dots, F_{zQ}\}$ 
5        $\Delta_z = \max F_z - \min F_z$ 
6       If  $\Delta_z > 0$ 
7            $I_z \rightarrow CP$ 
8       end
9   End
10   $N_a = 0$ 
11  While  $\text{size}(CP) > 0$ 
12      For all  $I_z \in I, GW_q \in W$ 
13           $F_z = \{F_{z1}, \dots, F_{zq}, \dots, F_{zQ}\}$ 
14           $\Delta_z = \max F_z - \min F_z$ 
15          If  $\Delta_z > 0$ 
16               $I_z \rightarrow CP$ 
17          end
18      End
19      Rank CP from max to min based on  $\Delta$ 
20      For  $n=1:1:\text{size}(CP)$ 
21          Find  $GW_a$ , where  $F_{cp_n a} == \min F_{cp_n}$ 
22           $N_a = N_a + 1$ 
23          If  $N_a < Size_a$ 
24              Get  $\{CP_n, GW_a\}$ 
25              Delete  $CP_n$  from CP & I
26              Update CP
27          Else
28              Get  $\{CP_n, GW_a\}$ 
29              Delete  $CP_n$  from CP & I
30              Delete  $GW_a$  from W
31              Update  $\Delta_z$ 
32              Update CP
33          End
34      End
35  End while

```

---

**Outputs**  $\{CP, GW\}$  the recommended work arrangement

---

**6.3.4 Case study in work arrangement**

There are eight work sectors at the VTS in Singapore. In other words, eight VTSOs must work at the same time to provide services to vessels in a designated area. According to the International Convention for the Safety of Life at Sea (SOLAS), Chapter V, Regulation 12, there are two types of VTS

operations, specifically, port and coastal, and there is a clear distinction between the two. Port operations focus on providing services to vessels entering or leaving ports, while coastal operations mainly provide services to vessels passing through a sea area. In the VTS in Singapore, there were three coastal operation work sectors and five port operation work sectors. Due to the distinction between port and coastal operations, operators performed different operations and thus experienced different workloads.

The work sectors were classified into two groups, port operations and coastal operations, which reduced the possible size of the work arrangements from  $8! = 40,320$  to 56. Twenty sets of historical data were randomly selected from the data set mentioned in Section 5.4. Each set of data was obtained at the same time, including information about the eight operators and their work sectors, environments and fatigue levels. Algorithm 1 was adopted to provide recommended work arrangements. The fatigue level related to the recommended work arrangements was obtained using the fatigue prediction model described in Chapter 4.

Figure 6.4 shows the number of operators rearranged according to Algorithm 6.1. On average, 27% of operators could benefit from the recommended work arrangements. Figure 6.5 shows the comparison of the original work arrangements and the recommended work arrangements. For each operator, 1 denotes “fatigued” and 0 denotes “alert”. Figure 6.5 shows that the recommended work arrangements can greatly reduce the summed fatigue levels of the eight operators.

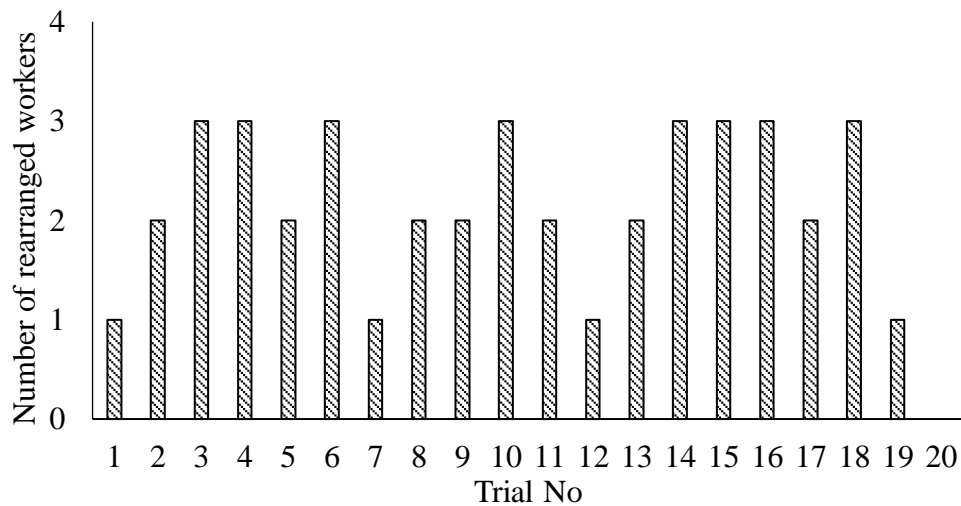


Figure 6.4 The number of operators should be arranged in 20 trials

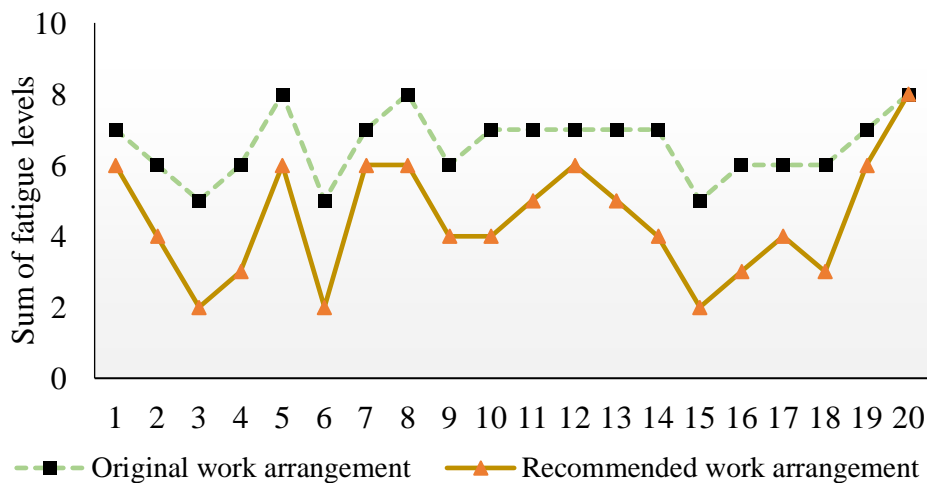


Figure 6.5 The sum of the fatigue levels of eight operators in 20 trials

In this section, the data collected from the local vessel traffic service center were analyzed by the proposed method. Owing to the limited data source, the performance of the proposed model might be affected. Specifically, proportionally few females participated in the questionnaire-based survey, resulting in biased data for model training. Hence, for female participants, the trained model may result in over-fitting. Nevertheless, the problem can be mitigated by selecting the appropriate affinity threshold. In addition, substantial individual differences in the susceptibility to become fatigued were observed,

which revealed the necessity of a promising adaptive work arrangement. The case study in the local VTS indicated that the adaptive work arrangement improved the states of 27% of the operators. By considering individual differences and work types, the novel scheduling algorithm can provide adaptive work arrangements to reduce the occurrence of fatigue. However, most of the operators still suffered from a high possibility of human fatigue with the proposed work arrangement. Specifically, Figure 6 shows that fewer than 50% of operators were fatigued in only 6 out of 20 trials. Hence, fatigue is still a critical problem in VTS. According to the field observations and expert interviews, monitoring vessel movements is monotonous and quickly induces human fatigue. Adaptive work arrangements can reduce monotony. However, the problem of monitoring still exists.

#### **6.4 An UR-driven approach incorporating TRIZ and QFD for designing an alarm system**

In this study, an innovative and integrated design framework called **PQT** (a combination of the initial letters of each phase of the design process) is proposed based on the quality characteristics of software, QFD and TRIZ to redesign alarm systems [171, 172]. Figure 6.6 illustrates the PQT framework, which includes three main phases: (1) a **p**rocess-based elicitation of URs, (2) a **Q**FD-enabled selection of design requirements (DRs) and (3) a **T**RIZ-based generation of innovative solutions.

In the first phase, the work logic of alarm systems, the operational process and the URs were investigated through field observations and SOP analysis. In the second phase, the nonfunctional requirements of alarm systems were

analyzed to determine the candidate DRs. QFD was adopted in the second phase to identify the critical DRs from the candidate DRs [173]. In the solution generation phase, the selected DRs were translated into TRIZ parameters to identify the suggested innovative principles. Finally, the approved solutions were developed following the TRIZ principles.

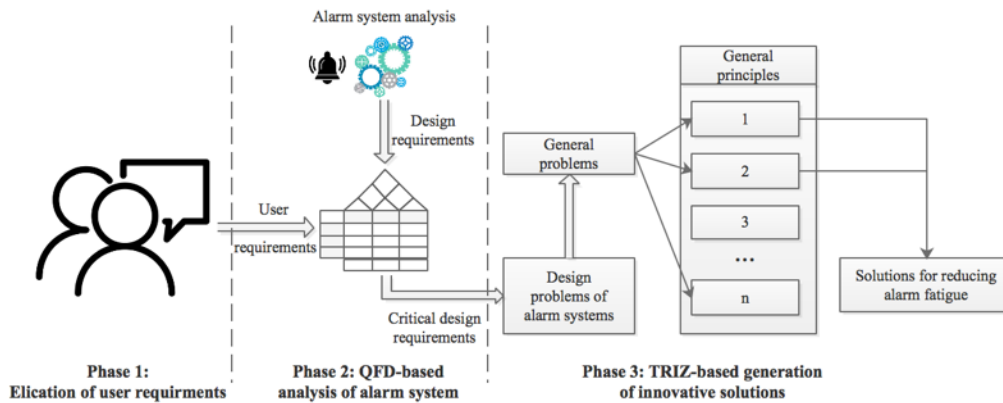


Figure 6.6 PQT Framework of URs-driven design of vessel alarm system

#### 6.4.1 Phase II: QFD-enabled selection of DRs

Figure 6.7 illustrates Phase II, the process of identifying the critical DRs of a vessel alarm system, which includes a house of quality (HoQ) chart. The URs elicited from the first step were used as the “whats” along the vertical axis of the chart, and the importance weights of the URs were added along this axis. Along the horizontal axis of the HoQ are the candidate DRs, that is, the “hows”. The candidate DRs were determined by analyzing nonfunctional requirements and alarm systems.

The International Organization for Standardization (ISO) defines five software quality characteristics: usability, efficiency, maintainability, reliability, and functionality. However, these characteristics are too broad to be used in the matrix of UR deployment. Şen and Baraçlı [174] broke them down into more

specific subcharacteristics to obtain enterprise software selection requirements. The summarized results for the quality subcharacteristics are shown in Table 6.1.

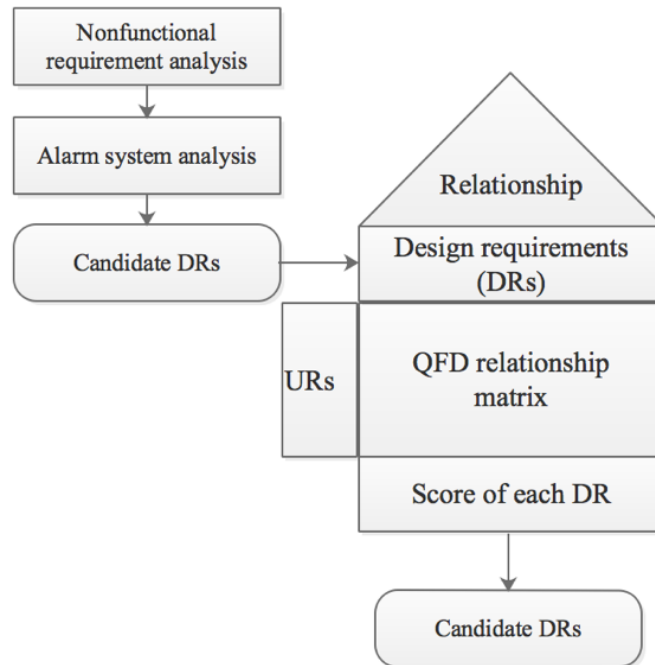


Figure 6.7 General processes of Phase II

To identify the specific DRs of the vessel alarm system, the quality subcharacteristics are combined with the modules of the vessel alarm system. In general, an alarm system involves five modules: a signal filter, alarm generation, alarm suppression, alarm shelving, and alarm presentation. Following this analysis, the DRs of an alarm system can be inferred from “module + quality characteristics.” For example, alarm presentation understandability means the readability and informativeness of the visual and/or audio alarm.

Table 6.1 The quality characteristics of software [174]

Usability	Functionality	Reliability	Maintainability	Efficiency
Understandability	Suitability	Recoverability	Testability	Time behavior
Operability	Security	Maturity	Stability	Resource behavior
Learnability	Interoperability Compliance Accuracy	Fault tolerance	Changeability Analyzability	

After determining the URs and DRs, the relationships between them can be investigated to select the critical DRs. The importance of each UR to each DR is reflected by the indicators ( $R_{ij}$ ), placed in the relationship matrix. A rating scale (0, 3, 5, and 9) was used to evaluate the relationships (no, weak, moderate, and strong, respectively) between the URs and DRs. The overall importance score of each DR was calculated using the following equation:

$$T_j = \sum_{i=1}^I R_{ij} * U_i, \quad (6.4)$$

where  $T_j$  is the overall score of the  $j$ th DR,  $U_i$  is the importance score of the  $i$ th UR, and  $R_{ij}$  is the score related to the relationship between the URs and DRs. The outputs of Phase II suggested the critical DRs waiting to be improved and the interrelationships among the DRs.

#### ***6.4.2 Phase III: TRIZ-based generation of innovative solutions***

This phase involved DR classification and TRIZ contradiction analysis. The critical DRs were classified into several types based on the modules of alarm systems. For example, if DR 1 was associated with module A, then DR 1 was classified as type A.

TRIZ contradiction analysis provides inventive principles based on the interrelationships among the DRs [175]. The interrelationships can be identified from the roof of the HoQ [176]. Compared to the conventional method, this novel combination of QFD and TRIZ makes the development of a contradiction matrix easier. First, the DRs were translated into TRIZ parameters. In this study, TRIZ parameters updated in 2003 [177] were utilized because they include most software qualities. Second, the TRIZ contradiction matrix was established

to generate the innovative principles. Directly applying the original inventive principles in software development is inappropriate and unworkable as original inventive principles are mainly used in the field of engineering. Therefore, TRIZ software analogies were proposed by Rea [178]. Finally, high-frequency principles were selected to generate effective solutions for specific problems. Figure 6.8 illustrates the logic of solution generation.

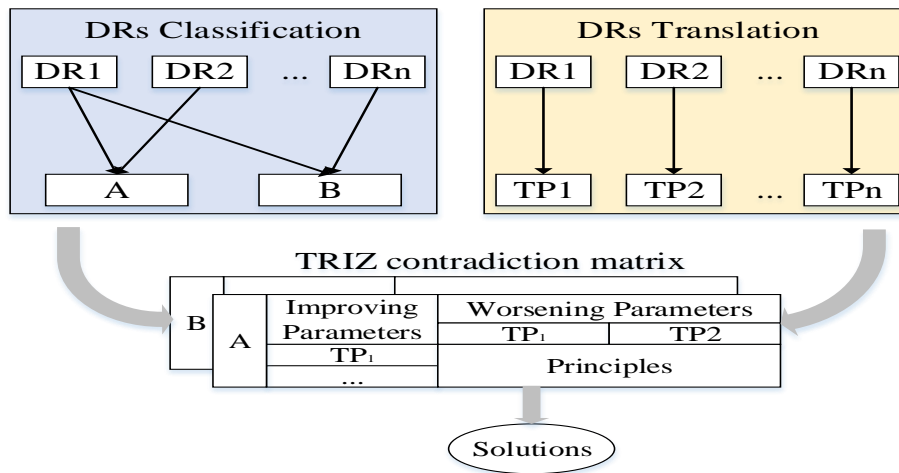


Figure 6.8 Solution generation process of Phase III (TP: TRIZ principles)

#### 6.4.3 Case study in alarm fatigue

To verify the proposed framework, an empirical study was conducted in a VTS center in Singapore. As one of the busiest ports in the world, the Singapore port especially requires efficient VTS to guarantee the safe and efficient navigation of ships in the water [158]. During the field observations at the VTS in Singapore, the study found that operators tended to ignore most of the alarms generated by the present vessel alarm system.

*“I receive hundreds of warnings per day, but I ignore most of them. I think they are unhelpful and useless...I detect abnormal situations before the alarm*

*system. I rarely use it...The voice alarms interrupt my communication. I preferred to silence them”.*

*1) Phase I: UR analysis of vessel traffic control alarm systems*

Field observation and SOP analysis were conducted to identify the current operational processes of the vessel traffic alarm system. The work logic of handling alarms is illustrated in Appendix B.1. First, operators should make a track assignment for vessels entering the Singapore Strait. Most alarm assignments are associated with one or more warnings. Different assignments may be made for different vessels; thus, operators must be familiar with the rules of setting track assignments.

Second, operators detect and analyze the triggered alarms. There are two types of alarm modes in the vessel alarm system: visual alarms and audio alarms. Operators can hear alarms or check the alarm list to identify alarms. After detecting an alarm, operators analyze the current conditions and make decisions about how to respond to the alarm. Finally, operators can acknowledge or cancel audio after correcting the current condition.

To identify the URs, unstructured interviews were conducted based on the abovementioned operational processes. Forty-two operators (32 males and 10 females) participated in this interview and described the problems that they face during work. Their average length of experience was 10 years. All interviews were recorded and fully transcribed. Then, the transcribed interviews were coded, resulting in an initial set of 27 codes (as shown in Appendix B.2). Prescreening was performed, which included eliminating, combining, and translating the 27 codes into UR attributes. Consequently, a total of seven URs

were summarized, as shown in Table 6.2. A total of 12 operators determined the importance score for each elicited UR based on a predetermined scheme; for example, 5 denoted “most important”, while 1 represented “least important”.

Table 6.2 Prescreened URs by eliminating, combining, and translating

URs	Definition	UR codes	Importance
<b>UR<sub>1</sub> Accurate alarms</b>	The system provides fewer false and missed alarms.	1,2, 12, 19, 20	5
<b>UR<sub>2</sub> Effective alarms</b>	The system provides fewer repeat alarms. The operator has enough time to deal with alarms.	3, 26,	5
<b>UR<sub>3</sub> Comfort</b>	The system is comfortable to use and matches the VTS console.	5,6,7,8,16,10	5
<b>UR<sub>4</sub> Safety</b>	The system provides human error protection.	9,11	4
<b>UR<sub>5</sub> Easy to use</b>	The system is simple to operate, e.g., alarm messages are easy to detect.	4,13,14, 18, 21, 22,23,24	4
<b>UR<sub>6</sub> Responsiveness</b>	The system provides rapid response.	15	4
<b>UR<sub>7</sub> Informative alarms</b>	Alarm messages provide enough information.	17,25,27	5

## 2) Phase II: DR analysis of the vessel traffic control alarm systems

### a) Alarm system analysis

Table 6.3 Current vessel alarm system of Singapore VTS

Modules	Functions	Description
<b>Track assignment module</b>	Vessel details	Identity of area, data area, notifications area
	Vessel alarm determination	Anchor watch, berthing watch, collision watch, domain watch, grounding watch, speed watch...
<b>Alarm generation module</b>	Threshold setting	Range
<b>Alarm presentation module</b>	Group vessel alarms	Grouped by selecting type, priority, or none
	Acknowledge alarms	Acknowledge single or multiple alarms, cancel audio alarms
	Alter option	Audio and/or visual alert

In this section, the existing vessel alarm system is analyzed. The alarm system involves three main modules: the track assignment module, alarm

generation module, and alarm presentation module. The functions and description of the current modules are shown in Table 6.3.

The track assignment module contains 40 types of alarms. Operators analyze vessel information integrated from the automated identification system (AuIS), radar and closed-circuit television (CCTV) and then determine what type of alarm should be assigned to the vessel. The alarm generation module allows operators to edit the alarm threshold in the range section of the module. Moreover, the alarm presentation module allows operators to choose between visual and audio alerts for each type of vessel. The visual option refers to a configured color in a shape (square, circle, or triangle) around the target vessel. To manage alarms, operators can group them by selecting the type or priority and then acknowledging or canceling alarms.

b) Candidate DRs

The full names and corresponding abbreviations used for the DRs can be found in Appendix B.3.

c) Determining critical DRs

Figure 6.9 shows the QFD relationship matrix, which was constructed with the help of VTSOs. The numbers utilized in the QFD matrix and their corresponding meanings are described as follows: 9 indicates strong correlation; 3 denotes ordinary correlation; and 1 represents weak correlation. For example, the “accurate alarms” UR presented a strong correlation with each of the three items “ATA accuracy,” “sensor accuracy,” and “ATA fault tolerance”. Not only does the alarm trigger algorithm affect the accuracy of the generated alarms; however, the signal obtained from the sensor also affects the accuracy of alarms.

“Safety” was found to correlate strongly with “system response speed,” as system response speed affects the system’s ability to respond.

The importance score resulted from dividing the absolute importance of each individual quality characteristic by the total absolute importance value. The *absolute importance* measure refers to the correlation score and importance of URs multiplied together to achieve a total value. The final five top-ranked DRs (as shown in Figure 6.9) are “ATA accuracy” (DR<sub>1</sub>, with a score of 192), “AAR complexity” (DR<sub>2</sub>, with a score of 180), “ATA aptness” (DR<sub>3</sub>, with a score of 171), “AP informativeness” (DR<sub>4</sub>, with a score of 162), and “AP aptness” (DR<sub>5</sub>, with a score of 132). They were selected as the requirements that best fit the URs to improve the vessel alarm system.

#### d) Investigating the contradictions between DRs

The DRs that contradict the five top-ranked DRs were also selected. The “roof” of the HoQ indicates contradictions between DRs, as represented by the “+” symbol. The contradictions between DRs are illustrated in Appendix B.3. According to the analysis of URs, the accuracy and aptness of generated alarms must be improved. However, there is a contradiction between “DR<sub>6</sub>: ATA complexity” and “DR<sub>3</sub>: ATA aptness”. There is also a contradiction between “DR<sub>1</sub>: ATA accuracy” and “DR<sub>7</sub>: ATA efficiency” as high accuracy requires a low time delay, which directly increases the latency in raising the alarm. The contradictions in vessel alarm-handling modules also require resolution. Adaptive and informative alarm messages are necessary for VTSOs to fully understand each situation; however, information overload may affect “DR<sub>8</sub>:

Readability of alarm messages” and “DR9: AH operability.” Nine DRs were selected.

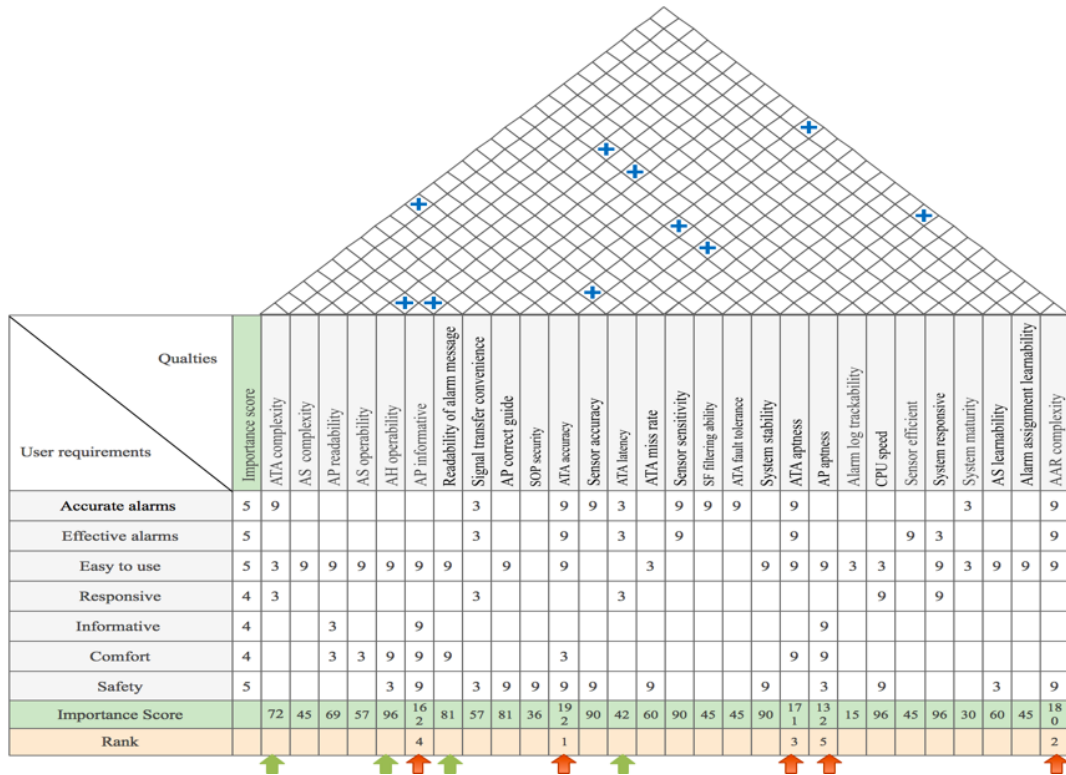


Figure 6.9 HoQ of the vessel alarm systems [159] (red arrows: highly ranked DRs; green arrows: DRs related to highly ranked DRs)

3) Phase III: Using TRIZ to resolve the contradictions identified by QFD

a) Classification of the selected DRs

To identify the problems in the current vessel traffic alarm system, the selected DR<sub>j</sub> (j=1 to 7) were classified based on the three modules. Table 6.4 represents the classification of the selected DR<sub>j</sub>.

b) The corresponding engineering parameters

Based on the literature [177, 179, 180], the relevant engineering parameters were summarized for the selected DR<sub>j</sub> (j=1 to 9). Table 6.5 shows the corresponding engineering parameters of the selected DR<sub>j</sub>. The DRs that are

a high priority are considered improving parameters, while the DRs that contradict them are regarded as worsening parameters.

Table 6.4 The contradictions extracted from QFD

<b>Modules</b>	<b>Positive qualities</b>	<b>Corresponding negative qualities</b>
<b>Track assignment module</b>	AAR complexity	ATA accuracy and ATA aptness
<b>Alarm generation module</b>	ATA accuracy and ATA aptness	ATA complexity and ATA efficiency
<b>Alarm presentation module</b>	AP informative and AP aptness	Appearance and AH operability

Table 6.5 TRIZ-based parameter of this case

<b>Design requirements</b>	<b>Corresponding TRIZ engineering parameters</b>
<b>DR1: AAR complexity</b>	45, Complexity
<b>DR2: ATA accuracy</b>	48, Measurement accuracy
<b>DR3: ATA aptness</b>	32, Adaptability
<b>DR4: ATA efficiency</b>	14, Speed
<b>DR5: AP informative</b>	11, Amount of information
<b>DR6: ATA complexity</b>	45, Complexity
<b>DR7: AP aptness</b>	32, Adaptability
<b>DR8: Appearance</b>	39, Appearance
<b>DR9: AH operability</b>	34, Ease of operation

c) Generation of solutions

The TRIZ contradiction matrices were established based on the DR classification and relevant TRIZ parameters. Tables 6.6 to 6.8 show the contradiction matrices of the three modules. The high-frequency principles were typically selected. These principles provided the direction of systematic resolutions and suggested the new functions or elements required in the new system model.

The recommended inventive principles for the track assignment module are shown in Table 6.6. In Table 6.6, No. 28 (replacement of the mechanical system) was chosen and underlined because of its relatively high frequency; Table 6.8 shows that “No. 28” appears twice. In contrast, No. 37 (thermal

expansion) was not selected because there is no corresponding interpretation in the software analogy [178]. Hence, principle No. 28 was adopted. It refers to replacing a mechanical means with a sensory means. The operational definition of No. 28 requires no change in the software analogy, which motivated an improvement in the current manual task assignment module to a new automated case-based track assignment module (as seen in Table 6.9). The automatic track assignment system is expected to alleviate the mechanical action of mouse clicks.

For the contradictions within the second module, the recommended inventive principles appear in Table 6.7. No. 10 (prior action), No. 13 (do it in reverse), No. 28 (replacement of the mechanical system) and No. 35 (transformation properties) have higher frequencies than other principles. Hence, they were selected and underlined to solve the contradictions. Table 6.10 shows the explanations and software analogies of these principles. The solutions based on these principles are also clearly described in Table 6.10. An adaptive multiparameter alarm generation module was proposed based on these principles to improve the accuracy and aptness of alarms. This module triggers alarms based on multiple parameters and can modify the trigger algorithm based on user feedback.

The inventive principles for the contradictions within the third module are listed in Table 6.8. As shown in Table 6.8, inventive principles No. 3 (local quality), No. 7 (nesting), No. 10 (prior action), No. 13 (do it in reverse), No. 17 (transition into new dimension), No. 19 (periodic action), No. 24 (mediator), No. 25 (self-service), No. 28 (replacement of the mechanical system) and No.

32 (changing the color) appear at least twice; therefore, they were selected and underlined. Table 6.11 shows the operational definitions and software analogies of all these principles. Furthermore, the innovative solutions based on these principles are presented and discussed in Table 6.11. To integrate these solutions, an adaptive multimodal alarm presentation module was proposed. Users are expected to be able to interact with the adaptive multimodal alarm presentation module to quickly identify alarms.

Table 6.6 TRIZ contradiction matrix of AAR innovative principles

Improving parameters	Worsening parameters	
		32 (Adaptability)
<b>45 (Complexity)</b>	29, 28, 1, 24, 15, 25, 37	28, 26, 10, 2, 34, 7, 37

Table 6.7 TRIZ contradiction matrix of ATA innovative principles

Improving parameters	Worsening parameters	
		14 (Speed)
<b>32 (Adaptability)</b>	10, 14, 35, 24, 15, 28, 12, 29	6, 28, 29, 31, 35, 40, 17, 25
<b>48 (Measurement accuracy)</b>	28, 13, 24, 5, 32, 35, 37	3, 35, 10, 27, 1, 13, 28, 26

Table 6.8 TRIZ contradiction matrix of AP innovative principles

Improving parameters	Worsening parameters	
		39 (Appearance)
<b>11 (Amount of information)</b>	7, 3, 32, 19, 25, 17	25, 10, 17, 6, 19, 13
<b>32 (Adaptability)</b>	29, 28, 2, 32, 3, 7, 24	15, 24, 3, 4, 28, 14, 13, 26, 10

Table 6.9 TRIZ principles for case-based track assignment module

TRIZ Principles	Original operational definition	Software Interpretation	Analogy	How to achieve these principles	Proposed Module
<b>28 Replacement of mechanical system</b>	Replace a mechanical means with a sensory (optical, acoustic, taste, or olfactory) means.	Add new functions or features that make the alarm system act in an opposite way.	Building case-based reasoning mechanism in the system to search for similar cases that should alarm operators.	Automated case-based track assignment module	

Table 6.10 TRIZ principles for multi-parameter alarm generation module

TRIZ Principles	Original operational definition	Software Analogy Interpretation	How to achieve these principles	Proposed Module
<b>10 Prior action</b>	Perform, before necessary, a required change of an object (either fully or partially). Carry out all or part of the required action in advance.	System can provide automatic and adaptive required information in advance.	Using signal selector to reduce repeat alarms.	
<b>13 Do it in reverse</b>	Invert the actions used to solve a problem (e.g., instead of cooling an object, heat it).	Think about a function from an opposite viewpoint.	Building reinforcement learning system to modify alarm trigger algorithm based on human performance.	Adaptive multi-parameter alarm generation module
<b>28 Replacement of mechanical system</b>	Replace a mechanical means with a sensory (optical, acoustic, taste, or olfactory) means.	Add new functions or features that make the alarm system act in an opposite way.	Applying neural network replaces simple threshold to generate alarms.	
<b>35 Parameter changes</b>	Change the degree of flexibility.	Change how the physical service is delivered.	Using multiple parameters Adaptive alarm thresholds to trigger alarms.	

Table 6.11 TRIZ principles for multimodal alarm presentation module

TRIZ Principles	Original operational definition	Software Analogy Interpretation	How to achieve these principles	Proposed Module
<b>3 Local Quality</b>	Change a technical system's structure from uniform (homogenous) to nonuniform; change an external environment (or external influence) from uniform to non-uniform. Make each part of a technical system fulfil a different and useful function.	Change an object's classification in a technical system from a homogenous hierarchy to a heterogeneous hierarchy.	Customizing colour, font, size of alarm presentation.	
<b>7 Nesting</b>	Place one object into another; place each object, in turn, inside the other.	Inherit functionality of other objects by "nesting" their respective classes inside a base class.	Combining related alarms together.	
<b>10 Prior action</b>	Perform, before necessary, a required change of an object (either fully or partially). Carry out all or part of the required action in advance.	Same as operational definition.	Combining alarms before present them.	
<b>13 Do it in reverse</b>	Invert the actions used to solve a problem (e.g., instead of cooling an object, heat it).	Think about a function from an opposite viewpoint.	Modifying alarm presentation based on human performance.	
<b>17 Transition into new dimension</b>	Difficulties involved in moving or relocating an object along a line are removed if the object acquires the ability to move in two dimensions (along a plane). Accordingly, problems connected with movement or relocation of an object on one plane is removed by switching to a three-dimensional space.	Use a multi-layered assembly of class objects instead of a single layer.	Utilizing multimodal interface to present alarms.	Adaptive multimodal alarm presentation module
<b>19 Periodic Action</b>	Instead of continuous action, use periodic or pulsating actions.	Instead of performing a task continually, determine the time boundaries and perform that task periodically.	Modifying alarm presentation periodically.	
<b>24 Mediator</b>	Use an intermediary carrier article or intermediary process.	Use a mediator to provide a view of data to a process in the context of the process application space.	Adding a mediator to combine alarms.	
<b>25 Self-service</b>	Make an object serve itself by performing auxiliary helpful functions.	Increase operator participation in the delivery of the function.	Operators can shelve alarms.	
<b>28 Replacement of mechanical system</b>	Replace a mechanical means with a sensory (optical, acoustic, taste, or olfactory) means.	Same as operational definition.	Utilizing multimodal interface to present alarms.	
<b>32 Change the colour</b>	Change the colour of an object or its external environment.	A colour change function in a photo or drawing program.	Customizing colour of user interface to be user friendly	

In conclusion, the study proposes a modular smart vessel alarm system with three submodules (as shown in Table 6.12): (1) an automated case-based track assignment module, (2) an adaptive multiparameter alarm generation module, and (3) an adaptive multimodal alarm presentation module. Appendix B.3 shows the alarm-handling process and illustrates how the proposed modules meet the URs.

Table 6.12 New adaptive alarm system for VTS

<b>Modules</b>	<b>Main Functions</b>	<b>Subfunctions</b>
Automated case-based track assignment module	Vessel information integration	Vessel movement report Vessel details
	Vessel alarm recommendation	Historical case data, decision tree
Adaptive multiparameter alarm generation module	Adaptive alter option	Audio and/or visual alert
	Reinforcement learning algorithm	Adaptive range based on human performance
Adaptive multimodal alarm presentation module	Adaptive color scheme	Day/dusk/night
	Alarm list	Customized and adaptive scheme, multimodal alarm presentation
	Shelve alarms	Unnecessary alarms can be shelved
	Alarm evaluation	Operators can evaluate alarms to provide a foundation of alarm generation

With the design logic from Phase I to Phase III, the system specifications for a smart vessel alarm system to reduce operators' workload and to improve their situational awareness are finally conceptualized.

#### 4) *Final design result: The smart vessel alarm system*

The smart vessel alarm system consists of three intelligent modules: (a) the automated case-based track assignment module, (b) adaptive multiparameter alarm generation module, and (c) adaptive multimodal alarm presentation module. The functions and advantages are discussed in this section:

a) The URs of safety and ease of operation are met through an automated case-based track assignment module.

First, to overcome the challenges of setting incorrect track assignments and missing track assignments, the study suggests replacing manual assignments with an automated assignment module and the automatic screening of the risk levels of entering vessels based on historical data. The automated case-based track assignment module, implemented with a case-based reasoning (CBR) mechanism, can systematically set track assignments through a self-learning feature.

b) The adaptive multiparameter alarm generation module can provide alarms that are more accurate.

A signal selector and multiparameter alarm trigger algorithm are implemented in the new module. The signal selector can be used to filter repeat signals, and the multiparameter algorithm is expected to provide correct and valid alarms under dynamic and complex vessel traffic conditions. Based on integrating the multiparameter algorithm and reinforcement learning mechanism, the alarm system can provide operators with more accurate and suitable alarms. A comparison of the original and new alarm generation system modules is shown in Figure 6.10.

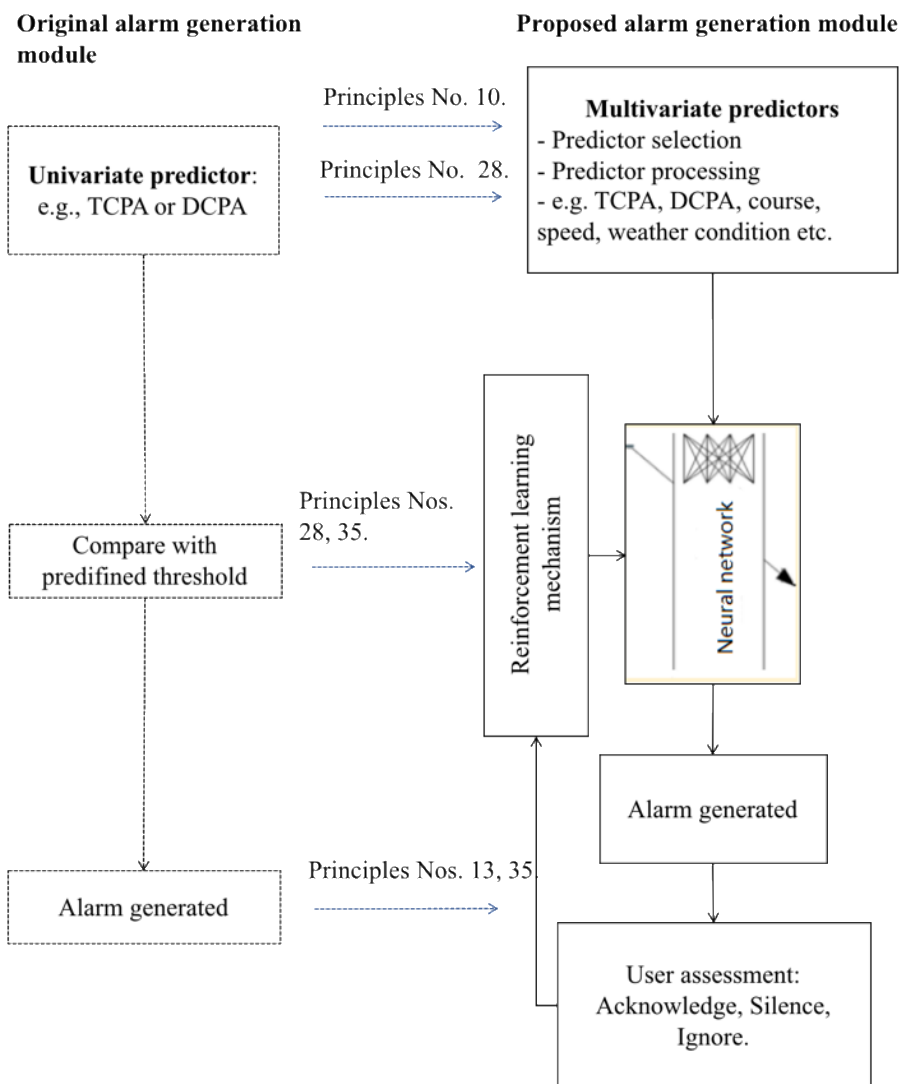


Figure 6.10 Comparison of the original alarm generation module and the proposed module

c) The adaptive multimodal alarm presentation module can assist operators in detecting alarms.

Multimodal alarms that involve a sound alarm, visual alarm, and haptic alarm are designed to gain operators' attention. Compared with traditional visual and audible alarms, haptic alarms have two distinct advantages: they can be detected even in a noisy environment, and they offer a particularly effective means of presenting directional signals to operators. Moreover, a mediator that combines related alarms can be implemented to reduce the number of presented

alarms. The comparison of the original and new alarm presentation system modules is shown in Figure 6.11.

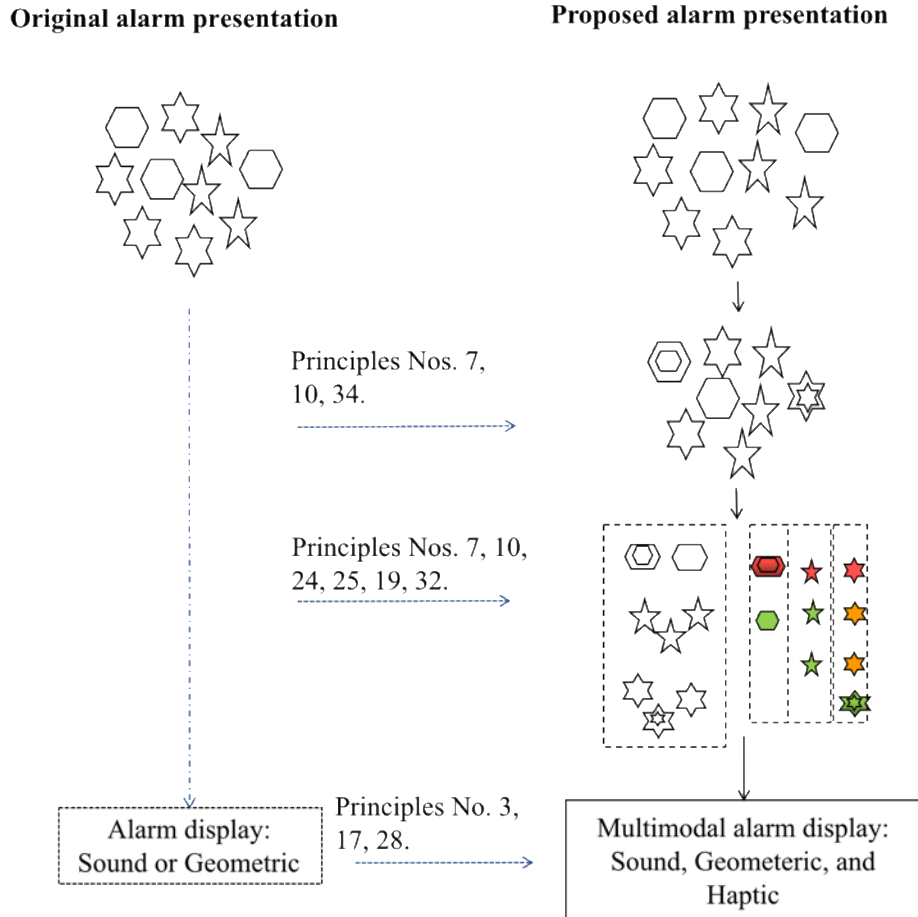


Figure 6.11 Comparison of the original alarm presentation module and the proposed module

## 6.5 Summary

In a TCC, human fatigue is a normal phenomenon that has a significant negative impact on human performance. This fact suggests that traffic controllers could benefit from real-time fatigue management, which motivated the proposal of a data-driven approach to reducing human fatigue by redesigning the alarm system and formulating adaptive work arrangements.

This chapter describes a novel framework for data-driven human fatigue management. This framework can proactively manage human fatigue using

connected physical objects and AI techniques. Moreover, it enables work schedules to be redesigned to reduce the risk of human fatigue. In addition, a novel PQT framework with three design phases based on operational processes, QFD, and TRIZ was proposed to solve the problems of alarm fatigue. This framework provides an original approach by integrating TRIZ and QFD with software quality characteristics to design a smart alarm system.

## Chapter 7 Conclusions and Future Research

In this chapter, the key findings and main contributions of this thesis are summarized in Section 7.1. Meanwhile, the limitations and future directions are further discussed in Section 7.2.

### 7.1 Contribution

This thesis presents a data-driven strategy for context-aware human fatigue management by integrating human factors and machine learning techniques. The critical issues associated with context data in each stage of human fatigue management, specifically, TCFA, EMFD, CHFP, and hybrid DID, are carefully studied. In general, this research offers a pioneering contribution to the exploration of context data for adaptive human fatigue management. Additionally, this thesis contributes to the adoption of AI techniques for human factor studies. With respect to the summary presented from Chapters 2 to 6, this section highlights the original scientific contributions of this research in terms of the following aspects.

1) *TCFA of human fatigue*. The first substudy aims to determine the key causal factors of human fatigue in TCCs. Specifically, the following contributions are made:

- It provides a clear definition of human fatigue in TCCs and a foundation for other substudies. The novel definition of human fatigue accounts for the interaction effects between subjective feelings and exertion on psychophysiological states.

- A task-driven approach for identifying causal factors and a causal network-based approach for selecting key causal factors are proposed. The proposed method enables fatigue causal networks to be established and fatigue symptoms to be analyzed. The causal network-based evaluation method integrates three dimensions of judgment and enables the identification of key causal factors from a holistic perspective.
- The case study reveals that TCOs suffered from multidimensional fatigue, especially physical fatigue. The results provide a foundation and future directions for designing interventions to manage human fatigue.

2) *EMFD*. In an effort to facilitate the proactive detection of mental fatigue, this substudy introduced a novel fatigue indicator and a semisupervised bagged tree method for developing the fatigue model. The following contributions are made:

- Instead of identifying events from eye-tracking data, a novel fatigue indicator, which presents the eye-tracking data with histograms, is proposed. The utilization of gaze-bin analysis enables the application of an eye tracker with a low sampling rate. Hence, it can significantly reduce the cost and improve the usability of an eye movement-based human fatigue detector.
- This substudy develops an innovative method that uses gaze-bin analysis as inputs of semisupervised bagged trees. This method outperforms the commonly used machine learning methods, such as

a decision tree and the SVM. The proposed approach can alleviate the burden of manual labels, eliminate the problem of overlapping data, and improve the performance of the fatigue detection model.

3) *CHFP*. Substudy 3 proposes a contextual information-based human fatigue model for human fatigue prediction. The following contributions are made:

- A novel presentation of causal factors is developed. The proposed fatigue causal network can properly store the information of causal factors and express the interrelationships among them.
- A machine learning-based method for human fatigue prediction called AIS-XGBFP is proposed. This method takes into account causal factors, such as work-related factors and weather-related factors, and adapts to dynamic traffic conditions. In addition, it attempts to analyze individual differences and utilize the results obtained to facilitate human fatigue prediction. Since human fatigue is a common phenomenon in many work settings, this method can be extended and utilized in these settings to reduce the risks associated with human fatigue.

4) *Intervention design for mitigating human fatigue*. Taking into account multidimensional human fatigue, two preventive interventions are proposed to reduce human fatigue and lower its occurrence. Specifically, a scheduling algorithm is provided to adaptively arrange work for operators considering individual differences and work types; additionally, a UR-driven design

framework called PQT is proposed to reduce alarm fatigue. The following contributions are made:

- This study proposes a framework for adaptive work arrangements. As a novel framework for developing a data-driven human fatigue model, decentralized data collection is proposed to improve computational efficiency and to maintain model performance in the event of data loss. This work is a pioneering study that applies IoT techniques to research on human factors.
- In this study, a UR-driven design framework called PQT is proposed to reduce alarm fatigue. As an exploratory study, this research can offer insightful guidance to traffic management authorities in their safety management process with better operational experience.

In summary, this thesis contributes to *context-aware human fatigue management* and *the advancement of AI applications in data-driven human fatigue management*.

## **7.2 Limitations and future research**

In this thesis, context data are studied to enhance human fatigue management in TCCs. Context-aware human fatigue management, which is still a relatively new concept, has not been experimentally investigated or comprehensively and systematically studied. Although great effort was put forth with regard to the context data analysis and processing, the limitations and constraints of the research are inevitable, as discussed in the following:

1) *Only VTS was used as a case study.* Some general methods were proposed; however, almost all case studies were conducted only in a VTS center. Although VTS has most attributes of TCCs, such as a 24-hour working schedule, monitoring operations, and a dynamic work environment, more case studies should be conducted in other TCCs, such as rail TCCs, to demonstrate the wider applicability of the proposed methods.

2) *Unavoidable subjective evaluation.* This research mainly identifies key causal factors from the subjective point of view of operators; thus, some objective measurements should also be considered in the future. In addition, the importance scores of the URs were collected using a Likert scale, which can induce subjective bias.

3) *No capability to detect medium fatigue.* There is no clear line for distinguishing between being alert, experiencing medium fatigue, and experiencing high fatigue. The proposed method can warn only fatigued users, and it cannot be used in fields that require operators to be very alert.

4) *Limited data collected.* In laboratory conditions, only a limited amount of data can be collected. For example, real-time traffic data, such as vehicle locations, traffic density and vehicle speeds, cannot be collected.

5) *Too many causal factors considered.* The great number of causal factors resulted in a tremendous workload during the data collection and training processes.

For future studies, the following four directions are proposed.

1) *Case studies in air TCCs and rail TCCs.* More case studies will be conducted to demonstrate the proposed general methods.

2) *Objective evaluation of causal factors.* It has been confirmed that the causal factors of human fatigue are normally task specific. Therefore, a study that classifies causal factors based on task type would greatly benefit fatigue management in various fields. The importance of a factor can be evaluated by the frequency of its corresponding task.

3) *Taking advantage of the prevailing information technologies (e.g., the IoT) to efficiently collect contextual information.* In the field of transportation, a vast amount of data, such as vehicle locations and vehicle speeds, can be collected from embedded sensors and AuISs. In the future, real-time data from embedded sensors can be used to manage human fatigue. With the presence of a large number of features, a learning model tends to overfit, resulting in performance degeneration. To address the problem of the curse of dimensionality, feature selection, which is a widely employed technique for reducing dimensionality, can be applied.

4). *A way to define importance by means of linguistic variables.* Some knowledge or requirement acquisition techniques, such as laddering, may be applied to systematically elicit URs. In addition, a fuzzy algorithm, such as symmetrical triangular fuzzy numbers, can be utilized to capture the vagueness in verbal assessments.

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**References**

- [1] A. Kouvelas, K. Aboudolas, E. B. Kosmatopoulos, and M. Papageorgiou, "Adaptive performance optimization for large-scale traffic control systems," *IEEE Transactions on Intelligent Transportation Systems*, vol. 12, no. 4, pp. 1434-1445, 2011.
- [2] O. D. Turnbull and A. G. Richards, "Human Control of Air Traffic Trajectory Optimizer," *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 4, pp. 1091-1099, 2018.
- [3] G. Xu, F. Li, and C.-H. Chen, "Local AIS data analytics for efficient operation management in Vessel Traffic Service," in *Automation Science and Engineering (CASE), 13th IEEE Conference on*, pp. 1668-1672: IEEE, 2017.
- [4] B. Roets and J. Christiaens, "Shift work, fatigue, and human error: An empirical analysis of railway traffic control," *Journal of Transportation Safety Security*, vol. 11, no. 2, pp. 207-224, 2019.
- [5] M. Härmä *et al.*, "Shift work with and without night work as a risk factor for fatigue and changes in sleep length: A cohort study with linkage to records on daily working hours," *Journal of sleep research*, vol. 28, no. 3, pp. e12658, 2019.
- [6] S. Charbonnier, R. N. Roy, S. Bonnet, and A. Campagne, "EEG index for control operators' mental fatigue monitoring using interactions between brain regions," *Expert Systems with Applications*, vol. 52, pp. 91-98, 2016.
- [7] Q. Ji, P. Lan, and C. Looney, "A probabilistic framework for modeling and real-time monitoring human fatigue," *IEEE Transactions on systems, man, and cybernetics-Part A: Systems and humans*, vol. 36, no. 5, pp. 862-875, 2006.
- [8] M. J. Akhtar and I. B. Utne, "Human fatigue's effect on the risk of maritime groundings—A Bayesian Network modeling approach," *Safety science*, vol. 62, pp. 427-440, 2014.
- [9] M. K. Li, J. J. Yu, L. Ma, and W. Zhang, "Modeling and mitigating fatigue-related accident risk of taxi drivers," *Accident Analysis Prevention*, vol. 123, pp. 79-87, 2019.
- [10] M. R. Rosekind, E. L. Co, K. B. Gregory, and D. L. Miller, "Crew Factors in Flight Operations. 8; A Survey of Fatigue Factors in Corporate/Executive Aviation Operations," 2000.
- [11] Y.-c. Huang, L.-p. Li, Z.-g. Liu, H.-y. Zhu, and L. Zhu, "Assessment of urban railway transit driver workload and fatigue under real working conditions," *Transportation research record*, vol. 2673, no. 11, pp. 891-900, 2019.
- [12] D. Darwent, D. Dawson, J. L. Paterson, G. D. Roach, and S. A. Ferguson, "Managing fatigue: It really is about sleep," *Accident Analysis & Prevention*, vol. 82, pp. 20-26, 2015.
- [13] P. Gander *et al.*, "Fatigue risk management: Organizational factors at the regulatory and industry/company level," *Accident Analysis & Prevention*, vol. 43, no. 2, pp. 573-590, 2011.

- [14] D. Dawson, D. Darwent, and G. D. Roach, "How should a bio-mathematical model be used within a fatigue risk management system to determine whether or not a working time arrangement is safe?," *Accident Analysis & Prevention*, vol. 99, pp. 469-473, 2017.
- [15] D. Dawson, Y. I. Noy, M. Härmä, T. Åkerstedt, and G. Belenky, "Modelling fatigue and the use of fatigue models in work settings," *Accident Analysis & Prevention*, vol. 43, no. 2, pp. 549-564, 2011.
- [16] T. Edwards, C. Gabets, J. Mercer, and N. Bienert, "Task demand variation in air traffic control: implications for workload, fatigue, and performance," in *Advances in Human Aspects of Transportation*: Springer, pp. 91-102, 2017.
- [17] E.-J. Shim, H.-I. Noh, J. Yoon, H. s. Mun, and B.-J. Hahm, "A longitudinal analysis of the relationships among daytime dysfunction, fatigue, and depression in college students," *Journal of American college health*, vol. 67, no. 1, pp. 51-58, 2019.
- [18] F. Li, C.-H. Chen, G. Xu, L. P. Khoo, and Y. Liu, "Proactive mental fatigue detection of traffic control operators using bagged trees and gaze-bin analysis," *Advanced Engineering Informatics*, vol. 42, pp. 100987, 2019.
- [19] J.-y. Hong, E.-h. Suh, and S.-J. Kim, "Context-aware systems: A literature review and classification," *Expert Systems with applications*, vol. 36, no. 4, pp. 8509-8522, 2009.
- [20] C. Strahan, B. Watson, and A. Lennonb, "Can organisational safety climate and occupational stress predict work-related driver fatigue?," *Transportation research part F: traffic psychology and behaviour*, vol. 11, no. 6, pp. 418-426, 2008.
- [21] L. J. Trejo, K. Kubitz, R. Rosipal, R. L. Kochavi, and L. D. Montgomery, "EEG-based estimation and classification of mental fatigue," *Psychology*, vol. 6, no. 05, pp. 572, 2015.
- [22] R. O. Phillips, "A review of definitions of fatigue—and a step towards a whole definition," *Transportation research part F: traffic psychology and behavior*, vol. 29, pp. 48-56, 2015.
- [23] L. A. Wolf, C. Perhats, A. Delao, and Z. Martinovich, "The effect of reported sleep, perceived fatigue, and sleepiness on cognitive performance in a sample of emergency nurses," *Journal of Nursing Administration*, vol. 47, no. 1, pp. 41-49, 2017.
- [24] M. Sallinen and C. Hublin, "Fatigue-inducing factors in transportation operators," *Reviews of human factors and ergonomics*, vol. 10, no. 1, pp. 138-173, 2015.
- [25] P. Liu *et al.*, "Identifying key performance shaping factors in digital main control rooms of nuclear power plants: A risk-based approach," *Reliability Engineering & System Safety*, vol. 167, pp. 264-275, 2017.
- [26] F. Alonso, C. Esteban, S. A. Useche, and E. López de Cózar, "Prevalence of physical and mental fatigue symptoms on Spanish drivers and its incidence on driving safety," *Advances in psychology neuroscience*, vol. 1, no. 2, pp. 10-18, 2016.
- [27] P. Gander, "Fatigue management in air traffic control: the New Zealand approach," *Transportation research part F: traffic psychology and behaviour*, vol. 4, no. 1, pp. 49-62, 2001.

- [28] F. Li, C.-H. Lee, C.-H. Chen, and L. P. Khoo, "Hybrid data-driven vigilance model in traffic control center using eye-tracking data and context data," *Advanced Engineering Informatics*, vol. 42, p. 100940, 2019.
- [29] M. C. Camden, A. Medina-Flintsch, J. S. Hickman, J. Bryce, G. Flintsch, and R. J. Hanowski, "Prevalence of operator fatigue in winter maintenance operations," *Accident Analysis Prevention*, vol. 126, pp. 47-53, 2019.
- [30] A. M. Lehrer, "A systems-based framework to measure, predict, and manage fatigue," *Reviews of human factors and ergonomics*, vol. 10, no. 1, pp. 194-252, 2015.
- [31] Y. Liu *et al.*, "Human Factors Evaluation of ATC Operational Procedures in Relation to Use of 3D Display," in *International Conference on Applied Human Factors and Ergonomics*, pp. 715-726: Springer, 2019.
- [32] A. Song, C. Niu, X. Ding, X. Xu, and Z. Song, "Mental Fatigue Prediction Model Based on Multimodal Fusion," *IEEE Access*, vol. 7, pp. 177056-177062, 2019.
- [33] C. J. de Naurois, C. Bourdin, A. Stratulat, E. Diaz, and J.-L. Vercher, "Detection and prediction of driver drowsiness using artificial neural network models," *Accident Analysis Prevention*, vol. 126, pp. 95-104, 2019.
- [34] J. Shen, J. Barbera, and C. M. Shapiro, "Distinguishing sleepiness and fatigue: focus on definition and measurement," *Sleep medicine reviews*, vol. 10, no. 1, pp. 63-76, 2006.
- [35] M. Hirshkowitz, "Fatigue, sleepiness, and safety: definitions, assessment, methodology," *Sleep Medicine Clinics*, vol. 8, no. 2, pp. 183-189, 2013.
- [36] R. E. Dodge, "Circadian rhythms and fatigue: A discrimination of their effects on performance," *Aviation, space, environmental medicine*, 1982.
- [37] A. Pimenta, D. Carneiro, J. Neves, and P. Novais, "A neural network to classify fatigue from human-computer interaction," *Neurocomputing*, vol. 172, pp. 413-426, 2016.
- [38] Y. Liang and J. D. Lee, "Combining cognitive and visual distraction: Less than the sum of its parts," *Accident Analysis Prevention*, vol. 42, no. 3, pp. 881-890, 2010.
- [39] S. Rahimian Aghdam, S. S. Alizadeh, Y. Rasoulzadeh, and A. Safaiyan, "Fatigue Assessment Scales: A comprehensive literature review," *Archives of Hygiene Sciences*, vol. 8, no. 3, pp. 145-153, 2019.
- [40] J. Van Cutsem, S. Marcora, K. De Pauw, S. Bailey, R. Meeusen, and B. Roelands, "The effects of mental fatigue on physical performance: a systematic review," *Sports medicine*, vol. 47, no. 8, pp. 1569-1588, 2017.
- [41] R. Hockey, *The psychology of fatigue: Work, effort and control*. Cambridge University Press, 2013.
- [42] L. D. Montgomery, R. W. Montgomery, and R. Guisado, "Rheoencephalographic and electroencephalographic measures of

- cognitive workload: analytical procedures," *Biological Psychology*, vol. 40, no. 1-2, pp. 143-159, 1995.
- [43] R. Job and J. Dalziel, "Defining fatigue as a condition of the organism and distinguishing it from habituation, adaptation, and boredom," 2001.
- [44] A. Fletcher, B. Hooper, I. Dunican, and K. Kogi, "Fatigue management in safety-critical operations: history, terminology, management system frameworks, and industry challenges," *Reviews of human factors ergonomics*, vol. 10, no. 1, pp. 6-28, 2015.
- [45] K. Sadeghniaat-Haghighi and Z. Yazdi, "Fatigue management in the workplace," *Industrial psychiatry journal*, vol. 24, no. 1, p. 12, 2015.
- [46] D. Dawson, J. Chapman, and M. J. Thomas, "Fatigue-proofing: a new approach to reducing fatigue-related risk using the principles of error management," *Sleep medicine reviews*, vol. 16, no. 2, pp. 167-175, 2012.
- [47] S. E. Lerman *et al.*, "Fatigue risk management in the workplace," *Journal of Occupational Environmental Medicine*, vol. 54, no. 2, pp. 231-258, 2012.
- [48] T. J. Balkin, W. J. Horrey, R. C. Graeber, C. A. Czeisler, and D. F. Dinges, "The challenges and opportunities of technological approaches to fatigue management," *Accident Analysis & Prevention*, vol. 43, no. 2, pp. 565-572, 2011.
- [49] M. R. Smith, R. Chai, H. T. Nguyen, S. M. Marcora, and A. J. Coutts, "Comparing the effects of three cognitive tasks on indicators of mental fatigue," *The Journal of psychology*, vol. 153, no. 8, pp. 759-783, 2019.
- [50] J. Shin, S. Kim, T. Yoon, C. Joo, and H.-I. Jung, "Smart Fatigue Phone: Real-time estimation of driver fatigue using smartphone-based cortisol detection," *Biosensors Bioelectronics*, vol. 136, pp. 106-111, 2019.
- [51] A. T. Welford, "Fundamentals of skill," 1968.
- [52] I. Völker, C. Kirchner, and O. L. Bock, "On the relationship between subjective and objective measures of fatigue," *Ergonomics*, vol. 59, no. 9, pp. 1259-1263, 2016.
- [53] R. Chai *et al.*, "Classification of EEG based-mental fatigue using principal component analysis and Bayesian neural network," in *Engineering in Medicine and Biology Society (EMBC), IEEE 38th Annual International Conference*, pp. 4654-4657: IEEE , 2016.
- [54] Z. Yin and J. Zhang, "Cross-session classification of mental workload levels using EEG and an adaptive deep learning model," *Biomedical Signal Processing and Control*, vol. 33, pp. 30-47, 2017.
- [55] F.-C. Lin, L.-W. Ko, C.-H. Chuang, T.-P. Su, and C.-T. Lin, "Generalized EEG-based drowsiness prediction system by using a self-organizing neural fuzzy system," *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 59, no. 9, pp. 2044-2055, 2012.
- [56] Y.-T. Liu, Y.-Y. Lin, S.-L. Wu, C.-H. Chuang, and C.-T. Lin, "Brain dynamics in predicting driving fatigue using a recurrent self-evolving fuzzy neural network," *IEEE transactions on neural networks and learning systems*, vol. 27, no. 2, pp. 347-360, 2016.
- [57] M. Patel, S. Lal, D. Kavanagh, and P. Rossiter, "Applying neural network analysis on heart rate variability data to assess driver fatigue," *Expert systems with Applications*, vol. 38, no. 6, pp. 7235-7242, 2011.

- [58] J. Meng, B. Zhao, Y. Ma, Y. Ji, and B. Nie, "Effects of fatigue on the physiological parameters of labor employees," *Natural hazards*, vol. 74, no. 2, pp. 1127-1140, 2014.
- [59] T. Radüntz, "A New Method for the Objective Registration of Mental Workload," in *Advances in Neuroergonomics and Cognitive Engineering*: Springer, pp. 279-290, 2017.
- [60] W. Han, Y. Yang, G.-B. Huang, O. Sourina, F. Klanner, and C. Denk, "Driver drowsiness detection based on novel eye openness recognition method and unsupervised feature learning," in *Systems, Man, and Cybernetics (SMC), 2015 IEEE International Conference on*, pp. 1470-1475: IEEE, 2015.
- [61] L.-H. Zhao, N. Duan, and C.-K. Yang, "Fatigue-driving recognition based on the state of the human eye and electroencephalographic signal," in *Chinese Control and Decision Conference (CCDC)* pp. 1567-1572: IEEE, 2016,.
- [62] Q. Ji, Z. Zhu, and P. Lan, "Real-time nonintrusive monitoring and prediction of driver fatigue," *IEEE transactions on vehicular technology*, vol. 53, no. 4, pp. 1052-1068, 2004.
- [63] L. M. Bergasa, J. Nuevo, M. A. Sotelo, R. Barea, and M. E. Lopez, "Real-time system for monitoring driver vigilance," *IEEE Transactions on Intelligent Transportation Systems*, vol. 7, no. 1, pp. 63-77, 2006.
- [64] S. Samn and L. Perelli, "Estimating Aircrew Fatigue: A Technique with Implications to Airlift Operations. USAF School of Aerospace Medicine, Brooks AFB," TX. Technical Report No. SAM-TR-82-211982.
- [65] S. A. Ferguson, G. M. Paech, C. Sargent, D. Darwent, D. J. Kennaway, and G. D. Roach, "The influence of circadian time and sleep dose on subjective fatigue ratings," *Accident Analysis & Prevention*, vol. 45, pp. 50-54, 2012.
- [66] L. B. Krupp, N. G. LaRocca, J. Muir-Nash, and A. D. Steinberg, "The fatigue severity scale: application to patients with multiple sclerosis and systemic lupus erythematosus," *Archives of neurology*, vol. 46, no. 10, pp. 1121-1123, 1989.
- [67] A. Shahid, K. Wilkinson, S. Marcu, and C. M. Shapiro, "Visual analogue scale to evaluate fatigue severity (VAS-F)," in *STOP, THAT and One Hundred Other Sleep Scales*: Springer, pp. 399-402, 2011.
- [68] B. Y. Tseng, B. J. Gajewski, and P. M. Kluding, "Reliability, responsiveness, and validity of the visual analog fatigue scale to measure exertion fatigue in people with chronic stroke: a preliminary study," *Stroke research treatment*, 2010.
- [69] B. P. Smith, M. Browne, T. A. Armstrong, and S. A. Ferguson, "The accuracy of subjective measures for assessing fatigue related decrements in multi-stressor environments," *Safety science*, vol. 86, pp. 238-244, 2016.
- [70] A. A. Borbély, "A two process model of sleep regulation," *Human neurobiology*, 1982.
- [71] A. J. Belyavin and M. B. Spencer, "Modeling performance and alertness: the QinetiQ approach," *Aviation, space, and environmental medicine*, vol. 75, no. 3, pp. A93-A103, 2004.

- [72] G. D. Roach, A. Fletcher, and D. DAWsON, "A model to predict work-related fatigue based on hours of work," *Aviation, space, and environmental medicine*, vol. 75, no. 3, pp. A61-A69, 2004.
- [73] S. R. Hursh *et al.*, "Fatigue models for applied research in warfighting," *Aviation, space, and environmental medicine*, vol. 75, no. 3, pp. A44-A53, 2004.
- [74] J. A. Caldwell, M. M. Mallis, J. L. Caldwell, M. A. Paul, J. C. Miller, and D. F. Neri, "Fatigue countermeasures in aviation," *Aviation, space, environmental medicine*, vol. 80, no. 1, pp. 29-59, 2009.
- [75] L. D. Scott, N. Hofmeister, N. Rogness, and A. E. Rogers, "An interventional approach for patient and nurse safety: a fatigue countermeasures feasibility study," *Nursing research*, vol. 59, no. 4, pp. 250-258, 2010.
- [76] P. Gershon, D. Shinar, and A. Ronen, "Evaluation of experience-based fatigue countermeasures," *Accident Analysis & Prevention*, vol. 41, no. 5, pp. 969-975, 2009.
- [77] P. Gershon, D. Shinar, T. Oron-Gilad, Y. Parmet, and A. Ronen, "Usage and perceived effectiveness of fatigue countermeasures for professional and nonprofessional drivers," *Accident Analysis & Prevention*, vol. 43, no. 3, pp. 797-803, 2011.
- [78] L. Bier, P. Wolf, H. Hilsenbek, and B. Abendroth, "How to measure monotony-related fatigue? A systematic review of fatigue measurement methods for use on driving tests," *Theoretical Issues in Ergonomics Science*, vol. 21, no. 1, pp. 22-55, 2020.
- [79] P. C. Winwood, A. H. Winefield, and K. Lushington, "Work - related fatigue and recovery: the contribution of age, domestic responsibilities and shiftwork," *Journal of Advanced Nursing*, vol. 56, no. 4, pp. 438-449, 2006.
- [80] J. E. Anderson *et al.*, "Obesity is associated with the future risk of heavy truck crashes among newly recruited commercial drivers," *Accident Analysis & Prevention*, vol. 49, pp. 378-384, 2012.
- [81] T. A. Hargens, A. S. Kaleth, E. S. Edwards, and K. L. Butner, "Association between sleep disorders, obesity, and exercise: a review," *Nat Sci Sleep*, vol. 5, pp. 27-35, 2013.
- [82] J. Dorrian, S. D. Baulk, and D. Dawson, "Work hours, workload, sleep and fatigue in Australian Rail Industry employees," *Applied ergonomics*, vol. 42, no. 2, pp. 202-209, 2011.
- [83] E. Grandjean, "Fatigue: its physiological and psychological significance," *Ergonomics*, vol. 11, no. 5, pp. 427-436, 1968.
- [84] C. D. Griffith and S. Mahadevan, "Inclusion of fatigue effects in human reliability analysis," *Reliability Engineering & System Safety*, vol. 96, no. 11, pp. 1437-1447, 2011.
- [85] M. R. Grech, A. Neal, G. Yeo, M. Humphreys, and S. Smith, "An examination of the relationship between workload and fatigue within and across consecutive days of work: Is the relationship static or dynamic?," *Journal of occupational health psychology*, vol. 14, no. 3, p. 231, 2009.
- [86] S. L. Morrow, A. K. McGonagle, M. L. Dove-Steinkamp, C. T. Walker, M. Marmet, and J. L. Barnes-Farrell, "Relationships between

- psychological safety climate facets and safety behavior in the rail industry: A dominance analysis," *Accident Analysis & Prevention*, vol. 42, no. 5, pp. 1460-1467, 2010.
- [87] F. Trapsilawati, X. Qu, C. D. Wickens, and C.-H. Chen, "Human factors assessment of conflict resolution aid reliability and time pressure in future air traffic control," *Ergonomics*, vol. 58, no. 6, pp. 897-908, 2015.
- [88] S. Folkard and P. Tucker, "Shift work, safety and productivity," *Occupational medicine*, vol. 53, no. 2, pp. 95-101, 2003.
- [89] S. H. Fairclough and R. Graham, "Impairment of driving performance caused by sleep deprivation or alcohol: a comparative study," *Human factors*, vol. 41, no. 1, pp. 118-128, 1999.
- [90] M. Ingre, T. Åkerstedt, B. Peters, A. Anund, and G. Kecklund, "Subjective sleepiness, simulated driving performance and blink duration: examining individual differences," *Journal of sleep research*, vol. 15, no. 1, pp. 47-53, 2006.
- [91] Z. Mu, J. Hu, and J. Yin, "Driving Fatigue Detecting Based on EEG Signals of Forehead Area," *International Journal of Pattern Recognition and Artificial Intelligence*, p. 1750011, 2016.
- [92] W. Kong, Z. Zhou, B. Jiang, F. Babiloni, and G. Borghini, "Assessment of driving fatigue based on intra/inter-region phase synchronization," *Neurocomputing*, vol. 219, pp. 474-482, 2017.
- [93] W. He, "Application heart rate variability to driver fatigue detection of dangerous chemicals vehicles," in *Intelligent Systems Design and Engineering Applications (ISDEA), 2014 Fifth International Conference on*, pp. 218-221: IEEE, 2014.
- [94] R. Sugie, T. Arakawa, and K. Kozuka, "Detection of Fatigue in Long-Distance Driving By Heart Rate Variability," 2016.
- [95] J. Vicente, P. Laguna, A. Bartra, and R. Bailón, "Drowsiness detection using heart rate variability," *Medical & biological engineering & computing*, vol. 54, no. 6, pp. 927-937, 2016.
- [96] S. Waite *et al.*, "Tired in the Reading Room: The Influence of Fatigue in Radiology," *Journal of the American College of Radiology*, 2016.
- [97] R. Schleicher, N. Galley, S. Briest, and L. Galley, "Blinks and saccades as indicators of fatigue in sleepiness warnings: looking tired?," *Ergonomics*, vol. 51, no. 7, pp. 982-1010, 2008.
- [98] S. Nakaso, J. Güttler, A. Mita, and T. Bock, "Human state estimation system implemented in an Office Deployable Getaway based on multiple bio information," in *ISARC. Proceedings of the International Symposium on Automation and Robotics in Construction*, vol. 33, p. 1, 2016.
- [99] J. Lavanya and R. E. Raj, "A Mobile Based Novice Detection of Driver's Fatigue Level and Accident Reporting Solution," in *Power Electronics and Renewable Energy Systems*: Springer, pp. 883-891, 2015.
- [100] K. Anjali, A. K. Thampi, A. Vijayaraman, M. F. Francis, N. J. James, and B. K. Rajan, "Real-time nonintrusive monitoring and detection of eye blinking in view of accident prevention due to drowsiness," in *Circuit, Power and Computing Technologies (ICCPCT)*, pp. 1-6: IEEE, 2016.

- [101] P. Ebrahim, W. Stolzmann, and B. Yang, "Eye movement detection for assessing driver drowsiness by electrooculography," in *IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pp. 4142-4148: IEEE, 2013.
- [102] L. L. Di Stasi, R. Renner, A. Catena, J. J. Cañas, B. M. Velichkovsky, and S. Pannasch, "Towards a driver fatigue test based on the saccadic main sequence: A partial validation by subjective report data," *Transportation research part C: emerging technologies*, vol. 21, no. 1, pp. 122-133, 2012.
- [103] C. Finke *et al.*, "Dynamics of saccade parameters in multiple sclerosis patients with fatigue," *Journal of neurology*, vol. 259, no. 12, pp. 2656-2663, 2012.
- [104] D. Kim, S. Choi, J. Choi, H. Shin, and K. Sohn, "Visual fatigue monitoring system based on eye-movement and eye-blink detection," in *IS&T/SPIE Electronic Imaging*, pp. 786303-786303-8: International Society for Optics and Photonics, 2011.
- [105] K. Hirvonen, S. Puttonen, K. Gould, J. Korpela, V. F. Koefoed, and K. Müller, "Improving the saccade peak velocity measurement for detecting fatigue," *Journal of neuroscience methods*, vol. 187, no. 2, pp. 199-206, 2010.
- [106] Y. Kim, Y. Kim, and M. Hahn, "Detecting driver fatigue based on the driver's response pattern and the front view environment of an automobile," in *Second International Symposium on Universal Communication*, pp. 237-240: IEEE, 2008.
- [107] S. Parhizi, L. M. Steege, and K. S. Pasupathy, "Mining the relationships between psychosocial factors and fatigue dimensions among registered nurses," *International Journal of Industrial Ergonomics*, vol. 43, no. 1, pp. 82-90, 2013.
- [108] R. Kamalian, E. Yeh, Y. Zhang, A. M. Agogino, and H. Takagi, "Reducing human fatigue in interactive evolutionary computation through fuzzy systems and machine learning systems," in *IEEE International Conference on Fuzzy Systems*, pp. 678-684: IEEE, 2006.
- [109] F. Tango and M. Botta, "Real-time detection system of driver distraction using machine learning," *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, no. 2, pp. 894-905, 2013.
- [110] K.-Q. Shen, X.-P. Li, C.-J. Ong, S.-Y. Shao, and E. P. Wilder-Smith, "EEG-based mental fatigue measurement using multi-class support vector machines with confidence estimate," *Clinical Neurophysiology*, vol. 119, no. 7, pp. 1524-1533, 2008.
- [111] Y. T. Chong and C.-H. Chen, "Management and forecast of dynamic customer needs: An artificial immune and neural system approach," *Advanced Engineering Informatics*, vol. 24, no. 1, pp. 96-106, 2010.
- [112] M.-H. Chen, C.-H. Teng, and P.-C. Chang, "Applying artificial immune systems to collaborative filtering for movie recommendation," *Advanced Engineering Informatics*, vol. 29, no. 4, pp. 830-839, 2015.
- [113] P. Zheng, T.-J. Lin, C.-H. Chen, and X. Xu, "A systematic design approach for service innovation of smart product-service systems," *Journal of Cleaner Production*, vol. 201, pp. 657-667, 2018.

- [114] S. Raza and C. Ding, "Progress in context-aware recommender systems—An overview," *Computer Science Review*, vol. 31, pp. 84-97, 2019.
- [115] M. H. Aghdam, "Context-aware recommender systems using hierarchical hidden Markov model," *Physica A: Statistical Mechanics and its Applications*, vol. 518, pp. 89-98, 2019.
- [116] M. Braunhofer, M. Elahi, F. Ricci, and T. Schievenin, "Context-aware points of interest suggestion with dynamic weather data management," in *Information and communication technologies in tourism*: Springer, pp. 87-100, 2013.
- [117] P. Zheng, X. Xu, and C.-H. Chen, "A data-driven cyber-physical approach for personalised smart, connected product co-development in a cloud-based environment," *Journal of Intelligent Manufacturing*, pp. 1-16, 2018.
- [118] P. Zheng, Y. Lin, C.-H. Chen, and X. Xu, "Smart, connected open architecture product: an IT-driven co-creation paradigm with lifecycle personalization concerns," *International Journal of Production Research*, pp. 1-14, 2018.
- [119] D. Vêras, R. Prudêncio, and C. Ferraz, "CD-CARS: Cross-domain context-aware recommender systems," *Expert Systems with Applications*, vol. 135, pp. 388-409, 2019.
- [120] H.-w. Chang, Y.-c. Tai, and J. Y.-j. Hsu, "Context-aware taxi demand hotspots prediction," *International Journal of Business Intelligence and Data Mining*, vol. 5, no. 1, p. 3, 2010.
- [121] M. E. Jewett and R. E. Kronauer, "Interactive mathematical models of subjective alertness and cognitive throughput in humans," *Journal of biological rhythms*, vol. 14, no. 6, pp. 588-597, 1999.
- [122] D. Cazzoli, C. A. Antoniadou, C. Kennard, T. Nyffeler, C. L. Bassetti, and R. M. Müri, "Eye movements discriminate fatigue due to chronotypical factors and time spent on task—a double dissociation," *PloS one*, vol. 9, no. 1, p. e87146, 2014.
- [123] J. F. May and C. L. Baldwin, "Driver fatigue: The importance of identifying causal factors of fatigue when considering detection and countermeasure technologies," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 12, no. 3, pp. 218-224, 2009.
- [124] E. Bal, O. Arslan, and L. J. S. s. Tavacioglu, "Prioritization of the causal factors of fatigue in seafarers and measurement of fatigue with the application of the Lactate Test," *Safety science*, vol. 72, pp. 46-54, 2015.
- [125] C. MacMahon, L. Schücker, N. Hagemann, and B. Strauss, "Cognitive fatigue effects on physical performance during running," *Journal of Sport Exercise Psychology*, vol. 36, no. 4, pp. 375-381, 2014.
- [126] R. Zuraida and H. Iridiastadi, "Evaluation of subjective fatigue tool—a study addressing restaurant employees in Indonesia," in *IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, pp. 1083-1086: IEEE, 2015.
- [127] E. Ahsberg, F. Gamberale, and K. Gustafsson, "Perceived fatigue after mental work: an experimental evaluation of a fatigue inventory," *Ergonomics*, vol. 43, no. 2, pp. 252-268, 2000.

- [128] A. Shepherd, "HTA as a framework for task analysis," *Ergonomics*, vol. 41, no. 11, pp. 1537-1552, 1998.
- [129] M. Edwards, "The design of an accident investigation procedure," *Applied Ergonomics*, vol. 12, no. 2, pp. 111-115, 1981.
- [130] A. Rostamabadi, M. Jahangiri, E. Zarei, M. Kamalinia, S. Banaee, and M. R. Samaei, "Model for A Novel Fuzzy Bayesian Network-HFACS (FBN-HFACS) model for analyzing Human and Organizational Factors (HOFs) in process accidents," *Process Safety Environmental Protection*, vol. 132, pp. 59-72, 2019.
- [131] K. Wróbel, J. Montewka, and P. Kujala, "Towards the assessment of potential impact of unmanned vessels on maritime transportation safety," *Reliability Engineering & System Safety*, vol. 165, pp. 155-169, 2017.
- [132] S.-T. Chen, A. Wall, P. Davies, Z. Yang, J. Wang, and Y.-H. Chou, "A Human and Organisational Factors (HOFs) analysis method for marine casualties using HFACS-Maritime Accidents (HFACS-MA)," *Safety science*, vol. 60, pp. 105-114, 2013.
- [133] M. De Ambroggi and P. Trucco, "Modelling and assessment of dependent performance shaping factors through Analytic Network Process," *Reliability Engineering & System Safety*, vol. 96, no. 7, pp. 849-860, 2011.
- [134] M. Masoudian and H. Razavi, "An investigation of the required vigilance for different occupations," *Safety Science*, 2018.
- [135] B. Cyganek and S. Gruszczyński, "Hybrid computer vision system for drivers' eye recognition and fatigue monitoring," *Neurocomputing*, vol. 126, pp. 78-94, 2014.
- [136] A. Olsen, "The Tobii I-VT fixation filter," *Tobii Technology*, 2012.
- [137] I. P. Bodala, N. I. Abbasi, Y. Sun, A. Bezerianos, H. Al-Nashash, and N. V. Thakor, "Measuring vigilance decrement using computer vision assisted eye tracking in dynamic naturalistic environments," in *Engineering in Medicine and Biology Society (EMBC), 39th Annual International Conference of the IEEE*, pp. 2478-2481: IEEE, 2017.
- [138] I. P. Bodala, J. Li, N. V. Thakor, and H. Al-Nashash, "EEG and eye tracking demonstrate vigilance enhancement with challenge integration," *Frontiers in human neuroscience*, vol. 10, p. 273, 2016.
- [139] L. L. Di Stasi *et al.*, "Saccadic eye movement metrics reflect surgical residents' fatigue," *Annals of surgery*, vol. 259, no. 4, pp. 824-829, 2014.
- [140] R. A. McKinley, L. K. McIntire, R. Schmidt, D. W. Repperger, and J. A. Caldwell, "Evaluation of eye metrics as a detector of fatigue," *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 53, no. 4, pp. 403-414, 2011.
- [141] M. Nyström and K. Holmqvist, "An adaptive algorithm for fixation, saccade, and glissade detection in eyetracking data," *Behavior research methods*, vol. 42, no. 1, pp. 188-204, 2010.
- [142] S. Saito, "Does fatigue exist in a quantitative measurement of eye movements?," *Ergonomics*, vol. 35, no. 5-6, pp. 607-615, 1992.

- [143] Y. Liang, M. L. Reyes, and J. D. Lee, "Real-time detection of driver cognitive distraction using support vector machines," *IEEE transactions on intelligent transportation systems*, vol. 8, no. 2, pp. 340-350, 2007.
- [144] H. Pham and S. Olafsson, "Bagged ensembles with tunable parameters," *Computational Intelligence*, vol. 35, no. 1, pp. 184-203, 2019.
- [145] J. R. Quinlan, *C4. 5: programs for machine learning*. Elsevier, 2014.
- [146] J. L. J. T. r. o. e. Gastwirth and statistics, "The estimation of the Lorenz curve and Gini index," pp. 306-316, 1972.
- [147] L. J. M. I. Breiman, "Bagging predictors," vol. 24, no. 2, pp. 123-140, 1996.
- [148] P. Blignaut and D. Wium, "Eye-tracking data quality as affected by ethnicity and experimental design," *Behavior research methods*, vol. 46, no. 1, pp. 67-80, 2014.
- [149] B. Liu, Q.-C. Zhao, Y.-Y. Ren, Q.-J. Wang, and X.-L. Zheng, "An elaborate algorithm for automatic processing of eye movement data and identifying fixations in eye-tracking experiments," *Advances in Mechanical Engineering*, vol. 10, no. 5, p. 1687814018773678, 2018.
- [150] D. Mollicone *et al.*, "Predicting performance and safety based on driver fatigue," *Accident Analysis Prevention*, vol. 126, pp. 142-145, 2019.
- [151] S. A. Hofmeyr and S. Forrest, "Architecture for an artificial immune system," *Evolutionary computation*, vol. 8, no. 4, pp. 443-473, 2000.
- [152] J. E. Hunt and D. E. Cooke, "Learning using an artificial immune system," *Journal of network and computer applications*, vol. 19, no. 2, pp. 189-212, 1996.
- [153] S. A. Ferguson, N. Lamond, K. Kandelaars, S. M. Jay, and D. Dawson, "The impact of short, irregular sleep opportunities at sea on the alertness of marine pilots working extended hours," *Chronobiology international*, vol. 25, no. 2-3, pp. 399-411, 2008.
- [154] P. Thiffault and J. Bergeron, "Fatigue and individual differences in monotonous simulated driving," *Personality and individual differences*, vol. 34, no. 1, pp. 159-176, 2003.
- [155] M. Shakouri, F. Aghazadeh, and L. H. Ikuma, "Individual differences in drivers' perceived workload near construction work zones," *Occupational Ergonomics*, vol. 13, no. 2, pp. 101-117, 2016.
- [156] K. H. Kim, B. Chang, and H. K. J. J. o. I. Choi, "Deep Learning Based Short-Term Electric Load Forecasting Models using One-Hot Encoding," *Journal of IKEEE*, vol. 23, no. 3, pp. 852-857, 2019.
- [157] T. Chen and C. Guestrin, "Xgboost: A scalable tree boosting system," in *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining*, 2016, pp. 785-794.
- [158] F. Li, C.-H. Chen, and L. P. Khoo, "Information Requirements for Vessel Traffic Service Operations," *World Academy of Science, Engineering and Technology, International Journal of Computer, Electrical, Automation, Control and Information Engineering*, vol. 10, no. 5, pp. 881-885, 2016.
- [159] F. Li, C. H. Chen, L. P. Khoo, and G. Xu, "Contextual information-based human fatigue prediction for integrated traffic control," in *Proceedings of International Conference on Computers and Industrial Engineering, CIE*, 2018.

- [160] S. W. Samn and L. P. Perelli, "Estimating aircrew fatigue: a technique with application to airlift operations," School of Aerospace Medicine Brooks Afb tx1982.
- [161] X.-Y. Lu, X.-Q. Chu, M.-H. Chen, P.-C. Chang, and S.-H. Chen, "Artificial immune network with feature selection for bank term deposit recommendation," *Journal of Intelligent Information Systems*, vol. 47, no. 2, pp. 267-285, 2016.
- [162] S. M. Casner and J. W. Schooler, "Vigilance impossible: Diligence, distraction, and daydreaming all lead to failures in a practical monitoring task," *Consciousness and cognition*, vol. 35, pp. 33-41, 2015.
- [163] G. H. Kamimori, T. M. McLellan, C. M. Tate, D. M. Voss, P. Niro, and H. R. Lieberman, "Caffeine improves reaction time, vigilance and logical reasoning during extended periods with restricted opportunities for sleep," *Psychopharmacology*, vol. 232, no. 12, pp. 2031-2042, 2015.
- [164] M. F. Rayo and S. D. Moffatt-Bruce, "Alarm system management: evidence-based guidance encouraging direct measurement of informativeness to improve alarm response," *BMJ quality & safety*, pp. bmjqs-2014-003373, 2015.
- [165] R. Akhavian and A. H. Behzadan, "Construction equipment activity recognition for simulation input modeling using mobile sensors and machine learning classifiers," *Advanced Engineering Informatics*, vol. 29, no. 4, pp. 867-877, 2015.
- [166] P. Zheng, X. Xu, S. Yu, and C. Liu, "Personalized product configuration framework in an adaptable open architecture product platform," *Journal of Manufacturing Systems*, vol. 43, pp. 422-435, 2017.
- [167] A. Löcken, P. Wintersberger, A.-K. Frison, and A. Riener, "Investigating user requirements for communication between automated vehicles and vulnerable road users," in *IEEE Intelligent Vehicles Symposium (IV)*, pp. 879-884: IEEE, 2019.
- [168] B. Hollifield, "Alarm Management," 2013.
- [169] E. Equipment and M. U. Association, *Alarm Systems: A Guide to Design, Management and Procurement*. Engineering Equipment and Materials Users Association London, 1999.
- [170] G. Praetorius and M. Lützhöft, "Decision support for vessel traffic service (VTS): user needs for dynamic risk management in the VTS," *Work*, vol. 41, no. Supplement 1, pp. 4866-4872, 2012.
- [171] F. Shaker, A. Shahin, and S. Jahanyan, "Developing a two-phase QFD for improving FMEA: an integrative approach," *International Journal of Quality Reliability Management*, 2019.
- [172] F. Li, Lee, C. H., Xu, G., Chen, C. H., & Khoo, L. P., "A QFD-Enabled Conceptualization for Reducing Alarm Fatigue in Vessel Traffic Service Centre. ," *Transdisciplinary Engineering: A Paradigm Shift: Proceedings of the 24th ISPE Inc. International Conference on Transdisciplinary Engineering*, vol. 5, 2017.
- [173] M. Yazdani, C. Kahraman, P. Zarate, and S. C. Onar, "A fuzzy multi attribute decision framework with integration of QFD and grey relational analysis," *Expert Systems with Applications*, vol. 115, pp. 474-485, 2019.

- 
- [174] C. G. Şen and H. Baraçlı, "Fuzzy quality function deployment based methodology for acquiring enterprise software selection requirements," *Expert Systems with Applications*, vol. 37, no. 4, pp. 3415-3426, 2010.
- [175] J. Karnjanasomwong and N. Thawesaengkulthai, "Dynamic sigma-TRIZ solution model for manufacturing improvement and innovation, case study in Thailand," *International Journal of Six Sigma Competitive Advantage*, vol. 11, no. 2-3, pp. 114-156, 2019.
- [176] I. Abdulkerim, M. Avvari, and T. Cherkos, "Design of house of quality using SERVQUAL and QFD for service quality improvement: a case of Bahir Dar city hotels," *International Journal of Applied Management Science*, vol. 11, no. 3, pp. 277-293, 2019.
- [177] D. Mann and S. Dewulf, "Updating the contradiction matrix," *TRIZCON12003, Philadelphia, March, 2003*.
- [178] K. C. Rea, "TRIZ and software-40 principle analogies, part 1," *The TRIZ Journal*, 2001.
- [179] D. Mann, "TRIZ for software," *TRIZ Journal*, Oct, 2004.
- [180] D. Kluender, "TRIZ for software architecture," *Procedia Engineering*, vol. 9, pp. 708-713, 2011.

## Appendix

### Appendix A.1 Fatigue severity scale

Items	Descriptions	Strongly disagree				Strongly agree		
<b>FS 1</b>	My motivation is lower when fatigued.	1	2	3	4	5	6	7
<b>FS 2</b>	Exercise brings on my fatigue.	1	2	3	4	5	6	7
<b>FS 3</b>	I am easily fatigued.	1	2	3	4	5	6	7
<b>FS 4</b>	Fatigue interferes with my physical functioning.	1	2	3	4	5	6	7
<b>FS 5</b>	Fatigue causes frequent problems for me.	1	2	3	4	5	6	7
<b>FS 6</b>	My fatigue prevents sustained physical functioning.	1	2	3	4	5	6	7
<b>FS 7</b>	Fatigue interferes with carrying out certain duties and responsibilities.	1	2	3	4	5	6	7
<b>FS 8</b>	Fatigue is among my most disabling symptoms.	1	2	3	4	5	6	7
<b>FS 9</b>	Fatigue interferes with my work, family, or social life.	1	2	3	4	5	6	7

### Appendix A.2: The Bortner type A scale

Item	Descriptions	Scale							Descriptions
<b>BT1</b>	Never Late	1	2	3	4	5	6	7	Causal about appointments
<b>BT2</b>	Not competitive	1	2	3	4	5	6	7	Very competitive
<b>BT3</b>	Anticipates what others are going to say	1	2	3	4	5	6	7	Good listener, hears others out
<b>BT4</b>	Always rushed	1	2	3	4	5	6	7	Never feels rushed, even under pressure
<b>BT5</b>	Can wait patiently	1	2	3	4	5	6	7	Impatient when waiting
<b>BT6</b>	Goes "all out"	1	2	3	4	5	6	7	Causal
<b>BT7</b>	Takes things one at a time	1	2	3	4	5	6	7	Tries to do many things at once
<b>BT8</b>	Emphatic in speech	1	2	3	4	5	6	7	Slow, deliberate talker
<b>BT9</b>	Wants good job recognized by others	1	2	3	4	5	6	7	Only cares about satisfying himself no matter what others may think
<b>BT10</b>	Fast	1	2	3	4	5	6	7	Slow doing things
<b>BT11</b>	Easy going	1	2	3	4	5	6	7	Hard driving
<b>BT12</b>	'Sits' on feelings	1	2	3	4	5	6	7	Expresses feelings
<b>BT13</b>	Many interests	1	2	3	4	5	6	7	Few interests outside work
<b>BT14</b>	Satisfied with job	1	2	3	4	5	6	7	Ambitious

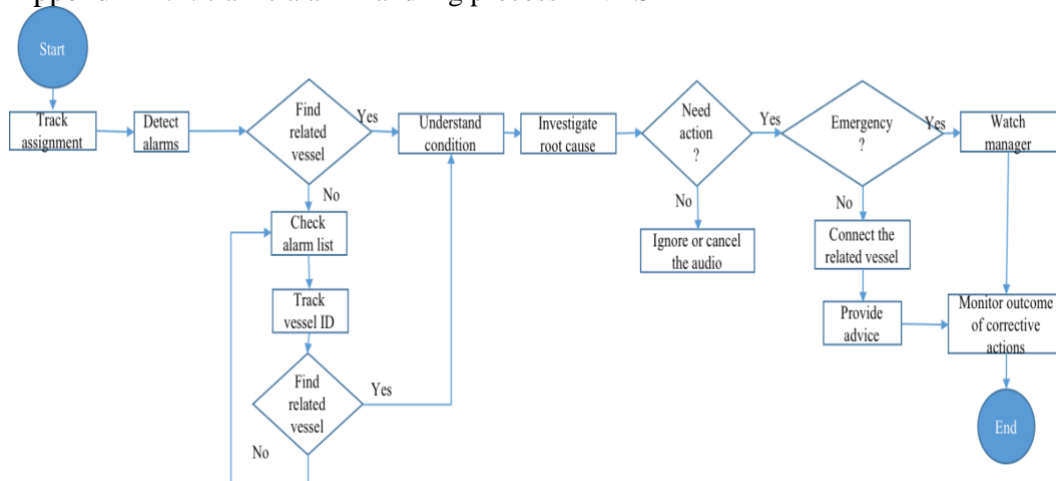
Appendix A.3: The k-fold cross validation results of testing data for each algorithm (Accuracy)

Data source	Algorithms	Trail 1	Trail 2	Trail 3	Trail 4	Trail 5	Trail 6	Trail 7	Trail 8	Trail 9	Trail 10	Ave.
All	LR	0.86	0.92	0.88	0.88	0.86	0.88	0.87	0.93	0.81	0.89	0.88
	SVR	0.83	0.81	0.81	0.81	0.84	0.85	0.84	0.77	0.81	0.85	0.82
	DTR	0.77	0.83	0.88	0.81	0.83	0.88	0.86	0.83	0.88	0.81	0.84
	RFR	0.80	0.84	0.88	0.81	0.82	0.88	0.86	0.87	0.88	0.81	0.85
	AIS-XGBFP	0.90	0.88	0.91	0.92	0.86	0.92	0.93	0.86	0.86	0.91	0.89
No PI	LR	0.66	0.79	0.75	0.76	0.79	0.78	0.78	0.64	0.79	0.74	0.75
	SVR	0.72	0.74	0.75	0.75	0.71	0.73	0.71	0.66	0.72	0.69	0.72
	DTR	0.73	0.73	0.71	0.73	0.76	0.76	0.76	0.69	0.72	0.75	0.73
	RFR	0.76	0.73	0.67	0.75	0.74	0.72	0.78	0.77	0.72	0.80	0.74
	AIS-XGBFP	0.85	0.85	0.82	0.81	0.83	0.79	0.78	0.81	0.75	0.85	0.81
No WeC	LR	0.85	0.88	0.86	0.86	0.88	0.90	0.86	0.87	0.86	0.90	0.87
	SVR	0.81	0.79	0.79	0.75	0.79	0.77	0.80	0.77	0.80	0.82	0.79
	DTR	0.85	0.79	0.85	0.79	0.82	0.81	0.79	0.83	0.81	0.84	0.82
	RFR	0.79	0.83	0.81	0.85	0.79	0.86	0.83	0.82	0.81	0.81	0.82
	AIS-XGBFP	0.86	0.88	0.88	0.91	0.83	0.89	0.84	0.88	0.89	0.87	0.87
No WC	LR	0.88	0.80	0.86	0.87	0.86	0.84	0.84	0.83	0.83	0.81	0.84
	SVR	0.70	0.75	0.78	0.76	0.75	0.73	0.73	0.72	0.74	0.71	0.74
	DTR	0.85	0.89	0.86	0.82	0.83	0.81	0.80	0.81	0.83	0.83	0.83
	RFR	0.85	0.84	0.83	0.88	0.87	0.83	0.83	0.82	0.80	0.87	0.84
	AIS-XGBFP	0.89	0.82	0.82	0.88	0.88	0.85	0.81	0.82	0.86	0.83	0.85

Appendix A.4: The k-fold cross validation results of testing data for each algorithm (Accuracy)

Data source	Algorithms	Trail 1	Trail 2	Trail 3	Trail 4	Trail 5	Trail 6	Trail 7	Trail 8	Trail 9	Trail 10	Ave.
All	LR	0.11	0.07	0.90	0.12	0.10	0.09	0.09	0.09	0.11	0.91	0.26
	SVR	0.12	0.15	0.17	0.14	0.20	0.16	0.15	0.19	0.17	0.13	0.16
	DTR	0.16	0.12	0.09	0.15	0.11	0.09	0.11	0.11	0.10	0.12	0.12
	RFR	0.14	0.11	0.08	0.14	0.11	0.09	0.11	0.10	0.09	0.01	0.10
	AIS-XGBFP	0.10	0.08	0.08	0.08	0.11	0.07	0.07	0.11	0.09	0.08	0.09
No PI	LR	0.20	0.16	0.18	0.17	0.17	0.15	0.17	0.20	0.16	0.17	0.17
	SVR	0.20	0.24	0.20	0.18	0.20	0.47	0.26	0.26	0.23	0.25	0.25
	DTR	0.19	0.19	0.20	0.19	0.17	0.13	0.17	0.20	0.18	0.18	0.18
	RFR	0.15	0.18	0.20	0.18	0.15	0.17	0.17	0.16	0.17	0.14	0.17
	AIS-XGBFP	0.12	0.13	0.15	0.14	0.12	0.15	0.15	0.16	0.18	0.13	0.14
No WeC	LR	0.12	0.11	0.12	0.10	0.10	0.11	0.12	0.12	0.11	0.09	0.11
	SVR	0.11	0.20	0.20	0.21	0.17	0.18	0.19	0.19	0.17	0.15	0.18
	DTR	0.11	0.13	0.11	0.15	0.11	0.12	0.13	0.12	0.14	0.11	0.12
	RFR	0.12	0.12	0.12	0.11	0.13	0.11	0.13	0.11	0.12	0.11	0.12
	AIS-XGBFP	0.10	0.10	0.09	0.10	0.11	0.10	0.11	0.09	0.09	0.11	0.10
No WC	LR	0.10	0.12	0.09	0.09	0.10	0.12	0.11	0.13	0.13	0.12	0.11
	SVR	0.24	0.24	0.20	0.23	0.23	0.19	0.24	0.27	0.25	0.31	0.24
	DTR	0.11	0.08	0.10	0.13	0.12	0.13	0.14	0.12	0.12	0.11	0.12
	RFR	0.10	0.10	0.10	0.08	0.09	0.13	0.11	0.13	0.13	0.10	0.11
	AIS-XGBFP	0.09	0.12	0.10	0.08	0.09	0.12	0.11	0.14	0.13	0.11	0.11

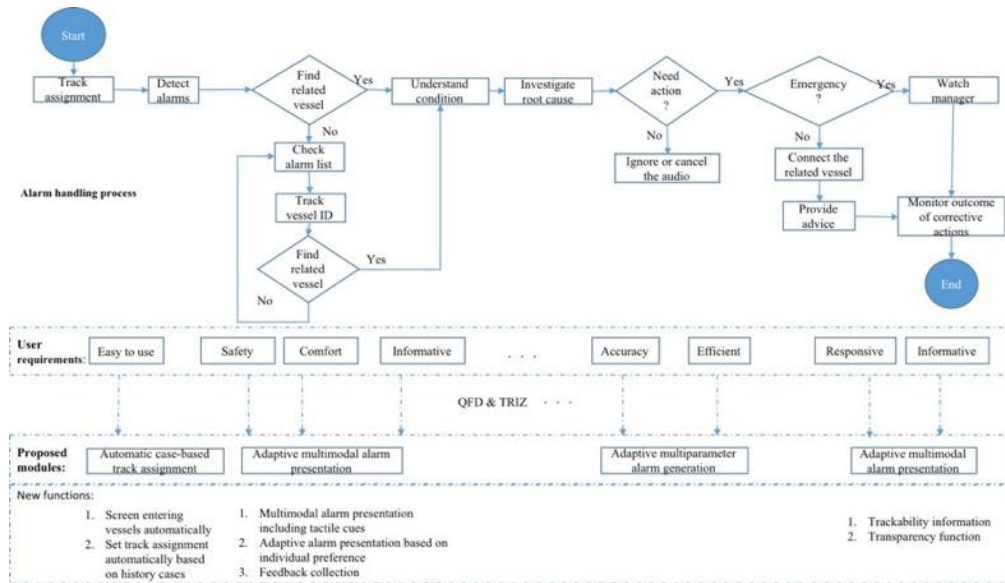
## Appendix B.1: traffic alarm handling process in VTS



## Appendix B.2: Initial UR codes

No	Initial UR codes	No	Initial UR codes
1	less false alarms	14	easy to detect
2	less missed alarms	15	short system response times
3	less repeat alarms	16	noise is not greater than 74db
4	less alarms per minute	17	no need recall
5	less noises	18	sound louder under fatigue
6	less colors to dazzle the eyes	19	different alarm time for different vessels
7	color is matching with background	20	different alarm time for different speed
8	good shape of alarm message	21	easy to learn
9	no need of manual assign alarms	22	easy to understand alarm message
10	be silent during normal situation	23	easy to select high priority alarms
11	operators can make minor errors	24	easy to respond to alarms
12	less annoying audible alarms	25	less unrelated information
13	less high priority alarms	26	more time to deal with alarms
		27	more information to understand alarms

Appendix B.3: User requirements and new traffic alarm handling process in VTS



## Appendix C: NTU Institutional Review Board Approval



**IRB-2018-04-007**

25 June 2018

Associate Professor Chen Chun-Hsien  
School of Mechanical & Aerospace Engineering

**NTU INSTITUTIONAL REVIEW BOARD APPROVAL**

**Project Title: Human Factors in Vessel Traffic Management: Casual Factors and Preventive Interventions**

(Amount Approved: SGD\$446,000; to be funded by SMI)

I refer to your application for ethics approval with respect to the above project.

The Board has considered your application and noted from your application that your research involves collecting behavioral data from participants through questionnaire-based survey and the simulation experiments.

You have also confirmed that informed consent will be obtained from the participants and you have guaranteed the confidentiality of your participants' biodata obtained from them.

The documents reviewed are:

- a) NTU IRB application form dated **7 June 2018**
- b) Participant information sheet and consent form: version 1 dated **7 June 2018**
- c) Data collection form: version 1 dated **7 June 2018**

The Board is therefore satisfied with the bioethical consideration for the project and approves the ethics application under **Expedited** review. The approval period is from **25 June 2018 to 1 August 2019**. The NTU IRB reference number for this study is **IRB-2018-04-007**. Please use this reference number for all future correspondence.

The following protocol and compliances are to be observed upon NTU IRB approval

1. Any research involving subjects less than 21 years old would require IRB approved written Parental Consent and consent from the participant before any research protocols can be administered unless waiver of consent is given by IRB. Minimal risk refers to an anticipated level of harm and discomfort that is no greater than that ordinarily encountered in daily life, or during the performance of routine educational, physical, or psychological examination.
2. Only the approved Participants Information Sheet and Consent Form should be used. It must be signed by each subject prior to initiation of any protocol procedures. In addition, each subject should be given a copy of the signed consent form.
3. Consent forms are important documents therefore they should be stored in the strictest arrangement. Loss of consent form would result in disciplinary action.
4. No deviation from, or changes of, the protocol should be initiated without prior written NTU IRB approval of an appropriate amendment.

**Research Integrity and Ethics Office, NTU Institutional Review Board**

50 Nanyang Avenue, NS4-05-92A, Singapore 639798, T: (65) 6592-2495, www.ntu.edu.sg



5. The Principal Investigator should report promptly to NTU IRB regarding:
  - a. Deviation from, or changes to the protocol.
  - b. Changes increasing the risk to the subjects and/or affecting significantly the conduct of the trial
  - c. All serious adverse events (SAEs) which are both serious and unexpected.
  - d. New information that may affect adversely the safety of the subjects of the conduct of the trial.
  - e. Completion of the study.
  
6. Continuing Review Request/ Notice of Study completion form should be submitted to NTU IRB for the following:
  - a. Annual review: Status of the study should be reported to the NTU IRB at least annually using the Continuing Review Request/ Notice of Study completion form.
  - b. Study completion or termination: Continuing Review Request/ Notice of Study completion form is to be submitted within 4 to 6 weeks of study completion or termination.
  
7. All Principal Investigators should comply with existing legislation that would have an impact on the domain of their research.
  
8. Advertisements/ Notices for recruitment of subjects must meet the following requirements:
  - a. Advertisements must clearly state that volunteers are being recruited to participate in an NTU research project with proper research title and NTU logo.
  - b. Name and contact details of Principal Investigator (usually a faculty member), and NTU-IRB contact details (Tel: 6592 2495; Email: [IRB@ntu.edu.sg](mailto:IRB@ntu.edu.sg)) should be provided.
  - c. The NTU-IRB project reference number should be stated.
  - d. Advertisements should include eligibility criteria.
  - e. Advertisements recruiting Minors must explicitly state that parental consent is required for participation (unless NTU-IRB has granted approval for a waiver of parental consent).

Advertisements/ Notices should NOT contain the following:

  - a. State or imply a certainty of favourable outcome or other benefits beyond what is outlined in the informed consent form and the application/protocol.
  - b. Make claims, either explicitly or implicitly, that a procedure or intervention is safe or effective or superior to other standard procedures or interventions.
  - c. Use catchy words like "free" or "exciting."
  - d. Advertisements may state that participants will be paid, but should not emphasize the payment or the amount to be paid (e.g. by such means of larger or bold type)

*lionel*

Professor Lionel Lee  
 Chair, NTU Institutional Review Board  
 encl.

**Research Integrity and Ethics Office, NTU Institutional Review Board**

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