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Path analysis of causal factors influencing marine traffic accident via structural equation numerical modeling

Shenping Hu [1]*, Zhuang Li [1], Yongtao Xi [1], Xunyu Gu [2], Xinxin Zhang [1]

[1] Merchant Marine College, Shanghai Maritime University, Shanghai 201306, China
[2] Ship Administration, Pudong Maritime Safety Administration, Shanghai 200135, China
* Correspondence: sphu@shmtu.edu.cn

Abstract: Many causal factors to marine traffic accidents (MTA) influence each other and have associated effects. It is necessary to quantify the correlation path mode of these factors to improve accident prevention measures and their effects. In the application of human factors to the accident mechanisms, the complex structural chains on causes to MTA systems were analyzed combining the Human Failure Analysis and Classification System (HFACS) with theoretical Structural Equation Modeling (SEM). First, the accident causation model was established as a human error analysis classification in sight of MTA, and the constituent elements of the causes of accident was conducted. Second, a hypothetical model of Human factors classification was proposed applying the practice of the structural model. Third, with the data resource from ship accident cases, this hypothetical model was discussed and simulated, and as a result the relationship path dependency mode between the latent independent variable of the accident was quantitatively analyzed based on the observed dependent variable of human behaviors. Application examples show that relationships in HFACS are verified and in line with the path developing mode, and resource management factors have a pronounced influence and a strong relevance to the causal chain of the accidents. Appropriate algorithms for the theoretical model can be used to numerically understand the safety performance of marine traffic systems under different parameters through mathematical analysis. Hierarchical assumptions in the HFACS model are quantitatively verified.

Keywords: maritime traffic; marine accident; accident causation theory; human factor; structural equation modeling; HFACS; path dependency

1. Introduction

Marine traffic safety is an important component of economics and trade between different countries. The volume of ship transportation has, over time, become an important measurement of the country's economic development. With the growth of China's national economy the shipping industry has developed rapidly and the scale of transportation has been expanding. With that growth, the marine traffic accidents (MTA) has consistently called attention to life safety, property safety and environment protection. Therefore, as a basic issue of safety research, the symptomatic problems of MTA always get attention by experts (Goerlandt and Montewka, 2015).

In order to reduce the incidence of MTA, many experts have conducted of research on the causes of MTA. Marine traffic is a complex system that includes people, ships, and environmental management. In the past, people focused on improving the safety of ships and equipment. Due to the continuous development of technology, the safety of ships and equipment has reached a very high level. Safety experts and scientists agree that the role and status of human factors and management factors in accidents have been proven. Thus, at present, many scholars believe that the root cause of accidents is management factors, i.e. the direct cause of accidents is the unsafe acts of personnel(Yang et al 2013).

The development of accident causation theory shows that most accidents are not caused by a single elementary event, but by a series of factors interacting with each other. Therefore, it is necessary to study the relationship between the different causes of MTA, in order to help decision-makers better understand the accident and thus fundamentally reduce the occurrence of such accidents.The analyses of the causes of MTA and the research on the interrelationship of the causes are being continuously developed. The complexity of the cause of the accident system has been established, and the chain model associated with the cause of the accident has basically been consistent(Xi et al, 2018).

However, it is still a difficult problem to explore the association pattern and intensity of the generic causal chain quantitatively. It is possible to use new algorithms to study the interactions and influence paths of the causes of accidents. In particular, the analysis of the causal chain path of big data can help us understand the characterization mechanism of accidents and provide scientific diagnosis of how those accidents occurred. To quantitatively analyze the relationships between the causes of MTA and clarify the causal mechanism of human factors in an accident and analyze the logical cause of the accident, this paper will combine with accident data, using the SEM method to analyze the complex relationship between the causal structures of MTA system.

The rest of this paper will be organized as follows. In section 2, the most recent studies about the cause of accidents and the mechanism of accident factors are reviewed. In section 3, our research theory and research hypothesis are presented. In section 4, we present the model in causal factors chain for MTA. In section 5 and 6 our research is applied to a specific case. The relevant data is collected, analyzed and applied to the model, and the sensitivity of the model tested. In section 7, the conclusions are drawn based on our research.

2. Literature Review

Increasing industry system safety through reducing infrequent events keeps a major challenge to safety scientists. Accident causation methods were broadly applied in marine traffic field.To study MTA occurrence mechanism, the first thing is to understand the causes of the accident and the interaction of the factors that cause the accident. (Pidgeon et al., 2000; Grant et al., 2018). marine accidents result from a combination of complex conditions. Japanese scholars proposed using the marine information structure, holding that independent action and interaction of human and maritime factors caused most accidents (Fukushima, 1976). The complexity of systems and the environments in which human operate means the process of safety is not directly forward or linear, but instead is driven by a complex network of relationships and behaviors between humans, technology and their environment.In comparison to other accident analysis methods, STAMP model uses a functional abstraction approach, to model the structure of a system and describe the interrelated functions(Leveson, 2015). A new risk management framework is put forward to solve a human control problem and modelling techniques are required to appreciate the direct or indirect operational requirements of systems(Rasmussen,1997). According to this work-flow, the structure of work systems is hierarchical which actors, objects and tasks are modeled across levels of the complex system and their relationships to each other are linked to explain causal connections. Dynamic work-flows are represented in the framework as inter-dependencies between the vertical integration levels of the system (Grant et al,2018).The FRAM accident model is different from the traditional model for analyzing accidents from the perspective of internal system operation mechanism or event causal sequence(Hollnagel, 2012). It does not stick to system structure decomposition and causal factor analysis, and avoids the analysis of accidents into the orderly occurrence of a single associated event, or avoids the analysis on hierarchical stacking of multiple potential factors. Combining Safety-I and Safety-II perspectives broadened understanding of safety management(Hollnagel, 2014; Jones et al, 2018).

Reason (1990) put forward the Swiss Cheese Model,the latent and active failures model, and pointed out, for the first time, that an accident is due to the latent defects or vulnerabilities in each part of the system, and that when the defects on each part are lined up, the final cause of the accident can be understood(Fan et al., 2015; Yang et al., 2013). The model has been criticized for being a reductionist and linear model that fails to account for a holistic representation of systems as dynamic and adaptive which forms the basis of systems theory (Grant et al,2018). Maintaining the notion of human error as a central concept in accident causation system disregards the basic fact, which the relevant performance usually is carried out by human- organization factor rather than by an individual. Furthermore, it can be shown that about 80% of MTA are related to human factors (Hu et al, 2007). The applications driven by qualitative accident causation models have been improved to investigate human factors in accidents. Subsequently, exploration of the correlation between the causes of the MTA and the consequences of accidents has made significant progress. The main qualitative research investigated the impact of different factors on the outcome of accidents. The relationship among causal factors in accidents has also been studied. Hänninen. (2014) used the directed acyclic graph of the Bayesian network to study the cause of marine accidents. Dai and Wang. (2011) utilized goal structure notion to analyze the associated rules of human factors to marine accidents. Graziano et al. (2016) used the tracer taxonomy to study human errors in collision accidents. Sotiralis et al. (2016) focused on human centered design aspects to incorporate human factors to ship collisions analysis. Lyu et al. (2018) studied the relationships among safety climate, safety behavior, and safety outcomes in construction workers. The novel drift into failure model(DFM) provides a set of philosophies that explain the nature of drift within a complex system. These embody principles from complexity theory such as path dependence, non-linearity and the impact of protective structures(Dekker et al, 2012).

The need to manage human error comes as no great revelation to anyone involved in operations where the consequences of failure are big serious.Exploring the formation methods and mechanism models of human error, and obtaining a generalized method for accident investigation, it is a topic that the industry is constantly studying. Based on the Swiss Cheese Model, the version of Human factors Analysis and Classification System (HFACS) was established. HFACS addresses human error at all levels of the system, including the condition of aircrew and organizational factors(Shappell and Wiegmann, 2000). This model is a general human error framework originally developed and firstly tested within the U.S. as a tool for investigating and analyzing the human causes of aviation accidents(Wiegmann et al, 2001). It has been identified several key safety factors that require intervention and proved that the HFACS framework can be a viable tool(Gaur. 2005). Krulak. (2004) proposed a maintenance extension of the HFACS method (HFACS-ME), and proved that human factors have a significant relationship with mishap frequency and severity in mishaps. Shappell et al. (2007) used HFACS put forward a logical method to analyze the human factors in the causes of accidents to provide a logical analysis of how accidents occur and how they can be prevented. Celik et al. (2007) sought to integrate those factors into the HFACS system to discover design-based human factors in marine accidents.

A general accident model describes the unexpected failures caused by characteristics of a system where interactions between factors behave in unpredictable ways and produce multiple and unexpected failures. Celik and Cebi. (2009) applied HFACS to qualitative analysis of Human Organizational factors (HOF) Structure in MTA. Chen. (2013) explored the structural relationship of human factors combined with “why-because” graphs. HU et al. (2008) used a relative risks model to analyze and evaluate ship navigation safety using Bayesian belief network. Chen et al. (2013) successfully studied the application of HFACS in coal mines and flight safety, and produced a qualitative list of human factors. Wang et al. (2013) first applied complexity theory to analyze the mechanism of the accident. Within complex systems, the relationships between factors can be described in terms of the interaction between them. Using multiple indicators to reflect latent variables, and also estimating the relationship between the entire model factors, a way to deal with measurement errors is necessary to be proposal which is more accurate and reasonable than traditional regression methods and useful to explore the path in accident causation style. It is necessary to find the principle of path dependence from complexity theory, which has the non-linearity and the impact of protective structures.

Structural equation modeling is a method for testing the relationship between assumed latent variables by using real data collected by researchers, Seo. (2005) used the Structural Equation Modeling method to reveal the mechanisms through which the contributory factors of unsafe work behavior influence safety actions of individuals at their workplaces.

In this paper, we reviewed the research on the mechanism of MTA. HFACS provides a new method for the study of human factors in marine accidents, but the lack of quantitative analysis limits its use. SEM method makes it possible to quantitatively analyze the relationships among human factors in accidents. Additionally, the lack of a clear path to analyze the causes of MTA motivated this paper to propose a correlation model in the causal factors chain for MTA, which is expected to explore the impact of human interactions in the mechanism of accidents.

3. Theoretical and research hypothesis

3.1 HFACS in MTA

Heinrich classifies the causes of an accident as unsafe behavior of human, unsafe status of materials, and unsafe conditions of environment(Marshall et al, 2018). More and more researchers have begun to study the influence of human factors on accidents. Human factors refer to the harmful effects of human behavior on the normal function or successful performance of the system when completing a specific task.

HFACS describes human error at each of four levels: the actions of the operators (e.g., bench-level scientists and field investigators in forensics); the preconditions for those actions (i.e., the conditions that influence human behavior); the middle management (i.e., the individuals whose role it is to assign work); and the organization itself(Shappell, et al. 2000). In the maritime field, here using HFACS for MTA to analyze human factors in marine accident (Chauvin et al., 2013; Wu et al., 2017), proposal the basic path of accident formation is described in Category I factors, which includes Organizational factors SL_4 - Unsafe Supervision SL_3 - Preconditions for Unsafe Acts SL_2 - Unsafe Acts SL_1 - Accident SL_0. Meanwhile, establishing accident causal factors and the classification of those factors are defined as shown in Table 1 (Category II factors was described as X_i,i=1,2,...17) . Here the original framework and structure proposed by Shappell (1997) was reserved, such as SL_0 (X_{17}), SL_1 (X_{13}, X_{14}, X_{15}, X_{16}), SL_2 (X_8, X_9, X_{10}, X_{11}, X_{12}),SL_3 (X_4, X_5, X_6, X_7), and SL_4 (X_1, X_2, X_3).

Based on CREAM and the theoretical basis for HFACS, a human structural cheese model can be constructed for a marine traffic accident. As shown in Figure 1, the following hypotheses were made:

Hypothesis H1: SL_3 has a significant effect on SL_4;

Hypothesis H2: SL_2 has a significant effect on SL_3;

Hypothesis H3: SL_1 has a significant effect on SL_2.

The quantitative relationship among human factors in maritime transportation is discussed thereafter.

Table 1 Relationship of Causal factors to Marine accident

Symbol	Item of Causal factors	Symbol	Item of Causal factors
SL_0	Accident	X_7	Violation Monitoring
SL_1	Unsafe Acts	X_8	Team factors
SL_2	Preconditions for Unsafe Acts	X_9	Individual factors
SL_3	Unsafe Supervision	X_{10}	Material factors
SL_4	Organizational Influence	X_{11}	Natural Environment
X_1	Resource Management	X_{12}	Physical Environment
X_2	Organizational Climate	X_{13}	Slip

X_3	Process Safety Control	X_{14}	Lapse
X_4	Inadequate Supervision	X_{15}	Mistake
X_5	Unsuitable Execution Plan	X_{16}	Violation
X_6	Error-Correction Parsing	X_{17}	Accident Consequence

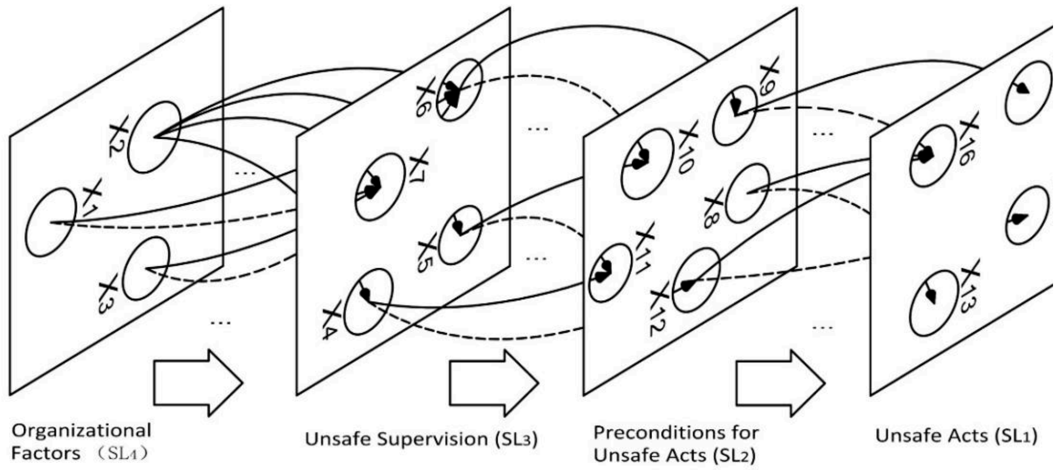

Figure 1 Path model of causal factors chain to MTA based on HFACS

3.2 Causal factors in MTA

The maritime industry stakeholder believes that the human component is a complex, multidimensional proposition that affects maritime safety and marine environmental protection, and includes crew, shore-based management, legislative and law enforcement agencies, shipyards, authorized organizations, and a series of behavioral activities of other relevant parties(Xi et al, 2017). All marine accidents will be affected and controlled by human factors, ship factors, environmental factors and management factors. However, the manifestations of system factors vary greatly in different accidents. In order to assist in the implementation of accident case analysis, an accident analysis system needs to be designed to fully define the description and characterization of the cause of the accident. This step relies on historical data and subject-matter experts analysis from the latent sources, such as databases, experiments, simulations, webs and logical analytical models. Detail items are shown in Table 2.

Table 2 Definition of Causal factors to Marine accident

No:	Item	Description and Observation character
X_1	Resource Management	Ship resource allocation, the allocation of ship resources, including operators, equipment and facilities, information support and monitoring, embodied in the suitability of personnel, the seaworthiness of the ship, and the suitability and effectiveness of external supporter.
X_2	Organizational Climate	The organizational climate can be shown that influence employees' events, activities, and procedures, as well as those that may be rewarded, supported, and expected. It can be divided into employees' internal perceptions and team climates
X_3	Process Safety Control	Process safety refers to how to prevent accidental loss of control and possible traffic accidents caused by installations and facilities during navigation, berthing and operation process, resulting in damage to employees and ships, environmental damage and property loss. .
X_4	Inadequate Supervision	No finding in operation arrangements or process issues Insufficient staff training time, VTS monitoring failure

X_5	Unsuitable Execution Plan	Improper arrangement of berths and anchorages, Operation plan negligence, Operation plan rationality defect
X_6	Error-Correction Parsing	Repeat the same nature accident
X_7	Violation Monitoring	Limit cause from Draught, weather, ship scale, etc.
X_8	Team factors	Crew member's mistake; Tug crew error; Communication and cooperation negligence
X_9	Individual factors	Illness or bad physiological state; Alcoholic beverage; Continuous operation, fatigue etc.
X_{10}	Material factors	Equipment defects, Structural defects, Cargo defects, latent defects, Overload
X_{11}	Natural Environment	Natural disasters, Poor visibility, Wind currents, Tides, Surges, Navigational environments, Waterway bends, Navigation aids, Navigable waters, Fishing areas
X_{12}	Physical Environment	Channel curvature; Obstacle (including dock or anchorage restrictions) Navigation aid; Navigation density; Navigable water depth; Navigable water width
X_{13}	Slip	Precaution to the natural conditions of the fairway; Precaution on ship traffic conditions; Precaution to encountering ship behavior; Visual hope negligence; Navigation instrument not used correctly
X_{14}	Lapse	Navigation operation; Avoidance collision behavior; Manipulation judgment
X_{15}	Mistake	Emergency treatment; Manipulating behavior(an anchorage, by mooring)
X_{16}	Violation	Violation operation (relevant ship); Violation operation (assisting tugboat);Violation operation (pilot);Deviation (pilot)
X_{17}	Accident Consequence	Degree of the consequences of the accident, including near miss

3.3 Relationship of causal factors in MTA

The relationship of factors has many pieces. When studying the correlation of human factors in the causes of MTA, the following aspects are mainly considered:

(1) Positive or negative factors of the correlation coefficient

If the correlation coefficient is positive, there is a positive correlation of the factors; if the correlation coefficient is negative, then there is a negative correlation of the factors.

(2) Scale of the correlation coefficient

For correlation coefficient, the greater the absolute value, the stronger the correlation of the factors is; if the minimum value is 0, at that time, in general, the factors do not depend on each other.

(3) Rank in Correlation of factors

The interaction of factors is reflected in the relationship of the factors, so some are directly associated, indicating that the factors are direct and influential, but some are indirect showing secondary effects.

The above associated accident analysis can form the path of the factors. The main content of path analysis is to solve: (a) Path direction; (b) Variable relationships of indicators; (c) Path load capacity; and (d) Whether the model hypothesis is actually matched.

3.4 Path analysis on causal factors of the MTA system

According to the complex network theory, the combination of accident factors and their associated relationships is called the accident network SOBIESKI J S. (2006). The node characteristics and associated characteristics in the accident network determine the main performance of the accident network.

The occurrence of complex system safety incidents is not caused by a single risk factor, but is the result of multiple risk causal factors. Corresponding to the accident network, the causal factors of the MTA system are generally not a single node, but an accident chain composed of multiple associated nodes, or an accident network consisting of an accident chain. Therefore, taking into account the dynamic nature of the risk, the accident is related to the accident path. However, the accident does not happen overnight, but needs to undergo a series of processes such as risk emergence, risk transfer, risk coupling, and accident emergence. In this process, there are many risk transfer paths, and the final accident path may be any one of them. One can analyze the risk transmission path of the complex accident system before the accident occurs, and identify the important parameters that affect the risk transfer. In an accident network, a path with more nodes is a critical path, and a path with fewer nodes is a non-critical path.

The causal path of the accident system includes two parts: the causes of the accident and the relationship of the causes. The path of the maritime causal system can show the beginning and ending of the MTA causal path, namely to express the direct and root causes in the MTA. It can show the causal path of a series of factors interacting with each other before the accident and help better explain the transmission process of the accident cause, reveal the evolution mechanism of the accident, and further help people to take effective measures based on the causal path of vulnerable defects.

4. Correlation model in causal factors chain for MTA

Usually, to study the safety of complex systems, it is impossible to test the actual system to observe the accident behavior; therefore, one must construct a theoretical model of the complex system. By constructing the corresponding simulation model for the theoretical model, computer simulation can be used to gain an in-depth understanding of system performance under different parameters. Traditional multivariate analysis methods such as complex regression, factor analysis, multivariate analysis of variance, correlation analysis, etc. can only test the relationship between a single independent variable and dependent variable at the same time, and these analytical methods often have deficiency in theoretical assumptions and application. Factor analysis can reflect the relationship between muti-variables, but it can not further analyze the causal relationship between variables. While path analysis can analyze the causal relationship between variables, the actual situation is difficult to meet the basic assumptions that the measurement error between the variables is zero, the residuals are irrelevant, and the causality is one-way function. In this paper, a novel method to analysis the causal factors is introduced via the network structural equation.

The Structural Equation Model(SEM) is a statistical method that analyzes the relationship among different variables by using a co-variance matrix of variables. The structural equation model integrates path analysis, confirmatory factor analysis and general statistical test methods to analyze the causal relationship between variables, including the advantages of factor analysis and path analysis. At the same time, it makes up for the shortcomings of factor analysis, taking into account the error factors, and does not need to be limited by the assumptions of path analysis. Based on this, we propose the strong and weak associated path of accident cause to quantitatively describe the mechanism of the accident.

The purpose of this paper is to find the path to the causes of the accident by finding the relationship among the causes of the accident. This differs from traditional statistical methods because in addition to quantitatively analyzing the effect of a cause on the results, the structural equation model also can quantitatively analyze the relationship between causes, so this paper will use the structural equation modeling method to decipher the relationships in the causes of the accident.

4.1 Methods and Models

The Structural Equation Model includes both the measurement model and the structure model (Crowley and Fan, 1997; Zhang et al., 2016). The measurement equation is used to describe the relationship between the observed dependent variable and the latent independent variable. The equation matrices of the measurement model are:

$$x = \lambda_x \xi + \delta \qquad (1)$$

$$y = \lambda_y \eta + \varepsilon \qquad (2)$$

Where among them,

x ---- Vector consisting of observed variables from exogenous latent variables

y ---- Vector consisting of observed variables from endogenous latent variables

λ_x---- The strength of association from exogenous observed variables.

λ_y---- The strength of association from endogenous observed variables

ξ ---- Unobserved exogenous latent variables

η----Unobserved endogenous latent variables

δ----The error items of the exogenous variables

ε---- The error items of the endogenous variables

The measurement model is shown in Figure 2.

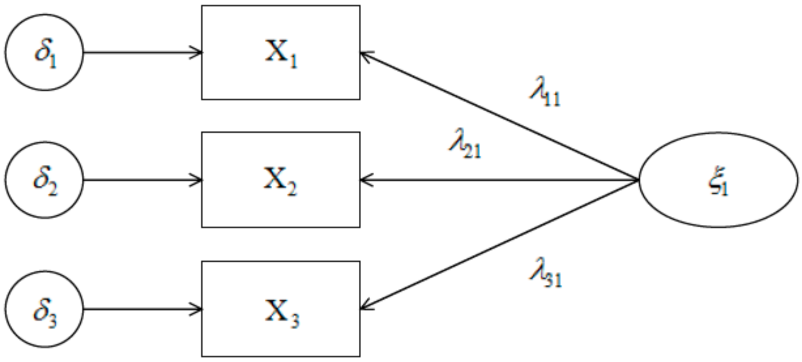

Figure 2 The measurement model

Structure equations are used to describe the relationship among latent variables. Equation matrix form of the structure model is:

$$\eta = \beta\eta + \gamma\xi + \zeta \qquad (3)$$

Where among them,

β---- the relationship between endogenous latent variables

ϒ---- the relationship between exogenous latent variables

ζ---- the residual term of the equation, and it represents the portion of the endogenous latent variable that is not interpreted in SEM.

The structural model is shown in Figure 3.

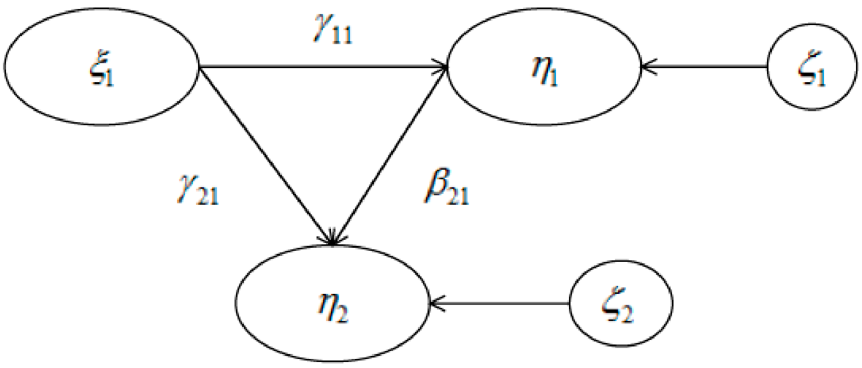

Figure 3 The structural model

The above three equations can form a general structural equation model (Byrne, 2009; Seo et al., 2015). Each line segment in the SEM has a path coefficient that characterizes the association between the two variables connected by the limit. After the path coefficients have been normalized, the values range from -1 to +1. In addition, the values by path factor can be divided into three categories:

(1) When 0<path coefficient<=1, it means that there is a positive correlation between variables or one variable has a positive effect on another variable, that is, the function between variables is monotonically increasing;

(2) When -1<= path coefficient <0, it means that there is a negative correlation between variables or one variable has a negative effect on the other variable, that is, the function between variables is monotonously decreasing;

(3) When the path coefficient is equal to 0, it means that the variables are independent of each other and not related to each other.

4.2 Hypothesis Structure model for the human factors of MTA

Use Category I factors of the human factors in section 1 as latent variables (indicated by ellipses), and use the corresponding Category II factors as observation variables (indicated by boxes), drawing a hierarchical classification and hypothesis model of human factors. e_i is the observation error. As shown in Figure 4.

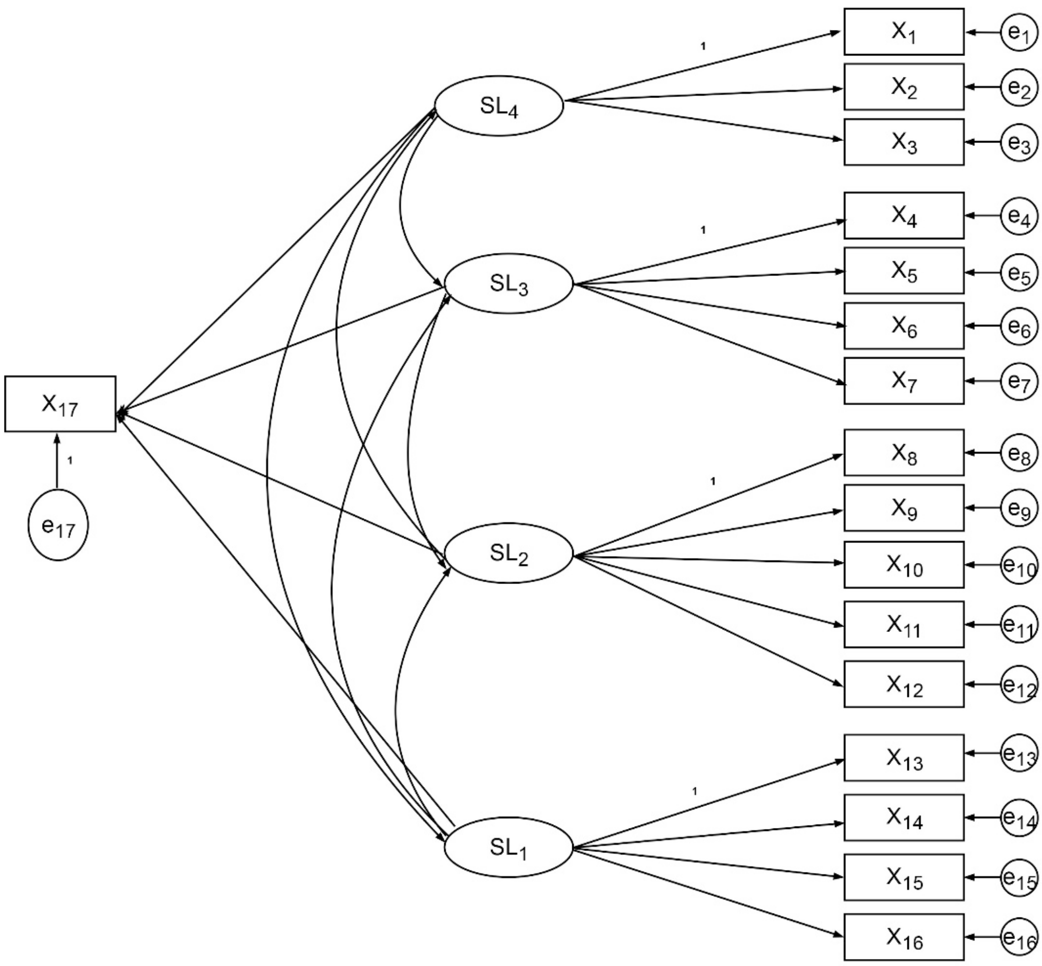

Figure 4 Structural Hypothetical Model of HFACS-MTA

5. Case study

This paper uses the accident case database from 2000 to 2009 in a certain area as an analytic sample (Hu et al., 2012; Huang et al., 2018), through the screening and extraction of the database, combining with the SEM hypothesis model and algorithm to apply to the model.

5.1 Accident samples analysis

5.1.1 Accident sample scale

Taking the human error in the area of MTA as the research object, a total of 894 samples of accidents were introduced. X_{17}"Accident" as an observation variable is used to examine the effects of different factors on the consequences of the accident. Use of the score of consequences of the accident depends on the actual level of the collection, including five levels: incidents, minor accidents, general accidents, major accidents, and serious accidents. They correspond to different accident consequences scores, as shown in Table 3.

Table 3 Accident consequence score table

Rank	value	Description
incidents	1	_ Near miss _hazard _An event considered to be worthy of attention
minor accidents	2	_ Failure that can be readily compensated by the crew _ No significant harm to people, property or the environment
general accidents	3	_ Local damage to ship _ Marginal conditions for, or injuries to crew
major accidents	4	_ Major casualties excluding total loss _ Single fatality or multiple severe injuries
serious accidents	5	_ Total loss (actual loss and constructive total loss) _ Many fatalities

5.1.2 Formatting causal factors of the accident

Among these samples, there were all kinds of consequence which included 12 incidents, 520 minor accidents, 148 general accidents, 123 major accidents, and 91 serious accidents. The cause analysis of the accidents is the process of determining the cause of the accident and measuring the impact of the accident.

As to HFACS, human factors are those factors related to people in the operation of the system. Human factors are beneficial to the safety side (such as people exert their own ingenuity, overcome the adverse effects of mechanical equipment or harsh environment, etc.), but also can have a negative effect. As a research object of human factors in MTA, the negative impact on human safety due to human factors, namely Human Error was more important. The detailed information about the observed characters in accident reports were structured and formatted(also shown in Table 2).

Each sample analysis for the causes of the accident is based on observed characters items, such as management software , ship (cargo) hardware, environment(including natural conditions, geographical conditions, traffic conditions), and liveware (Xi et al., 2017). In research of human factors in marine traffic safety, the following four interfaces should be analyzed:

1) Liveware- liveware interface (L-L): The interaction between people in the system, such as leadership, management, communication and cooperation between people.

2)Liveware-hardware interface (L-H): The relationship between people and ships, equipment and other hardware, such as whether the design or layout of the ship or equipment conforms to human characteristics, whether it is convenient for people to manage and maintain the hardware, use or operate the hardware.

3) Liveware-software interface (L-S): The relationship between people and software, such as whether the information is complete and easy to follow as well as the ease of the operation of the software.

4) Liveware-environment interface (L-E): The relationship between humans and the environment, such as whether working conditions limit human's behavior and whether external conditions affect people's judgments.

In the case of structured accidents' documents, the observed characters in causes of the accidents are divided into the following 7 categories:

(1) Management items: maritime administration limit, company management limit;

(2) Natural items: natural disasters, poor visibility, wind, tides, surges;

(3) Channel or terminal items: navigation loops, channel bends, aids to navigation, navigable waters, chart publications, fishing areas;

(4) Traffic items: navigation order, traffic accident, berth anchorage, navigation management;

(5) Ship cargo items: structural defects, equipment defects, cargo defects, latent defects, over workload;

(6) Personnel involved items: the tugboat operator, the ship operator, and the outboard operator.

(7) Crew items: violation operation, negligence of route planning, negligence of navigation operation, negligence in avoidance of collision, negligent manipulation, emergency-handling, communication and cooperation negligence.

According to the different effects of the observed character on the outcome of these accidents, the factors influence level are divided into four grades:

Level I, the factor may not impact the accident outcome, *no effect*

Level II, the factor may partly impact the accident outcome, *involved*

Level III, the factor may mainly impact the accident outcome, *mainly*

Level IV, the factor may apparently impact the accident outcome, *directly*.

5.2 Data acquisition and reliability analysis

In order to enable the fitting of the collected data into the hypothesis model, the collected accident factors must be quantified according to the level of impact on the consequences of the accidents. In this paper, to evaluate and synthesis the samples collected, a workshop was conducted with subject-matter experts in accident analysis and systems thinking. Furthermore the data in accident causation are measured by the "Likert scale", using a five-level scale.

First, quantitative data assignment is used for the extent of each factor's effect. According to the Level of impact, the rating is separately defined. Such as *no effect, 5; involved, 4; mainly, 2; directly, 1.* As to how the accident is described , for example, those which are described as a general accident, the detail influence factors which result to a certain accident includes observed characters such as "non finding in operation arrangements or process issues", "Insufficient staff training time" and "VTS monitoring failure" (variable in Table 2). These factors effect the accident at different levels of influence as discussed above, namely, "directly"," involved" and "no effect" respectively. That means the score is 1, 4, 5 respectively.Each accident sample can be described by the influence factors.

Second, the score of the xi(i=1,2,...16) accident causal factors depends on the minimum score among the corresponding observed characters collected. As to the case statemented above, those 3 observed characters involved "Inadequate Supervision" were numerical analyse, and the lowest score is measured as 1, which means "directly". Therefore, x_4"Inadequate Supervision" is measured as 1. All the structured observed characters in accident reports were formatted to numerical analysis data. The tested data statistics are shown in Table 4.

Table 4 Tested data from accident database

Case No :	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15	X16	X17
1	5	4	4	5	1	5	1	1	1	4	2	4	1	4	4	1	3
2	4	4	5	5	5	5	5	5	1	5	2	4	1	4	4	5	5
3	4	5	5	5	4	4	4	1	1	5	4	5	1	4	4	5	4
4	4	4	4	5	5	4	5	5	5	5	5	4	5	4	5	5	4
5	5	5	4	4	5	5	4	1	1	5	5	4	1	4	5	4	4

6	4	4	5	4	5	4	4	1	1	5	2	4	1	4	5	4	4
7	4	5	4	5	5	4	5	4	5	5	5	5	5	5	4	4	4
8	5	4	5	4	5	4	5	5	1	4	2	5	1	4	4	4	5
9	5	5	5	5	1	5	1	1	1	4	5	5	1	4	5	1	3
10	5	5	5	4	1	4	1	1	1	5	4	5	1	5	4	1	3

891	4	5	4	4	5	5	5	1	1	2	4	4	1	4	4	4	2
892	4	5	4	5	5	5	5	1	1	2	5	5	1	4	5	4	2
893	4	4	4	4	1	5	1	1	1	5	2	4	1	5	5	1	1
894	4	5	5	5	1	4	1	1	1	5	4	4	1	4	5	1	1
μ	4.1	4.2	4.1	4.2	4.0	4.1	2.7	2.9	2.3	4.1	3.7	4.4	2.1	4.5	4.5	4.0	4.3
σ	0.8	0.7	0.7	0.7	1.3	0.8	1.3	1.7	1.7	0.9	1.1	0.4	1.6	0.4	0.4	1.3	1.1

The collected accident factors were categorized according to the literature (Celik and Cebi, 2009), and finally the data was integrated into the 16 major accident factors. Thereby, a scoring of the 16 accident factors (variable in Figure 6) depends on the corresponding minimum score among the accident factors collected.

In addition to the correlation of factors in different MTAs, the impact of different factors on the consequences of the MTA is also analyzed. Therefore, the observation variable "Accident Consequence"(X_{17}) is added to examine the influence of different factors on the consequences of accidents.

5.3 Model fitting and correction

The paths that do not conform to the SEM hypothesis are as follows: (a) the path of the error term of the observed variable to the latent variable; (b) the path of the observed variable to other observed variables; (c) the error term of the observed variable for other observations The path of influence of the variable; (d) the path of the error term of the observed variable to the error term of other observed variables.

When the model is changed, the researcher should add new paths one by one instead of adding multiple paths all at once. The processed data are fitted with the hypothetical model, and modify the model with the output of the modification indices. The resulting path dependency is shown in Figure 5.

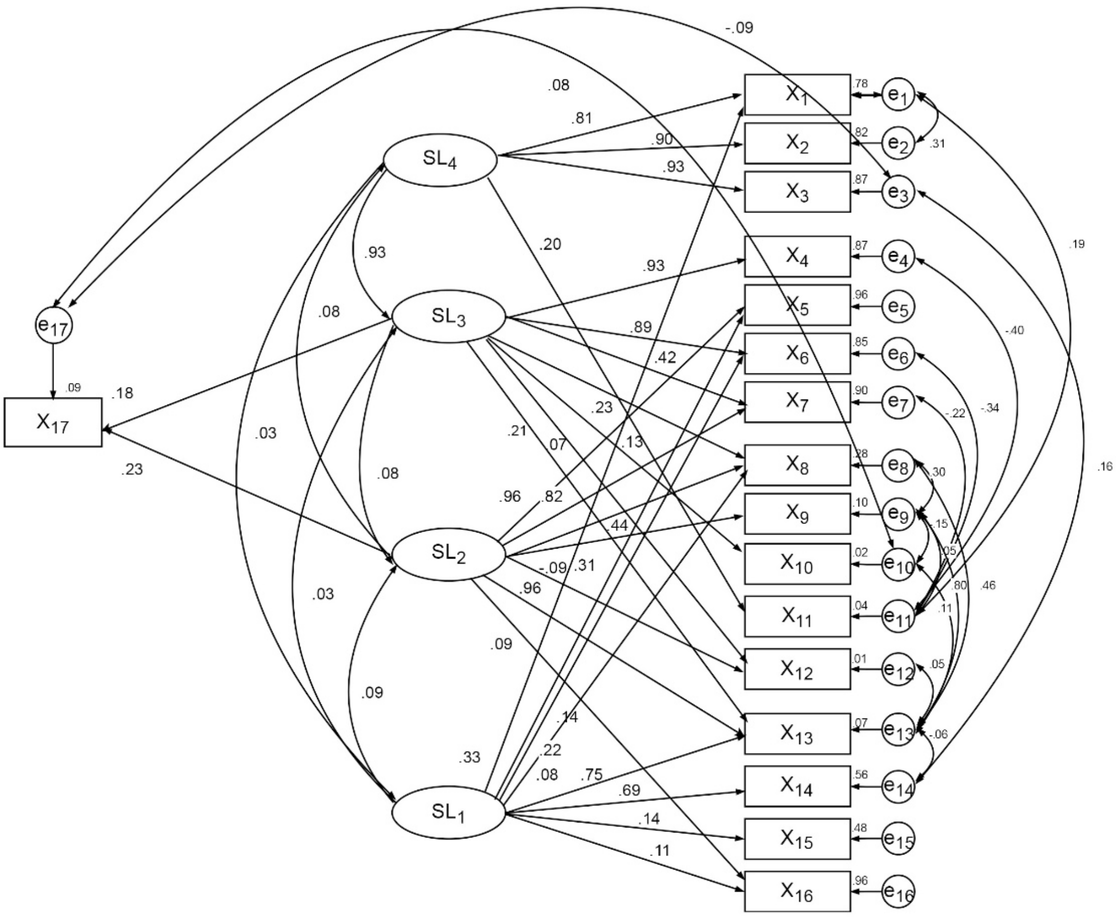

Figure 5 Path Diagram of MTA Forming using SEM simulation

5.4 Reliability analysis in path dependency

An analysis of the reliability of the sample data table should be performed before fitting the sample data to the hypothetical model(Byrne, 2009). Cronbach's Alpha coefficient (CA) is a measure of the intrinsic consistency of a set of data used to determine whether the set of data represents the same attitude tendencies and whether it can form an attitude measurement index.

The Cranach's Alpha test was performed on observation variables to measure a set of hypothetical "internal consistency" coefficients (Byrne, 2009), so as to judge whether this group of hypotheses represents the same tendency of attitude and whether it can constitute an attitude measurement index.

In general, if the CA is greater than 0.7, this indicates that the data has good reliability. When the CA is below 0.7, the entries in the data may represent different dimensions and need to be filtered.

The results show that after deleting some of the items, the check coefficient values of the observed variables are all above 0.7, and the overall reliability value reaches 0.797, indicating that this figure has good reliability.

Data statistics are shown in Tab 4, which is shown mean and standard variation of each variable.

Since the modified model used in this paper has some differences with the theory, it is necessary to test the sensitivity of the model in order to verify whether the modified model used in this paper is applicable to different types and sizes.

The critical ratio (C.R.) is used to test the significance of evaluation of the parameter in the model (Crowley and Fan, 1997). The critical ratio is the proportion of the evaluation of the parameter estimate to its standard deviation. When the significance level is 0.05, it means that the parameter evaluation is not equal to 0 significantly, and the null hypothesis can be rejected if the absolute value of C.R. is greater than 1.96. The calculation results are presented in Table 5.

Table 5 Statics data of critical ratio on variable

Hypothesis	Estimate value	Critical ratio	Conclusion
H1: SL_3->SL_4	0.944	33.727	Exist significant influences , defined hypothesis is true
H2: SL_2->SL_3	0.077	2.175	Exist significant influences , defined hypothesis is true
H3: SL_1->SL_2	0.125	2.921	Exist significant influences , defined hypothesis is true

The goodness-of-fit index of the amended model was shown in Table 6. From Tables 5 and 6, it is shown that the goodness-of-fit index of the model meets the criteria, indicating that the model and the data fit well.

Table 6 Statics data of variable via SEM simulation

Evaluation index	Estimate Value	Adaptation standard
Absolute index		
χ^2 Significant probability value	0.281	>0.05
Goodness-of-fit index (GFI)	0.989	>0.90
Adjusted goodness-of-fit index (AGFI)	0.980	>0.90
Root mean square residual (RMR)	0.031	<0.05
Root mean square error of approximation (RMSEA)	0.010	<0.05
Relative index		
Normal fit index (NFI)	0.993	>0.90
Relative fitness index (RFI)	0.988	>0.90
Incremental fit index (IFI)	0.999	>0.90
Tracker—Lewis index (TLI)	0.999	>0.90
Comparative-fit index (CFI)	0.999	>0.90
Parsimony index		
Parsimony goodness-of-fit Index (PGFI)	0.552	>0.50
Parsimony-adjusted (PNFI)	0.629	>0.50
χ^2/df (NC) indicating the degree of minimalist fit	1.088	1<NC<3

It can be seen from Table 5 that the path coefficient of SL_4->SL_3 is 0.94 and the *t*-check value is 33.727; the path coefficient of SL_3->SL_2 is 0.08 and the *t*-check value is 2.175; the path coefficient of SL_2->SL_1 is 0.13 and the *t*-check value is 2.921. These indicate that the *H1, H2, and H3* hypotheses are true and have a significant positive relationship. This proves the correctness of the HFACS-MTA framework from a quantitative point of view.

5.5 Sensitivity analysis of HFACS-MTA based on SEM model

Sensitivity analysis is used to qualitatively or quantitatively analyze changes in model results when model parameters or samples change. It classifies the collected documented cases according to different types of accidents (such as collisions, grounding, fires, etc.), which fit different types of accident data to the revised model of Figure 5, and carry out model analysis of the changes in the goodness-of-fit index and estimated parameters, in order to test the reliability and stability of the model. The post-test data prove that: although the significance level of the chi-square value obtained by fitting the modified model with the test sample did not reach the goodness-of-fit index, other fitness indexes met the requirements, and most of the path coefficients shown by the model were consistent. Therefore, the modification model of the MTA cause path is stable and suitable to be applied to samples under different conditions, and can provide guidance in those situations.

There are some differences between the model results and HFAC-MTA in the corresponding relationship of the Category I factors and Category II factors, as presented in Table 7.

Table 7 factors correlation characters via SEM simulation

Correlation Mode			Standardized path coefficient
SL_4	->	X_{11}	0.24
SL_3	->	X_5	No significant effect
		X_{13}	0.21
SL_2	->	X_5	0.94
		X_7	0.82
SL_1	->	X_1	0.27
		X_5	0.16
		X_6	0.23
		X_8	0.08
		X_{10}	0.09

Table 7 shows that:

(1) Organizational factors SL_4 are not only related to the three types of human factors in the theory, but also related to the Natural Environment.

(2) There is no significant correlation between Unsafe Supervision SL_3 and Unsuitable Execution Plan in HFACS theory, but there is a correlation with Slip.

(3) The Preconditions for Unsafe Acts SL_2 are related to Unsuitable Execution Plan and Violation Monitoring.

(4) There are correlations between Unsafe Acts SL_1 and Resource Management, Unsuitable Execution Plan, Error-Correction Parsing, Team factors, and Material factors.

6. Path analysis and discussion

Path analysis is used to test the hypothesis relationship of observation variables or indicator variables. The purpose of path analysis is to check the accuracy and reliability of the hypothetical model and analyze the relation intensity of different variables. Figure 5 mainly shows the path diagrams of latent variables and latent variables with their corresponding observed variables. However, the relationship among observed variables cannot be obtained, and there is a correlation in measurement error items of the model. The correlation between the two measurement error items indicates that there is a certain degree of latent correlation between the corresponding two measurement variables. From this, the MTA causal system path diagram can be as shown in Figure 7 (Only select the part that normalized path coefficients greater than 0.2 between Category I factors and Category II factors).

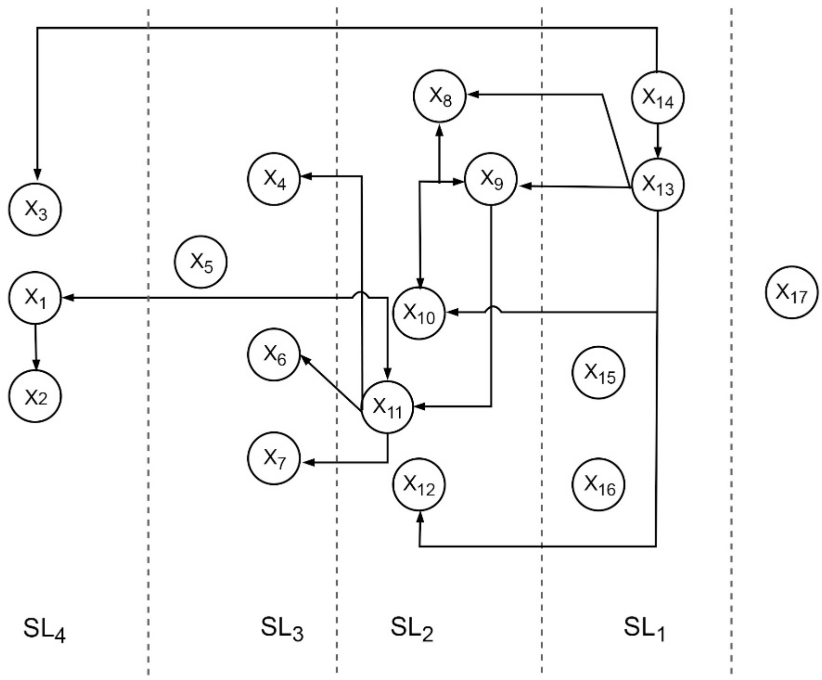

Figure 6　Path and trace representation of MTA network

Figure 6 presents some path dependencies that may lead to accident, such as:

Path dependency I (PD-I)：Resource Management - Natural Environment - Individual factors - Slip;

Path dependency II (PD-II): Organizational Climate - Resource Management -Natural Environment - Error-correction Parsing.

Decision-makers can find the influence and mode of action in the causes of MTA based on these path dependencies. For example, PD-I link indicates that there is interaction between the "Resource Management" & "Natural Environment", "Natural Environment" & "Individual factors", "Individual factors" & "Slip" and these interactions eventually result in accidents.

- The "Natural Environment" is the important reason for the entire accident system, and it is the key link between the previous factor and the next.
- "Resource Management" has a prominent position in the Organizational factors level (root cause) and is highly relevant.
- "Process Safety Control" directly affects the "Slip" of human unsafe acts.

Therefore, the decision-maker can strengthen the control and management of the four structural factors for the causal path to avoid interaction and ultimately prevent the accident from occurring. It is also possible to intervene in only some of the key items, so as to cut off the progression of the causal path and eventually avoid the accident.

(1) The Organizational factors SL_4 corresponding to Category II human factors are Resource Management, Organizational Climate, Process Safety Control, and Natural Environment. Category II human factors corresponding to Inadequate Supervision are: Error-Correction Parsing, Inadequate Supervision, Violation Monitoring, Team factors, and Slip.

(2) The Preconditions for Unsafe Acts SL_2 corresponding to Category II human factors are Violation Monitoring, Team factors, Unsuitable Execution Plan, Individual factors, and Violation.

(3)The Unsafe Acts SL_1 corresponding to Category II human factors are Resource Management, Error-Correction Parsing, Lapse and Mistake. Among them, Resource Management, Error-Correction Parsing, Team factors, and Violation Monitoring distribution are related to two Categories I human factors.

7. Conclusion

The formation of MTA is complex, but the degree of influence and the mode of action of factors in the cause system are different. The strength of the correlation of the factors determines the path of the accident. Example verification shows that there are different correlations of various factors in HFACS, and the observed variables manifest form conforms to the path dependency mode. Resource management factors in the sub-hierarchy of organizational factors have a prominent position in the accident formation and a strong correlation to same.

(1) The HFACS-MTA generic texture hypothesis paradigm based on the SEM can develop system pathway maps between the latent (independent) variable and observed (dependent) variable , which could quantitatively study the interrelationships in the various causes. The hypothesis model application shows that the relationship of human factors in the MTA is consistent with HFACS, and the direction of human error in the MTA is in the order of Organizational factors, Inadequate Supervision, and Preconditions for Unsafe Acts, and finally passed on to Unsafe Acts. The mutual influences in factors of the accident causes are obviously different.

(2) Structural equation modeling is a powerful research tool in the field of safety sciences, but the establishment of related models relies on the knowledge of relevant scientific fields. The setting of the implicit variables of the structural equations of accident causation theory and the setting of the relationship between hidden variables have the theoretical knowledge base of the maritime field. The setting and measurement of the measured variables corresponding to the hidden variables also have their theoretical basis. The structural equation model is only a mathematical expression of the theoretical knowledge base of the relevant scientific field, and it provides a tool for us to study related safety sciences.

(3) We have seen that in recent times, the theory of accident causation based on system theory has greatly changed and developed the understanding of traditional accidents forming. In particular, the characteristics of safety is seen as the emergence of systems, with safety issues as a matter of control. The cause of the accident is not only to describe the components in system structure, but also to explain the interaction and coupling between the causal factors. This paper believes that a certain mathematical algorithm is used to analyze the degree of cross-linking between factors, describe the process of action between factors, and then determine the path of accident formation. This is a quantitative demonstration of the cheese model, revealing the path dependence of management defects in the field of marine safety affecting human behavior.

We also see that, to study the safety problems of the complex marine traffic system, it constructs a theoretical model of a complex system and proposes an accident cause structural hypothesis. Appropriate algorithms for the theoretical human-machine-control model can be used to understand the safety performance of marine traffic systems under different parameters through mathematical analysis. Combined with big data ideas and intelligent prediction theory, it provides an important basis for risk pre-warning and accident prevention. This will be a problem that will require further research.

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