Using risk data as a source for human reliability assessment during shipping LNG offloading work

Renyou Zhang[a*], Qinhao Zhang[a], Zhiqiang Hou[a], Wei Xv[b], Shanguang Chen[c], Henry Tan[d]

[a] School of Safety Engineering, Beijing Institute of Petrochemical Technology, Beijing 102617, China

[b] SINOPEC Safety Engineering Institute Co.ltd, Qingdao, 266000, China

[c] China Astronaut Research and Training Center, National Key Laboratory of Human Factors Engineering, Beijing, 100094, China

[d] School of Engineering, University of Aberdeen, Aberdeen, AB24 3UE, Scotland, UK

[*] Corresponding author. Email address: zhangry89@126.com (Renyou Zhang)

Abstract

Shipping Liquefied Natural Gas (LNG) has become a popular method for transporting LNG. However, offloading work poses significant risks, many of which are attributed to human errors. Considering that most accidents are associated with human errors, the Human Reliability Analysis (HRA) method is a critical option to prevent accidents and to predict Human Error Probability (HEP). One such method is fuzzy CREAM, a well-known HRA methods. However, this method has some limitations. The method uses Common Performance Conditions (CPCs) to estimate HEP, but the source of CPC data is insufficient. Without enough and reliable CPC data, the process and the result of fuzzy CREAM are questionable and criticized. Therefore, this study proposes a modified approach to address this issue. The proposed method uses the definition of "Risk" as the support to collect each CPC's data from aspects of likelihood and impact. Then, using the collected risk data as the source to determine each CPC's fuzzy degree, to determine each CPC's weight by combining with Grey Relationship Analysis (GRA), and to identify each activated fuzzy If-Then rules and the rule weight. Afterwards, the proposed method integrates the fuzzy degree of each CPC, the weight of each CPC, and the weight of each activated If-Then rule together to estimate HEP. Finally, the proposed method is validated through a real engineering case of shipping LNG offloading work.

Keywords: Risk, Human reliability analysis, Human error probability, Shipping LNG

1. Introduction

Shipping Liquefied Natural Gas (LNG) is the most widely used method for LNG transportation. However, LNG is flammable and explosive, making its shipping LNG risky. Offloading LNG is a crucial aspect of its shipping process, which involves a high level of risk. This work requires people's correct operations to connect two different systems (LNG ship and LNG terminal); even a minor operational error can result in severe consequences such as fire, explosion, and even fatalities. In addition, many researches have indicated that in marine and shipping process, operational risk should be analyzed seriously (Meng and An, 2021; Liu et al., 2024). As a large number of accident statistics show, 75%–90% of accidents are related to human error (Tao et al., 2020). Therefore, assessing human reliability and predicting Human Error Probability (HEP) are necessary in ensuring safe LNG offloading operations.

Human Reliability Analysis (HRA) methods are widely used today to assess and estimate human reliability and HEP. Since the first HRA method was applied in the 1980s, dozens of HRA methods have been published for commercial use. Those methods can be divided into three generations. The typical first-generation HRA methods include Technique for Human Error Rate Prediction (THERP), Human Error Assessment and Reduction Technique (HEART), and Success Likelihood Index Methodology (SLIM). The representative methods of second-generation HRA methods are Cognitive Reliability and Error Analysis Method (CREAM), and A Technique for Human Error Analysis (ATHEANA). The representation of third-generation HRA methods is the IntegrateD Human Event Analysis System (IDHEAS). The objective of HRA is to identify potential forms of human errors for each task, to analyze the factors that could potentially precipitate these errors, and to recommend solutions for mitigating human errors (Morais et al., 2021). Those HRA methods have been successfully and effectively used in many engineering cases including nuclear energy industry, aerospace industry, transportation industry, healthcare industry, chemical industry, petroleum industry (Taylor et al., 2020; Sujan et al., 2020; Lin et al., 2021; Zare et al., 2022; Elidolu et al., 2022; Ciani et al., 2022; Shi et al., 2023).

However, the first-generation HRA methods focus on the task characteristics, and they lack consideration of other important influence factors, so this group of HRA methods is criticized and questioned. Moreover, the first-generation HRA methods are designed for the nuclear industry, and may not be suitable for shipping LNG process. The ATHEANA method is time-consuming, it is weak in quantification analysis, and it is also focused on the nuclear industry. The IDHEAS considers cognitive and psychological factors more, but it is still designed for the nuclear industry. As a result, the CREAM method is selected as the main structure for further research. This method applies to general industry and is robust in quantitative analysis, so it is suitable for human safety assessment during the shipping LNG process. Work processes like shipping LNG offloading work often expose operators to complex scenarios involving danger like installations with explosive potential and flammability hazards, so the impact of environmental factors deserves great concern (He et al., 2021). CREAM emphasizes the influence of the work environment on individuals' behavior (Wu et al., 2021), suggesting that human performance in production is influenced by the working environment and conditions, rather than being random (Abrishami et al., 2020). According to the descriptions above, CREAM is determined to be the framework of this study.

The CREAM method is designed by Professor Erik Hollnagel (Hollnagel, 1998). It is a logical analysis framework that can predict HEP at each step of a task (Chen et al., 2019). CREAM provides information on both the mechanisms and probabilities of human errors, ranging from cognitive activities to behavioral executions (Li et al., 2023). It selects nine CPCs to determine the four Contextual Control Models (COCOMs) levels for predicting HEP for the targeted task. Since its first publication, CREAM has received many further developments. Among them, fuzzy CREAM is one of the most attractive developments because fuzzy theory is an effective way to handle uncertainties. In fuzzy CREAM, fuzzy membership function and fuzzy membership degree are used to express each CPC and each COCOM. Since the first publication of fuzzy CREAM in 2006 by Konstandinidou (Konstandinidou et al., 2006), it has received many developments. Marseguerra integrated fuzzy logic operation (Min-Max operation) with CREAM (Marseguerra et al., 2006), and through this approach, fuzzy CREAM has become a useful way for HEP quantification. Many mathematical methods have been combined with fuzzy CREAM in the past 10 years. Many researchers have selected Bayesian networks to combine with fuzzy CREAM for better estimating HEP value (Yang et al., 2013; Fan et al., 2022). Besides the Bayesian network, some researchers adopt a genetic algorithm for defuzzification to find the optimal HEP result (Zhang and Tan, 2018). Although those mathematical methods are beneficial to the fuzzy CREAM process, there are still issues on the fuzzy operation process. The fuzzy CREAM methods mentioned above are mathematical models that utilize fuzzy Min-Max operations for conducting fuzzy calculations. However, the fuzzy Min-Max operation only considers the maximum and the minimum fuzzy data, and it is hard to consider the weight of each fuzzy data. Therefore, a Product-Sum-based fuzzy CREAM has been proposed to make it consider fuzzy data and corresponding weight values together (Ung, 2015). This Product-Sum-based fuzzy CREAM has also been connected with the Bayesian network (Ung, 2019). Although the weight and degree are effectively combined, there are still issues that need to be addressed. According to the fuzzy CREAM procedure and fuzzy theory, nine CPCs will activate several fuzzy if-then rules, and each rule should have corresponding rule weights (Ishibuchi and Nakashima, 2001; Zhang et al., 2021). However, the above-mentioned fuzzy CREAM methods have not considered fuzzy if-then rule weight. To integrate fuzzy if-then rule weights into fuzzy CREAM, researchers have successfully adopted the T-norm theory to calculate fuzzy if-then rule weight and integrated the rule weight values with Product-Sum-based fuzzy CREAM (Zhang et al., 2021).

Based on the above descriptions, fuzzy CREAM has become a method that can take CPCs' fuzzy degree, CPCs' weight, and fuzzy if-then rule weight together. Although the fuzzy operation in fuzzy CREAM has been improved, still significant limitations exist. In most past applications of fuzzy CREAM, the source data of each CPC for HEP estimation is insufficient and has poor explainability. The historical recording data is always limited, and the data collected by experts' judgments has no standard for evaluation. No matter how robust the fuzzy CREAM process is, if the source data are questionable, the produced results will be unreliable. Therefore, it is essential to have a reliable and reasonable procedure along with trustworthy data to ensure the accuracy and dependability of the results produced.

To deal with the limitations of CPC data, some researchers have introduced the definition of risk to reveal the different importance levels of each Performance Shaping Factor (PSF) in the SPAR-H method (Liu and Li, 2014). Based on the definition of risk, our team also has proposed a method that combines the risk data of each PSF with Grey Relational Analysis (GRA) to calculate the significance value of each PSF in the Petro-HRA method (Zhang et al., 2023). These researches provide an idea that it is possible to use the definition of risk as the support to collect CPC's source data for addressing the insufficient recording of CPC data. Using the collected risk data for CPC fuzzification, CPC weight analysis (with GRA), if-then rule weight analysis, and final HEP calculation is possible. Therefore, enhancing the data explainability and making it more understandable is possible. The definition of risk, which considers both likelihood and impact, is familiar to many since it is a more friendly approach to data analysis.

This study improves the fuzzy CREAM approach for estimating HEP in shipping LNG offloading work. The proposed approach aims to provide reliable source data and calculation process. The study is organized as follows: Section 1 presents the main work and method of this study. Section 2 further explains the risk-based fuzzy CREAM and other major support methods. Section 3 is based on a real shipping LNG offloading case to verify the effectiveness of the proposed approach. Section 4 provides a discussion to indicate the advantages and the issues of the proposed method. Finally, Section 5 concludes the final findings and suggests future research.

2. Methodology

This study involves the definition of risk, fuzzy theory, GRA and Center Of Area (COA) methods based on the framework of CREAM. The methodology is divided into 5 parts shown below. Part 1 expresses the main methodological steps, and Part 2 introduces the main framework of the method. Parts 3−5 list the key approaches contributing to the final result.

2.1. Methodological procedure

This study aims to propose a risk-based fuzzy CREAM method that handles the defects of traditional CREAM. The approach is divided into five steps shown in Fig. 1.

Fig. 1. Procedure flow of the proposed fuzzy CREAM model.

Step 1 is to collect risk data and construct fuzzy membership function. To restrain the influence of subjectivity, this study collects 15 sets of "risk data" in different classifications to be the CPC data. Each set has two parts: severity and probability. Afterwards, the fuzzy function is determined based on the risk data. The fuzzy membership function is widely used to express and explain some uncertainties. This study adopts trapezoidal fuzzy membership function because the trapezoidal fuzzy function takes the risk data of CPC located in an interval to be "1", which avoids massive if-then rules activated by those CPC.

Step 2 is to obtain the fuzzy membership degree and the weight of each CPC. With the fuzzy membership functions defined in the last step, the fuzzy degrees can be determined, and through GRA, the weight of each CPC can be calculated with the risk data of CPC.

Step 3 is to establish the if-then rule and calculate the rule weight. This study identifies the activated if-then rules according to the fuzzy membership degree and the risk-based fuzzy functions. And the weight of the rule is collected by multiplying the corresponding fuzzy degree of each CPC. Then, the initial weighted fuzzy degree of each activated rule's COCOM can be identified with the fuzzy membership degree and weight of CPC.

Step 4 is to obtain the final weighted fuzzy degree of COCOMs. To estimate the HEP, the final weighted fuzzy degree ought to be collect based on the initial fuzzy degree of each activated rule's COCOM and the rule weight. This study uses the fuzzy product-sum method (Ung, 2015) combined with if-then rule weight, to multiply the initial weighted fuzzy degree of each activated rule's COCOM and the rule weight. Next it sums the products for the final weighted fuzzy degree of COCOM.

Step 5 is defuzzification. The COA method calculates the crisp HEP, with the final weighted fuzzy degrees of COCOMs collected in step 4.

2.2. CREAM

Table 1 lists nine CPCs of this study: adequacy of organization, work condition, adequacy of the man-machine interface (MMI) and operational support, availability of procedures/plans, number of simultaneous goals, available time, time of day, adequacy of training and experience, and crew collaboration quality (Ung, 2018; Hollnagel, 1998).

Table 1 Description of CPCs.

No.	CPC	Description
1	Adequacy of organization	Effectiveness of Safety Management System (SMS); Level of shore-based support for ships
2	Working condition	Work condition
3	Adequacy of MMI and operational support	User-friendliness level of control panel of navigation instruments, including radar, GPS, helm, and echo sounder

4	Availability of procedures/plans	Effectiveness of the international safety management (ISM) related procedures and plans
5	Number of simultaneous goals	Number of simultaneous goals when ship crew are on duty
6	Available time	Available time of day
7	Time of day	The time period of work
8	Adequacy of training and experience	Adequacy level of crew training and experience
9	Crew collaboration quality	Level of crew collaboration quality

CREAM provides a contextual control model, arranged in ascending order based on the degree of control, and categorizes the control mode into four groups: scrambled, opportunistic, tactical, and strategic (Abrishami, et al., 2020). In this study, the four COCOMs are determined using the nine CPCs listed above. The evaluation form of CREAM is shown in Table 2. Each CPC has different levels, and the corresponding effects match the CPC level regarding human reliability performance. Every specific level has three reliability influences; as shown in the last column, “1” represents a positive effect, “0” is equivalent to no effect, and “−1” represents a negative effect.

Table 2 Evaluation form of CREAM.

CPC	Level	Effect on reliability
1. Adequacy of organization	Very efficient	Improved (+1)
	Efficient	Not significant (0)
	Inefficient	Reduced (−1)
	Deficient	Reduced (−1)
2. Working condition	Advantageous	Improved (+1)
	Compatible	Not significant (0)
	Incompatible	Reduced (−1)
3. Adequacy of MMI and operational support	Supportive	Improved (+1)
	Adequate	Not significant (0)
	Tolerable	Not significant (0)
	Inappropriate	Reduced (−1)
4. Availability of procedures/plans	Appropriate	Improved (+1)
	Acceptable	Not significant (0)
	Inappropriate	Reduced (−1)
	Fewer than capacity	Not significant (0)

5. Number of simultaneous goals	Matching current capacity	Not significant (0)
	More than capacity	Reduced (−1)
6. Available time	Adequate	Improved (+1)
	Temporarily inadequate	Not significant (0)
	Continuously inadequate	Reduced (−1)
7. Time of day	Day	Not significant (0)
	Evening	Reduced (−1)
	Night	Reduced (−1)
8. Adequacy of training and expertise	Adequate high experience	Improved (+1)
	Adequate limited experience	Not significant (0)
	Inadequate	Reduced (−1)
9. Crew collaboration quality	Very efficient	Improved (+1)
	Efficient	Not significant (0)
	Inefficient	Not significant (0)
	Deficient	Reduced (−1)

Then, identify the demand for the relationship of each CPC and COCOM, the definition of the HEP interval, the logarithm interval of each COCOM, and the context influence index (CII) value to determine the COCOMs and the HEP interval. The CII value is calculated using Eq. (1).

$$CII = \sum|Improved| - \sum|Reduced| \tag{1}$$

where CII is used as the value to determine each COCOM. ∑|Improved| and ∑|Reduced| represent the sum of CPCs with the improved reliability effect (+1) and the reduced reliability effect (−1), respectively. Furthermore, Fig. 2 shows four control modes in COCOM: strategic, tactical, opportunistic, and scrambled. The CII is introduced to decide the COCOM, as depicted in Fig. 2 (Sun et al., 2012).

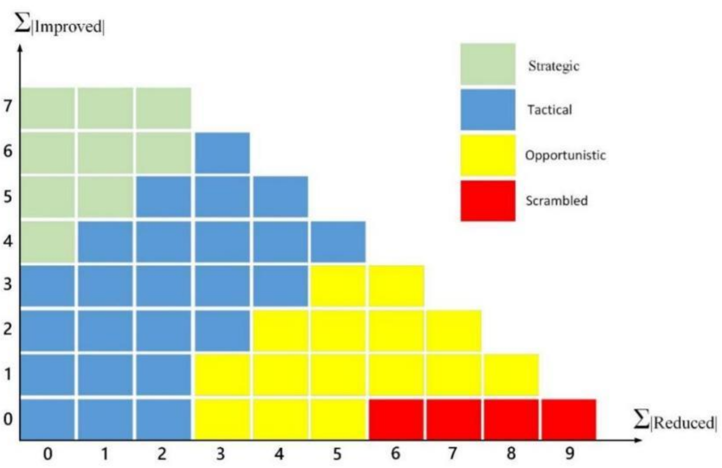


Fig. 2. Relationship between each CPC and COCOM.

Table 3 presents the HEP interval, the logarithm interval of each COCOM, and the CII value.

Table 3 HEP and $\log_{10}$ HEP interval of each COCOM.

COCOM	HEP interval	Log_{10}HEP interval	CII values
Strategic	(0.00005, 0.01)	(−5.3, −2)	[−7, −3]
Tactical	(0.001, 0.1)	(−3, −1)	[−3, 1]
Opportunistic	(0.01, 0.5)	(−2, −0.3)	[2, 5]
Scrambled	(0.1, 1.0)	(−1, 0)	[6, 9]

As for the data, this method introduces the definition of risk and collects risk data as the data resource of CPC to address the explainability of the data. The replacement of the expert scoring mechanism avoids the influence on data caused by the level and experience of experts and fundamentally diminishes subjectivity. Eq. (2) expresses the way to collect the risk data of CPC.

$$CPC_r^n = \frac{\sum_{i=1}^{6} D_{li}^i \times D_{im}^i}{6} \tag{2}$$

where r, li and im indicate the definition of risk ($risk = likelihood \times impact$). Moreover, CPC_r^n represents the risk data of the nth CPC, which are collected by multiplying each group of the severity data and the probability data correspondingly, and the average of the product is just the nth risk-based CPC data. Besides, the two parts data of each CPC both have six values, D_{li}^i and D_{im}^i represent the ith data of "likelihood" and "impact". This study collects 15 groups of risk data through a Likert scale ranging from 0 to 5, as shown in Fig. 3, and then 15 sets of CPC data are collected from the risk data after repeating the operation.

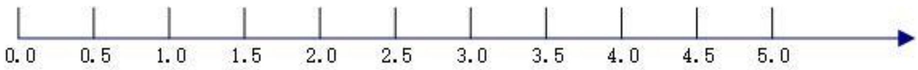


Fig. 3. Likert scale for risk data collection.

2.3. Fuzzy membership function construction based on risk data

Fuzzy logic is a type of many-valued logic in which the truth values of variables may be any real number between 0 and 1, considered "fuzzy" (Novk et al., 1999). Fuzzy logic is a useful tool that can effectively solve problems in an uncertain environment, especially in modeling processes that are too complex for conventional quantitative techniques or when the available information from the process is qualitative, inexact, or uncertain (Konstandinidou et al. 2006; Wang, 2012; Wang et al., 2009; Zhou and Thai, 2016). Fuzzy logic has been successfully used in many fields. Moreover, several kinds of prevalent fuzzy functions exist, including triangular, trapezoid, Gaussian, and bell-shaped. Among these functions, the trapezoidal fuzzy function is well-known for its high flexibility, which helps express different situations better. Therefore, the trapezoidal fuzzy function is chosen to describe the CPC and the level of each COCOM. According to the risk definition ($risk = likelihood \times impact$), the risk data of CPC is collected by Eq. (2) shown in Section 2.2, where D_{li}^{i} and D_{im}^{i} is collected by a Likert scale range from 0–5, so the CPC_r^n which represent the product of D_{li}^{i} and D_{im}^{i} range from 0 to 25. As a result, the nine trapezoidal fuzzy functions are defined with grade scopes ranging from 0 to 25 based on the risk data of CPC.

This approach constructs nine different fuzzy functions matched to each of the nine CPCs. Fuzzy statistical methods and expert judgment are always used to determine the expression of a fuzzy membership function. The fuzzy membership degree is calculated by the trapezoid membership function which is presented as Eq. (3).

$$\mu_{[a,b,c,d]}(x) = \begin{cases} 0 \ (x \leq a) \\ \frac{x-a}{b-a} \ (a \leq x \leq b) \\ 1 \ (b \leq x \leq c) \\ \frac{d-x}{d-c} \ (c \leq x \leq d) \\ 0 \ (x \geq d) \end{cases} \tag{3}$$

where the four parameters a, b, c, and d represent the abscissa of the four nodes of the trapezoidal fuzzy function. In addition, x represents the data of the fuzzy membership function; it acts as both the grade, ranging from 0 to 25, and the logarithm of COCOMs' probability interval, ranging from −5.3 to 0.

2.4. GRA based on the definition of risk

GRA is broadly applied in evaluating or judging the performance of a complex project with meager information (Senthilkumar et al., 2014). AHP is also a widely-used method to calculate the weight value, and it uses a standard scale to distinguish the weight level among different elements. However, in this study, there is no such as scale to let people realize which is the best or the worst risk-based CPC data, so GRA method is selected to calculate the CPC. GRA method is based on the relative importance concept which takes the best and the worst data as the relative maximum or minimum data to complete the analysis when there is no comparison standard. It involves five steps, shown in Fig. 4.

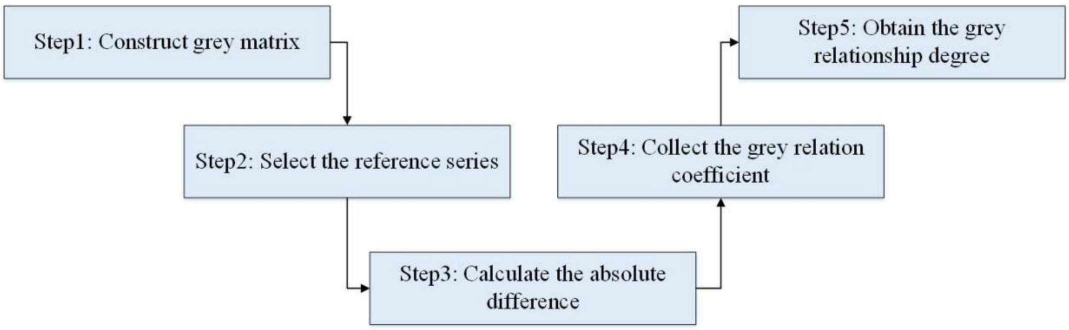


Fig. 4. Steps of GRA.

Step 1: To take the data collection work as the beginning, and to construct the grey matrixes which is expressed as Eq. (4).

$$T_G = \begin{pmatrix} T_1(1) & T_1(2) & \dots & T_1(n) \\ T_2(1) & T_2(2) & \dots & T_2(n) \\ \vdots & \vdots & \ddots & \vdots \\ T_m(1) & T_m(2) & \dots & T_m(n) \end{pmatrix} \quad (4)$$

where T_G is the grey matrix, $T_m(n)$, which represents the element for the *n*th criteria in the data series of the *m*th attribute, is defined by risk data.

Step 2: The reference series and each comparative series can be decided from the grey matrix. It is the set of the maximum or minimum data that are defined to be the reference series for the most part. The maximum data are selected to build reference series for this study. Eq. (5) shows the expression:

$$T_O = (T_O(1), T_O(2), \cdots, T_O(n)) \quad (5)$$

where T_O is the reference series. $T_O(n)$ represents the maximum data of the *n*th column in the grey matrix, and it also represents the maximum data in the *n*th criteria.

Step 3: To calculate the absolute differences between the reference series and other comparative series in this step. Eq. (6) shows the expression:

$$\Delta_{Oj}(k) = |X_O(k) - X_j(k)|, (k = 1,2, \cdots, a; j = 1,2, \cdots, b) \quad (6)$$

where the term $X_O(k)$ is the *k*th element in the reference series, $X_j(k)$ is the *k*th element in the *j*th comparative series, and $\Delta_{Oj}(h)$ is the absolute difference between them.

Step 4: Using Eq. (7) to calculate the grey relation coefficient as follows:

$$r_k^j = \frac{min_{1\le j\le b} min_{1\le k\le a} \Delta_{Oj}(k) + \delta \times max_{1\le j\le b} max_{1\le k\le a} \Delta_{Oj}(k)}{\Delta_{Oj}(k) + \delta \times max_{1\le j\le b} max_{1\le k\le a} \Delta_{Oj}(k)} \quad (7)$$

where r_k^j is the grey relation coefficient, while the terms $min_{1\le j\le b} min_{1\le k\le a} \Delta_{Oj}(k)$ and $max_{1\le j\le b} max_{1\le k\le a} \Delta_{Oj}(k)$ are the minimum data and the maximum data of each $\Delta_{Oj}(k)$, respectively. For δ ranging from 0 to 1, this method uses it as an identifier to make the difference of the grey coefficient for each element identifiable. Moreover, this method takes 0.5 as the value of this parameter, referring to the suggestion from most application cases and the designer of GRA.

Step 5: With the absolute differences and the grey relation coefficient determined before, the grey relationship degree can be calculated as follows:

$$G_j = \sum_{k=1}^{n} W_k \cdot r_j^k \quad (8)$$

Furthermore, the final grey degree for each attribute is calculated by Eq. (9).

$$G_j^{Con.} = G_j^{Likeli.} \cdot G_j^{Imp.} \quad (9)$$

where the term $G_j^{Likeli.}$ and G_j^{Imp} represent the relationship degrees of the likelihood and the impact, respectively, while $G_j^{Con.}$ is the final "risk-based" grey degree. Finally, the CPC weight is collected using Eq. (10) which is expressed in below.

$$\delta_i = \frac{G_j^{Con.}}{\sum_{n=1}^{9} G_j^{Con.}} \quad (10)$$

where the δ_i represents the weight of the nth CPC, and $G_j^{Con.}$ is the final "risk-based" grey degree.

2.5. HEP calculation

HEP value is the conclusion of the risk-based fuzzy CREAM method, it directly determines the practicability and efficacy of the proposed method. This study newly designed a valid approach to achieve the HEP calculation. This study collects the fuzzy membership degree based on the risk data of CPC and the risk-based fuzzy function, calculates the CPC weight according to the risk data of CPC, identifies every activated if-then rule, calculate the rule weight, and calculates the final weighted fuzzy degree of COCOMs. The HEP value is determined by considering the fuzzy degree of each CPC, the weight of each CPC, and the weight of each activated If-Then rule together.

2.5.1. Fuzzy membership degree collection

The fuzzy membership degree of CPC is the key operator that contributes to the final HEP result. This study establishes a fuzzy membership function based on risk data and decides the risk data of CPC as input to collect the fuzzy degree of CPC. Fig.5 lists the nine fuzzy functions constructed based on risk data match to 9 CPCs, then the fuzzy degree of CPC would be obtained by Eq. (3) once the risk data of CPC was taken into the function.

2.5.2. Calculation of CPC weight based on risk data

This study introduces fuzzy logic, and the trapezoidal fuzzy membership functions of this research are established based on risk data to calculate the fuzzy membership degree of CPC. Moreover, GRA is introduced to solve the issue of weight differences among the CPCs in this research, and the weight of CPC is assessed based on the risk data of CPC using Eq. (4) to Eq. (10).

2.5.3. If-then rule identification and weight calculation

The if-then rule does well in dealing with uncertainty. The rule base was established in combination with the fuzzy membership degree of CPC obtained in the previous step. Eq. (11) shows the common expression of a fuzzy if-then rule:

$$P_m\text{: if } (x_1\ is\ x_{m1}) \text{ and} \cdots \text{and, } (x_n\ is\ x_{mn}) \text{ then the answer goes to } C_m \text{ with the rule weight } W_{Pm} \tag{11}$$

where P_m is the *m*th activated fuzzy if-then rule, while x_1 represent the nine CPCs for this study. x_{m1}–x_{mn} denote the concrete corresponding fuzzy linguistic variables for all the CPCs, and C_m represents all kinds of the corresponding relationships between x_n and x_{mn}. W_{Pm} is the weight of the *m*th rule, which is calculated as Eq. (12) expressed.

$$W_{Pm} = \prod_{i=1}^{9} D_i \tag{12}$$

where D_i is the fuzzy membership degree of the *i*th CPC in the rule P_m.

2.5.4. Calculation of the final weighted fuzzy degree of COCOMs

In this section, the product-sum method proposed by Ung in 2015 is introduced to calculate the final weighted fuzzy degree of COCOMs with the initial weighted fuzzy degree of each activated rule's COCOM and each activated rule's weight. The initial weighted fuzzy degree of each activated rule's COCOM expresses each attribute's fuzzy degree and importance weight. To obtain the final weighted fuzzy degree of COCOMs, the initial weighted fuzzy degree of each activated rule's COCOM can be calculated using Eq. (13).

$$Z_{initial}^{n} = \sum_{i=1}^{p} Z_{Rn}(x_i) \cdot \delta_i \tag{13}$$

where $Z_{initial}^{n}$ represents the initial weighted fuzzy degree of each activated rule's COCOM for the *n*th activated fuzzy if-then rule, $Z_{Rn}(x_i)$ represents the 1st to *p*th CPC in the *n*th rule, and δ_i is the weight of the *i*th CPC.

Then, the final weighted fuzzy degree can be calculated with the initial weighted fuzzy degree of each activated rule's COCOM and each activated rule's weight in the fuzzy product-sum method shown as Eq. (14).

$$Z_{final}^{h}(X) = \sum_{n=1}^{m_h} Z_{initial}^{n} \cdot W_{Pm} \tag{14}$$

where $Z_{final}^{h}(X)$ is the final weighted fuzzy degree for the *h*th task, and $Z_{initial}^{n}$ represents the initial weighted fuzzy degree of the activated fuzzy if-then rules. It is m_h that represents the number of rules for *h*th task and W_{Pm} is the rule weight collected as the way Eq. (12) expressed.

2.5.5. Defuzzification

Through the procedures mentioned above, the final weighted fuzzy degree of each COCOM can be determined using the fuzzy risk data. In this section, the final HEP value is calculated by defuzzification. The most common defuzzification methods include the COA, maxima, Mean Of Maxima (MOM), Weighted Mean Of Maximums (WMOM), and Center Average Weighting (CAW) methods (Runkler and Glesner, 1993; Rao and Saraf, 1995; Runkler, 1996; Roychowdhury and Pedrycz, 2001; Ung and Shen, 2011). Owing to the relatively high level of accuracy, the COA method, shown as Eq. (15), is adopted to transfer the fuzzy results into the crisp value.

$$Log_{10}HEP = \frac{\sum_{i=1}^{n}[\int_{x_L}^{x_U} Z_i(x)xd(x)]}{\sum_{i=1}^{n}[\int_{x_L}^{x_U} Z_i(x)d(x)]} \tag{15}$$

where Z_i(x) represents the *i*th fuzzy membership function; x is the logarithm data of COCOM ranging from −5.3 to 0 in this study, and the upper and lower limits of the integration for Z_i(x) are respectively expressed by X_U and X_L. The crisp value of this study is transformed into the logarithmic value of HEP.

3. Case study

This study presents a comprehensive and rigorous approach to calculating the fuzzy CREAM and develops a modified method that ensures accurate and reliable results by utilizing 15 sets of risk data contributing to the risk data of nine CPCs. Then, the fuzzy membership functions and GRA are adopted to help complete the calculation of fuzzy CREAM. Finally, the COA method is also introduced to achieve the crisp HEP value and demonstrate the reliability of the modified method. All calculation processes of this study are completed with the assistance of MATLAB. The procedures adopted in this study comprise six steps, as shown in Fig. 1, involving applying and validating the modified fuzzy weighted CREAM.

3.1. Risk data collection

This study collects risk data as input and then obtains the fuzzy membership degree and the weight of each CPC. Some applications of CREAM are used to attain the data by expert scoring. However, the result would be greatly affected by the level and experience of the experts. Unlike the typical expert scoring mechanism, this study uses risk data as the data resource. Moreover, a hierarchical task analysis (HTA) is introduced to analyze the main work during the marine transportation of LNG, and the classifications are shown in Table 4. This study collects 15 sets of "risk data" based on the 15 tasks and the third task is selected to be the example for case study since the data of Task 3 are representative in the calculation process.

Table 4 Classifications of risk data.

Task No.	Name
1	Inspect each piece of safety-critical equipment to ensure that it is at the correct position.
2	Test the sensors and monitoring system to ensure that they are functional.
3	Check the LNG transfer arms, pipelines, valves, and flanges to guarantee that there is no leakage.
4	Maintain communication with the central control room, both at the LNG ship and at the LNG terminal.
5	Finish all documentation work and get it approved by both the LNG port and the LNG ship.
6	Start oil-loading arms one by one and move them toward the LNG ship.
7	Connect LNG loading arms one by one with manifolds at the LNG ship.
8	Periodically perform a safety inspection of the pipelines, valves, flanges, and transfer arms.
9	Continuously monitor the ship's conditions and maintain effective communication.
10	Control the transfer arms and move them toward the LNG terminal.

11	Vent all the remaining LNG in each transfer arm.
12	Deice the ice and disconnect each transfer arm with manifolds at the LNG ship.
13	Quickly install a blind flange and seal it on manifolds to avoid LNG leakage.
14	Locate the LNG transfer arms at the correct position and lock them.
15	Finish documentation work.

The CPC data are collected based on the definition of "risk." Risk was determined by "impact" and "likelihood." Thus, each group of risk data has the impact and likelihood, two groups of data, as Task 1 shows in Tables 5 and 6.

Table 5 Grey data of likelihood for Task 1.

CPC No.	Expert A	Expert B	Expert C	Expert D	Expert E	Expert F
CPC1	1.5	1	1.25	1.25	1.5	0.75
CPC2	0.5	0.5	0.25	0.25	0.5	0.5
CPC3	2	2	2.5	1.5	1.75	1.5
CPC4	1	1	0.5	0.75	1	0.5
CPC5	1.5	1	0.5	0.5	0.75	0.5
CPC6	1	1	0.25	0.25	0.5	0.25
CPC7	1.5	2	2	1.25	1.5	1.25
CPC8	1	1	0.75	0.5	0.75	0.75
CPC9	0.5	1	0.5	1	1.25	1

Table 6 Grey data of impact for Task 1.

CPC No.	Expert A	Expert B	Expert C	Expert D	Expert E	Expert F
CPC1	1.5	1.5	1.5	1.5	1.75	1.75
CPC2	2	2	2	2	1.5	1.5
CPC3	1.5	1.5	1.5	1	1.75	1.5
CPC4	2	2	2	2	2	2
CPC5	1.5	1.5	1.5	2	2.25	2.25
CPC6	1.75	1.5	1.5	1.5	1.25	1.25
CPC7	1.5	1.5	1	1	1	1
CPC8	2.5	2	2	2.5	2.25	2.25
CPC9	1.5	1.5	1.5	1	1.5	1

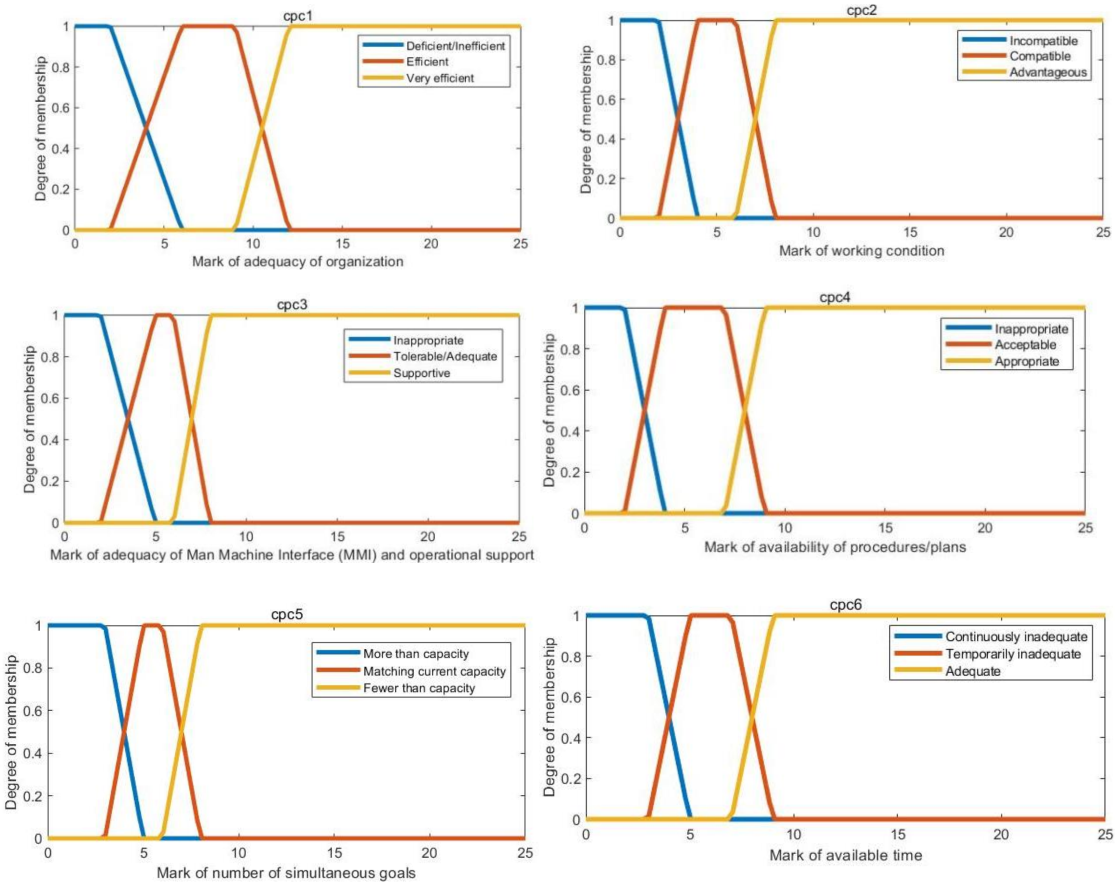
This study collects 15 sets of CPC data through Eq. (2) based on the 15 sets of risk data. The risk data of Task 1 is shown in Table 7. Then, the risk data of CPC are used as the data input to verify the proposed approach.

Table 7 CPC data based on risk for Task 1.

CPC No.	1	2	3	4	5	6	7	8	9
CPC data	1.91	0.75	2.76	1.58	1.39	0.82	1.88	1.77	1.15

3.2. Calculation of fuzzy CREAM

Next, the risk-based CPC data are taken to the modified fuzzy CREAM to calculate the HEP value. In the beginning, the construction of fuzzy membership functions is completed based on the risk data of CPC. Fuzzy logic has an excellent track record as a critical tool for dealing with a complex process coupled with uncertain factors. The trapezoidal fuzzy function is adopted in this study, among other popular ones, owing to its outstanding performance with massive calculations. Matching them with nine CPCs, this study constructs nine trapezoidal fuzzy functions, as shown in Fig. 5.



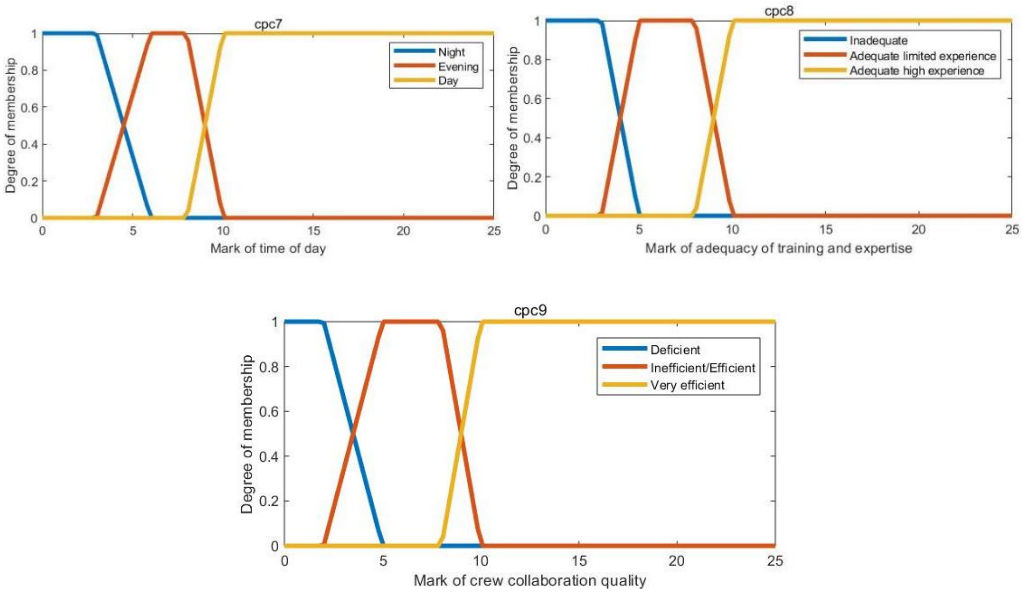


Fig. 5. Fuzzy membership functions constructed based on risk data.

Fuzzy membership functions effectively help describe the intricate impact of the environment on operators during LNG shipping. In the fuzzy membership function, the number of functions corresponds to the number of the CPC effect level. In each trapezoidal function, four abscissa joints are determined by the risk data of CPC; for instance, three trapezoidal functions match the three levels (deficient/inefficient, efficient, very efficient) in the fuzzy membership function of CPC 1; the four abscissa joints of the trapezoidal function of the level " deficient/inefficient " are (0, 0, 2, 6), the four abscissa joints of the trapezoidal function of the level "efficient" are (2, 6, 9, 12), and the four abscissa joints of the trapezoidal function of the level "very efficient" are (9, 12, 25, 25). Then, taking the risk data of CPC, the CPC data lie in different intervals and obtain different fuzzy membership degrees ranging from 0 to 1 by Eq. (3). With the nine different fuzzy membership functions constructed based on the risk data of CPC, the fuzzy membership degree of each CPC can be calculated, as the CPCs of the first task shown in Table 8.

Table 8 Fuzzy membership degree of CPCs for Task 1.

CPC No.	Fuzzy membership degree	Impact level
1	1/0	(Deficient, Inefficient)/Efficient
2	1/0	Incompatible/ Compatible
3	0.27/0.73	Inappropriate/ Tolerable
4	0.03/0.97	Inappropriate/ Acceptable
5	0/1	Matching/ Fewer
6	1/0	Continuously inadequate/ Temporarily inadequate
7	0/1	Evening/Day
8	0.05/0.95	Inadequate/ Adequate limited experience

9	1/0	Deficient/ Inefficient

Moreover, the weight of CPC can be calculated using GRA based on the calculation of risk data. Eq. (4) to Eq. (10) express the calculation process of the CPC weight. Table 9 lists the weight of CPC for the third task.

Table 9 CPC weight of Task 3.

CPC No.	1	2	3	4	5	6	7	8	9
Weight ($\times 10^{-2}$)	9.66	6.32	18.07	11.33	8.66	8.82	14.32	14.23	8.55

Next, to identify the if-then rules based on the fuzzy membership degree of CPC after the CPC calculation. As shown in Table 8, the fuzzy membership degree moves to 1, 0, or the two figures range from 0 to 1. Then, when p CPCs lead to two figures, the number of rules moves to 2^p. For example, in the third task, the third CPC, as well as the fourth and eighth CPCs, results in two fuzzy membership degree data, the input sample (1.33, 0.55, 3.06, 2.10, 1.04, 1.047, 1.71, 2.20, 1.25) activated eight rules, as shown in Table 10.

Table 10 If-then rules for Task 3.

Rule No.	CPC 1	CPC 2	CPC 3	CPC 4	CPC 5	CPC 6	CPC 7	CPC 8	CPC 9
Rule 1	1.00	1.00	0.27	0.03	1.00	1.00	1.00	0.05	1.00
Rule 2	1.00	1.00	0.73	0.03	1.00	1.00	1.00	0.05	1.00
Rule 3	1.00	1.00	0.27	0.97	1.00	1.00	1.00	0.05	1.00
Rule 4	1.00	1.00	0.73	0.97	1.00	1.00	1.00	0.05	1.00
Rule 5	1.00	1.00	0.27	0.03	1.00	1.00	1.00	0.95	1.00
Rule 6	1.00	1.00	0.73	0.03	1.00	1.00	1.00	0.95	1.00
Rule 7	1.00	1.00	0.27	0.97	1.00	1.00	1.00	0.95	1.00
Rule 8	1.00	1.00	0.73	0.97	1.00	1.00	1.00	0.95	1.00

This study constructs a rule base containing 145 if-then rules. The weight of the if-then rule is calculated based on the rule base and the fuzzy membership degree of CPC as the way Eq. (11) and Eq. (12) expressed. Table 11 shows the weights of the eight rules of the third task.

Table 11 Rule weight of Task 3.

Rule No.	1	2	3	4	5	6	7	8
Weight	3.42×10^{-4}	9.45×10^{-4}	1.28×10^{-2}	3.54×10^{-2}	0.66×10^{-2}	1.81×10^{-2}	2.46×10^{-1}	6.80×10^{-1}

Based on the if-then rule base, this method calculates the fuzzy membership degree and the weight of CPC (Table 8 and Table 9), as well as the initial weighted fuzzy degree of each activated rule's

COCOM, using Eq. (13). As the if-then rule of the third task presents, the initial degree of COCOM is listed in Table 12.

Table 12 Initial weighted fuzzy degree of COCOM for Task 3.

Rule No.	1	2	3	4	5	6	7	8
Initial degree	0.62	0.71	0.73	0.81	0.75	0.83	0.86	0.94

Afterwards, the final weighted degree of COCOM can be calculated with the initial weighted fuzzy degree of COCOM shown in Table 12 and the weight of each activated rule listed in Table 11. Eq. (14) is used to calculate it. The final weighted degree of COCOM for the third task is presented in Table 13. Table 14 shows the final membership degree of COCOM for all tasks of this study.

Table 13 Final weighted degree of COCOM for Task 3.

Rule No.	1	2	3	4	5	6	7	8
Final degree	2.1×10^{-4}	6.7×10^{-4}	9.3×10^{-3}	2.9×10^{-2}	4.9×10^{-3}	1.5×10^{-2}	2.1×10^{-1}	6.4×10^{-1}

Table 14 Final membership degree of COCOM for Task 3.

Task No.	Strategic	Tactical	Opportunistic	Scramble
3	0.91	0.09	0	0

3.3. Defuzzification

According to the HEP interval of each COCOM listed in Table 3, the fuzzy membership functions of each COCOM are constructed shown in Fig. 6. All 15 tasks are analyzed in the way shown as the third task. With the COA method, the final crisp Log_{10}HEP value for all the 15 tasks are calculated as shown in Table 15 and Fig. 7, using Eq. (15).

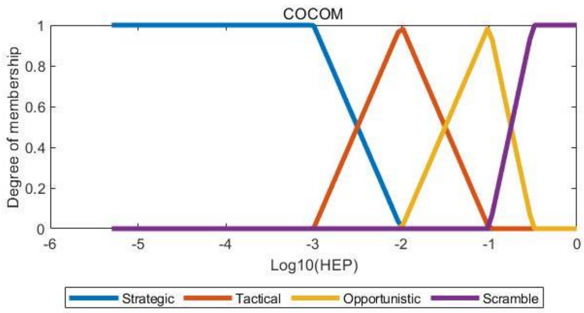


Fig. 6. Fuzzy membership function of COCOM.

Table 15 Final crisp value of HEP for the 15 tasks.

Task	Log_{10}HEP	HEP

Inspect each piece of safety-critical equipment to ensure it is in the correct position.	−3.87	1.33×10^{-4}
Test the sensors and monitoring system to ensure that they are functional.	−3.88	1.32×10^{-4}
Check LNG transfer arms, pipelines, valves, and flanges to guarantee no leakage.	−3.87	1.36×10^{-4}
Maintain communication with the central control room, both at the LNG ship and at the LNG terminal.	−3.89	1.30×10^{-4}
Finish all documentation work and get it approved by both the LNG port and the LNG ship.	−3.89	1.30×10^{-4}
Start the oil loading arms one by one and move them toward the LNG ship.	−3.03	9.38×10^{-4}
Connect the LNG loading arms one by one with manifolds at the LNG ship.	−2.48	3.30×10^{-3}
Periodically perform a safety inspection of the pipelines, valves, flanges, and transfer arms.	−3.88	1.32×10^{-4}
Continuously monitor the ship's conditions and maintain effective communication.	−3.89	1.30×10^{-4}
Control the transfer arms and move them toward the LNG terminal.	−3.87	1.35×10^{-4}
Vent all of the remaining LNGs in each transfer arm.	−3.84	1.43×10^{-4}
Deice and disconnect each transfer arm from the manifolds at the LNG ship.	−2.02	9.56×10^{-3}
Quickly install a blind flange and seal it on the manifolds to avoid LNG leakage.	−3.73	1.87×10^{-4}
Locate the LNG transfer arms at the correct position and lock them.	−3.89	1.30×10^{-4}
Finish documentation work.	−3.89	1.30×10^{-4}

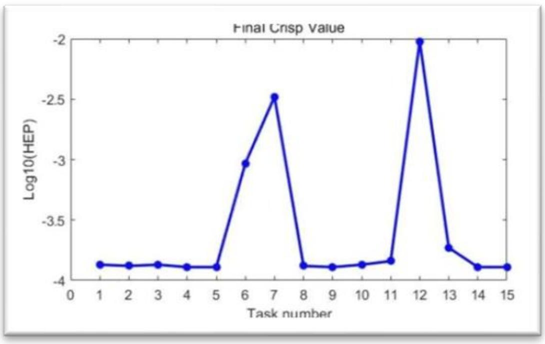


Fig. 7. Final Log_{10}HEP value of the 15 tasks.

The HEP, which stands for Human Error Probability, represents the probability of action failure. It is defined as the likelihood of unsuccessful or failed human performance under specific circumstances specified by the CPCs (Zhou et al., 2018). As shown in Fig. 7, the tasks with top three highest HEP values are respectively task 6 (Start the oil loading arms one by one and move them toward the LNG ship), task 7 (Connect the LNG loading arms one by one with manifolds at the LNG ship) and task 12 (Deice and disconnect each transfer arm from the manifolds at the LNG ship), which means existing hazards with high risk, and more effort must be made to deal with human-related risks during the complex process. Among them, task 6 and task 7 are related to the safety of the offloading process. While task 12 is vital to the safety marine transportation. For each of the three tasks, once some human-related error happened, there could be a leak or even an explosion at the terminal or on the ship. Thus, adequate measures must be taken to enhance the human reliability in the tasks.

Here are some recommended management measures for the three tasks in high risk levels. The first measure is to maintain equipment regularly, to increase staff training, and to perform regular appraisals. The second measure is to keep the speed of movement of the loading arm in a proper interval, to ensure the valid communication between the operators on the ship and terminal. The third measure is to add real-time video surveillance, ensure effectiveness of de-icing operations and introduce segmented communication technique. Lastly, the fourth measure suggests increasing job rotation to ensure the physical and mental condition of operators. The final HEP result has been applied to the work team of shipping LNG offloading, and the application result shows that after 3 months there is no recorded event and the work efficiency has improved about 30%.

4. Discussion

This study proposes a modified approach that incorporates CREAM with the definition of risk for source data collection, fuzzy theory for HEP estimation, and GRA for CPC weight calculation together. The improved CREAM model is applied to evaluate human reliability in real shipping LNG offloading work. Compared to traditional fuzzy CREAM method, the major highlights of the proposed method in this study are as follows:

1) The concept of risk is innovatively used as the support for CPC data collection, so as to address the lack of CPC data and to improve the explainability of CPC data;

2) Different from previous research, the collected risk data of each CPC in this study are used as the source data to determine CPC's fuzzy degree, CPC's weight, and the weight of each activated if-then rule by CPC;

3) The proposed approach in this study develops a hybrid fuzzy operation which integrates the fuzzy degree of each CPC, the weight of each CPC, and the weight of each activated if-then rule together to estimate HEP values;

4) The proposed method is practicable to real engineering cases.

Other methods such as IDHEAS and SPAR-H are also useful HRA methods, but they are designed for the nuclear industry, so they may not suitable for shipping LNG. As a result, the general industry used HRA method "CREAM" is finally decided to be as the main framework of this study.

Compared to the traditional fuzzy CREAM, the proposed method uses the definition of risk as the support for CPC data collection and CPC fuzzy degree determination, so that to improve the data quality and reliability, since it provides more dimensions (likelihood and impact) to collect and to explain data. However, in many other HRA methods, the support for source data collection is limited. Apart from the advantage in source data collection, the calculation process also improves the proposed method. As there is no certain standard to determine the different weights of each CPC, different from traditionally-used Analytic Hierarchy Process (AHP) method, the Grey Relationship Analysis (GRA) method is selected for CPC weight analysis in the proposed research to decrease subjectivity by using relative importance analysis. In addition, according to fuzzy theory, fuzzy if-then rule has weight on final result, and this study considers the weight of each activated fuzzy if-then rule for calculation. However, most previous research ignores this weight.

To better present the practicability and superiority of the proposed method, this study chooses traditional product-sum fuzzy CREAM approach as comparison to estimate HEP during shipping LNG offloading work. The final membership degree of COCOM and the HEP value of the proposed fuzzy CREAM and the traditional product-sum fuzzy CREAM are shown as Table 16 and Table 17 (where S and T respectively represent the COCOM level Strategic and Tactical) in bellow.

Table 16 Final COCOM level and HEP value of the risk-based fuzzy CREAM for the 15 tasks.

Task	COCOM level	HEP
1	S(0.95), T(0.05)	1.33×10^{-4}
2	S(0.97), T(0.03)	1.32×10^{-4}
3	S(0.91), T(0.09)	1.36×10^{-4}
4	S(1), T(0)	1.30×10^{-4}
5	S(1), T(0)	1.30×10^{-4}
6	S(0.36), T(0.64)	9.38×10^{-4}
7	S(0.12), T(0.88)	3.30×10^{-3}

8	S(0.98), T(0.02)	1.32×10^{-4}
9	S(1) ,T(0)	1.30×10^{-4}
10	S(0.93), T(0.07)	1.35×10^{-4}
11	S(0.81), T(0.19)	1.43×10^{-4}
12	S(0.08), T(0.92)	9.56×10^{-3}
13	S(0.75), T(0.25)	1.87×10^{-4}
14	S(1), T(0)	1.30×10^{-4}
15	S(1), T(0)	1.30×10^{-4}

Table 17 Final COCOM level and HEP value of the traditional fuzzy CREAM for the 15 tasks.

Task	COCOM level	HEP
1	S(0.94), T(0.06)	1.32×10^{-4}
2	S(0.94), T(0.06)	1.30×10^{-4}
3	S(0.83), T(0.17)	1.49×10^{-4}
4	S(1), T(0)	1.30×10^{-4}
5	S(1), T(0)	1.30×10^{-4}
6	S(0.74), T(0.26)	1.87×10^{-4}
7	S(0.56), T(0.44)	3.00×10^{-4}
8	S(0.89), T(0.11)	1.30×10^{-4}
9	S(1), T(0)	1.30×10^{-4}
10	S(0.89), T(0.11)	1.31×10^{-4}
11	S(0.83), T(0.17)	1.32×10^{-4}
12	S(0.13), T(0.87)	3.00×10^{-3}
13	S(0.81), T(0.19)	1.69×10^{-4}
14	S(1), T(0)	1.30×10^{-4}
15	S(1), T(0)	1.30×10^{-4}

As shown in Table 16 and 17, the COCOM level and HEP value of the proposed fuzzy CREAM method are close to the traditional fuzzy CREAM. Besides, the outcomes of the two approaches both show that Task 6, 7 and 12 have the top three highest risk levels. All in all, the comparison indicates the feasibility, reliability, and explainability of the proposed risk-based fuzzy CREAM.

Although the proposed method has many advantages, still there are some issues that should be addressed. For the source of data, although using risk data to replace the traditional way is commendable, the recording work on CPC should be continuously carried out for HRA application in the future. In addition, as human behavior has uncertainties, when individuals perform a task, they may not strictly follow the designed procedures, so it is necessary to promote the mathematical method to consider human behavior, to express uncertainties, and to express human-machine interaction. Furthermore, software method should be developed to make this proposed method can be practiced friendly in real industry.

5. Conclusion

This study analyzes the human reliability during shipping LNG offloading work, The proposed method firstly divides the entire offloading task into 15 key human-related tasks by HTA, and then adopts a risk-based modified fuzzy CREAM to estimate the HEP values. The proposed method innovatively uses the risk data of each CPC as the source data to determine CPC's fuzzy degree, CPC's weight, if-then rule weight, COCOM degree, and final HEP value with a more reasonable mathematical way. Through the proposed method, it indicates that the sixth task, the seventh task, and the twelfth task are the top three risky tasks with the highest HEP values 9.38×10^{-4}, 3.30×10^{-3}, and 9.56×10^{-3}.

It shows that during the connection and disconnection task in shipping LNG offloading work, operators have high probability to make errors. Therefore, some particular work should be done. For instance, operators need to receive more targeted training on transfer arm connection and disconnection; adopting communication skill training to ensure efficient and accurate communication. In addition, shipping LNG offloading work procedures should be reviewed, modified, and practiced to ensure safe operations.

Although using risk data as the source for HEP estimation is beneficial for HEP estimation during risky and complex tasks, as mentioned in the discussion, this study still needs improvements. Therefore, in future studies, the type-II fuzzy theory, the safety-II theory, and the currently proposed method could be integrated together to express uncertainties of human behavior and human-machine interactions. In addition, it is necessary to design a computer-based software way for people to collect CPC data, to analyze CPC data, and to calculate HEP value, not only for shipping LNG offloading work, but also for broader applications.

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