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Accident analysis model based on Bayesian Network and Evidential Reasoning approach

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ABSTRACT

In this paper, an accident analysis model is proposed to develop the cost-efficient safety measures for preventing accidents. The model comprises two parts. In the first part, a quantitative accident analysis model is built by integrating Human Factors Analysis and Classification System (HFACS) with Bayesian Network (BN), which can be utilized to present the corresponding prevention measures. In the second part, the proposed prevention measures are ranked in a cost-effectiveness manner through Best-Fit method and Evidential Reasoning (ER) approach. A case study of vessel collision is analyzed as an illustration. The case study shows that the proposed model can be used to seek out accident causes and rank the derived safety measures from a cost-effectiveness perspective. The proposed model can provide accident investigators with a tool to generate cost-efficient safety intervention strategies.

1. Introduction

When an accident occurs, it is important to understand the root cause in order to take effective preventive measures. Accident analysis always implies an accident model is a set of assumptions of what the underlying "mechanisms" are (Hollnagel, 2002). An accident model is an abstract conceptual representation of the occurrence and development of an accident; it describes the way of viewing and thinking about how and why an accident occurs (Huang, Ljung, Sandin, & Hollnagel, 2004). Accident model is also a very important process for providing input to the development of proactive and cost-effectiveness safety measures (Psarros, Skjong, & Vanem, 2010).

There are extensive literatures about accident model, most of which analyzes accidents using conceptual representation or summary statistics. For example, Wang, Pillay, Kwon, Wall, and Loughran (2005) carried out marine accident analysis to determine the most common causes of accidents on fishing vessels using accident data collected from the Marine Accident Investigation Branch. They carried out a statistical study of accident type, deaths and vessels lost in period from 1994 to 1999, which showed that there was a real safety problem in the fishing vessel industry. Similarly, Toffoli, Lefevre, Bitner-Gregersen, and Monbaliu (2005) investigated 270 ship accidents reported as being caused by bad weather to contribute toward the definition of adequate warning criteria. Antão, Almeida, Jacinto, and Soares (2008) analyzed the sequence of events leading to accidents using historical data. Summary statistics are important but not sufficient to explain the accident. However, the existing accident models lack the capability of proposing and ranking cost-efficient safety measures in preventing the occurrence of accidents. To improve the existing models, this paper presents an extended accident analysis model by integrating 4 methods which consist of Human Factors Analysis and Classification System (HFACS), Bayesian Network (BN), Best-Fit and Evidential Reasoning (ER) method.

HFACS is a reliable human error analysis method that is able to assist investigators in the identification of human and organizational factors and their relationships in an accident (Wiegmann & Shappell, 2003). However, HFACS remains as a qualitative model. This weakness is overcome by the quantitative calculation of BN in this study. At the same time, the HFACS' 4-level structure provides a systematic guideline in the construction of BN to model how

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Nomenclature

BN	Bayesian Network
CPT	Conditional probability table
HFACS	Human Factors Analysis and Classification System
CBA	Cost–Benefit Analysis
ER	Evidential Reasoning
FSA	Formal safety assessment
DAG	Directed acyclic graph
AHP	Analytic Hierarchy Process
CAF	Cost of Averting a Fatality
GCAF	Gross Cost of Averting a Fatality
NCAF	Net Cost of Averting a Fatality

human errors are related to form a network. With a hierarchy of nodes and states defined, BN, which represents the relationship among the human errors, can be constructed. In the HFACS model, human errors at a particular level directly influence human errors at the next lower level. This relationship depicted in the HFACS will be mapped onto the BN via its graphical representation with edges connecting nodes at a particular level to those located one level below. The BN is systematically constructed with the help of the HFACS' hierarchal structure.

The purpose of CBA is to compare the costs and benefits associated with the implementation of safety measures. There are many papers carrying out safety assessment using formal safety assessment (FSA) method, in line with well-established cost-effectiveness criteria (IMO, 1997; Norway, 2000). For instance, Lois, Wang, Wall, and Ruxton (2004) selected cost-effectiveness risk control options after CBA using risk matrix approach and expert judgment. Psarros et al. (2010) also used FSA to investigate cost-effectiveness criteria whether can be used to evaluate safety measures. Vanem and Ellis (2010) presented an evaluation of the cost-effectiveness of a novel passenger monitoring system using FSA. Their analysis found that the cost-effectiveness criterion could be considered as the best candidate. Evidence showed that the cost-effectiveness approach was practical by including examples of successful applications in actual risk assessments. However, some experts pointed out that CBA, as suggested for use in FSA, was not a precise science but a way of evaluation. It might not be used mechanistically, but only as a consulting instrument in decision making (Wang & Foinikis, 2001). In previous works, common limitations were present when carrying out CBA, which mainly came from unavailability of data and uncertainty. To deal with it, Yang, Wang, Bonsall, and Fang (2009) proposed a subjective security-based assessment and management framework using fuzzy evidential reasoning (ER) approach. Several types of uncertainty such as ignorance and fuzziness can be consistently modeled using the ER method (Guo, Yang, Chin, & Wang, 2006). The ER approach provides a procedure for aggregating calculations, which can preserve the original features of multiple attributes with various types of information. It provides a solution for processing subjective risk assessment possibly with academic bias resulting from various opinions of different individuals. However, these works paid little attention to the calculation of risk reduction achieved by implementing the safety measures. In this paper, an ER-based CBA method considering risk reduction is proposed to combine CBA with risk assessment.

Lessons learned from accidents are important for identifying weaknesses in the present system and avoiding them in future (European Communities, 2001). For existing accident models, the quantitative analysis for accidents and cost-effectiveness analysis for safety measures are not sufficient. As a response, an extended accident analysis model is constructed to seek accident causes and propose cost-effectiveness safety measures in this paper. The remainder of this paper is organized as follows: In Section 2, an accident analysis model is constructed and illustrated in detail. Section 2.1 and Section 2.2 present how to analyze accidents by integrating HFACS with BN. Section 2.3 carries out cost-effectiveness assessment of the proposed safety measures using Best-Fit method and ER approach. In Section 3, an illustrative study is conducted to demonstrate the feasibility of applying the model in the area of vessel collision.

2. Accident analysis model

The proposed accident analysis model consists of two parts. The first part of the model investigates accident causes and proposes corresponding safety measures using a two-phase accident analysis framework (Wang, Roohi, Hu, & Xie, 2011). The second part of the model ranks the proposed safety measures using Best-Fit method and ER approach from a cost-effectiveness perspective. The model is summarized as shown in Fig. 1.

In this model, there are four main steps:

1. Analyze accidents using HFACS &BN to identify/rank the main causes of accidents.
2. Propose corresponding safety measures in line with the rank of causes, and then calculate the reduction of accident probability after implementing each safety measure using BN.
3. Carry out CBA using Best-Fit method and ER approach.
4. Rank the proposed safety measures based on the reduced risk and CBA results.

2.1. Accident analysis

This section presents a two-phase accident analysis framework, which is shown in Fig. 2, to assess human and organizational errors in both qualitative and quantitative manners. In the first phase, the qualitative analysis of an accident is carried out to analyze various human errors using HFACS. In the second phase, the human errors identified in the first phase are quantitatively analyzed. This quantification process is achieved using BN, which enables quantification of the relationships among the human errors identified, enhancing the power of HFACS.

The application of HFACS provides a systematic guideline for accident investigations. Investigation starts from defining the accident of concern and proceeds upwards to identify active errors. This continues till organizational influences errors are identified. The systematic level-by-level procedure ensures that as comprehensive human errors as possible are uncovered. They are the lessons to be learnt from the accident. This helps to improve the current situation under which marine accident surveyors usually explain an accident from some pieces of experiential evidences (Celik, Lavasani, & Wang, 2010).

BN is a probabilistic graphical model that represents a set of random variables and their conditional independencies via a directed acyclic graph (DAG) (Detcher & Mateescu, 2004). Conditional probability table (CPT) elicitation is a complicated issue due to a large number of judgments required to quantify the relationships of BN (Rajabally, Sen, Whittle, & Dalton, 2004). In this paper, Analytic Hierarchy Process (AHP) and the decomposition method is used to estimate CPT for BN nodes.

Suppose that a node X (with k states $x_1, x_2, \ldots x_k$) has n parents ($T^{(1)}, T^{(2)}, \ldots T^{(n)}$). The determination of the conditional distribution

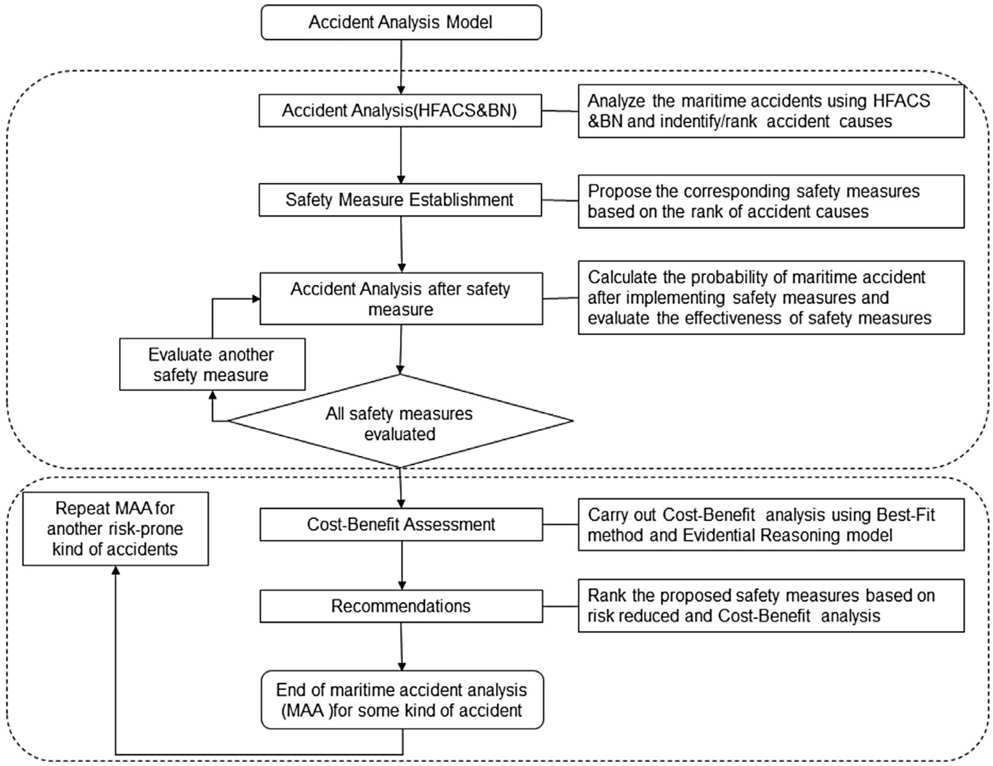

Fig. 1. The proposed accident analysis model.

$P(X = x_i|.T^{(1)}, T^{(2)}, ...T^{(n)})$ for all possible state combinations of the parents is a complicated process, especially when n is large or when each parent has a large number of states. The probability can be decomposed into:

$$P\left(X = x_i|T^{(1)}, T^{(2)}, \ldots T^{(n)}\right) = \alpha P\left(X = x_i|T^{(1)}\right)P\left(X = x_i|T^{(2)}\right)\ldots P\left(X = x_i|T^{(n)}\right)$$

where α is a normalizing constant to ensure that $\sum P(X = x_i|.T^{(1)}, T^{(2)}, ...T^{(n)}) = 1$. The decomposition method means that the conditional probability with each of the n parents can be calculated separately and then be combined.

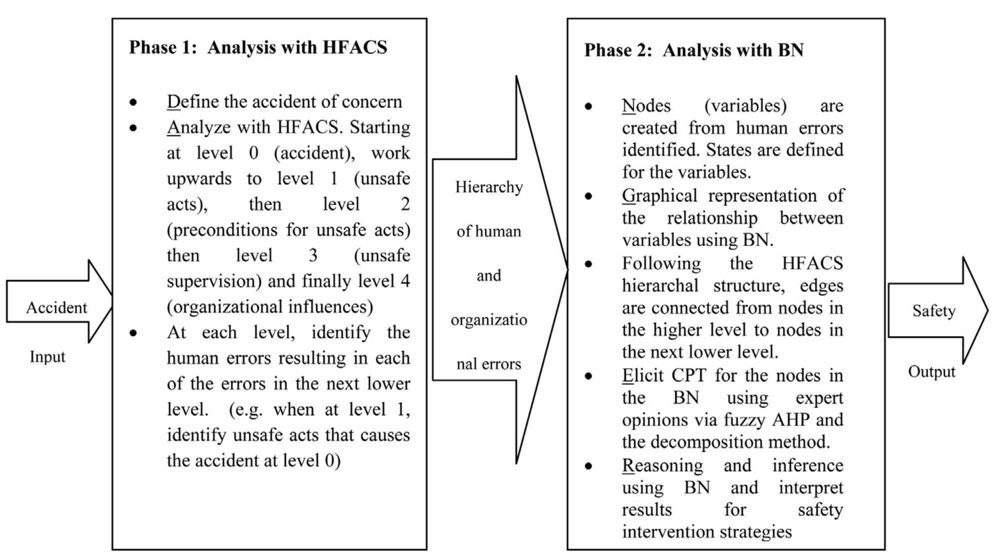

Fig. 2. Accident analysis framework.

Each of the required $P(X = x_i|.T^{(r)})$ is determined using AHP method. Let $w_p = [w_{p1}, w_{p2} \dots w_{pk}]$, where w_{ps} is the probability of $X = x_s$ $(s = [1,k])$ given that the parent $T^{(r)}$ is at state $p(p = [1,m])$. w_{ps} can be quantified by the following pair-wise comparison matrix (Hsieh, Lu, & Tzeng, 2004):

$$A = \begin{matrix} 1 & \tilde{c}_{12} & \dots & \tilde{c}_{1k} \\ \tilde{c}_{21} & 1 & \dots & \tilde{c}_{2k} \\ \vdots & \vdots & \dots & \vdots \\ \tilde{c}_{k1} & \tilde{c}_{k2} & \dots & 1 \end{matrix}$$

If there is more than one expert, the following equation can be used to aggregate the opinions of the experts.

$$\tilde{c}_{ij} = \frac{1}{N}\left(\tilde{c}_{ij}^1 + \tilde{c}_{ij}^2 + \dots + \tilde{c}_{ij}^t + \tilde{c}_{ij}^k\right)$$

where N is the number of experts, $\tilde{c}_{ij}$ is specified by asking experts questions like "Comparing states x_i and x_j, which one is more likely to occur and how much more?" Experts will answer the questions using a 9-point scale as shown in Table 1.

A number λ and a non-zero vector w satisfying $Aw = \lambda w$ are called an eigenvalue and an eigenvector of A respectively:

$$\det(A - \lambda I) = 0$$

$$w'w = 1$$

From the above two equations, we can obtain the maximum eigenvector $w = (w_1, w_2, \dots, w_n)^T$ of the matrix A, from which w_{ps} can be defined.

The consistency of the pair-wise comparisons can be checked using consistency ratio (CR), calculated as $CR = CI_n/RI_n$, where consistency index $CI_n = (\lambda - n)/(n - 1)$, n is the size of pair-wise comparison matrix A, and RI_n is a random index obtained from the Table 2.

A matrix with $CR \leq 0.10$ is considered acceptable. If $CR > 0.10$, the pair-wise comparisons have to be examined and corrected.

Table 2
Random index for calculating CR.

Size of matrix, n	Random index, RI_n
3	0.58
4	0.90
5	1.12
6	1.24
7	1.32
8	1.41

2.2. Evaluate the effectiveness of safety measures

After the main accident causes are discerned in Section 2.1, the corresponding safety measures are proposed to prevent the recurrence of accidents. In order to evaluate the effectiveness of the proposed safety measures, the reduction of accident probability after implementing every safety measure is calculated using the posterior inference of BN.

By using BN, the value of each source of evidence is reflected in posterior distribution, which can be used as the basis of making decision accordingly. Bayes' theorem modifies probabilities (Hubbard, 2007), given new pieces of evidence, in the following way:

$$P(H/E) = \frac{P(E/H)P(H)}{P(E)}$$

where

H represents a specific hypothesis, which may or may not be some null hypothesis.
E represents the evidence that has been observed.
$P(H)$ is called the prior probability of H that was inferred before new evidence became available.
$P(E/H)$ is called the conditional probability of seeing the evidence E if the hypothesis H happens to be true.
$P(E)$ is called the marginal probability of E, the priori probability of witnessing the new evidence E under all possible hypotheses.

The idea behind BN is probability inference of an event conditional on observed evidence. This posterior probability can be estimated using computer intensive algorithms. The reduction of accident probability after implementing each safety measure is calculated to evaluate the effectiveness of safety measures.

2.3. Cost–benefit assessment

Upon proposing the various safety measures, the next step is to carry out CBA on each safety measure. CBA aims to rank different safety measures by identifying the benefit from accident prevention and the cost associated with safety measures. The evaluation of costs and benefits may be conducted using various techniques (IMO, 2007). However, due to the unavailability of reliable data, the cost and benefit of safety measures are very difficult to assess in an exact manner. Safety experts often like to estimate costs and benefits incurred in safety improvement using linguistic variables. Under such considerations, it may be more appropriate to estimate those using fuzzy sets like ER approach. ER approach allows experts to express their subjective judgments using belief structures, which are based on the theory of evidence. It also allows expert judgments to be aggregated in a rigorous yet nonlinear rather than linear manner (Chin, Yang, Guo, & Lam, 2009).

Table 1
9 Point scale in AHP.

Intensity importance	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Weak importance of one over another	Experience and judgment slightly favor one activity over another
5	Essential or strong importance	Experience and judgment strongly favor one activity over another
7	Demonstrated importance	An activity is strongly favored and its dominance demonstrated in practice
9	Absolute importance	The evidence favoring one activity over another is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate values between the two adjacent judgments	When compromise is needed
Reciprocal of above non-zero numbers	If activity i has one of the above non-zero numbers assigned to it when compared with activity j, then has the reciprocal when compared with i.	

In this section, an ER-based CBA methodology is developed to deal with various types of uncertainties in CBA. Linguistic variables are characterized by a membership function to a set of categories. It is often recommended that the number of categories is restricted to no more than seven to remain within the practical bounds of human discrimination. The cost and benefit can be described in terms of membership values with respect to seven categories, defined in Table 3 (Wang, 2000).

The cost and benefit of ith safety measure estimated by expert l can be described in terms of membership values as follows:

$$C_i^l = \left[\mu_{C_i^l}^1/1, \mu_{C_i^l}^2/2, \mu_{C_i^l}^3/3, \mu_{C_i^l}^4/4, \mu_{C_i^l}^5/5, \mu_{C_i^l}^6/6, \mu_{C_i^l}^7/7\right]$$

$$B_i^l = \left[\mu_{B_i^l}^1/1, \mu_{B_i^l}^2/2, \mu_{B_i^l}^3/3, \mu_{B_i^l}^4/4, \mu_{B_i^l}^5/5, \mu_{B_i^l}^6/6, \mu_{B_i^l}^7/7\right]$$

where,

$\mu_{C_i^l}^n$ represents a degree to which C_i^l belongs to the nth category;
$\mu_{B_i^l}^n$ represents a degree to which B_i^l belongs to the nth category.

After rating the values of each C_i^l and B_i^l, the cost and benefit of ith safety measure can be obtained using Best-Fit method and ER approach.

The rest of this section is organized as follows. Section 2.3.1 presents how to calculate the cost of ith safety measure estimated by expert l using the Best-Fit method. Section 2.3.2 deals with how to combine the estimations of each expert to calculate the cost of ith safety measure using ER approach. Thereafter, the proposed safety measures are ranked by evaluating cost and benefit values with the corresponding risk reduction in Section 2.3.3.

2.3.1. Cost estimation of each expert in the utility space

Given the membership value of a cost description for a safety measure, the fuzzy cost description onto the defined utility expressions can be obtained using the Best-Fit method. The cost of the ith safety measure estimated by expert l (C_i^l) can then be evaluated in terms of the utility expressions (Table 4):

$$U\left(C_i^l\right) = \left\{ \begin{array}{c} \left(U_{C_i^l}^1, \text{“Slightly preferred”}\right), \left(U_{C_i^l}^2, \text{“Moderately preferred”}\right), \\ \left(U_{C_i^l}^3, \text{“Preferred”}\right), \left(U_{C_i^l}^4, \text{“Greatly preferred”}\right) \end{array} \right\}$$

Table 3
Cost–benefit expressions.

Linguistic variable	1	2	3	4	5	6	7
Very high	0	0	0	0	0	0.75	1
High	0	0	0	0	0.75	1	0.25
Moderately high	0	0	0	0.75	1	0.25	0
Average	0	0	0.5	1	0.5	0	0
Moderately low	0	0.25	1	0.75	0	0	0
Low	0.25	1	0.75	0	0	0	0
Very low	1	0.75	0	0	0	0	0

Table 4
Utility expressions (μ_u^j).

Linguistic variables	1	2	3	4	5	6	7
Slightly preferred	0	0	0	0	0	0.75	1
Moderately preferred	0	0	0	0.5	1	0.25	0
Preferred	0	0.25	1	0.5	0	0	0
Greatly preferred	1	0.75	0	0	0	0	0

where $U_{C_i^l}^j (j = 1,2,3,4)$ represents the degree to which C_i^l belongs to the jth utility expression (Wang, 2000).

$$U_{C_i^l}^j = \frac{\alpha_{ij}^l}{\sum_{j=1}^4 \alpha_{ij}^l} \quad (j = 1,2,3,4)$$

where α_{ij}^l represents the reciprocal of the relative distance between C_i^l and the jth utility expression, which can be defined as:

$$\alpha_{ij}^l = \frac{1}{d_{ij}^l/d_H} \quad (j = 1,2,3,4)$$

where, d_{ij}^l is the Euclidean distance between C_i^l and the jth utility expression, and d_H is the minimum value of d_{ij}^l. If $d_{ij}^l = 0$, α_{ij}^l is defined to be 1. d_{ij}^l can be quantified as:

$$d_{ij}^l\left(C_i^l, U_j\right) = \left(\sum_{j=1}^7 \left(\mu_{C_i^l}^l - \mu_u^j\right)^2\right)^{1/2}$$

2.3.2. Combining all estimations of each expert

In Section 2.3.1, the cost of ith safety measure estimated by expert l (C_i^l) is obtained from uncertain subjective judgments. Then, the cost of ith safety measure (C_i) can be calculated by combining all estimations of each expert (C_i^l) using ER approach.

The ER approach is well suitable for dealing with analysis problems of both quantitative and qualitative nature with uncertainty (Yang, 2001). Suppose there are N safety experts who assign membership degrees of cost. To obtain the extent to which the cost of ith safety measure belong to the jth utility expression ($U_{C_i}^j$), ER approach is employed to synthesize $U_{C_i^l}^j$ ($l = 1,\ldots$, and N).

Let $E(C_i^l)$ be the expected score obtained from the belief structure of expert l in assessing the relative importance of C_i. The total expected score for the relative importance of C_i can be expressed as the weighted sum of the expected scores of the lth expert. We have

$$E(C_i) = \sum_{l=1}^N \lambda_l E\left(C_i^l\right) \quad i = 1,\ldots,n$$

where λ_l is the relative weight of lth expert. The relative importance of C_i is defined as (Chin, Wang, Yang, & Poon, 2009)

$$w_i = \frac{E(C_i)}{\sum_{k=1}^{n} E(C_k)} \quad i = 1, \ldots, n$$

Suppose $M_l^j (l = 1, 2, \ldots, N)$ is a degree to which C_i^l supports the hypothesis that the cost of the ith safety measure estimated by expert l is confirmed to jth utility expression (j = 1,2,3,4) (Wang, Yang, & Sen, 1995). That is

$$M_l^j = w_i \times U_{C_i^l}^j$$

Suppose $M_l^H (l = 1, 2, \ldots, N)$ is the remaining belief unassigned after commitment of belief to all utility expressions for C_i^l, then M_l^H can be obtained as:

$$M_l^H = 1 - \sum_{j=1}^{4} M_l^j = 1 - w_i$$

Suppose $SM_l^j (j = 1, 2, 3, 4;\ l = 1, 2, \ldots, N)$ represents the degree to which the cost of the ith safety measure belongs to $H_m(m = 1,2,3,4)$ as a result of the synthesis of the judgments produced by expert l. Suppose SM_l^H represents the remaining belief unassigned after commitment of belief to all H_m as a result of the synthesis of the judgments produced by expert l. The algorithm for synthesizing all experts' judgments can be stated as follows (Yang & Sen, 1994):

$$SM_1^j = M_1^j$$

$$\{H_m\} SM_{l+1}^j = K_{l+1} \left(SM_l^j M_{l+1}^j + SM_l^j M_{l+1}^H + SM_l^M M_{l+1}^j \right) \quad (l = 1, 2, \ldots, N-1)$$

$$SM_1^M = M_1^H$$

$$\{H_m\} SM_{l+1}^H = 1 - SM_{l+1}^j \quad (j = 1, 2, 3, 4;\ l = 1, \ldots, N-1)$$

$$K_{l+1} = \left[1 - \sum_{m=1}^{4} \sum_{n=1, n \neq m}^{4} SM_l^m M_{l+1}^n \right]^{-1} \quad (l = 1, \ldots, N-1)$$

SM_N^j can be obtained by $N-1$ iterations of the above algorithm, which is the degree to which the cost evaluation belongs to $H_m(m = 1,2,3,4)$. That is

$$U_{C_i}^j = SM_N^j$$

The cost and benefit incurred during the implementation of each safety measure can be estimated from the above model. Subsequently, these safety measures can be compared and ranked through cost-effectiveness index.

2.3.3. Ranking of safety measures

After the costs and benefits of each safety measure are assessed, the outputs should be combined with the corresponding risk reduction to provide an overall assessment for the safety measures. There are several indices that express the effectiveness of a safety measure. However, only Cost of Averting a Fatality (CAF) is being widely used. CAF can be expressed in two forms: Gross (GCAF) and Net (NCAF). GCAF and NCAF are defined as the indices for CBA (IMO, 2002a). Definitions of these indexes are given as:

$$\mathrm{GCAF} = \frac{\Delta C}{\Delta R}$$

$$\mathrm{NCAF} = \frac{\Delta C - \Delta B}{\Delta R}$$

where,

ΔC is the cost of a safety measure,
ΔB is the economic benefit resulting from the implementation of safety measure,
ΔR is the risk reduction after implementing the safety measure.

It should be noted that in this step the risk reduction (ΔR) is not measured as the product of probability and consequence, but is calculated in terms of reduction in the expected number of fatalities once a specific safety measure is implemented. This implies that, at least for the moment, only consequences incurring fatalities are considered. The risk reduction is calculated by

$$\Delta R = \Delta P_f \cdot C_f$$

where

ΔR: Risk reduction [fatalities year^{-1}];
ΔP_f: Reduction of accident probability after adopting safety measure [year^{-1}];
C_f: Accident consequence [fatalities].

The linguistic evaluation scale, given in Table 5 (IMO, 2002b), can be used to estimate the accident consequence.

In this paper, ΔC and ΔB are substituted by fuzzy sets and preference degree. To synthesize both cost and benefit analysis for ranking purposes, Best-Fit method is applied to map the subjective cost and benefit estimation onto the defined utility expressions (Wang, Yang, & Sen, 1996). The cost and benefit of the ith safety measure can be evaluated in terms of the following utility expressions:

Table 5
Accident consequence.

SI	Severity	Effect on human safety	Effect on ship	Equivalent fatalities
1	Minor	Single/minor injuries	Local equipment damage	0.01
2	Significant	Multiple/severe injuries	Non-severe ship damage	0.1
3	Severe	Single fatality/ multiple severe injuries	Severe damage	1
4	Catastrophic	Multiple fatalities	Total loss	10

$$U(C_i) = \left\{ \begin{matrix} \left(\mu_{C_i}^1, \text{“Slightly preferred”}\right), \left(\mu_{C_i}^2, \text{“Moderately preferred”}\right), \\ \left(\mu_{C_i}^3, \text{“Preferred”}\right), \left(\mu_{C_i}^4, \text{“Greatly preferred”}\right) \end{matrix} \right\}$$

$$U(B_i) = \left\{ \begin{matrix} \left(\mu_{B_i}^1, \text{“Slightly preferred”}\right), \left(\mu_{B_i}^2, \text{“Moderately preferred”}\right), \\ \left(\mu_{B_i}^3, \text{“Preferred”}\right), \left(\mu_{B_i}^4, \text{“Greatly preferred”}\right) \end{matrix} \right\}$$

$U(C_i)$ and $U(B_i)$ is synthesized to obtain a preference estimate of the ith safety measure in terms of the utility expressions, which is presented as follows:

$$U(CB_i) = \left\{ \begin{matrix} \left(\mu_{C_i}^1 - \mu_{B_i}^1, \text{“Slightly preferred”}\right), \left(\left(\mu_{C_i}^2 - \mu_{CB_i}^2\right), \text{“Moderately preferred”}\right), \\ \left(\mu_{C_i}^3 - \mu_{CB_i}^3, \text{“Preferred”}\right), \left(\mu_{C_i}^4 - \mu_{CB_i}^4, \text{“Greatly preferred”}\right) \end{matrix} \right\}$$

Preference degree P_i of the ith safety measure can be quantified by Wang (2000):

$$P_i = \sum_{j=1}^{4} \mu_{CB_i}^j \times K_j + \left(1 - \sum_{j=1}^{4} \mu_{CB_i}^j\right) \times \frac{1}{4} \times \sum_{j=1}^{4} K_j$$

where, $[K_1, K_2, K_3, K_4] = [0.217, 0.478, 0.739, 1]$;

$1 - \sum_{j=1}^{4} \mu_{CB_i}^j$ describes the remaining belief unassigned after commitment of belief in the synthesis of cost and benefit.

After the preference degree of the ith safety measure is calculated, it will be combined with the corresponding risk reduction. The final preference degree considering the risk reduction is calculated as follows:

$$RP_i = \frac{\frac{1}{P_i}}{\Delta R_i} = \frac{1}{P_i \times \Delta R_i}$$

ΔR_i is the risk reduction implied by the ith safety measure.

Each RP_i represents the comparison with others. A smaller RP_i means that the ith safety measure is more desirable. According to the value of RP_i, each safety measure can be ranked against others.

3. An illustrative example

In this section, an illustrative example is analyzed to demonstrate the application of the proposed model. Analysis of historical accident data suggests that grounding and ship–ship collisions are the most frequent maritime accidents (Kujala, Hänninen, Arola, & Ylitalo, 2009). Therefore, we adopt an example about the collision of two vessels resulting in one casualty. Section 3.1 describes the case of the collision accident briefly. In Section 3.2, the maritime accident is analyzed step by step using the proposed model.

3.1. Case description

On 20 December 2009, the Singapore registered bulk carrier Alam Pintar was in collision with the UK registered fishing vessel Etoile des Ondes 15 nm north of the Cherbourg peninsula. As a result of the collision, the fishing vessel sank and one of four crews tragically lost his life.

Alam Pintar was on an east–north-easterly course on her way to Hamburg. The bridge was manned by an inexperienced officer and an unqualified deck cadet. The officer of the watch (OOW) had seen Etoile des Ondes and realized there was a risk of collision, but his initial course alterations to avoid collision were rendered ineffective. Finally, Alam Pintar's OOW ordered the wheel hard-a-starboard, but this was too late to prevent the collision. The data of the illustrative example is collected by Maritime Accident Investigation Branch of United Kingdom in September 2010 (Maritime Accident Investigation Branch, 2010).

3.2. Application of the proposed model

3.2.1. Identify the main accident causes

The experts invited for elicitation process are a group of four experts. The first one is a professor of Shanghai Jiao tong University, who is an expert of maritime safety. The second one is an experienced engineer of Great ship Global Offshore Service Company in Singapore. The third one is an associate professor of fuzzy reliability from Goa College of Engineering. The fourth one is an associate professor of safety engineering from China University of Petroleum. After reviewing the accident report from Maritime Accident Investigation Branch, the accident is defined as “Collision causing one fatality”. The list of human and organizational errors generated for the case study is shown in Table 6.

3.2.2. Inference with BN

The human and organizational errors identified in Section 3.2.1 are converted to variables of BN. With the nodes and states defined, the BN can be constructed as shown in Fig. 3. The conditional probability tables of BN nodes are estimated through integrating AHP with decomposition method as mentioned in Section 2.1. The relationships between the human errors are modeled via edges connecting the nodes.

Given the occurrence of “Collision_causing_one_fatality”, a backward inference to determine the main accident causes can be performed. According to Bayesian inference, the posterior probabilities of the accident causes given the accident happened are shown in Fig. 4.

To assess the robustness of the inference results derived from the proposed model, sensitivity analysis is conducted in this section. The importance degree of each accident cause to the node “Collision_causing_one_fatality” can be assessed using entropy reduction (mutual information). All calculation results are compared in Table 7.

From Table 7, it can be seen that the posterior probability of those nodes “Ineffective_emergency_measure”, “Insufficient_check”, “Disregard_requirement”, “Not_wear_flotation_device”,

Table 6
Main accident causes

Nodes/Errors	Descriptions	States
Level 0: Accidents		
Collision causing one fatality	Collision between bulk carrier and fishing vessel resulting one fatality	Yes, No
Level 1: Unsafe acts		
Ineffective emergency measure	The officer of the watch's initial alterations to avoid collision were rendered ineffective	Yes, No
Insufficient check	A quick visual check, without referring to the radar, was insufficient to fully assess the danger	
Did not wear flotation device	Flotation devices not worn while working on the deck	
Level 2: Preconditions for unsafe acts		
Lacked experience	Watch keepers were not aware that a vessel engaged in fishing may make sudden changes of course and speed	Yes, No
Unsuitable equipment	Powerful deck lights probably impaired the skipper's night vision; There is not alarm indication signal unit in the fishing vessel	
Disregard requirement	At the time of the accident, the bridge was manned by an inexperienced 4th officer	
Good lookout not kept	The level of concentration needed when fishing led to less attention being paid to keep a good lookout.	
Level 3: Unsafe supervision		
Unsuitable modification	Enclosing both the bow and stern areas were made without considering the effect of the modification on the visibility from the wheelhouse.	Yes, No
Did not comply with instruction	Non-compliance with the instruction of PACC Ship (UK) SMS instructions on the use of the 4th officer	
No risk assessment	The skipper resumed shooting without comprehensively assessing if it was safe	
No lookout	Not appointing a lookout while on the ocean passages.	
Level 4: Organizational influences		
No effective bridge teams	There was evidence of non conformance in relation to the formation of effective bridge teams	Yes, No
No appraisal procedures	PACC Ship (UK) had no formal system in place to monitor or appraise the performance of its masters.	
Did not enforcing safety standard	If action had been taken in accordance with safety standard, the collision would not have happened.	
Poor lookout standard	The absence of an effective lookout was noted during a port state inspection	

"Lacked_experience", "Not_comply_with_instruction", "Unsuitable_equipment" and "No risk assessment" have larger increase when the accident occurs. This suggests that those causal nodes have more effect to the occurrence of the accident.

3.2.3. Evaluate safety measure

With the above inferences with BN, the main safety measures to prevent the recurrence of the accident can be briefly derived as follows.

1) Comply with the instructions. For instance, appoint a suitably qualified officer as a watch keeper.
2) Respect all kinds of requirements. For example, establish an effective and experienced bridge team.
3) Keep sufficient check in case the actions of other vessels are ineffective in avoiding collision or close quarters situations.
4) Encourage fishermen to wear flotation device while working.
5) A risk assessment should be conducted before any alteration, especially when deciding where to fish or when structural modifications to vessel are being planned.
6) Watch keepers should be experienced enough to be able to foresee the possible change, such as sudden change course of fishing vessels.

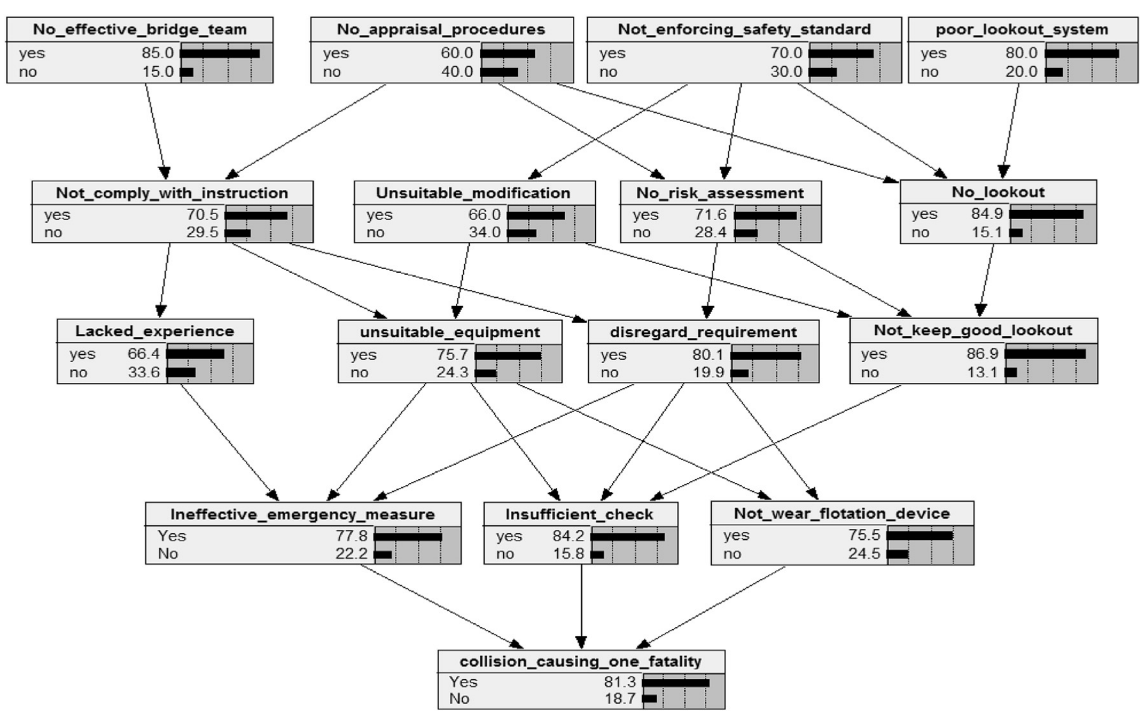

Fig. 3. Graphical representation of collision accident with BN.

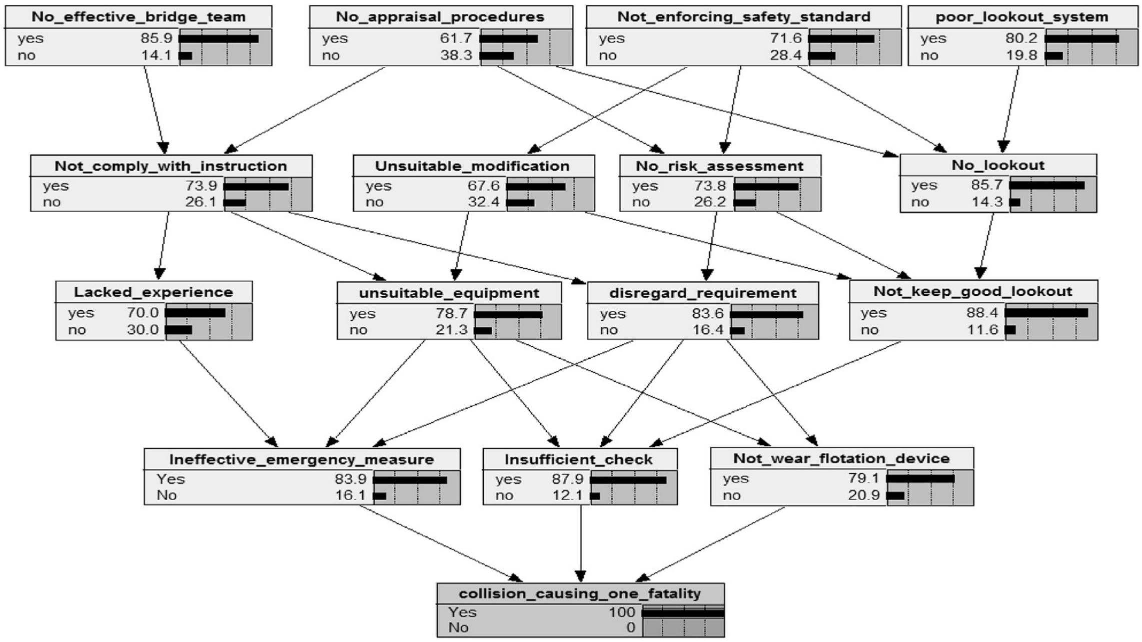

Fig. 4. Posterior probabilities of the accident causes given the accident happened.

7) Providing emergency drilling and training to the bridge team about collision avoidance.
8) Using suitable equipment, such as fitting an AIS unit to the fishing vessels.

In order to evaluate the effectiveness of the proposed safety measures, the probability of maritime accident after implementing safety measure is calculated using BN inference. The probability reduction of the accident after implementing each safety measure is shown in Table 8.

From Table 8, we can get the rank of the effectiveness of all safety measures in accordance with the reduction of the accident probability. "Comply with the instruction" is the most effective measure to reduce the occurrence probability of the collision accident.

3.2.4. Cost–benefit assessment

After studying above safety measures, we carry out CBA to evaluate the effectiveness of each safety measure to identify the most cost-efficient safety measures. Firstly, the cost and benefit of ith safety measure estimated by expert l are described in terms of membership values (C_i^l and B_i^l). Secondly, the cost and benefit of each safety measure estimated by expert l are calculated in terms of the utility expressions via the Best-Fit method. Thirdly, the cost and benefit of each safety measure are obtained by combining all estimations of each expert using ER approach.

The first safety measure is taken as an example to demonstrate how to carry out CBA. It is shown in Appendix A. The calculation results of cost and benefit associated with the implementation of each safety measure are shown in Table 9. All safety measures are ranked in accordance with the preference degree considering the risk reduction (RP_i) as shown in Table 10.

From Table 8, it can be seen that "Comply with the instruction" is the most cost-efficient safety measure to prevent the collision accident and "Encourage fishermen to wear lifejackets while working" take second place to reduce the fatality. In accordance with the calculation results, it's easy to rank the derived safety measures from a cost-effectiveness perspective.

Through the case study of applying the proposed accident analysis model, it can be concluded that the model is reliable and useful in identifying main accident causes and ranking the safety measures from a cost-effectiveness perspective.

Table 7
Prior probability, posterior probability and mutual information.

Accident cause	Prior probability (%)	Posterior probability (%)	Change rate of probability (%)	Mutual information
No_effective_bridge_team	85	86	1.176	0.00234
No_appraisal_procedures	60	61.9	3.167	0.00439
Not_enforcing_safety_standard	70	72	2.857	0.00568
Poor_lookout_ standard	80	80.1	0.125	1.228e-005
Not_comply_with_instruction	70.5	74.2	5.248	0.0192
Unsuitable_modification	66	68	3.030	0.00522
No_risk_assessment	71.6	74.2	3.631	0.00976
No_lookout	79.2	80.4	1.515	0.00261
Lacked_experience	66.4	70.3	5.873	0.0195
Unsuitable_equipment	75.7	79.1	4.491	0.0182
Disregard_requirement	80.1	84.1	4.993	0.0265
Not_keep_good_lookout	81.1	83.4	2.836	0.00903
Ineffective_emergency_measure	77.8	84.3	8.355	0.0654
Insufficient_check	82.7	87	5.2	0.0347
Not_wear_flotation_device	75.5	79.5	5.298	0.0242

Table 8
Probability reduction of the accident after implementing each safety measure.

Sequence number of safety measure	Probability of maritime accident after implementing safety measure (%)	Probability reduction of maritime accident (ΔP_f)	Priority sequence
1	58.6	0.227	1
2	76.3	0.05	7
3	80.6	0.007	8
4	69.3	0.12	2
5	75	0.063	6
6	71.9	0.094	4
7	72.7	0.086	5
8	71.1	0.102	3

Table 9
Cost and benefit of each safety measure.

Sequence number	$\mu^1_{C_i}$	$\mu^2_{C_i}$	$\mu^3_{C_i}$	$\mu^4_{C_i}$	$\mu^1_{B_i}$	$\mu^2_{B_i}$	$\mu^3_{B_i}$	$\mu^4_{B_i}$
1	0.012	0.0162	0.956	0.014	0.524	0.28	0.0988	0.0912
2	0.091	0.724	0.101	0.0842	0.16	0.242	0.437	0.16
3	0.173	0.181	0.275	0.371	0.225	0.437	0.437	0.225
4	0	0	0	1	1	0	0	0
5	0.297	0.334	0.189	0.181	0.17	0.33	0.33	0.17
6	0.25	0.25	0.25	0.25	0.19	0.29	0.37	0.16
7	0.297	0.334	0.189	0.181	0.102	0.686	0.116	0.096
8	1	0	0	0	0.297	0.334	0.188	0.183

Table 10
Safety measures ranking.

Sequence number	Risk reduction(ΔR)	P_i	RP_i	Priority sequence
1	0.227	0.925	4.762	1
2	0.05	0.499	40.075	7
3	0.007	0.698	204.569	8
4	0.12	1.392	5.989	2
5	0.063	0.544	29.162	5
6	0.094	0.609	17.483	3
7	0.086	0.621	18.721	4
8	0.102	0.281	34.865	6

4. Conclusions

This paper proposes an accident analysis model, which can be used to identify the leading accident causes and, thereafter, to propose the most cost-efficient safety measures to prevent the occurrence of accidents. In the first part of the model, we jointly taps on the abilities of HFACS and BN for investigating causes and proposing the corresponding prevention measures. In the second part, we use Best-Fit method and ER approach to rank the proposed safety measures from a cost-effectiveness perspective. The case study of the vessel collision accident shows the effectiveness of the proposed model.

The ER-based CBA method not only allows experts to express their subjective judgments using belief structures, but also allows experts' judgment to be aggregated in a rigorous yet nonlinear rather than linear manner. The accident analysis model has the ability to quantitatively evaluate the safety measures to facilitate the decision-making for preventing accidents.

Due to the lack of reliable historical data, it is difficult to calculate the exact cost and benefit associated with the implementation of safety measures. In this circumstance, many fuzzy models are proposed to evaluate the cost and benefit according to expert estimations. Although fuzzy models can be applied to estimate the comparative rankings more easily, the expert judgments are more or less subjected to biases. In our future work, we will gather enough reliable statistical data to get the real cost and benefit of safety measures. In addition, the model will be further improved to be able to carry out general analysis of all kinds of accidents. We will focus on seeking out exhaustive accident causes and summarizing the generic cost-effectiveness safety measures for each type of accident basing on more case studies and empirical data.

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Appendix A

The first safety measure is taken as an example to demonstrate how to carry out CBA. The costs of the first safety measure estimated by four experts are described in Table A.1. After rating the value of each C_i^l, the cost of the first safety measure is obtained by combining all estimations of four experts. The calculation results are shown in Table A.2.

The benefits of the first safety measure estimated by four experts are described in Table A.3. After rating the value of each B_i^l, the benefit resulting from the implementation of the first safety measure is calculated by combining all estimations of four experts. The calculation results are shown in Table A.4.

Table A.1
Cost estimation value of four experts ($\mu^j_{C_i^l}$).

Expert	1	2	3	4	5	6	7
1	0	0.6	1	0.7	0	0	0
2	0	0.3	1	0.6	0	0	0
3	0	0.2	1	0.8	0	0	0
4	0	0.2	1	0.8	0.2	0	0

Table A.2
Calculation of the cost for the first safety measure.

Expert	$U^j_{C_i^l}$	$J = 1$	$J = 2$	$J = 3$	$J = 4$
1 $M_1^H = 0.1$	$d^1_{ij}(C_i^1, U_j)$	1.847	1.569	0.403	1.585
	α^1_{ij}	0.218	0.257	1.000	0.254
	$u^j_{C_i^1}$	0.126	0.149	0.578	0.147
	M_l^j	0.114	0.134	0.520	0.132
2 $M_2^H = 0.1$	$d^2_{ij}(C_i^1, U_j)$	1.736	1.471	0.112	1.601
	α^2_{ij}	0.064	0.076	1.000	0.070
	$u^j_{C_i^2}$	0.053	0.063	0.826	0.058
	M_l^j	0.048	0.057	0.744	0.052
3 $M_3^H = 0.1$	$d^3_{ij}(C_i^1, U_j)$	1.801	1.481	0.304	1.715
	α^3_{ij}	0.169	0.205	1.000	0.177
	$u^j_{C_i^3}$	0.109	0.132	0.644	0.114
	M_l^j	0.098	0.119	0.580	0.103
4 $M_4^H = 0.7$	$d^4_{ij}(C_i^1, U_j)$	1.812	1.354	0.364	1.727
	α^4_{ij}	0.201	0.269	1.000	0.211
	$u^j_{C_i^4}$	0.120	0.160	0.595	0.125
	M_l^j	0.036	0.048	0.179	0.038

$$U\left(C_i^l\right) = \left\{ \begin{array}{c} (0.012, \text{“Slightly preferred”}), (0.0162, \text{“Moderately preferred”}), \\ (0.956, \text{“Preferred”}), (0.014, \text{“Greatly preferred”}) \end{array} \right\}$$

Table A.3
Benefit estimation value of four experts ($\mu^j_{B_i^l}$).

Expert	1	2	3	4	5	6	7
1	0	0	0	0	0.6	1	0.5
2	0	0	0	0	0.7	1	0.3
3	0	0	0	0	0.7	1	0.4
4	0	0	0	0	0	0.75	1

Table A.4
Calculation of the benefit resulting from the implementation of the first safety measure.

Expert	$U^j_{B_i^l}$	$J = 1$	$J = 2$	$J = 3$	$J = 4$
1 $M_1^H = 0.1$	$d^1_{ij}(B_i^1, U_f)$	0.820	1.106	1.710	1.781
	α^1_{ij}	1.000	0.742	0.480	0.460
	$u^j_{B_i^1}$	0.373	0.277	0.179	0.172
	M_l^j	0.336	0.249	0.161	0.155
2 $M_2^H = 0.1$	$d^2_{ij}(B_i^1, U_f)$	1.021	0.996	1.701	1.773
	α^2_{ij}	0.976	1.000	0.586	0.562
	$u^j_{B_i^2}$	0.312	0.320	0.188	0.180
	M_l^j	0.281	0.288	0.169	0.162
3 $M_3^H = 0.1$	$d^3_{ij}(B_i^1, U_f)$	0.955	1.031	1.721	1.792
	α^3_{ij}	1.000	0.927	0.555	0.533
	$u^j_{B_i^3}$	0.332	0.307	0.184	0.177
	M_l^j	0.299	0.277	0.166	0.159
4 $M_4^H = 0.7$	$d^4_{ij}(B_i^1, U_f)$	0.000	1.581	1.696	1.768
	α^4_{ij}	1.000	0.000	0.000	0.000
	$u^j_{B_i^4}$	1.000	0.000	0.000	0.000
	M_l^j	0.300	0.000	0.000	0.000

$$U\left(B_i^l\right) = \left\{ \begin{array}{c} (0.524109, \text{“Slightly preferred”}), (0.280252, \text{“Moderately preferred”}), \\ (0.09884, \text{“Preferred”}), (0.091196, \text{“Greatly preferred”}) \end{array} \right\}$$

Based on above cost and benefit value, preference degree of the first safety measure can be obtained by:

$$P_i = \sum_{j=1}^{4} \mu^j_{CB_i} \times K_j + \left(1 - \sum_{j=1}^{4} \mu^j_{CB_i}\right) \times \frac{1}{4} \times \sum_{j=1}^{4} K_j$$
$$P_i = 0.925071$$

The final preference degree of the first safety measure considering the risk reduction can be calculated as follows:

$$RP_i = \frac{1}{P_i \times \Delta R_i} = \frac{1}{0.925071 \times 0.227} = 4.762$$

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