Thesis for the Master's Degree in Navigation Science

A Study of the Contribution of Human Error to Management Tasks Based on Questionnaire Survey

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ABSTRACT

A modern ship is comprised of many elements which may be fully automated, they still require a degree of human intervention. A number of recent vessels related incidents suggests due to the absence of a fully implemented safety culture is still an issue.

The experiences indicate that an average of 90% of marine casualties is rooted in human error worldwide. In order to minimize maritime accidents, it is essential to focus on the factors of human errors. However, human error prediction is quite a difficult task in maritime transportation due to the uncertainty and inadequacy of quantitative human error data.

The purpose of this study is to identify and analyze the main factors affecting the human error using factor analysis on masters and officers' responses in the ship navigation field. The survey questionnaire related to the research subjects were identified as fatigue, training, operational skill, workloads, management task and human error.

First, the preliminary variables of education and training outcomes were researched and designed, and hypotheses were set up. For collecting the basic data, statistical analysis was conducted to analyze the effects of the descriptive statistics, reliability, and validity of variables, structural equation analysis, and mediation effects. This study analyzes human error by taking the perspectives of vessel operating master and chief officers using structural equation modeling.

From an academic standpoint, this issue of measuring human error has become increasingly important in the topic in this field as we mentioned early. The existing human error model is very rare and comes from the general aviation, nuclear and chemical plants. Most of them are not adjustable for the maritime, especially shipping navigation.

The scale comprised 17 variables representing the six latent variables of fatigue, training, operational skills, workloads, management tasks, and human error. Several statistical examinations were conducted in an effort to evaluate the effectiveness of this study. The results show that there is a significant effect of workload, training and management tasks to the human error occurrences. The direct experience of manager tasks can decrease human error and also influence more by increasing training courses. The indirect experience such as workloads can increase human error. However, increasing manager controls over workloads well can reduce its effect on human error occurrence.

The study not only confirms the observation that training is an important part of managerial tasks, but also it is important for reducing accidents frequency. Proper management control is an important factor influencing human error. However, the managers should pay attention to the strict control over masters cannot reduce all human errors, because more workloads affect to human error increase.

As the shipping navigation becomes automated, there still continues to increase in human error. To establish a strong strategy to decrease human error, the shipping companies could focus to increase its control over the master and officers and also should increase training courses updated navigation equipment. However, there is a lack of supporting empirical evidence in the shipping field. This study was designed to explore this gap in the research. Therefore, the results derived from this research provide several practical implications for shipping navigation managers, master, and officers, specifically, in terms of how to decrease the accidents in the vessel.

Chapter 1. Introduction

1. Background

Merchant ships transport over 90% of the world's cargo due to various reasons, including that it is the cheapest form of transportation. A modern ship is comprised of many elements, each of which has a varying degree of effect on the overall performance of that ship. Although many of these systems may be fully automated, they still require a degree of human intervention, such as set initial tolerances and respond to alarms. In addition, the non-automated systems may require direct human inputs for their operation and maintenance, humans to interact with other humans, etc. Berg (2013) highlights that the maritime transport system is 25 times riskier than the air transport system. In addition, a number of recent high profile incidents suggest that the absence of a fully implemented safety culture is still an issue, which addresses some shipping companies as a matter of priority (Veiga, 2002).

Over the decades, both international and domestic maritime authorities have devoted immense efforts to enhance ship safety. However, the maritime sector is facing many challenges with recent reports of an increase in the frequency of accidents both in shipping and at ports (Global Risk Reports, 2016). According to the marine accident statistics from Canada Transportation Safety Board (TSB) and Taiwan Ministry of Transportation and Communications (MOTC), the most frequent type of shipping accidents is collision with the occurrence rate of 30.20% in 2,649 casualties in Canada from 2007 to 2016, and 34.98% in Taiwan from 2010 to 2016, and 9% (2017) in worldwide. It also is the most common accident type in Turkey between 2005 and 2015.

The experiences indicate that around 75–96% of marine casualties are rooted in human error worldwide (Pennie et al., 2007; Berg, 2013; Uğurlu et al., 2015). Catherine and Rhona (2006) mentioned 90% reason for the ship collision belongs to the human elements. According to the accident data of Canada Transport Safety Board from 1981 to 1992, 74% of the ship collision is related to the human error, 16% had occurred the problem of vessel's hardware, and other causes from the mistake by other vessel (3%), uncomfortable port and port facilities (2%), and the problem of navigation technology (1%). The ration of human error in ship collision is higher with 98% in Korea during 2010 and 2016. While enormous endeavors are devoted to deal with such an issue, the occurrence of human error in marine accidents still remains at an undesired level (Gaonkar et al., 2011; Noroozi et al., 2014). Such a statement still holds when investigating the causes of oil tanker collisions (Uğurlu et al., 2013).

In order to minimize maritime accidents, it is essential to focus on the types of human errors (Abujaafar, 2012; Akyuz, 2016). The maritime authorities have been adopting a set of rules and regulations to minimize human error and enhance safety awareness such as SOLAS, STCW, ISM Code (Akyuz et al., 2016; Karahalios, 2014; Chauvin, 2013; Karahalios, 2011). On the other hand, maritime safety practitioners are also seeking creative solutions to reduce human error.

However, human error prediction is quite a difficult task in maritime transportation due to the uncertainty and inadequacy of quantitative human error data (Akyuz and Celik, 2018). To overcome these limitations, some scientific researches have been undertaken in the past decades. For instance, Macrae (2009) conducted an extensive study to identify a potential human error in the event of two major types of marine accident: grounding and collision. A similar study has been performed in recent time to quantify human errors related to grounding and collision accidents at sea (Akyuz, 2017). Furthermore, a couple of scientific research papers have been conducted through human error and system failure in maritime and offshore industries (Hou et al., 2017; Abbassi et al., 2015; Akyuz and Celik, 2015; Lavasani et al., 2015; Noroozi et al., 2014; Deacon et al., 2013; Abascal et al., 2010). The papers contributed guidelines to adopt various human error assessment techniques such as HEART (Human Error Assessment and Reduction Technique), SLIM (Success Likelihood Index Method) and THERP (Technique of Human Error Rate Prediction) in the application of numerous procedures on maritime and offshore industries in order to reduce human error and improve operational safety.

To date, most of the research and practice has been concerned with "human behavior aboard seagoing vessels, with the major focus being on maritime transport – the merchant or merchant marine" (McLachlan, 2017). De Oses and Ventikos (2014) found that the majority of the human error (45%) occurred by the wrong decision of master and pilots, 23% is the incaution activities by pilot and crews, 10% is related to the communication problem.

2. Problem statement and research purpose

Safety is a part of complex systems operating in an uncertain market environment. The interest of different shipping players i.e. ship owners, operating people, terminal operators, and other related service providers are sometimes in conflict.

The understanding of these cognitive systems, their functions, and human capabilities and limitations is the subject of decades of scientific inquiry. Experts in human factors, like the experts in other domains, may seem to have simple intuitions about human behaviors, but these are the results of expertise, analysis, and the massive amount of internally networked information that experts amass over a lifetime of learning.

The descriptions of how humans succeed, and sometimes fail, often differ only by the outcome. The expression of expertise and error is governed by the same processes. Our scientific understanding of human error does not come from studying error as a separate process but by understanding human behavior.

The purpose of this study is to identify the leading factors affecting the human error using actor analysis on masters and officers' responses in the ship navigation field. The survey questionnaire related to the research subjects were identified as fatigue, training, operational skill, workloads, management task and human error. The important task of this study is to analyze the main factors affected human error based on practical questionnaire responses.

The results of this study are summarized as follows. First, the preliminary variables of education and training outcomes were researched and designed, and hypotheses were set up. For the basic data collected, statistical analysis was conducted to analyze the effects of the descriptive statistics, reliability, and validity of variables, structural equation analysis, and mediation effects.

This study analyzes human error by taking the perspectives of vessel operating master and chief officers using structural equation modeling. The main aim of the study is to analyze the human error in the shipping industry.

First, the objectivity to find the main factors related to human error through a literature review. The preliminary variables of human error outcomes were designed, and hypotheses were set up.

Second, the survey questionnaires were written and collected data from different kind of shipping companies where Turkish masters and officers operate.

Third, for the basic data collected, exploratory factor analysis was conducted to analyze the effects of the descriptive statistics, and Confirmatory factor analysis were conduct to the identification of reliability and validity of variables, structural equation analysis, and mediation effects.

3. Research methodology and significance

The scope of the study falls into the shipping navigation literature on human error in the maritime industry. The study develops a model using structural equation modeling. After the survey questions are collected, they were conducted explanatory factor analysis through SPSS 22 and Confirmatory analysis and meditation effect through AMOS 19.

The study contributes to the shipping navigation literature in the following ways:

1) It finds the effects management tasks and workload to the human error.
2) The corresponding questionnaire is prepared to identify the cognitive causes of master and officers before the accident occurs in the vessel.
3) The study results are very significant in recent technology changing period from mechanic operation to automation in the shipping.

4. Research Structure

The research paper is organized into six sections as follows:

Chapter 1 introduces the background and purpose of the study, as well as its structure.

Chapter 2 gives the definition of the essential variables, especially the characteristics of human error and factors in the ship navigation. The chapter explores the previous studies related to human error in different industries.

Chapter 3 describes the design of the study, hypothesis setting, definition of the variables, data collection method, and analysis procedure.

Chapter 4 analyzes the data using exploratory factor analysis and conformity factor analysis, model fitting analysis as well as do hypothesis testing.

Chapter 5 concludes by suggesting managerial implementations and recommendations according to the analysis results.

Chapter 2. Theoretical and Literature review

1. Human error meaning and its trend

There are many definitions of *human error*, though they all have a common feature. Human error is a label given to an action that has negative consequences or fails to achieve the desired outcome.

Swain and Guttmann (1983) state that a *human error* is an out of tolerance action, where the limits of tolerable performance are defined by the system.

Reason (1990) describes that a *generic term* to encompass all those occasions in which a planned sequence of mental or physical activities fails to achieve its intended outcome, and when these failures cannot be attributed to some chance agency. Sender and Moray (1991) define *a human error* means that something has been done which was: not intended by the actor; not desired by a set of rules or an external observer, or that led the task or system outside its acceptable limits. Hollnagel (1993) defines *human error in the* nuclear industry as *an erroneous action which* can be failed to produce the expected result and/or which produces an unwanted consequence.

Either *an action* that is not intended or desired by the human or failure on the part of the human to perform a prescribed action within specified limits of accuracy, sequence, or time that fails to produce the expected result and has led or has the potential to lead to an unwanted consequence.

An operator who follows the nominal procedure, as prescribed, can be judged to have made a human error if any steps in the procedure are determined to be inconsistent with a specific unexpected condition, after the accident. The sources of the successful operation of systems under one set of conditions can be labeled errors after a failure occurs (Woods et al., 2010).

Rodgers and Blanchard (1993) observe that personality factors have shown little usefulness is predicting accidents, despite the folklore that errors are related to an individual predisposition to make errors or take risks. It is often convenient to blame individuals and ignore the context in which errors are committed. Paries (2011) explains that both automation and procedure have been applied in safety-critical systems to reduce system uncertainty though processes that reduce variety, diversity, deviation, and instability. The side effect has been to reduce autonomy, creativity, and reactivity of human operators and make systems increasing brittle outside the boundaries of the normal operating envelope. Years of taking an approach to safety that focused on protecting systems from their operators did not increase safety. Such efforts often have multiple unintended consequences including increasing system complexity, reducing the operator's flexibility to resolve unexpected failures and increasing workload.

Human behaviors are understood as the product of systematic processes inside the cognitive, operation, and the organizational world in which we operate (Woods et al., 2010). According to Reason (1990), errors are seen as consequences, not causes, having their origins in "upstream" systemic factors. The descriptions of how humans succeed, and sometimes fail, often differ only by the outcome. That is, the exact same sequence of events and human actions can have many different results, for a large variety of reasons. Woods, Dekker, and others have argued that human errors are the symptoms of deeper system issues organizational and technological. Errors arise while people are pursuing success in an uncertain, resource-constrained world (Dekker, 2014). Hollnagel (2005) argues that human error, as a sought-after signal in accident analysis, is fundamentally inconsistent with understanding that human behavior is primarily a reflection of environmental complexity.

Human error is an after-the-fact designation that is sensitive to hindsight bias. Once the outcome is known, an oversimplified sequence of events often becomes the event model. Hindsight bias is the tendency for people who already know the outcome of an event to believe, falsely, that they would have predicted that outcome (Hawkins and Hastie, 1990). There is a rich scientific literature on hindsight bias (e.g., Blank and Nestler, 2007; Fischhoff, 2007) that informs those that try to understand mishaps and accidents (Woods et al., 2010).

2. Human error classification

Several taxonomies have been suggested for classifying human errors, depending on elements of the error, including the intention, the action, and the context (Reason, 2008). As an intention, doing the wrong activity becomes a human error when the operator does not avoid an accident. As an *action*, the classification might include omission, extraneous actions, incorrect actions in the wrong order, at the wrong time, or wrong speed. As a *context*, the activities are accounted such as anticipation of action or continuing with a plan, interruptions or distractions, number of concurrent tasks, and stressors.

Rasmussen (1983) proposed that skilled human performance could be divided into three categories: skill based, rule-based, and knowledge-based (SRK). Skill-based performance includes highly practiced, sensory-motor performance. Increasing skill can lead to long and complex movements that can be performed without conscious control. Rasmussen (2003) noted that skilled performance errors serve a function in fine-tuning movement patterns and skill maintenance. Rule-based human performance triggers routine procedures that are goal oriented and based on previous experience. Rule-based performance can become skill-based performance as expertise increases. The ability to deal with vast amounts of information swiftly and efficiently is a marker of skilled performance (Kahneman, 2011).

Knowledge-based human performance is the top-down process of resolving issues, reasoning, and solving problems, where the rules are not known from previous experiences.

Human error taxonomies have been expanded to include the internal and external stressors, which impact the operators' behavior. Internal stressors often referred to a condition of the operator, include adverse physiological states, adverse mental states, and physical limitations. External stressors include the physical environment, team dynamics, supervision, and organization dynamics, as well as the tools and technology that define the system.

3. Human error assessment methods

The evaluation of human error in the maritime domain has been regarded as an onerous mission due to the absence of empirical data. A number of human error studies are proposed notwithstanding the existence of such a dilemma. Considering safety and pollution prevention, a certain amount of literature conducts human error probability (HEP) evaluations for the operations onboard oil tankers or Liquefied Petroleum Gas (LPG) carriers. Some of such studies are under Cognitive Reliability Error Analysis Method (CREAM) scheme while others are based on fuzzy Success Likelihood Index Method (SLIM), Human Error Assessment and Reduction Technique (HEART) and Analytic Hierarchy Process (AHP) techniques (Akyuz, 2015, 2016; Akyuz and Celik, 2014, 2015; Yang et al., 2013). While the aforementioned studies have the capability of generating HEPs particularly in situations where the lack of data exists, such models lack the consideration of input weights.

Human error identification (HEI) methods are used to identify latent human or operational errors that may arise as a result of human-machine interactions in complex systems and to identify the casual factors, consequences, and recovery strategies associated with the errors (Stanton et al., 2005). HEI methods can be categorized into qualitative and quantitative approaches. Qualitative approaches typically use the taxonomies of various error modes and apply these error modes to the analysis of the activity in question. Various such qualitative approaches exist, including the Systematic Human Error Reduction and Prediction Approach (SHERPA) (Embrey, 1986), the Human Error Template (HET) (Stanton et al., 2006), the Technique for the Retrospective and Predictive Analysis of Cognitive Errors (TRACEr) (Shorrock, 1997; Shorrock and Kirwan, 2002), and the Cognitive Reliability and Error Analysis Method (CREAM) (Hollnagel, 1998). Qualitative approaches are successful in terms of sensitivity, use limited resources, and are simpler and easier to apply than quantitative methods.

Quantitative methods are used to assign numerical probability values to the associated errors. One of these methods is the human error assessment and reduction technique (HEART) (Williams, 1986, 1988), which predicts and quantifies the likelihood of operational errors and system failure. The main advantage of quantitative methods is that they provide objective numerical data of the occurrence of errors, but they are difficult to use and may require more resources and extensive knowledge of mathematical procedures.

Even the error sufficiency and difference with shipping environment, at the present time, safety assessment and analysis are still conducted using past concepts and methods. The result is that system failures are usually attributed to the operational design of the system, and efforts to prevent such failures involve increasing the protective measures of the machine and the environment.

Table 1. Types of human error identification methods

Approach	Type	Domain	Training time	Error Modes	Execution time
SHERPA	Qualitative	Nuclear power	Low	Insufficient	Long
HET	Qualitative	Aviation	Low	Insufficient	Quick
TRACer	Qualitative	Aviation	High	Sufficient	Long
CREAM	Qualitative	Generic	High	Sufficient	Long
HEART	Quantitive	Nuclear power	Low	Insufficient	Quick
HEAR	Quantitive	Railway			

Source: Cheng and Hwang (2015) and Shin et al. (2008)

4. Literature review

4.1 Maritime industry

Ship collision is one of the most frequent marine accidents worldwide. According to the IMO, the marine accidents are;

a) related to the vessel when someone died or suffered in its board;

b) related to the vessel when someone missed in;

c) loss of ship, loss of presumption or resignation

d) damage in ship

e) sink, or collision of the ship

f) related to the vessel when its facility is broken

g) related to the vessel when the ship has environment pollution

There is various kind of issues in the marine industry that directly or indirectly influences the occurrence of human error. Human error analysis may be complicated, and more factors may need to contemplate in order to appreciate the root causes of the slips, lapses, mistakes, and violations. It may seem logical to blame accidents on the lapses of individuals or a small group of ship crews. However, the latent conditions influencing crew behavior during navigation are often ignored. These involve the number of simultaneous missions, availability of procedures or plans, availability of time, crew collaboration quality, adequacy of experience and training. In the research, the human error factors, one of the main causes in marine accidents, are investigated.

The marine accidents can be classified into 3 groups: fishery to fishery, fishery to non-fishery, non-fishery to non-fishery. Even the system against the ship collision is strong; the vessel accidents are in an increasing trend. According to the shipping statistical handbook by the Korea Maritime Institute (KMI), the number of vessel accidents in 2017 increased by 13.1% from the previous year to 2,882 vessels. By the type of vessels, 1939 fishing vessels accounted for over 2/3 of all accidents, followed by aquatic leisure equipment ships, passenger ships, other ships, and cargo ships.

Table 2. Recent vessel accidents in Korea

Year	Passenger	Cargo	Fishing	Tanker	Tugboat	Aquatic Leisure	Others	Total
2008	21	74	864	27	59	-	76	**1,121**
2009	17	110	1,568	33	70	-	305	**2,103**
2010	22	133	1,380	45	97	-	265	**1,942**
2011	22	118	1,573	43	86	-	297	**2,139**
2012	32	109	1,315	45	104	-	249	**1,854**
2013	29	107	839	52	78	-	201	**1,306**
2014	51	111	1,029	51	102	-	221	**1,565**
2015	66	115	1,621	65	94	-	401	**2,362**
2016	65	116	1,794	67	77	-	430	**2,549**
2017	46	127	1,939	73	91	472	134	**2,882**

Source: Shipping Statistics handbook 2018, KMI, Seoul.

According to the HIS Fair play, the foundered accident is the most occurred accident (about half of all accidents) in the deep sea in 2017 (Table 3). Next accidents are accounted as wrecking (21), cause of the fire (18), machinery problems (18), collision (13), contact (6) and others. As the main accident carrier, cargo (38%) and general cargo (24%) vessels are accounted; fishing (13%) and other (11%) vessels did once in 10 accidents in average.

Table 3. World causality cause and results

Year	Foundered	Fire	Collision	Contact	Wrecked	Hull / Machinery	Other	Total
2017	63	18	13	6	21	18	-	139

Source: HIS Fair play, World Causality Statistics, 2017

Table 4. Vessel causality worldwide (2017)

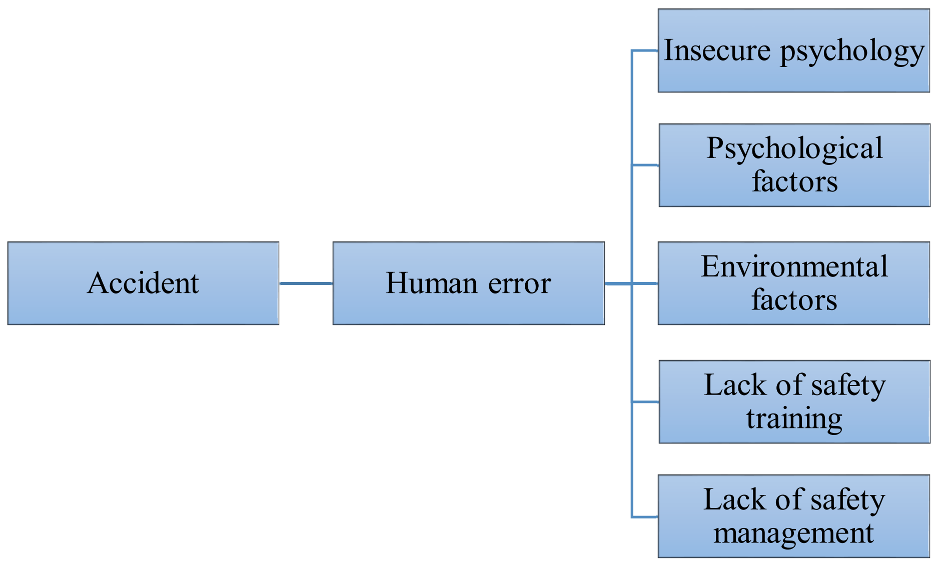
LPG/LNG	Chemical	Crude	Bulk	General	Container
1	5	2	7	54	8
Ro/Ro	Passenger	Cargo	Fishing	Other	Total
6	2	85	29	25	224

Source: HIS Fair play, World Causality Statistics, 2017

The statistical report by International Maritime Organization indicates that the main causes of accidents in ports are slips and trips (one in five personal injury accidents in the maritime industry is due to slips, trips and falls (IMO, 2006)) being hit by moving or falling objects, falls and manual handling (International Shipping Federation (ISF), 2011). Threats to the health of persons working in ports and docks include back and other musculoskeletal injuries, noise, and dust related injuries. A high proportion of accidents to port workers occur on container ships. There is also an increasing trend in the number of accidents involving port cranes and other port mobile equipment, which have resulted in serious injuries and fatalities (Darbra et al., 2006). Contributing factors have been identified as lack of an e ective safety culture, inadequate risk assessment and operations management, inadequate operating procedures, lack of training and awareness, bigger and faster port equipment, bigger ships, increased port throughputs, faster ship turnarounds, more extreme weather conditions (International Shipping Federation, ISF, 2011).

Chae (2015) analyzed the probability of human error on dynamic positioning ship loss of position incidents. He classifies 103 cases that correspond to human error during 612 cases to DP LOP submitted to IMCA from 2001 to 2010 and analyzed them using a Bayesian network. As a result, all 103 incidents were caused by an unsafe act (68%) and a skill-based error accounted for the largest ratio of unsafe acts. Moreover, the greatest potential for unsafe acts proved to be unsafe supervision (68%).

Kim and Kwak (2011) evaluated the factors of human error in ship accidents in Korea domestic sea. He investigated the investigation reports of 413 cases submitted to KMST from 2005 to 2009 and calculated the importance and priority by deriving the characteristics of ship accidents and the factors of human error. As a result, the frequency of collision accidents is highest during the ship accident, and analysis of accidents has proved that human errors are highly related to collision accidents. In addition, it showed that the biggest factors in a collision are guard negligence and navigation. Otherwise, it was proved that the highest risk type in ship accident is the sinking, which is mainly caused by safety compliance and reducing job negligence.



Source: Shi et al. (2011).

Figure 1. Human error case

Kim and Kwak (2011) evaluated the factors of human error in ship accidents in Korea domestic sea. He investigated the investigation reports of 413 cases submitted to KMST from 2005 to 2009 and calculated the importance and priority by deriving the characteristics of ship accidents and the factors of human error. As a result, the frequency of collision accidents peaked up during the ship accident, and analysis of acciden8ts has proved that human errors are highly related to collision accidents. In addition, the biggest factors in a collision are guard negligence and navigation. Otherwise, it was proved that the highest risk type in ship accident is the sinking, which is mainly caused by safety compliance and reducing job negligence.

Kim et al. (2011) investigated the factors of human error that affects the occurrence of marine accidents through the case study of marine accidents investigation. Moreover, they examined classification schemes and analytical techniques for scientific analysis of human errors. As a result, this study suggested a human error analysis model suitable for marine accidents through the case study and emphasized the necessity of analyzing the causes of accidents based on human factors.

Kim (2018) analyzed the factors of human error that cause collision in ship accidents, focused on captain and OOW. They examined the investigation reports of 109 cases submitted to KMST from 2010 to 2016 and divided into give-way vessels and stand-on vessel. As a result, it showed that the main factor was the neglect of lookout in the case of give-way vessels. On the other hand, it was analyzed that the main factor was not to carry out proper cooperation in the case of stand-on vessels.

Park (2017) conducted a survey from 106 respondents asking primary factors involved in accidents during navigation and found the most serious human factors related issues in maritime operations are communication failure, lack of situation awareness, and improper training. Especially for the communications, contents organization and equipment failure are listed as serious problems.

In Taiwan, Ung (2019) evaluated the collision probability of oil tanker using a Fault Tree Analysis (FTA) structure using a modified Fuzzy-Bayesian Network based Cognitive Reliability Error Analysis Method (CREAM) to conduct human error assessment. His proposed methodology provides a higher degree of result which concluded that lack of Bridge Resource Management Communication, lack of Communication between Ships, Fatigue and Collision Regulation Violations are the elements with higher occurrence rates and would also have great potential contributing to oil tanker collision. Akyuz et al. (2018) presented a comprehensive human error prediction during bunkering operation demonstrated with a case study at a chemical tanker platform using Shipboard Operation Human Reliability Analysis (SOHRA) method.

4.2 In other industries

Kim, Paek, and Yoon (2010) reviewed four recent accident causation model and proposed a new model for the analysis of human error accidents in railway operations. They also tested the model by explaining 12 railway accident cases with the model.

Lee, Kim, Kim, and Baek(2009) studied accident investigation reports of UK RAIB (Rail Accident Investigation Branch) and find out causes more in organizational, environmental and job factors, which implies the necessity to improve investigation process of human error accident in Korea.

The big accident in the nuclear industry was the Chernobyl Nuclear Power Plant accident in the former USSR. Although huge accidents including Monju fast breeder reactor fire, US Davis-Besse reactor vessel head degradation event, Japan JCO's criticality accident, and Japan TEPCO's inspection report falsification event occurred, people paid attention to the lack of safety culture as the main cause, and the climax can be the Fukushima Nuclear Power Plant accident.

Most accidents in enterprise production are due to human error. The reasons for human error are complicated, such as employees' own psychological and physiological factors, enterprise training, imperfect management system, and poor social environment. They also mentioned that the accident rate is decreasing in recent years while the death rates in the accidents are still unchanged. They put forward the relevant control measures, specific aim, and applicability, and suggested a certain promoting significance to the research and development of the human error. Jeo (2018) describes the accidents under human error working with hazardous materials in Korea port areas (Table 5.). He identified the accidents increased 62.5%

(from 32 in 2014 to 52 in 2016) and human injury increased by 1.64% (from 14 in 2014 to 37 in 2016) with human error in last three years. He stated the main reason for these accidents were the careless management monitoring (64%).

Table 5. Accidents, human and physical error with hazardous materials

		Human error	Physical error	Other	Unnamed	Total
Accidents	2016	52	13	10	6	81
	2015	45	18	13	9	85
	2014	32	11	15	4	62
	Reason	Careless management monitoring	Careless machine operation	Careless side work	The omission in the operation area	Total
Human error	2016	33	4	5	10	52
	2015	27	2	2	14	45
	2014	20	1	1	10	32
	Reason	Corrosion	Poor design	Breakage	Poor construction	Total
Physical error	2016	4	0	9	0	13
	2015	5	0	13	0	18
	2014	3	0	8	0	11
	Reason	Distraction	Traffic accident	Natural disaster	Other	Total
Other	2016	0	8	0	2	10
	2015	1	9	0	3	13
	2014	1	7	1	6	15
	Year	Human error	Physical error	Other	Unnamed	Total
Human injury	2016	37	6	3	1	47
	2015	24	4	10	1	39
	2014	14	1	17	1	33

Source: Jeo, H. J. (2018). A Study on the Safety Education and Training for Hazardous Material Handlers in the Distripark Logistics Center. Master's Thesis. Korea Maritime and Ocean University.

Chapter 3. Research methodology

1. Independent variables

These are poor communications, fatigue, poor automation design, poor general technical knowledge, poor maintenance, decisions based on inadequate information, faulty policies, practices, or standards, poor knowledge of own ship systems, and hazardous natural environment. Mainly, the human error causes can be grouped as psychological and physiological effects, skill and education on navigational equipment, management pressure from the main office in the land, workloads in the sea.

a) psychological effects of seafarers

b) training and education on safety

c) management pressure in land and sea

d) high load working environment

e) environmental effects

Moreover, factors including organization structure, workplace culture, and social distances may influence on the system performance and reliability. The main variables used in this study are as follows.

1.1 Fatigue

The fatigue can be defined in different ways. Generally, it is described as a tired physical and mental feeling caused by the long-term working with anxiety, worry, and exposure. Due to the long-term fatigue condition, the ability and the performance of the crewman are reduced, and also his alertness is declined (Yang et al., 2004). According to the IMO, the fatigue is defined as a decrease in the physical and mental ability of the person who has physical, mental and emotional exhaustion (IMO, 1995).

There are some main causes of fatigue, such as sleep quality and duration, stress, health and nutrition, environment, sickness, body stability, work schedule, physical condition and etc. Moreover, noise and vibration, temperature, humidity, the vessel movement can affect the ability of the crewman in the vessel.

The fatigue of the crew has not been considered as a potential cause of marine accidents, and human error, because the fatigue concept was mentioned under human characteristics, such as education, training, skill, concentration, motivation, power, professionalism. However, a recent survey and data on maritime accidents the fatigue have a close relationship with human error. The fatigue is widely recognized as the cause of many disasters and accidents. According to the report of the US Coast Guard Research and Development Center, the fatigue of the crewman is about 16% in the marine accidents; and about 33% in human injuries (USCG, 1996).

1.2 Management pressure

The lack of good communication in organization and management is one of the main causes of marine accidents. Organizational and management factors in land and board affect the crew's performance. A strict command structure can break the effective teamwork in a board. The company policies on work schedule and safety can influence the operational safety and the degree of risk-taking behavior of the crew.

The decisions on inadequate information tend to rely on either a favored piece of equipment and in other cases, critical information could be incorrect. This situation can lead to navigation errors. The issue of faulty policies and procedures covers a variety of problems including the lack of available precisely written and comprehensible operational procedures aboard ship, management policies that encourage risk-taking, and the lack of standard traffic rules from port to port. Attitude and management skills, cultural awareness, communication, and briefings are important in minimizing human errors. One of the previous studies found that organizational incongruity such as lack of proper training, hierarchical structure, and ineffective communication, can cause the occurrence of human-related accidents.

The issue of ineffective communication is referred to as communications between shipmates, between masters and pilots, ship to ship, and board to land. Better training and practices can help to promote better communications and coordination. Group thinking and high frequency of communication will decrease the human error probability.

1.3 Workload

Working on board requires a lot of efforts. According to the statistical data by the Korea Maritime Safety Tribunal during 5 years (2009-2013), the operator's negligence (82.1%) led to marine accidents. The negligence occurred after excessive workload and fatigue. Excessively high level of physical and mental workload leads to human error and accidents (Braby et al., 1993). USGC also found that working continuously in 18 hours without sleep can reduce the crewman's working ability to about 30%, and in 48 hours without sleep can reduce it to more than 60%. Moreover, the hazardous natural environment, such as currents, winds, and fog, can make excessive working conditions.

There are five categories of workload measurement techniques (Williges and Wierwille, 1979):

1) primary task measurement;
2) secondary task measurement;
3) physiological measurement;
4) subjective technique;
5) input control.

1.4 Technical training and skill

The issue of technical knowledge is connected with the poor understanding of how the automation works or under what conditions it was designed to work effectively. Consequently, the crews sometimes do errors in using the equipment. Training programs will decrease the probability of human error. Poor knowledge of the vessel's systems is a frequent contributing factor to marine casualties because of various difficulties encountered by crews working on ships of different sizes, with different types of equipment and carrying different cargoes. The error in the navigational watch is mostly related to the crew's ability to handle of navigational equipment. The ability to handle the navigational device include an understanding of the system related to the navigational circumstances.

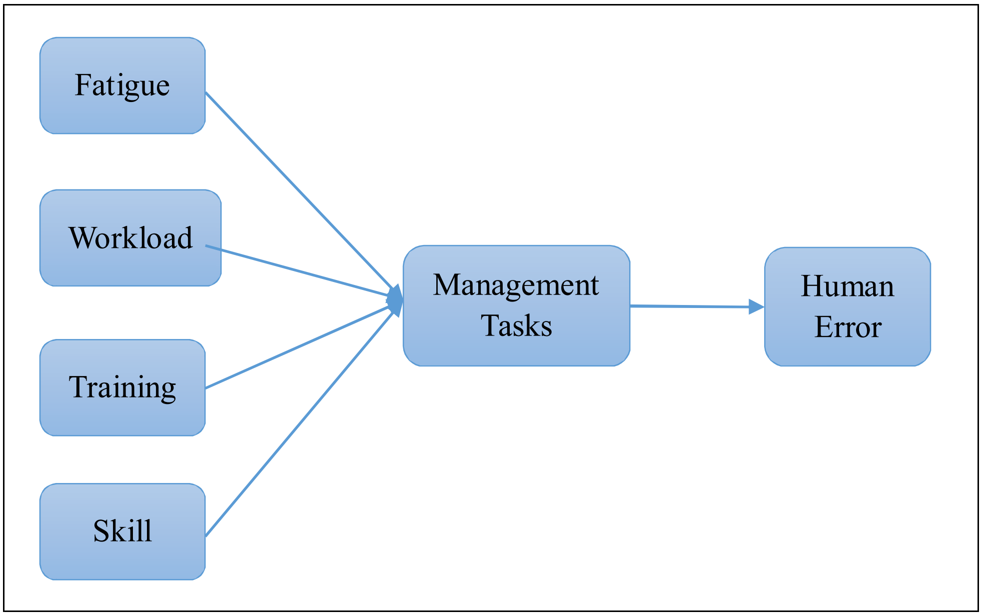
According to the study (Lee et al., 2016), the primary causes of the surveyed accidents are lacking understanding of ECDIS system, wrong presentation of information, wrong safety settings working with ECDIS system, missing charts update. Moreover, IMO requires shipping companies to use the ECDIS in international voyages. As the new navigation device is set, seafarers are frequently required to attend the training courses.

2. Research model and hypothesis

1. Research model

The research model in the study is illustrated as below.

Figure 2. Hypothesis setting



In this study, the relationship of the fatigue, the workload, the training environment, the operational skill to the management tasks, and the relationship of the management tasks to the human error. The management tasks are analyzed whether it has the mediation effects when exogenous variables cause to the human error.

2. Hypothesis setting

H1. Fatigue will affect positively to the management tasks. (+).

H2. Workload will affect negatively to the management tasks. (-).

H3. The training environment will affect positively the management tasks. (-)

H4. Operational skills will affect positively to the management tasks. (+)

H5. Management tasks will affect negatively to human error. (-)

H6. Fatigue will affect positively to the human error in mediating of management tasks. (+)

H7. Workload will affect positively to the human error in mediating of management tasks. (+)

H8. Training will affect negatively to the human error in mediating of management tasks. (-)

H9. Skill will affect negatively to the human error in mediating of management tasks. (-)

The equations will be written in 3 steps:

Step 1:

Regression of the dependent variable (Human error) on the independent variables to confirm that the independent variables are significant predictors of the human error.

Independent variable → dependent variable (For Hypothesizes 1 to 4):

$$\mathbf{Y = a + \beta_{11}X_1 + \beta_{12}X_2 + \beta_{13}X_3 + \beta_{14}X_4 + \varepsilon}$$

where, β_{11}, β_{12}, β_{13}, β_{14} are significant

Step 2:

Regression of the mediator (Management task) on the independent variables to confirm that the independent variables are significant predictors of the management task.

Independent variable → mediator

$$Me = \mathbf{a} + \boldsymbol{\beta}_{21}\mathbf{X}_1 + \boldsymbol{\beta}_{22}\mathbf{X}_2 + \boldsymbol{\beta}_{23}\mathbf{X}_3 + \boldsymbol{\beta}_{24}\mathbf{X}_4 + \boldsymbol{\varepsilon}$$

where, $\beta_{21}, \beta_{22}, \beta_{23}, \beta_{24}$ are significant

Step 3:

Regression of the dependent variables on both the mediator (Management task) and independent variables (4 variables) to confirm that the mediator is a significant predictor of the dependent variable. (For Hypothesizes 5 to 9)

$$\mathbf{Y} = \mathbf{a} + \boldsymbol{\beta}_{31}\mathbf{X}_1 + \boldsymbol{\beta}_{32}\mathbf{X}_2 + \boldsymbol{\beta}_{33}\mathbf{X}_3 + \boldsymbol{\beta}_{34}\mathbf{X}_4 + \boldsymbol{\beta}_{35}\mathbf{Me} + \boldsymbol{\varepsilon}$$

where, $\beta_{31}, \beta_{32}, \beta_{33}, \beta_{34}$ should be smaller in absolute value than the original mediation effect ($\beta_{11}, \beta_{12}, \beta_{13}, \beta_{14}$ above).

3. Data selection

The research survey was conducted four months from March to June 2018 from the masters, chief officers, second and third rank officers in Turkish shipping companies. The questionnaire was distributed via E-mail and direct meeting with Turkish shipping companies, and 197 valid questionnaires were used for statistical analysis.

Table 6. Survey characteristics

Survey period	Companies	Respondents	Valid Responses	Ratio (%)
March-June, 2018	Turkish shipping companies	Masters, Chief officers, 2^{nd} and 3^{rd} rank officers (220)	197	89.5

The survey respondents answered in full (100%) without any missing data (missing value=0). The table shows the valid and missing data on four factors, such as Duty on board, Years on board, Age, and Vessel types. The data includes all 197 responses with no missing data.

Table 7. Data validity

	Duty on Board	Years on Board	Age	Type of vessels
Valid	197	197	197	197
Missing	0	0	0	0

Measurement scale development for each factor in the model is done through by following steps. A relevant literature review was conducted to identify available measures on human error in the shipping field. In addition, we created relevant questionnaires derived from the literature review. The questionnaires items were measured on a seven-point Likert's scale ranging from never do (1) to frequently do (7) in order to ensure high statistical variability among the survey response: '1' as 'never', '2' as 'rarely', '3' as 'sometimes', '4' as 'normal', '5' as 'usually', '6' as 'often', and '7' as 'very frequently', respectively.

This study used two statistical packages to analyze the hypotheses: SPSS 22, and AMOS 19. After finishing the data coding of the collected questionnaires in SPSS 22, the reliability and validity analysis, analysis of structural equations, and mediating effects are conducted in via AMOS 19.

Factor analysis is a statistical method that extracts the interrelationships of many variables into a small number of factors, finds the commonalities of the variables, and determines the degree of influence of each variable and the characteristics of the group.

The purposes of factor analysis are:

1) to reduce the variables by grouping into a small number of factors.

2) to eliminate unnecessary variables. Since the variables with low importance can be found, unnecessary variables are removed.

3) to characterize the variables. The related variables are grouped together, and these factors have mutually independent characteristics, so the characteristics of the variables can be known.

4) to evaluate the validity of measurement items. Observed variables to measure one characteristic are grouped into one factor. Therefore, it is judged that unclassified variables have different characteristics by using such characteristics, this makes it evaluate if the measurement item of the character is valid.

5) to apply the obtained factor scores to regression analysis, discriminant analysis, and cluster analysis. In this study, some items were

removed through the factoring process. First, exploratory factor analysis was conducted to verify validity. All measured variables used Principal Component Analysis to extract constructive factors, and Varimax rotation method was adopted for simplification of factorial loading.

Chapter 4. Research analysis results

1. Descriptive analysis

The questionnaire responses were obtained through shipping company seafarers in Turkey. In order to check outliers in which the value of one measure is very different from that of the rest of the sample, the frequency of the Z-score normality test of SPSS was used to analyze the multivariate anomaly. The total number of valid respondents was 197; however, after the Z-score normality test, 12 samples were deleted from the list.

The total numbers of valid respondents are 185, such as masters (77), and 2nd officers (41), followed by chief officers (34) and 3rd officers (33). Over 95% of participants' board sailing period is under 15 years: 0-4 years (33%), 5-9 years (29.7%), 10-14 years (32.4%). The majority of survey participants are 30-39 years old (63.2%), followed by under 29 years old (29.7%), middle age (7.0%) and over 50s (2.7%). The 2/3 (60%) of the respondents were from the tanker, 21.6% from bulk carriers, 9.2% from each container vessels and other types of vessels.

Table 9. Descriptive statistics of respondents

Respondents		Before the Z-score test		After the Z-score test	
		Number (People)	Frequency rate (%)	Number (People)	Frequency rate (%)
Duty on Board	Master	81	41.1	77	41.6
	2nd Officer	44	22.3	41	22.2
	3rd Officer	35	17.8	33	17.8
	Chief Officer	37	18.8	34	18.4
Years on Board	0-4 years	65	33.0	61	33.0
	5-9 years	62	31.5	55	29.7
	10-14 years	61	31.0	60	32.4
	15-19 years	6	3.0	6	3.2
	Over 20 years	3	1.5	3	1.6
Age	Under 29 years old	55	27.9	50	27.0
	30-39 years old	124	62.9	117	63.2
	40-49 years old	13	6.6	13	7.0
	Over 50 years old	5	2.5	5	2.7
Type of vessel	Tanker	121	61.4	111	60.0
	Bulk carrier	41	20.8	40	21.6
	Container	17	8.6	17	9.2
	Others	18	9.1	17	9.2

2. Reliability and validity analysis

2.1 EFA and reliability of latent variables

Before exploratory factor analysis, Bartlett's test of sphericity and sample fit (KMO: Kaiser Meyer Olkin) were analyzed to see if there was a common factor in factor analysis. In the Bartlett Formation Verification, the null hypothesis is not adopted if the significance probability is 0.000. Therefore, there is no problem in using factor analysis. Generally, a factor of less than 0.05 is considered to be a common factor (Kang, 2013). For more accurate analysis, factor loadings of 0.60 or more were used in this study. The approximate chi-square of the results was 648.966 ($p = 0.000$), KMO= .637.

In this study, some items were removed through the factoring process. First, exploratory factor analysis was conducted to verify validity. All measured variables used Principal Component Analysis to extract constructive factors, and Varimax rotation method was adopted for simplification of factorial loading.

Factor loading shows the degree of correlation between each variable and factor. Therefore, each variable belongs to the factor with the highest factor load the value. In addition, the eigenvalue refers to the sum of squares of the loadings of all variables loaded on a specific factor and refers to the standardized variance associated with a particular factor. In general, in the social science field, the selection criteria of factors and items are considered significant variables when the eigenvalue is 1.0 or more and the factor loading value is 0.40 or more. Therefore, in this study, the eigenvalue is fixed as 1.0 or more and the factor loading value is fixed at 0.4 or more according to these criteria.

The factor analysis reduced into 6 groups including 18 questions from a total of 48 questions. <Table 8> shows the results of factor analysis on the relationship between variables and the factors. In independent constructs, 6 factors were yielded and totally explained 62.375% of the variance. Through this analysis, a stable factor structure that did not have cross-loaded items were found.

The factors are named as fatigue, training, management tasks, workload, and human error (Table 9). Fatigue includes five variables, human error has three variables, and other factors have every three variables.

Table 8. Results of EFA on Independent Constructs

Factors	Variables	Factor loading	Commonality	Eigenvalue	Variance (%)
Fatigue	FA3	.552	.502	2.962	12.539
	FA1	.705	.547		
	FA4	.682	.500		
	FA5	.686	.566		
	FA2	.576	.442		
Workloads	WL2	.854	.759	2.120	11.473
	WL1	.854	.744		
Training	TR1	.868	.802	1.879	10.878
	TR2	.887	.813		
Management task	MT3	.722	.543	1.334	9.834
	MT1	.620	.495		
	MT2	.486	.511		
Human error	HE3	.857	.790	1.188	8.878
	HE1	.591	.562		
	HE2	.521	.537		
Operational Skill	SK1	.794	.725	1.121	8.774
	SK2	.831	.764		
Rotation Method; Varimax with Kaiser Normalization.					62.375

Table 9. Latent and measured variables

Factors	Variables	Questions
Fatigue	FA1	Do you get distracted easily (e.g. by background noise, other people's conversations, etc.)?
	FA2	Personal phone from parents?
	FA3	How often do you catch yourself daydreaming at the watch?
	FA4	Do you jump from task to task because you just cannot seem to focus long enough to finish one completely?
	FA5	When reading a book or magazine, how often do you find yourself re-reading the same paragraph or skipping ahead?
Training	TR1	How do you rate your ECDIS generic and type-specific training adequacy?
	TR2	Do you believe your ECDIS trainer is capable of this job?
Workload	WL1	How often do you compare electronic data sources with actual circumstances outside of bridge?
	WL2	How often do you do cross and double check navigational data?
Management task	MT1	Do you believe your company's PMS system is working properly?
	MT2	How often do you compare echo sounder with charted depth on ECDIS?
	MT3	During your watch how often do you go back side of the bridge to check the situation?
Human error	HE1	How often did you just sign the checklist without properly reading during company briefing?
	HE2	Do you find yourself just clicking reset buttons to silence the alarms on bridge equipment?
	HE3	Do you use AIS as a collision avoidance device?
Operational skill	SK1	Do you have basic computer skills? Is your skill enough to solve the software problem on board?
	SK2	In case of any electric navigation equipment problem, how much can you intervene? Can you fix the device?

2.1 CFA and reliability

2.1.1 General results

All variables are transformed into the main factors. On the basis of the reliability analysis results, we summed each factor scores due to the given items. A reliability test was conducted to test the internal consistency of results using the coefficient alpha. Cronbach alpha coefficient is the most general measure of reliability for a multi-item scale (Sekaran, 1992). The Cronbach alpha coefficients for all constructs in the main study were greater than .70 for CFA and .50 for EFA. The coefficient alpha estimates for each of the six constructs in the main study are listed as follows: fatigue (α= .648), workload (α= .773), training (α= .821), operational skill (α= .614) management task (α= .519) and human error (α= .504). Based on the suggested cut off points, all measures appeared to be good indicators of each construct with multiple items.

By examining the multicollinearity of variables, we need to look at the output between potential variables. If the output is large, there is a problem with the variables, so we should correct the variables. The corrective actions are the removal of variables or resetting the system from the beginning. The mean, standard deviation, and correlation matrix are given in <Table 11>.

Table 10. Reliability analysis of observed variables

Variables	Factor analysis							Reliability	
	1	2	3	4	5	6	Communality	Alpha if Item deleted	Cronbach α
FA3	**.552**						.502	.618	.648
FA1	**.705**						.547	.566	
FA4	**.682**						.500	.589	
FA5	**.686**						.566	.572	
FA2	**.576**						.442	.630	
TR1		**.868**					.802	.700	.821
TR2		**.887**					.813	.700	
WL2			**.854**				.759	.631	.773
WL1			**.854**				. 744	.631	
MT3				**.722**			.543	.474	.519
MT1				**.620**			.495	.462	
MT2				**.486**			.511	.307	
HE3					**.857**		.790	.399	.504
HE1					**.591**		.562	.360	
HE2					**.521**		.537	.452	
SK2						**.831**	.764	.530	.614
SK1						**.794**	.725	.530	

Through the correlation analysis, we can find that there is no multicollinearity of the variables. The multicollinearity occurs when the correction between variables is over 0.8. Since there is no multicollinearity of latent variables, we can use the variables further steps. If the tolerance value is less than 0.1, there is a multicollinearity problem. However, the tolerance values in the study were all higher than at least 0.3, which that the perforation was not problematic.

Table 11. Inter-construct correlation

Research variable	Mean	St. dev.	Inter-Construct Correlations					
			1	2	3	4	5	6
1. FA	5.0400	1.03900	1.00					
2. TR	3.1514	1.67586	.050	1.00				
3. WL	5.4432	1.33851	-.067	-.0.61	1.00			
4. MT	3.0468	1.21244	.157*	.243**	-.364**	1.00		
5. HE	4.4685	1.47495	.042	-.117	.242*	-.242**	1.00	
6. SK	3.7649	1.48090	.135	2.68*	-0.42	160*	-.029	1.00

* Correlation coefficients are significant at α=.05 level
** Correlation coefficients are significant at α=.01 level

The purpose of this study is to investigate the effects of five factors on a human error which are extracted through EFA on the basis of the measured variables. The reason for using the structural equation model in this study is the latent variable is derived by the common variable of the observed variables, the measurement error of the variable is controlled and is more accurate than the coefficient obtained from the multiple regression analysis based on the observed variables. Structural Equation Modeling (SEM), a statistical methodology with a confirmatory approach to analyze multivariate data, is a frequently and widely used technique in psychology and social sciences research (Hair et al., 2010; Schmacker & Lomax, 2004). SEM allows the observation of separate relationships for each of a set of dependent variables. It indicates a direct and indirect influence between particular latent variables and certain other latent variables in the model (Byrne, 2001). SEM is the appropriate and most efficient estimation technique for a series of separate multiple regression equations estimated simultaneously (Hair et al., 2010). Since the structural equation model is generally composed of two measurement models and structural models, it is necessary to verify whether the observational indicators measure plausible latent variables at the same time, the causal relationship between exogenous variables, endogenous variables, and endogenous variables can be examined.

2.1.2 Regression Weights latent variables

In this part, the unstandardized estimates, standard error (S.E.), Critical ratio (C.R.) of each variable are presented. The causal effect is 1, which means that the parameter estimate value of the measurement variable is fixed to 1 as a main factor in the group. When C.R., which has equal value with t-test value, is greater than +1.96, then the causal coefficient is significant. The C.R. values are presented in <Table 12>.

Table 12. Regression weights

Measured variable		LV	Estimate	S.E.	C.R.	P
FA1	←	DS	1.000			
FA3	←	DS	.728	.169	4.303	***
FA4	←	DS	.802	.168	4.762	***
FA2	←	DS	.837	.200	4.193	***
FA5	←	DS	1.132	.214	5.280	***
WL1	←	MP	1.000			
WL2	←	MP	1.290	.214	6.018	***
SK2	←	SK	1.000			
SK1	←	SK	1.953	.702	2.781	.005
MT3	←	WL	1.000			
MT1	←	WL	1.449	.398	3.644	***
MT2	←	WL	1.968	.488	4.035	***
HE3	←	HE	1.000			
HE1	←	HE	1.597	.531	3.008	.003
HE2	←	HE	1.523	.513	2.969	.003
TR1	←	TR	1.000			
TR2	←	TR	.650	.123	5.273	***

2.1.3 Standardized Regression weights of latent variables, covariance, correlations

We can identify the causal relationship between variable and factors by looking at the magnitude of Estimate values. The standardized coefficients have the same variance, and its maximum value is 1. The larger the magnitude of the estimated value, the greater the significance of the relationship between variable and factors.

Table 13. Standardized regression weights

Measured variable		Latent variable	Estimate
FA1	←	DS	.623
FA3	←	DS	.437
FA4	←	DS	.506
FA2	←	DS	.422
FA5	←	DS	.627
WL1	←	MP	.725
WL2	←	MP	.871
SK2	←	SK	.488
SK1	←	SK	.908
MT3	←	WL	.399
MT1	←	WL	.467
MT2	←	WL	.703
HE3	←	HE	.324
HE1	←	HE	.601
HE2	←	HE	.529
TR1	←	TR	.987
TR2	←	TR	.710

Covariance and correlation which are used to determine the relationship between 2 variables and to measure how much the variables change at the same time are given in Table 14 and Table 15, respectively.

Table 14. Correlations

Correlation of latent variable			Estimate	Correlation of latent variable			Estimate
DS	↔	MP	-.081	HE	↔	TR	-.227
MP	↔	SK	-.071	DS	↔	SK	.199
SK	↔	TR	.353	DS	↔	WL	.276
MP	↔	WL	-.577	DS	↔	HE	.075
MP	↔	HE	.473	SK	↔	WL	.126
MP	↔	TR	-.093	WL	↔	HE	-.601
DS	↔	TR	.072	SK	↔	HE	-.050
WL	↔	TR	.294				

Table 15. Covariances

Covariances of the latent variables			Estimate	S.E.	C.R.	P	Label
DS	↔	MP	-.078	.097	-.808	.419	
MP	↔	SK	-.061	.080	-.759	.448	
SK	↔	TR	.549	.228	2.405	.016	**
MP	↔	WL	-.359	.112	-3.210	.001	***
MP	↔	HE	.353	.139	2.541	.011	**
MP	↔	TR	-.181	.163	-1.107	.268	
DS	↔	TR	.126	.159	.792	.428	
WL	↔	TR	.333	.132	2.524	.012	**
HE	↔	TR	-.308	.166	-1.853	.064	*
DS	↔	SK	.153	.094	1.633	.103	
DS	↔	WL	.154	.075	2.048	.041	**
DS	↔	HE	.050	.085	.592	.554	
SK	↔	WL	.063	.058	1.079	.280	
WL	↔	HE	-.261	.109	-2.402	.016	**
SK	↔	HE	-.030	.068	-.434	.665	

2.1.4. Squared Multiple Correlation

It shows the explanation of the measured variable on the latent variable. The estimated value should be higher than 0.4. There are two types of fitness tests which show the overall goodness fittest and fit of each unknown. The fitness of the overall model does not mean the collected data describes the model suitably, but it is theoretically developed to represent how well the model estimates the data in the model. In this study, to verify the fitness of the structural equation model, GFI, AGFI, RMSEA, RMR, NFI, CFI, and IFI are used. The fitness index is divided into two categories, the main fitness index, and relative fitness index.

Table 16. Squared multiple correlations

Measured variables	Estimate	Measured variables	Estimate
TR2	.504	SK2	.238
TR1	.974	WL2	.759
HE2	.280	WL1	.525
HE1	.362	FA5	.394
HE3	.105	FA2	.178
MT2	.495	FA4	.256
MT1	.219	FA3	.191
MT3	.159	FA1	.388
SK1	.825		

The results of the overall fitness test for the model fit (Table 17) are

χ^2=138.795, DF=104, p=.013, CMIN/DF=1.335, GFI=.920, AGFI=.883, CFI=.935, RMR=.194, RMSEA=.043, NFI=794, IFI=.939. Except for the result of NFI, the index of the part was found to exceed the acceptable standard, and the AGFI was calculated to be very close to the acceptor of .90. Considering the fitness indexes of the structural equation model, the collected data were suitable for explaining the research model.

Table 17. Model fitting results

Category	Results	Standard	Accept/Reject
Cmin/p	10676.539	P>0.05	Accepted
Cmin/DF	1.335	< 2.00	Accepted
RMR	.194	0.05 <	Accepted
GFI	.920	0.9 <	Accepted
AGFI	.883	0.9 <	Rejected
CFI	.935	0.9 <	Accepted
NFI	.794	0.9 <	Rejected
IFI	.939	0.9 <	Accepted
RMSEA	.043	< 0.05; < 0.08	Accepted

CMIN/DF

CMIN/DF is the minimum discrepancy, divided by its degrees of freedom. Several writers have suggested the use of this ratio as a measure of fit. The ratio should be close to one for correct models. Marsh & Hocevar (1985) have recommended using ratios as low as 2 or as high as 5 to indicate a reasonable fit. Byrne (1989) recommended using a ratio higher than 2.00 represents an inadequate fit.

RMR

The RMR (Root mean square residual) is the square root of the average squared amount by which the sample variances and covariances differ from their estimates obtained under the assumption that your model is correct. The smaller the RMR is, the better. An RMR of zero indicates a perfect fit.

GFI

The GFI (goodness of fit index) was devised by Jöreskog and Sörbom (1984) and generalized to other estimation criteria by Tanaka and Huba (1985). GFI is less than or equal to 1.00. A value of 1 indicates a perfect fit.

AGFI

The AGFI (adjusted goodness of fit index) takes into account the degrees of freedom available for testing the model. The AGFI is bounded above by one, which indicates a perfect fit. It is not, however, bounded below by zero, as the GFI is.

CFI

The comparative fit index (CFI) (Bentler, 1990) is identical to McDonald and Marsh (1990) relative non-centrality index (RNI), except that the CFI is truncated to fall in the range from 0 to 1. CFI values close to 1 indicate a very good fit.

RMSEA

It incorporates no penalty for model complexity and will tend to favor models with many parameters. In comparing two nested models, will never favor the simpler model. Steiger and Lind (1980) suggested compensating for the effect of model complexity by dividing by the number of degrees of freedom for testing the model. Taking the square root of the resulting ratio gives the population "root mean square error of approximation" is called RMSEA by Browne and Cudeck (1993). Practical experience has made us feel that the value of the RMSEA of about .05 or less would indicate a close fit of the model in relation to the degrees of freedom.

The main measurements to evaluate the measurement model is the reliability test and the mean-variance extraction index. The reliability test is a measure of the internal consistency of the variable. The high-reliability indicator means that internal consistency is high. The mean-variance extraction index shows the magnitude of the variance. In this study, a confirmatory factor analysis is conducted to verify the reliability and validity of the measurement model. The confirmatory factor analysis is based on reliability and factor loading.

The results of this study are as follows. The validity factor analysis verifies whether the observed variables accurately measure the latent variables. The estimation of the measurement model is Critical ratio (C.R.) or t-test, standard error (S.E.), and Standardized Factor loading of Observation Variables. The results are shown in <Table 18>. Analysis results are χ^2=138.795, df=104, p=.013, CMIN/DF=1.335, GFI=.920, AGFI=.883, CFI=.935, RMR=.194, RMSEA=.043, NFI=794, IFI=.730. Chi-square test measures how much model is suitable for the data. In the study, chi-square test results show that the hypothesis is rejected with χ^2=138.795 (p=.013). Model is fitted in all measurements, except AGFI and NFI.

3. Hypothesis testing results

The hypotheses were tested using structural equation model (SEM). As indicated in <Table 19>, the overall fit statistics for the proposed model was acceptable (χ^2= 144.524, χ^2/df = 1.338, Root Mean Square Error of Approximation (RMSEA) = .043, RMR=.204; Comparative Fit Index (CFI) = .932, GFI=.918; AGFI=.884; Incremental Fit Index (IFI) = .935).

Hypotheses 1 to 8 were examined to determine whether significant relationships existed in the proposed model. A summary of the nine hypothesized paths and the results of total effects are presented in <Figure 2>.

Hypotheses 1 stated has no significance between fatigue and management tasks. The estimation value (β) was .46, an C.R. = 1.474 (p=.141). Hypothesis 1 was rejected.

Table 18. Estimation model analysis results

Latent Variable	Measured variable	Factor loading	Standardized factor loading	S.E.	C.R.	SMC	p-value	Reliability
Fatigue	FA1	1.000	0.623			0.388		0.648
	FA2	0.728	0.437	0.169	4.303	0.191	***	
	FA3	0.802	0.506	0.168	4.762	0.256	***	
	FA4	0.837	0.422	0.2	4.193	0.178	***	
	FA5	1.132	0.627	0.214	5.28	0.394	***	
Workload	WL1	1.000	0.725			0.525		0.773
	WL2	1.29	0.871	0.214	6.018	0.759	***	
Skill	SK1	1.000	0.488			0.238		0.614
	SK3	1.953	0.908	0.702	2.781	0.825	0.005	
Manage. task	MT1	1.000	0.399			0.159		0.519
	MT2	1.449	0.467	0.398	3.644	0.219	***	
	MT3	1.968	0.703	0.488	4.035	0.495	***	
Training	TR1	1.000	0.987			0.974		0.821
	TR2	0.65	0.710	0.123	5.273	0.504	***	
Human error	HE1	1.000	0.324			0.105		0.504
	HE2	1.597	0.601	0.531	3.008	0.362	0.003	
	HE3	1.523	0.529	0.513	2.969	0.28	0.003	
Model fitness		χ^2=138.795, df=104, p=.013, CMIN/DF=1.335, GFI=.920, AGFI=.883, CFI=.935, RMR=.194, RMSEA=.043, NFI=794, IFI=.730						

Hypothesis 2 and 3 posited the significant relationship between workload and management task (H2) as well as training and management tasks (H3). The results reported mixed results that the workload was negatively related to the management tasks (β= -.325, C.R.=-3.652, p=.000) and training was positively related to the management tasks (β= .081, C.R.=2.206, p=.027). Thus, Hypotheses 2 and 3 were accepted.

Table 19. Model fitting results

The goodness of Fit Statistics	The proposed model	Desired value for Good Fit
X^2	144.524	
p	0.011	< 0.05
CMIN/P	13138.545	0.05 <
CMIN/DF	1.338	< 2.00
RMSEA	0.043	< 0.08
RMR	.204	0.05 <
CFI	.932	0.9 <
GFI	.918	0.9 <
AGFI	.884	0.9 <
IFI	.935	0.9 <

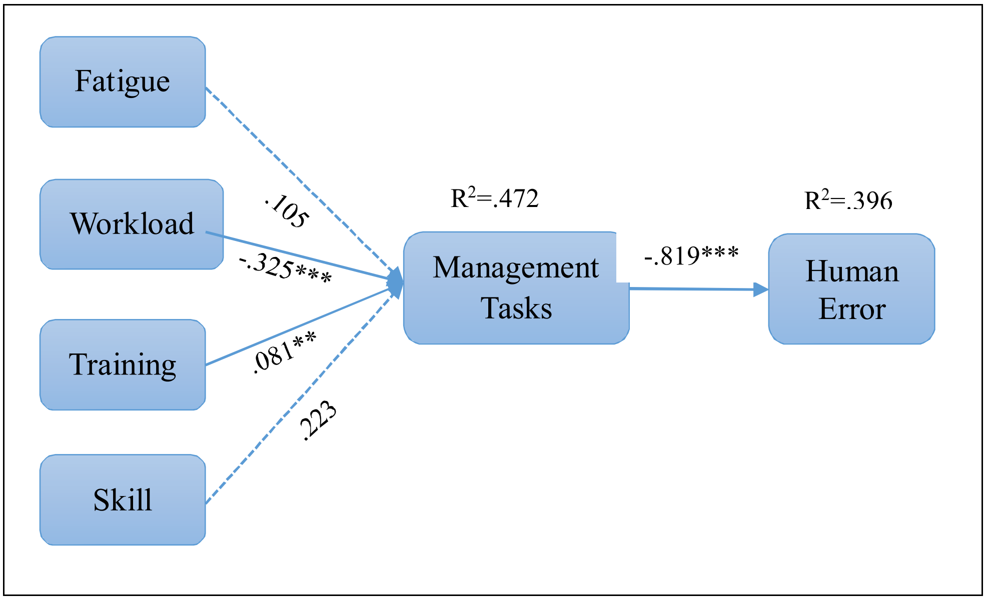
Hypotheses 4 was not supported with significant causal relations between operational skills and management tasks (β=-.031, C.R.=-.430, p>.05). And these four latent variables define 47.2% of the management task (R^2=0.472).

Table 20. Hypothesis results (1-5)

Hypothesis	Estimate	C.R.	p-value	Results	R^2
1. FA → MT	0.105	1.474	0.141	Rejected	0.472
2. WL → MT	-0.325	-3.652	***	Accepted	
3. TR → MT	0.081	2.206	0.027**	Accepted	
4. SK → MT	-0.031	-0.430	0.667	Rejected	
5. MT → HE	-0.819	-2.590	0.010***	Accepted	0.396

** p<0.05, *** p<0.01

Figure 2. Hypothesis results



Hypotheses 5 suggests that management tasks had a strong and significant negative relationship with human error (β= -.819, C.R.=-2.590, p=.010). This result was supported. Here, the mediator variable (Management Task) explains 39.6% of the human error (R^2=0.396).

Next hypotheses were calculated using a mediator variable. For knowing whether there is a mediator effect or not, we use a bootstrapping method in AMOS.

Hypothesis 6 was not supported, indicating that there is no indirect effect between fatigue and Human error mediating of management tasks (β= -.103, p= .211). Hypothesis 6 was rejected.

Table 21. Hypothesis results (6-9)

Hypothesis	Indirect effect	p-value	Results
6. FA → MT → HE	-0.103	0.211	Rejected
7. WL → MT → HE	0.368	0.010***	Accepted
8. TR → MT → HE	-0.163	0.033**	Accepted
9. SK → MT → HE	0.028	0.981	Rejected

1) ** $p<0.05$, *** $p<0.01$
2) The indirect effect is a standardized indirect effect

Hypothesis 7 proposed that workload would indirectly influence positively and significantly to human error. The results revealed that the workload has a strong significant positive indirect relationship with human error (β= .368, p= .010). Therefore, Hypothesis 7 was supported.

Hypothesis 8 believed that training would negatively and significant indirect influence on human error. The results agreed that training has a significant negative indirect relationship with human error mediating management tasks (β= -.163, p= .033). Therefore, Hypothesis 8 was also supported.

Finally, the paths from operational skill related negatively to human error were rejected, indicating that operational skill cannot significantly influence human error through manager tasks (β=.028, p=.981).

Chapter 5. Conclusion

1. Results summary

The purpose of this research was to investigate the main factors of human error and to model them in the shipping operations. This chapter is divided into three sections: (1) findings and discussion; (2) implications; and (3) limitations and recommendations for future research.

The first section summarizes the empirical research findings and discussion according to the objectives of the present study. Based on these findings, the theoretical and managerial implications, as well as contributions, are discussed in the second section. The final section will address the limitations of the study and recommend further research.

The purpose of the study was not just to predict behavior based upon experiences, but to investigate the role that management tasks affects to human error, and analyzed an integrated model of the causal relationship of direct and indirect experiences affect the human error in the navigation. The scale comprised 17 variables representing the six latent variables of fatigue, training, operational skills, workloads, management tasks, and human error. Several statistical examinations were conducted in an effort to evaluate the effectiveness of this study proposed the hypothesized model. The table summarizes the results of the hypotheses test.

The hypothesized model was tested along with the nine-research hypothesis postulated to evaluate how direct and indirect experience, workload, and management tasks influence human error in shipping navigation. Hypotheses 1 proposed that direct experience – fatigue would have a positive causal relationship with the management tasks. In other words, the more fatigue creates more tasks. This was rejected indicating fatigue is not an important variable related to management tasks.

However, the relationship between workload and management task was significantly negative, suggesting that with increases in workload, management tasks would decrease nearly the same. The implication here is that hard and long working days break the management control rules.

Hypothesis 3 was also supported by causal relations between training and management tasks. The results show training can be a part of management control tasks.

However, Hypothesis 4 was not supported by causal relations between operational skills and management tasks. Operational skills are cannot affect management tasks.

Hypothesis 5, the main hypothesis, supports the model, indicating management tasks can decrease the human error. For reducing human error, shipping companies should focus to increase management tasks.

Hypothesis 6 was not supported. There are no causal relations between fatigue and human error mediating management tasks. This result is different from previous researches, which mentioned that fatigue could affect human error.

Table 22. Summary of Hypothesized findings

N	Hypothesis	Result
1	H1. Fatigue will affect positively to the management ta	Rejected
2	H2. Workload will affect negatively to the managemen	Accepted
3	H3. The training environment will affect posi management tasks.	Accepted
4	H4. Operational skills will affect positively to the management tasks.	Rejected
5	H5. Management tasks will affect negatively to human	Accepted
6	H6. Fatigue will affect positively to the human error ir of management tasks.	Rejected
7	H7. Workload will affect positively to the huma mediating of management tasks.	Accepted
8	H8. Training will affect negatively to the human error ir of management tasks.	Accepted
9	H9. Skill will affect negatively to the human error in mediating of management tasks.	Rejected

Hypothesis 7 was supported. There is a strong causal relationship between workload and human error and human error in mediating with management tasks. It can be concluded that long and hark workloads are likely to have more human errors. Even management tasks and workloads affect differently, management tasks cannot reduce absolutely the effect of workloads in the occurrence of human errors. H7 was supported.

H8 was supported that training by management tasks have negative effects on human errors. For masters and officers, training should use frequently to increase knowledge and reduce risk or minimize human errors.

Hypothesis 9 was not supported. As skill has no relationship with management tasks, it has also no relationship with human error. It also has no effect through management tasks to human error.

This research provides important insights concerning past experience, which was found to be the most influential predictor of a human error.

2. Implementation

This section will address the contributions to theory that derive from the research. There are a number of important theoretical and managerial implications that will improve human error research in shipping navigation. This section will first address the theoretical implications before focusing on managerial implications. The major theoretical contribution of this study was building a valid and reliable model of human error in the shipping navigation field.

From an academic standpoint, this issue of measuring human error has become increasingly important in the topic in this field as we mentioned early. The existing human error model is very few and comes from the general aviation, nuclear and chemical plants, are not suitable in the maritime, especially shipping navigation.

Another contribution of this research is the development of a theoretical framework identifying how the direct experiences and indirect experiences influence the workloads and management tasks to human errors in this field. Moreover, this model could be led to the development of new models related to human error. As the shipping navigation becomes automated, there still continues to increase in human error. To establish a strong strategy to decrease human error the company could focus to increase its control over the master and officers and also should increase training courses ion updated navigation equipment. However, there is a lack of supporting empirical evidence in the shipping field. This study was designed to explore this gap in the research. Therefore, the results derived from this research provide several practical implications for shipping navigation managers, master, and officers, specifically, in terms of how to decrease the accidents in the vessel.

From the managerial point of view, this study shows that the direct experience of manager tasks can decrease human error and also influence more by increasing training courses. Indirect experience such as workloads can increase human error. However, increasing manager controls over workloads well can reduce its effect on human error occurrence. Another point of view, more operational skill and fatigue are less important in the occurrence of human error. The operational skill was an important factor before automation, as much automation increases in usage, so much new training will be important than skills.

The study not only confirms the observation that training is an important part of managerial tasks, but also it is important for reducing accidents frequency. However, the important aspect of training that influencing human error can be identified not directly but from another factor, namely management tasks. This research shows that proper management control is an important factor influencing human error. However, the managers should pay attention to the strict control over masters cannot reduce all human errors, because more workloads affect to human error increase.

3. Limitation and Future studies

Several limitations are recognized in this research, that relate to interpretation and generalization of the findings: the First limitation of this research relates to a generalization of the findings. The present study conducted surveys only for human errors in shipping navigation. As a result, the findings of this study are limited in their generalizations. The proposed model of this study requires more rigorous tests by replications in different industries. Furthermore, the questionnaire of the research has no universal for shipping navigation, it should be filled and updated in new studies. The participation of a different work experienced masters and officers may cause different fit indices and different results. Therefore, future research could evaluate the model's applicability across a wider range of participants.

Another limitation relates to the sampling method. The most part of samples for this study was collected from short experienced masters and officers, hence the sample was collected from geographically known to the researcher. Although the individuals were independently and randomly selected from each group, the results of this research may not be generalized to the entire population.

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