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# A Human-Centered Risk Model for the Construction Safety

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**ABSTRACT** The paper aims at quantifying the human errors in the construction work and analysing their potential impact on the construction accident. It proposes to analysis the risks in the construction safety with the human reliability analysis (HRA) method. The paper adopted a fuzzy Bayesian network (BNN) approach to incorporate the cognitive reliability and error analysis method (CREAM), which is one of the representative HRA method, into the construction safety analysis. This fuzzy BNN was developed into a human-centered risk model. The model used the intuitionistic fuzzy sets (IFS) to represent the expert's judgment and generated the probability distribution by the mass assignment theory. A case study on the fire accident in the construction of Xiamen Metro Line 2 in China was provided. The model has proved to be able to analysis the construction accident from the human factor perspective and elicit meaningful quantification results.

**INDEX TERMS** Cognitive science, construction, human factor, safety management.

## I. INTRODUCTION

The construction industry is considered as one of the most significant contributors to the Gross Domestic Product (GDP) for most industrialized and developing countries [1]. In China, the GDP from building construction was 6180.8 billion RMB in 2018, which accounted for 6.87% of the total GDP of the whole year [2]. In the first half of the 2018, there were 85933 Chinese construction enterprises taking construction activities. The number of Chinese construction industry employees was up to 4.4 million over the same period. However, the large demand of new housing construction comes up with the increasing risks to the construction safety. The construction worker may take risky behaviour in the practical operations and these behaviours can eventually lead to the catastrophic accidents [3].

A series approaches have been taken to assess and manage the risks in the construction safety. For example, Tam *et al.* [4] identify the weaknesses in the safety management for the construction project. These weaknesses include but not limited to the poor safety awareness, the lack of training and so on. Zou and Wang [5] take a broad view on

the risks in construction projects and emphasizes on the risk management strategies. The work of Shao *et al.* [6] reveals the accident pattern for the building construction and covers aspects such as the timing and the geographic condition for the accident. To manage the potential risks in the safety construction, more advanced approaches such as the building information modelling (BIM) [7], [8], unmanned aerial vehicle (UAV) [9], [10], etc., have been proposed and applied in practice. The general trends in the construction safety analysis that revealed in these studies includes the access and analysis of the huge data [7], [11], the collaborations and interaction between human and machine [9], [12] the comprehensive evaluation over both spatial and temporal information [7] and so on. All these studies have deepened the understanding of risks associated with the construction work. Nevertheless, it remains certain critical issues for analysing risks in construction project that need to be answered.

Firstly, most relative studies are focus on qualitative analysis, such as identifying the potential risks in the construction work, but without conducting quantitative evaluations on these risks. Actually, in a well-developed risk analysis model, the quantitative risk analysis can provide necessary support for making decision and guide the future projects. The lack and even omit of the quantitative risk analysis can lead the

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imprecision of the safety analysis. Without the quantitative analysis, it cannot determine whether the system meets the quantitative standard or not. Also, in the engineering, the requirement of design and the determination of the safety envelope are all based on the quantification results from risk analysis.

Another unsolved issue is the less attention on the human factors and their influences on the construction risk. As the technology improvements in the engineering fields, the interactions between human and machine are becoming more and more frequent. Consequently, besides the unsafe conditions such as the hazards in the construction site, the unsafe act of the construction worker is becoming a more prominent reason for the incident to happen [3]. Under this circumstance, it is necessary and important to incorporate the human factors into the risk analysis for construction safety.

The major motivation of this study is to solve the above two issues. Generally, the quantitative method in risk analysis combines two quantitative components: the probability of the risk occurring and the size of the risk impact. Our study focuses on the first component as producing the risk probability rather than the second component as evaluating the risk severity. In addition, the quantitative risk analysis is also referred to the probabilistic risk assessment (PRA), probabilistic safety assessment (PSA), concept safety evaluation (CSE) and total risk analysis (TRA). As there is no clear distinction between the definitions of these references, the PRA would be used to refer all these quantitative risk analyses in this study.

To incorporate the human factors into the construction risk analysis, the human reliability analysis (HRA) is introduced into this study. The HRA is viewed as a necessary part in a comprehensive PRA model and determines the human errors in both the qualitative and quantitative ways. A typical HRA method can identify the risks in the task context, which are usually named as performance shaping factors (PSFs), and produce the human error probability (HEP) with the math model [13]. The real challenges in evaluating human factors come from both the natural uncertainty in human behaviour and the data scarcity in the relative field. To tackle the challenges, two promising approaches have been widely used in the HRA study: the Bayesian belief network (BBN) and the fuzzy expert system (FES) [14]. As a probabilistic graph model, the BBN takes Bayesian inference for probabilistic computation. The BBN is favored by HRA study because of its ability to represent complex relationship between PSFs and combine multiple information resources [15]. By contrast, the FES is designed to help experts make judgement under a non-probabilistic framework and represent the uncertainty when very limited information can be offered.

In this study, the cognitive reliability and error analysis method (CREAM) [16], which is one of the representative second-generation HRA method, has been modified to analyse the human performance in the construction work. The cognitive analysis in CREAM is following a causal reasoning process. This process evaluates human performance in a

specific task based on the PSFs in task context and exactly fits with the causal relationship in BBN. Also, like most HRA methods, the CREAM is heavily relied on the expert judgements. Due to the inherited subjectivity in human interpretation, such judgements can be biased when translating to probability directly. Promisingly, the fuzzy processing offers an applicable way to solve this issue. Using fuzzy set, the ambiguity and uncertainty in expert's opinion can be fully represented. In general, to apply the HRA in construction safety analysis, we have designed a fuzzy BBN model based on the analytical structure in the CREAM method. The model follows a possibility to probability transformation framework [17] and making Bayesian inference on human performance with the experts' opinions. Specifically, in the practical application, the experts' judgement are collected and represented them as fuzzy numbers in the fuzzy set. Then, using the mass theory [17], the membership function of the fuzzy number (possibility) are transformed to the prior probability of PSFs. Taking advantage of the causal reasoning in BBN, the worker's HEP can be quantified under different PSFs in the construction task. Furtherly, the HEP is included into the probabilistic risk model for evaluating the construction safety and producing the probability of having an accident.

This article is structured as follows: The fundamental theory supporting this study and the model reasoning processes are presented in the Section II. Section III firstly introduces the HRA into the risk analysis of construction safety and then, based on the HRA method CREAM, moves on to develop a fuzzy BBN risk model on quantifying the HEP and the probability of construction accident. In the Section IV, a case study with accident in the tunnelling construction is used to demonstrate the applicability of the proposed risk model. Section V concludes the contribution, the limits and the future work of this study.

## II. METHODOLOGY

Three methodology are reviewed in this section. The first method is BBN. In our study, the BBN is mainly for building the model structure. The BBN constructs the probabilistic graphical model for the critical factors in construction safety, such as the PSFs, the human error, the construction accident, based on the causal relationship between them. Once the nodes in BBN have been determined, the probability inference can be conducted. The second method is the fuzzy set and possibility theory. The fuzzy set is used to represent the uncertainty in experts' opinion and the possibility is the measurement of the uncertainty. Specifically, the intuitionistic fuzzy set (IFS) is used here as it offers a more general way to represent the uncertainty and vagueness [18]–[20]. To convert the possibility to the probability, the third method as the mass theory (possibility-probability transformation) is introduced into the study. Using the mass theory, the experts' opinions being represented as fuzzy set can be incorporated into the BBN as prior probability for further analysis.

### A. BAYESIAN NETWORK

The BNN is a probabilistic directed acyclic graphical model that combines the two different math areas: the graph theory and the probability theory [21]. In the BNN, the node represents a random variable and the link between two variables represents a dependence between them. For each node in the BNN, it is conditional independent of its non-descendant nodes whenever given its parent nodes. Taking advantage of this local conditional dependence, the BNN can factorize the joint probability distribution into small set of factors. Specially, let  $G$  be a BNN graph over the variables  $X_1, \dots, X_n$ , then a joint distribution  $P$  over the same space factorize according to  $G$  can be expressed as a product:

$$P(X_1, \dots, X_n) = \prod_{i=1}^n P(X_i | Pa_{X_i}^G). \quad (1)$$

where  $Pa_{X_i}^G$  is the parent nodes of  $X_i$ .

The BNN is able to incorporate multiple information sources and make reasoning under uncertainty. This reasoning is achieved with the Baye's theorem, which indicates that to update the belief in the hypothesis  $H$  with given evidence  $E$ , the conditional probability  $P(H|E)$  can be computed from the "inverse" conditional probability  $P(E|H)$  and is described as the following equation

$$P(H|E) = \frac{P(E|H)P(H)}{P(E)}. \quad (2)$$

where the  $P(E)$  and  $P(H)$  are the prior belief in  $E$  and  $H$  respectively. In the BNN reasoning analysis, both the forward and backward reasoning can be performed. The forward analysis is followed the directed path between the root node and the leaf node while the backward analysis is towards the opposite direction. In the practical use of BNN for PRA, the forward reasoning can determine the probability of the occurrence relative to different incidents and accidents in the engineering system. By contrast, the backward analysis is taken to determine the relative factors' effects on the risk.

When it comes to the application of BNN in PRA, three basic stages need to be taken. The first stage is to identify the variables corresponding to the risks and the relative influencing factors. In addition, the causal relationships between the variables have to be determined in this stage. The second stage is to specify the condition probability for each variable given its parent variable. This process needs to combine different data sources such as the empirical data, the theoretical model and the expert judgement. The third stage is inference. In this stage, the input data is entered into the BNN and the probabilities for all the nodes are calculated based on the causal relationships.

### B. FUZZY SET AND POSSIBILITY THEORY

The concepts of fuzziness and probability are related. The probability theory is measuring the uncertainty arising from the lack of knowledge relating to the concepts while the fuzzy set theory is characterizing the uncertainty due to

inherent vagueness in concepts themselves. The fuzziness is viewed as a type of deterministic uncertainty that describes the event class ambiguity and measures the degree to which an event occurs. According to the theory of fuzzy sets raised by Zadeh [22], [23], a fuzzy set  $S$  is a collection of elements in a universe of information whose elements have degrees of membership and can be defined by the following:  $S = \{ \langle x, \mu_S(x) \rangle | x \in X \}$ , where  $\mu_S$  is the membership function of the fuzzy set  $S$  and valued in the real unit interval  $[0,1]$ . Obviously, the non-membership function of  $x$  to  $S$  is defined as  $\nu_S(x) = 1 - \mu_S(x)$ .

Considering the lack of knowledge of whether the  $x$  belongs to  $S$  or not, the IFS theory has introduced another degree of uncertainty into a set description. An IFS  $A$  in  $X$  is defined by the following:  $A = \{ \langle x, \mu_A(x), \nu_A(x) \rangle | x \in X \}$  where  $\mu_A(x)$  and  $\nu_A(x)$  denote the degree of membership function and non-membership function of  $x$  to  $A$  with the condition  $0 \leq \mu_A(x) + \nu_A(x) \leq 1$ . In the IFS  $A$ , the degree of uncertainty can be defined as the intuitionistic fuzzy index  $\pi_A(x) = 1 - \mu_A(x) - \nu_A(x)$ . For each  $x \in X, 0 \leq \pi_A(x) \leq 1$ .

As an extension on the fuzzy set theory, the possibility theory offers an alternative to probability when dealing with uncertainty. The possibility measures the degree to which an event is feasible and can be used to quantify the likelihood of this event would occur. Specifically, if  $A$  is a fuzzy subset of a finite universe  $\Omega$  that is characterized by its membership function  $\mu_A$ , then a proposition of the form "X is A" induces a possibility distribution  $X$ . There are two distinct features in the possibility theory. Firstly, the first elements in  $A$  is totally possible for the proposition. Secondly, each subsequent element has a smaller degree of possibility of being  $A$ .

### C. POSSIBILITY-PROBABILITY TRANSFORMATION

As described in the last subsection, there is a structural difference between the probability and the possibility measures. The probability has fully taken advantage of the algebraic structure of the unit interval. The uncertainty described by the probability is additivity. For example, in a system constituting of identical independent components, the probability for an event as one component being failure and its complement must add up to one. Also, the failure probability of the system increases with the number of components in it. By contrast, the possibility measures use the unit interval as a total ordering. Still taking the system and its components as an example, the possibility of the system failure is equal to the failure possibility of one component.

To fuse the uncertain information from the two different resources, it is necessary to adopt an automated reasoning procedure. In this study, the mass assignment theory has been taken to transform the possibility to the probability [17]. The crucial idea in the mass assignment theory is offering a normalised fuzzy subset  $A$  of the  $\Omega$  and generating a family of probability distribution on  $\Omega$ . In this distribution family, each distribution corresponds to some redistribution of the masses associated with sets to elements of those sets.

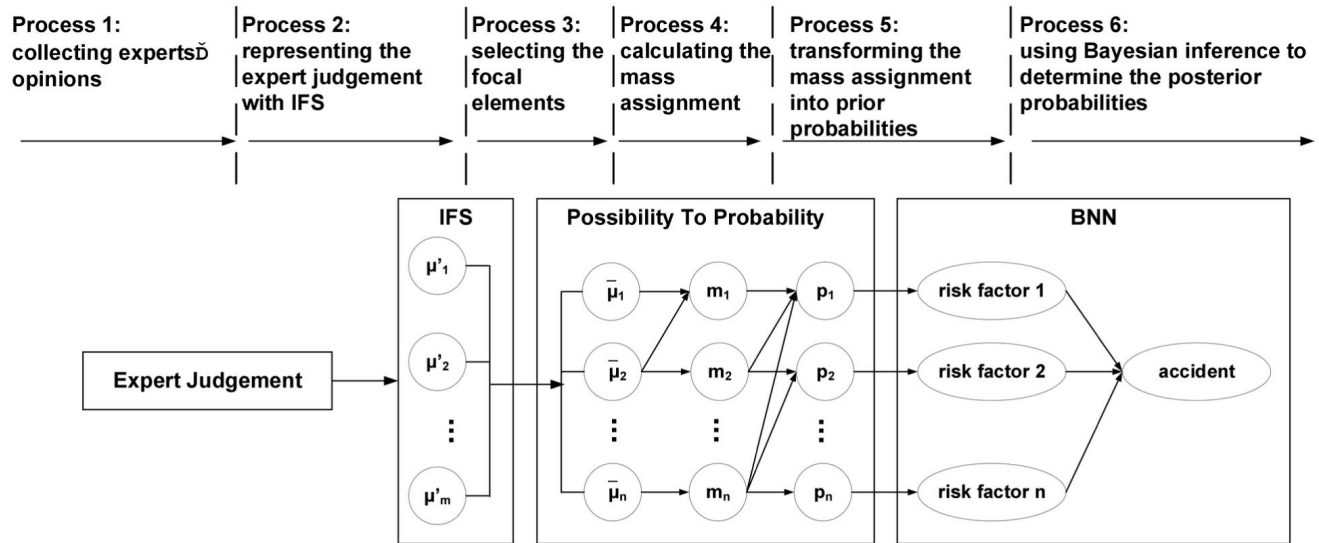


FIGURE 1. The reasoning process of the risk model.

The possibility probability transformation process in mass assignment theory can be explained with the discrete fuzzy set  $A$  mentioned in the last subsection. In this case, the focal elements in  $A$ , which are the elements with the positive membership degrees, are selected into a normalized set  $\bar{A}$  and reorganized based on their corresponding membership degree in descending order. Then the mass assignment (MA) for the  $\bar{A}$  denoted  $m_{\bar{A}}$  is a probability distribution on  $2^{\Omega}$  and can be derived with the following equation:

$$m_{\bar{A}(F_i)} = \bar{\mu}_i - \mu_{i+1}. \quad (3)$$

where  $F_i = \{x \in \Omega | \mu(x) \geq \mu_i\}$ , for  $i=1, \dots, n$ . After converting a fuzzy set into a MA, the least prejudiced probability of  $A$  is given by the following:

$$lp_{\bar{A}}(x) = \sum_{F_i: x \in F_i} \frac{ms(F)}{|F|}. \quad (4)$$

where  $|F|$  denotes the module of  $F$ .

#### D. A FUZZY BBN APPROACH

While using expert judgements in risk analysis, as Bayesian probabilities cannot adequately model ignorance, imprecise or qualitative judgements of uncertainty, or vague predicates in natural language, the fuzzy theory has natural advantages in representing ambiguous information and subjective knowledge. Taking the MA as intermediate variable, the representation of fuzzy sets can be further transformed into probability distribution for Bayesian inference. In this subsection, a fuzzy BBN has been proposed to offer an analytical framework for the risk analysis in construction safety.

The Fig. 1 demonstrates the four major modules in the flow chart of the fuzzy BBN approach. These modules are the expert judgement, the IFS, the possibility to probability transformation and the BNN. To complete the reasoning from

one module to another, six basic processes need to be taken. The first process is to collect experts' opinions on the relative factors. In the second process, these opinions are represented with the IFS as the degree of membership  $\mu$  and the uncertainty  $\pi$ . Then, the corresponding possibility distribution to the fuzzy set can be determined. The possibility to probability transformation includes three processes as selecting the focal elements from the fuzzy set, calculating the MA with Eq. (3) and transforming the MA into the least prejudiced probability with Eq. (4), which would be used as the prior probabilities for the risk influencing factors in the BBN. The last process is conduct probability reasoning with the BBN.

### III. RISK MODEL FOR CONSTRUCTION SAFETY WITH HUMAN FACTOR

#### A. INCORPORATING THE HRA INTO THE RISK ANALYSIS

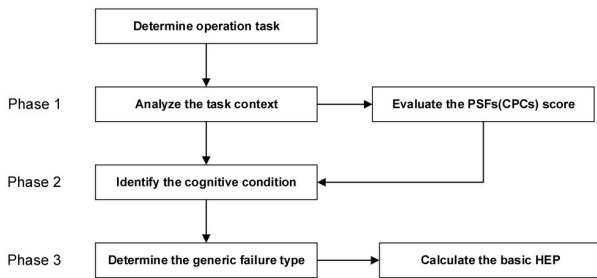
As described in the Section I, the risk analysis plays an important role in evaluating and improving the construction safety. Also, among all the risk influencing factors, the unsafe act of the construction worker can produce direct and significant impact on the construction accident. To build a risk model for construction safety with human factor, the HRA offers promising tools and strategies.

Since the very beginning of human reliability studies, the primary purposes of HRA have been settled as identifying, quantifying and eliminating human errors in the operation tasks. To reach this purpose, various HRA modelling approaches have been put forward to determine the HEP. For example, to obtain the quantified HEP, the Technique for Human Error Rate Prediction (THERP) uses the PSFs that related to the current task to modify the nominal HEP. By contrast, the Success Likelihood Index Method (SLIM) has combined the effects of PSFs into a single index, the success likelihood index (SLI), and converting the SLI values to

probabilities with a linear logarithmic function. The Human Cognitive Reliability (HCR) takes a rather unique approach as building a time-related model. The HEP in HCR is equal to the probability of non-response time of the operator and decreases with the available time in the task. Among all the efforts have been made in the development of HRA, one that marks a watershed is introducing the cognitive model into the HEP quantification [24], [25]. The HRA methods based on cognitive model are viewed as the second generation HRA methods, which are differed from the first generation HRA methods that not considering the cognitive activity of the operator. As a representative method of the second generation HRA methods, the CREAM offers both the rough estimations for the probability interval of action failure and the accurate quantifications of the HEP value [26].

**B. DESCRIPTION OF THE BASIC CREAM**

The CREAM method, which was introduced by Hollnagel [15], [27] is frequently used in the safety field. As described by its developer, there are two versions of CREAM: the CREAM I and the CREAM II. The CREAM I is the basic version of CREAM and uses screen technique to offer HEP intervals. The CREAM II is the extended version of CREAM and operates at a fine-grained level. In this study, the CREAM I, or the basic CREAM, is taken to analysis the construction risk.

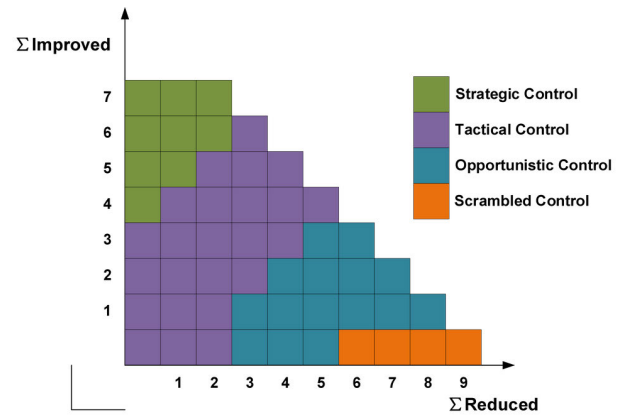


**FIGURE 2. The analytical phases in the CREAM.**

As indicated in the Fig. 2, the basic CREAM follows three general phases to make inference on the human error. In the first phase, the analyst has to give a broad evaluation on the context for the targeted task. Specifically, nine PSFs have to be evaluated (it has to be noted that the CREAM uses common performance conditions (CPCs) as the name for PSFs, as there is no significant difference between the meaning of these two names, the PSFs would be used when referring to the CPCs in this study). As shown in the Table 1, each PSF is assessed with its level and corresponding effect on the operator’s performance. The evaluation result on the task context is presented with the overall PSFs score. This score is translated by the number of PSFs with improved and reduced effects using Eq. (5):

$$PSFs\ score = (reduced\ PSFs, improved\ PSFs). \quad (5)$$

The second phase is about converting the PSFs score into the operator’s contextual control mode (COCOM).



**FIGURE 3. COCOM determination in CREAM.**

In CREAM, four operator’s COCOMs are used to describe the characteristic in accordance with the human cognition and task context. strategic control, the tactical control, the opportunistic control and the scrambled control. As indicated in the Fig. 3, one of COCOMs can be selected with the PSFs score. Specifically, the process for this determination is defined as follow: firstly, the effect for each PSF is assessed; secondly, based on the assessment, each PSF is classified into one of the three types: positive (improved), negative (reduced) or neutral (not significant); thirdly, following Eq. (5), the numbers of the PSFs with improved and reduced effects are counted and expressed as the PSFs score; finally, one of the four COCOMs, which are the strategic control, the tactical control, the opportunistic control and the scrambled control. In the last phase, each COCOM is assigned with a task failure probability interval. Furtherly, the nominal HEP for the COCOM can be obtained using a Weighted Mean of Maximum method as 2.24e10-4, 0.01, 0.0708 and 0.316, respectively [27].

**C. A BBN VERSION OF CREAM**

The application of BBN in HRA has received increasing attentions [15], [28]. Actually, the causal reasoning in the network is in consistent with the quantification strategy used in most existing HRA method. Based on this consistency, the original CREAM can be transferred into a BNN. In the existing CREAM, the reasoning processes for determining the control mode with the PSFs can be explained by a series discrete function. For each of this function, a corresponding local BNN can be defined. The conditional probability table (CPT) for the BNN follows the Boolean logic in the discrete function. With combining all the local BNNs in accordance with the reasoning processes of the original CREAM, a BBN version of CREAM is built. The CREAM BNN determines the probability distribution of the control modes with assigning the probability distribution of the PSFs.

The procedures in building the BBN consists of the following four steps. One thing to be noted is that the following steps

TABLE 1. The PSFs (CPCs), PSFs’ levels and effects on human performance.

PSFs (CPCs)	Description	Level	Effects
Adequacy of organization	The process of organising, planning, leading and controlling when doing operations during task. Effect of organisation, supervision and administration.	Very efficient	I
		Efficient	NS
		Inefficient	R
		Deficient	R
Working conditions	Work stress, task characteristics when carrying out the operation.	Advantageous	I
		Compatible	NS
		Incompatible	R
Adequacy of MMI and operational support	The accessibility of the machine controls; the ergonomic design in the workplace.	Supportive	I
		Adequate	NS
		Tolerable	NS
		Inappropriate	R
Availability of procedures/plans	The procedures and plans include operating and emergency procedures, familiar patterns of response heuristics, routines, etc.	Appropriate	I
		Acceptable	NS
		Inappropriate	R
Number of simultaneous goals	The number of tasks a person is required to pursue or attend to at the same time.	Fewer than capacity	NS
		Matching current capacity	NS
		More than capacity	R
Available time	The time available to carry out a task and corresponds to how well the task execution is synchronised to the process dynamics	Adequate	I
		Temporarily inadequate	NS
		Continuously inadequate	R
Time of day (circadian rhythm)	The time at which the task is carried out, in particular whether or not the person is adjusted to the current time (circadian rhythm).	Day time	NS
		Night time	R
Adequacy of training/experience	The quality and effect of training; the knowledge, skills and experience of the operator.	Adequate (high experience)	I
		Adequate (low experience)	NS
		Inadequate	R
Crew collaboration quality	The quality of the collaboration between crew members, including the level of trust, the communication and the general social climate among operators.	Very efficient	I
		Efficient	NS
		Inefficient	R
		Deficient	R

Note: Improved: I; Not significant: NS; Reduced: R.

are for illustrating the reasoning process in the CREAM BBN and all the specific numbers are only for explanation but not from real cases:

1) PRIMARY EFFECTS OF THE PSFs

The first step is to determine the primary effect of the PSF with a discrete function  $g_i$  ( $i=1, 2, \dots, 9$ ). The  $g_i$  is defined as  $g_i : X_i \rightarrow E_i$  ( $i=1, 2, \dots, 9$ ), where  $X_i$  is the level of the  $i$ th PSF and  $E_i$  is the set of primary effects for the  $i$ th PSF, which consists of three states: reduced, not significant, improved. In the original CREAM, there is a deterministic relationship for converting different level of PSFs into different effects on the PSF’s performance reliability. As indicated in the Fig. 4, the deterministic relationship between the  $i$ th PSF and the  $i$ th primary effect can be characterized with a BBN.

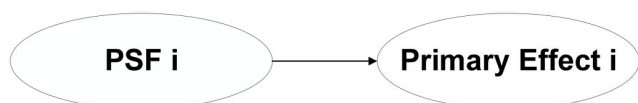


FIGURE 4. The local BBN for determining the  $i$ th PSF’s primary effect.

Take the PSF1, the adequacy of organization, as an example, the  $X_1$  is defined as Very efficient, Efficient, Inefficient, Deficient. Specifically, when the PSF1 is considered as very efficient, the expected effect on the performance reliability would be improved. The relationship between all the different levels of PSF1 and the expected effects is described with the CPT showed in Table 2.

TABLE 2. The conditional probability table corresponding to  $g_1$ .

Level/descriptors( $X_1$ )	Expected effect (E)		
	Improved	Not significant	Reduced
Very efficient	1	0	0
Efficient	0	1	0
Inefficient	0	0	1
Deficient	0	0	1

2) ADJUSTED EFFECT OF THE PSFs

One of the advantages in CREAM is taking the dependences between PSFs into consideration. Correspondingly, the PSFs’ effect has to be adjusted based on the dependencies among them. For example, referring to the Hollnagel’s analysis, the PSF9 as the crew collaboration quality, can be affected by the PSF1 as the adequacy of organization and the PSF8 as the adequacy of training and experience. Consequently, besides the primary effect of the PSF9 itself, the adjusted effect of PSF2 is determined by other PSFs. As indicated in the Fig.5, the causal relationship between the adjusted effect of PSF9 and the primary effects of the related PSFs is described as a BNN.

According to the rule for adjusting PSFs in the original CREAM method, the CPTs corresponding to the dependencies are determined. Still taking the PSF9 as an example, when its primary effect is considered as not significant, this effect has to be adjusted with the synergic effect of the PSF1 and PSF8. As indicated in Table 3, the PSF9’s primary effect would either be changed to improved or reduced if both the PSF1 and PSF8 point in the same direction.

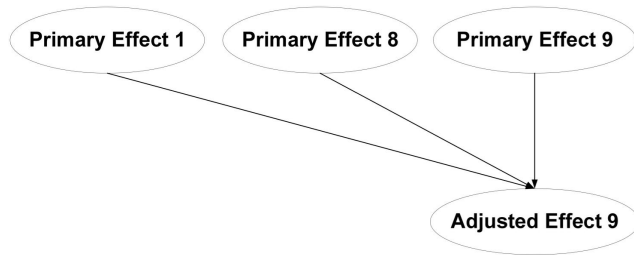


FIGURE 5. The local BNN for adjusting the PSF9’s effect.

TABLE 3. The conditional probability table for adjusting the PSF9’s effect.

PrimaryEffect9	PrimaryEffect1	PrimaryEffect8	AdjustedEffect9	
NS	I	I	I	
		NS	NS	
	NS	R	NS	
		I	NS	
	R	NS	NS	
		R	NS	
	R	I	NS	
		NS	NS	
			R	R

Note: Improved: I; Not significant: NS; Reduced: R.

### 3) EVALUATING THE PSFs SCORE

After adjusting the PSFs’ effects, the PSF5 is expected to have a positive effect in certain conditions. As a result, the number of permutations on the set of PSFs’ effects changes to 54. As indicated in the Fig. 6, the adjusted effect of PSF5 leads two extra combinations of the PSFs score.

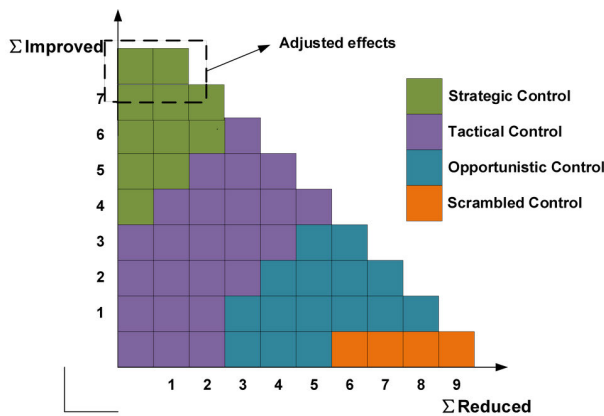


FIGURE 6. COCOM determination in CREAM after adjustment.

The third step is determining the PSFs score from expected effects on performance reliability of the nine PSFs. To simplify the number of input parameters, the PSFs are divided into three groups at the first place. The first group consists of the PSF1 as the adequacy of organization, the PSF2 as the working conditions and the PSF3 as the adequacy of MMI and operational support. The second group consists of the PSF4 as the availability of procedures/plans, PSF5 as the number of simultaneous goals and PSF6 as the available time. The third group consists of the PSF7 as the time of day, PSF8 as the adequacy of training/experience and PSF9 as the crew collaboration quality.

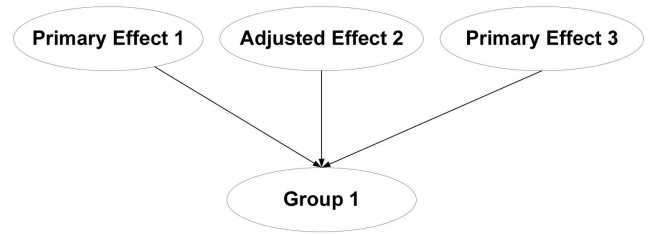


FIGURE 7. The local BNN for combining the primary effects of the first three PSFs into group 1.

Based on the grouping, a discrete function  $h_j$  ( $j=1,2,3$ ) is defined as  $h_j : E_j^3 \rightarrow G_j$ , where  $E_j^3$  is the set of permutation on the three PSFs’ primary effects in the  $j$ th group;  $G_j$  is the set of PSFs scores for the  $j$ th group of PSFs. A local BNN is defined to model the relationship between the first three PSFs’ effects and the group 1, as indicated in the Fig. 7. For the PSFs in group 1, there are ten possible PSFs scores. Therefore, the  $G$  for group 1 is defined as:  $G_1 = \{(0, 0), (0, 1), (0, 2), (0, 3), (1, 0), (1, 1), (1, 2), (2, 0), (2, 1), (3, 0)\}$ .

The CPT for the PSFs score under different PSFs’ effects is indicated in Table 4. The exact same probabilistic relationship can be applied to the PSFs in group 2. As the PSF7 in group 3 is not able to produce positive effect, the  $G$  for group 3 is defined as:  $G_3 = \{(0, 0), (0, 1), (0, 2), (1, 0), (1, 1), (1, 2), (2, 0), (2, 1), (3, 0)\}$ . The CPT for group 3 also needs to be modified.

With the PSFs scores of the three groups of PSFs, the PSFs score for all the nine PSFs can be calculated. To reach this purpose, a discrete function  $l$  is defined as  $l : G3 \rightarrow S$ , where  $S$  is the set of PSFs score for all nine PSFs. As indicated in Fig. 6, there are totally 54 possible PSF scores. The  $S$  is defined as:  $S = \{(0, 0), (0, 1), \dots, (8, 1), (9, 0)\}$ . As indicated in Fig. 8, a BNN is defined to model the relationship between the PSFs score of three groups and the total PSFs score. As the corresponding CPT involves too many parameters, it would not be presented here.

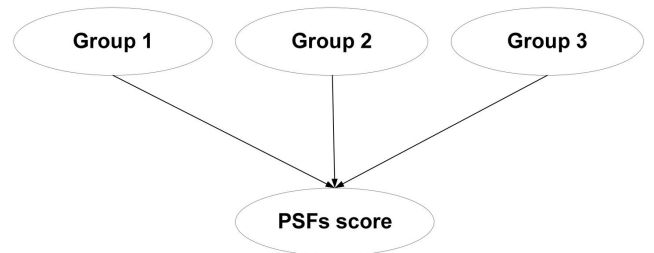


FIGURE 8. The local BNN for determining the PSFs score.

### 4) ESTIMATION OF THE HEP

To calculate an accurate HEP, an appropriate utility values  $UC_m$  ( $m=1,2,3,4$ ) must be assigned to the COCOM. The HEP is eventually reached with the following equation:

$$HEP = \sum_{m=1}^4 p(C_m)UC_m \tag{6}$$

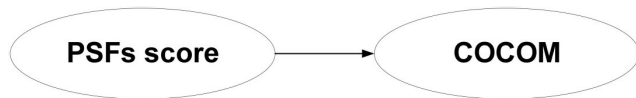
**TABLE 4.** The conditional probability table for the  $h_1$ .

E <sub>1</sub> <sup>3</sup>			G <sub>1</sub>			E <sub>1</sub> <sup>3</sup>			G <sub>1</sub>				
I	I	I	(0,3)	I	I	(0,2)	I	I	I	I	(1,2)		
		NS	(0,2)			NS					(0,1)	NS	(1,1)
		R	(1,2)			R					(1,1)	R	(2,1)
I	NS	I	(0,2)	NS	NS	(0,1)	NS	NS	NS	NS	(1,0)		
		NS	(0,1)			R					(1,0)	R	(2,0)
		R	(1,1)			I					(1,1)	I	(2,1)
I	R	I	(1,2)	R	R	(1,1)	R	R	R	R	(2,0)		
		NS	(1,1)			NS					(1,0)	NS	(2,0)
		R	(2,1)			R					(2,0)	R	(3,0)

Note: Improved: I; Not significant: NS; Reduced: R.

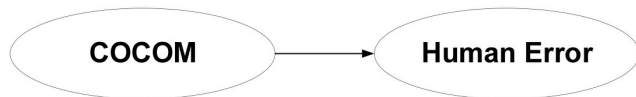
where  $C_m$  denotes the  $m$ th COCOM,  $UC_m$  denotes the nominal HEP for the  $m$ th COCOM, and the  $p(C_m)$  denotes the probability of the  $m$ th COCOM

Based on the PSFs' score for all the PSFs, the control mode can be determined. A discrete function  $u$  is defined as  $u : S \rightarrow Y$ , where  $Y$  is the set of the four control modes. The BNN for the discrete function is described as the node of PSFs score having causal effect on the node of COCOM, as indicated in the Fig. 9. As the size of the parameter numbers is extremely huge, the CPT for this BNN cannot be presented here.



**FIGURE 9.** The local BNN for determining the COCOM.

Once the distribution of the COCOM is determined, the BNN can be further developed to calculate the HEP. As indicated in the Fig. 10, a new node of the human error is added next to the node of COCOM. It is noted that the newly added relationship is not causal but definitional, the probability of the human error needs to be calculated with the Eq.(6).



**FIGURE 10.** The local BNN for determining the human error.

**D. RISK MODEL FOR CONSTRUCTION SAFETY**

As mentioned in the Section I, the main motivation of this study is to build a fuzzy BBN based risk model for construction safety. The model should incorporate the human factors that influencing the construction safety and produces the quantification results on the human error and the construction accident. The risk model building process is presented from both the qualitative and the quantitative perspectives. In the qualitative analysis, a literature review on the construction safety topics is utilized to identify the primary risk influencing factors and determine the basic nodes in the model. The review result indicates that the CREAM method has covered most concerned topics in the construction safety and the CREAM BNN offers a valid basis for the risk model. Thusly,

**TABLE 5.** Review results of the risk influencing factors in construction safety.

Reference	Risk influencing factors in the construction safety
Cheng et al. [29]	Safety protection
	Safety management
	Safety training
	Safety level
	Tiredness
Tam et al. [4]	Construction materials and equipment
	Safety awareness
	Training
	Safety resources
Zhang et al. [30]	Operation
	Geological Conditions
	Design Parameters
	Construction Quality
Chen et al. [31]	Management
	Management Commitment
	Awareness
	Coworker Safety Perception
	Management Commitment
	Reporting
	Learning

the CREAM BNN is furtherly modified to analysis the accident in the construction. The quantification of the model mainly follows the Bayesian inference rules in the CREAM BNN. To reduce the experts' burden, the noisy-MAX model is introduced in calculating the probability of the eventual construction accident.

**1) REVIEW ON THE FACTORS AFFECTING CONSTRUCTION SAFETY**

To identify the factors affecting the construction safety, a literature review has performed, as indicated in Table 5. According to the review results, most risk influencing factors in the construction safety can be attributed to the following two aspects:

*a: SAFETY MANAGEMENT OF ORGANIZATION*

Multiples studies have emphasized the importance of the safety management in the construction work [29]–[31]. Among all the factors related to safety management, the management commitment is the most concerned [31]–[33]. Also, the safety management in the construction is often discussed with the safety climate or the safety culture of the organization [34]. Despite different views on this issue, one thing for certain is that the quality of the safety management is reflected in the safety performance of the construction



worker. The defects and deficiencies in the management would firstly lead the operational deviation of worker and then to the failure of the task. Following this causal relationship, the CREAM offers a convenient way to analysis the safety management in the construction work. In the CREAM, the PSF1 as adequacy of organization is defined as the quality of the support and resources provided by the organization for the task or work being performed. This adequacy involves the factors as the communication systems, the safety management system, the support for external activities and so on. While applying the CREAM BNN in the risk analysis, as indicated in the Section III.B, the interactive effect between the adequacy of organization and other PSFs is also considered. With using the CREAM BNN for construction risk analysis, the safety management's effect can be identified and quantified.

#### *b: AWARENESS AND BEHAVIOR OF WORKER*

Another major risk influencing factor concerned in the construction safety study is the safety awareness and safety behavior of the construction worker [3], [4], [31]. The workers' awareness and behavior can be affected by various factors such as the company size [35], the management method [36], the safety program [37], the supervision [38] and so on. Nevertheless, an apparent limit in these studies is the lack of exploration on the cognitive process of the worker [39]. By contrast, there have been numerous HRA studies on the cognitive model of operator's safety perception and behavior [16]. In the CREAM, the human error is analyzed based on the four major cognitive processes as observation/identification, interpretation, planning/choice and action/execution. The cognitive analysis in the CREAM helps to reveal the mechanism of the operator's behavior and offers an insight to the happening of the accident. As a result, the use of the CREAM BNN in construction safety would much deepen the understanding of the worker's perception and behavior.

#### 2) DEVELOPING THE CREAM BNN INTO THE RISK MODEL

To develop the CREAM BNN introduced in the Section III.B into the complete risk model, two following modifications have to be made.

Firstly, differing from the limited definition in the CREAM, the working condition in the risk model refers a much broader scope. As one of the PSFs having impact on the human performance, the working condition undoubtedly covers the physical factors in the task context such as the ambient lighting, glare on screens, noise from alarms, interruptions from the task, etc. Besides simply influencing the constructor, the working condition node in the model is considered having direct influences on the construction accident node. The factors under the definition of working condition are expanded to all the mechanical, physical and environmental factors affecting the construction safety directly. For example, the geological condition of the construction site, the usage of

the apparatus and equipment, etc. are all viewed as part of the working condition.

The second modification is introducing the concept of unsafe acts into the risk model. According to Reason's work [40], the unsafe acts can be classified into two categories: errors and violations. The errors represent the mental or physical activities of individuals that fails to achieve their intended outcome. Naturally, most accident leading acts can attribute to the human errors. While the violation is referring to the willful disregard for the rules and regulations. For example, even with knowing the potential risk, the construction worker may break safety rules for convenience. Although the violation may not routinely happen, it should be considered as an unsafe act leading catastrophic results in the construction safety.

The completed BNN based risk model for the construction safety is shown in the following Fig. 11. In the model, the construction accident is determined by the combined effects of the working condition, the human error and the violation. Referring to the official regulations issued by the State Council of China [6], the severity of the construction accident is determined by the number of fatalities and the economic loss in the accident. In specific, the construction accident severity can be classified into four categories: the ordinary accident, the serious accident, the major accident and the particularly major accident. Correspondingly, with considering the extra possibility as no accident, there are totally five states for the construction accident node.

#### IV. CASE STUDY

To infer the probability distribution for the construction accident, it needs the expert to offer the CPT values. To ease the difficulties in offering the large amount of probabilities, the noisy-MAX model [41] is adopted here to help experts make their own judgements. The noisy-MAX model is the generalization of the noisy-or gate [42], which assumes that all the causes in the net are independent to each other and each of these causes can lead to the effect independently. The noisy-MAX extends this assumption to the parent nodes with multi-valued (non-Boolean) domains. As indicated in the Fig. 12, the noisy-MAX uses three immediate variables  $W'$ ,  $H'$  and  $V'$  to reveal the associated causal mechanisms. The  $W'$  is true if the working condition is considered as in the advantageous condition; the  $H'$  is true if the human error is not happening; the  $V'$  is true if there is no violation. The construction accident is on the no accident condition if and only if one of those events hold. The detailed calculation in the noisy-MAX model is following the rule in the Diez's work [42] and would not be fully presented in the paper.

#### V. CASE STUDY

In this section, a numerical example is presented using the proposed fuzzy BNN CREAM approach. This example refers to the construction accident happened in the tunnelling process of the Xiamen Metro Line 2 (XML2) in Xiamen, Fujian, China in 2017.

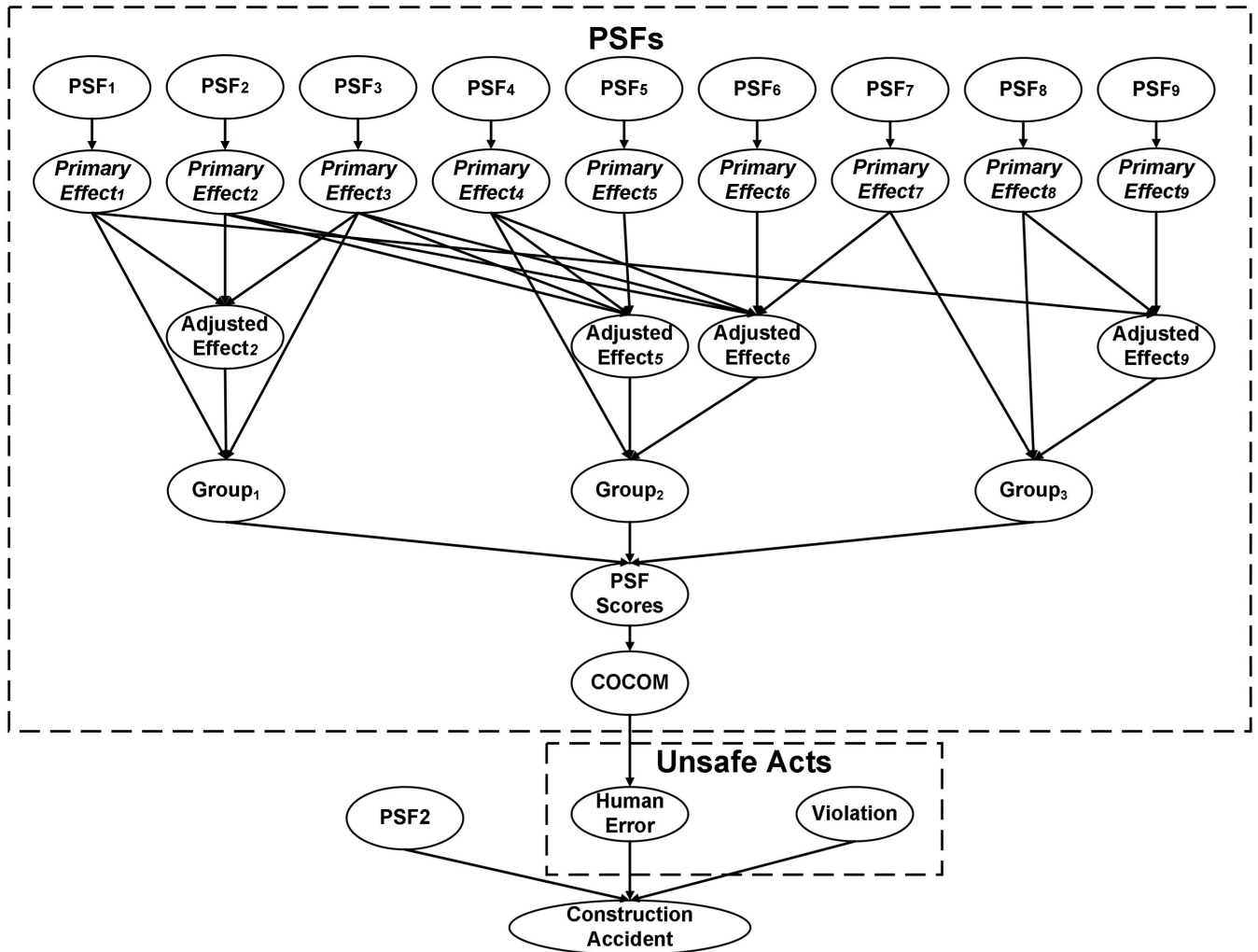


FIGURE 11. The risk model for construction safety.

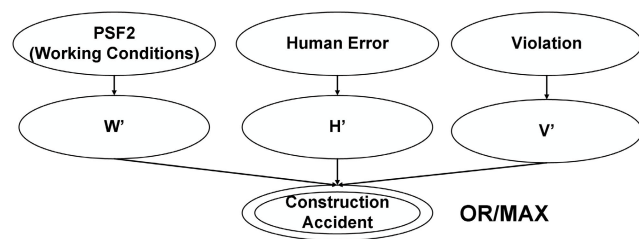


FIGURE 12. Decomposition of the noisy-MAX model for construction accident.

As the first cross-sea subway in China, the XML2 consists of more than two kilo-meters of the tunnel passing through the sea. In the practical construction of the tunnel, to maintain the stability of the excavation face, the support pressure is given to the excavation chamber in the tunnelling boring machine (TBM). While performing the works in the TBM, the workers are working in a pressured environment. Each time the workers entering the excavation chamber, they must firstly enter the man lock to be pressurized to the same pressure as exists in the excavation chamber. The man lock is divided

into the main chamber and the auxiliary chamber. Once completing the work, all the workers have to be depressurized in the man lock before exiting. Fig. 13 provides a general view on the TBM and an inside look of the man lock in the TBM.

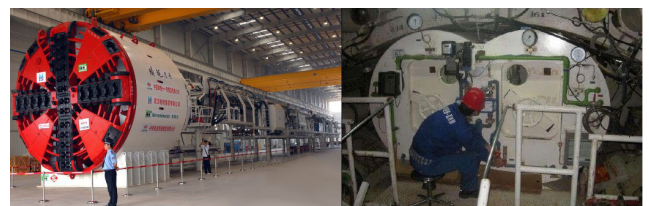


FIGURE 13. The general view of the TBM (left) and the inside look of the man lock (right).

On February 2nd, 2017 at approximate 16:30, after completing the work in the excavation chamber, three construction workers entered into the man lock of the TBM of the XML2 to get depressurized. About 18:10, the auxiliary chamber of the man lock caught on fire. Twenty minutes later, with

taking series emergency measures as opening the emergent vents, closing the oxygen valve and spraying the fire by fire extinguisher, the rescuers were able to get into the man lock. At about 20:30, after being sent to the hospital, all three injured workers have passed away.

During the investigation, it was found that the movement of the foldable seats in the auxiliary chamber started static electricity and generated fire in the oxygen-enriched environment. One of the workers caught on fire between the seats and escaped to the main chamber of the man lock. This unsafe act led to a great burning and explosion. Several important facts from the accident investigation report include the following:

- The chamber atmosphere is not checked before work and the oxygen content is too high.
- The foldable seats cushions are non-flame retardant.
- The construction worker did not follow the safety procedure as wearing flame-resistant clothing while entering into the man lock.
- The screening process for the flammable objects have not been conducted before the work in chamber. There were non-flame retardant materials, such as chemical fabric clothes, woven bag, the plastic drinking bottles, rags and so on, in the man lock.
- The fixed gas detection system in the man lock was not able to provide real-time indications of the gases and vapours.

To analysis this case, the model is demonstrated in three subsections (IV.A to IV.C) with taking one expert’s opinion. In Section IV.A, an expert’s evaluation on one PSF (adequacy of organization) is presented in fuzzy set and the uncertainty in the evaluation is measured as the possibility. The subsection IV.B takes the mass theory to transform the possibility to the prior probability. After transforming the expert’s opinions on all the PSFs into the prior probability, the subsection IV.C shows the inference results with the BNN CREAM. The last subsection (IV.D) gathers all the expert’s opinion and present them in a general way. It is necessary to point out that the use of the model is not to analysis or explain the accident, but shows the failure probability can be calculated for a given scenario.

**A. EVALUATING THE PSFs’ EFFECTS (PROCESS 1 AND 2)**

To analysis construction accident with the risk model, the first process is to collect the expert opinions on the PSFs. Seven experts with construction safety background were invited to offer their own judgments. Each expert had carefully read the accident investigation report for the XML2 accident and made further analysis based on the report. The fundamental theory with respect to the methodology used in the study, such as the fuzzy set and the Bayesian inference, was introduced to the experts. The context of each variable and the causal relationship between these variables in the risk model was explained to the experts with detail. In addition, some historical data from the literature review were provided to the experts for reference.

Subjected to the limited expertise and the incomplete information on the accident, the experts may not be able to produce

confident judgements on all the PSFs. Thusly, the uncertainty of the expert judgement is allowed in the practical evaluation. In this study, an even distribution is given for the factors that expert is unclear and unable to provide judgement. Also, for those provided judgement, the uncertainty arising from the expert’s limited experience needs to be considered. To combine this uncertainty into the evaluation result, the original IFS introduced in the Section II.B is modified with a parameter of the reliability degree,  $\alpha$ . An adjusted uncertainty,  $\alpha\pi$ , is added to the membership degree  $\mu_A$ . The membership degree  $\mu'_A$  for the IFS is corrected as:  $\mu'_A = \mu_A + \alpha\pi$ . In the practical evaluation, the parameter  $\alpha$  is related to the working experience of the expert. The more experience the expert has, the less adjustment would be conducted to the membership degree the expert assigned. Specifically, corresponding to the three working experience intervals: less than three years, three to seven years and more than seven years, the  $\alpha$  is designed as 1.0, 0.7 and 0.5 separately.

**TABLE 6. The expert 1’s judgements on the PSF1 as adequacy of organization.**

PSF	Elements	$\mu_A$	$\pi$	$\alpha$	$\mu'_A$
		Very efficient (A1)	0.0	0.0	1.0
Adequacy of organization (A)	Efficient (A2)	0.0	0.1	1.0	0.1
	Inefficient (A3)	0.8	0.1	1.0	0.9
	Deficient (A4)	0.5	0.1	1.0	0.6

The Table 6 shows the result of the expert 1’s evaluation on the PSF1 as the adequacy of organization. As there is obvious defect in the safety management of the XML2 construction, the expert 1 assigned the membership degrees as  $\mu_{A1} = 0.0$ ,  $\mu_{A2} = 0.0$ ,  $\mu_{A3} = 0.8$  and  $\mu_{A4} = 0.5$  to the elements: Very efficient (A1), Efficient (A2), Inefficient(A3) and Deficient(A4). Also, the expert 1 offered the subjective uncertainties as  $\pi_{A1} = 0.0$ ,  $\pi_{A2} = 0.1$ ,  $\pi_{A3} = 0.1$  and  $\pi_{A4} = 0.1$  to the four elements. The expert 1 is a researcher who has two years experiences in PRA and human factor study. The reliability parameter  $\alpha$  for expert 1 is set as 1.0. Eventually, the corrected membership degrees based on the expert 1’s judgement are achieved as  $\mu'_{A1} = 0.0$ ,  $\mu'_{A2} = 0.1$ ,  $\mu'_{A3} = 0.9$  and  $\mu'_{A4} = 0.6$ .

**B. CONVERTING THE POSSIBILITY INTO THE PRIOR PROBABILITY (PROCESS 3,4 AND 5)**

The membership degrees given by the expert judgements need to be further converted into the probability. Still taking the expert 1’s judgement of the PSF1 as an example. The focal elements  $A_3$ ,  $A_4$  and  $A_2$ , which are those elements having nonzero MA, are selected from the set and the corresponding membership degree are normalized as  $\bar{\mu}_1 = 1.00$ ,  $\bar{\mu}_2 = 0.67$  and  $\bar{\mu}_3 = 0.11$ . Then, the normalized fuzzy set  $\bar{A}$  is represented as:  $\bar{A} = \{A_3/\bar{\mu}_1 + A_4/\bar{\mu}_2 + A_2/\bar{\mu}_3\} = \{A_3/1.00 + A_4/0.67 + A_2/0.11\}$ . Using equation (3), the  $m_{\bar{A}}$  for fuzzy set  $\bar{A}$  can be generated as:  $m_{\bar{A}} = \{A_3\} : \bar{\mu}_1 - \bar{\mu}_2, \{A_3, A_4\} : \bar{\mu}_2 - \bar{\mu}_3, \{A_3, A_4, A_2\} : \bar{\mu}_3 = \{A_3\} : 0.33, \{A_3, A_4\} : 0.56, \{A_3, A_4, A_2\} : 0.11$ .

The obtained MA plays a role as crucial link between probability and fuzzy set. It can be further converted to the least prejudiced distribution. This probability distribution is defined as a discrete distribution across the normalized fuzzy set A. To generate the distribution, the magnitude of masses in A is determined as:  $|\{A\}| = |\{A_3\}| : 1, |\{A_3, A_4\}| : 2, |\{A_3, A_4, A_2\}| : 3$ .

Using the equation (4), the probability distribution is provided as follows:  $P(A_3) = \frac{|\{A_3\}|}{|\{A_3\}| + |\{A_3, A_4\}| + |\{A_3, A_4, A_2\}|} = 0.33 + 0.56(\frac{1}{2}) + 0.11(\frac{1}{3}) \approx 0.65$ ,  $P(A_4) = \frac{|\{A_3, A_4\}|}{|\{A_3, A_4\}| + |\{A_3, A_4, A_2\}|} = 0.56(\frac{1}{2}) + 0.11(\frac{1}{3}) \approx 0.32$ ,  $P(A_2) = \frac{|\{A_3, A_4, A_2\}|}{|\{A_3, A_4, A_2\}|} = 0.11(\frac{1}{3}) \approx 0.03$ .

**TABLE 7. The prior probability for the node adequacy of organization based on the expert 1’s evaluation.**

Node	Level	Prior probability
Adequacy of organization	Very efficient	0.00
	Efficient	0.03
	Inefficient	0.65
	Deficient	0.32

Based on the calculation results, the expert 1’s evaluation on the PSF1 has been converted to the prior probabilities as indicated in the Table 7. The probability can be used as input to the risk model for further Bayesian inference.

**TABLE 8. Probability distribution of the control mode inferred by the expert 1’s judgement.**

COCOM	Strategic	Tactical	Opportunistic	Scrambled
Probability	0.0008	0.4969	0.4955	0.0068

**C. BAYESIAN INFERENCE WITH THE RISK MODEL (PROCESS 6)**

After converting the expert’s judgements with the mass assignment theory introduced before, the prior probability distribution for all the PSFs can be determined. Using the BBN-based risk model to perform the inferences, the discrete distribution for the four COCOM based on the expert 1’s evaluation is summarized in the Table 8.

**TABLE 9. The nominal HEP for the COCOM.**

COCOM	Strategic	Tactical	Opportunistic	Scrambled
Nominal HEP	0.00022	0.01	0.071	0.32

As there is lack of data on each COCOM in space, the results from the previous studies have employed to determine the nominal HEP for each COCOM, as indicated in the Table 9 [43], [44]. Using the equation (6), the HEP is calculated as  $HEP = 0.00022 * 0.0008 + 0.01 * 0.4969 + 0.071 * 0.4955 + 0.32 * 0.0068 = 0.0423$ . The BNN for the HEP calculation is indicated in the Fig. 14.

The last step in the Bayesian inference with the risk model is to determine the probability distribution of the construction accident. As indicated in the Fig. 15, the prior probability of the working condition and the human error have already achieved in the above analysis. Although it has been revealed that the construction worker would choose to take intentional

**TABLE 10. The probability distribution of the control mode and the HEP.**

Exp No.	Experience(year)	ST	T	O	SC	Control mode	HEP
1	2	0%	50%	49%	1%	T	4.23E-02
2	5	0%	30%	67%	3%	O	6.07E-02
3	5	0%	22%	68%	10%	O	8.17E-02
4	5	0%	29%	63%	8%	O	7.36E-02
5	11	0%	13%	67%	20%	O	1.13E-01
6	2	0%	30%	62%	8%	O	7.20E-02
7	1	0%	2%	37%	61%	SC	2.23E-01

unsafe acts while being fully aware of the potential risk [3], the violation behaviour in this case cannot easily be identified as all three relative workers were dead. Thusly, an even prior probability distribution is given to the variable violation. Then, the expert has to offer the key parameters to describe the three parent nodes’ influences on the construction accident. Taking advantage of the noisy-MAX model, the CPT for the construction accident is calculated based on these parameters. The calculated probability distribution of the construction accident based on the expert 1’s judgement is indicated in the Fig. 15.

**D. RESULT ANALYSIS**

Section IV-A, IV-B and IV-C explained the calculation of the probability distribution of the construction accident based on one expert’s judgement in detail. The calculations have been conducted for all the seven experts in the same way.

As shown in the Table 10, based on most experts’ opinions, the construction workers in the accident are considered most likely under the opportunistic control mode. The opportunistic control mode is associated with very little planning or anticipation. When construction workers are performing task in this mode, their action is determined by the salient features of the current context rather than on more stable intentions or goals. The worker does not very little planning or anticipation, perhaps because the context is not clearly understood or because time is too constrained. This analysis results are consistent with what happened in the accident. When the fire started in the man lock, the construction workers were apparently not understanding the situation. Instead of turning on the sprinkler, the workers brought the tinder to the main chamber in evacuating, which has led the fire explosion and causalities. Clearly, the unsafe acts of the workers were driven by their own habits but not the task target.

**TABLE 11. The probability distribution of the construction accident.**

Exp No.	NA	OA	SA	MA	PMA
1	9.28E-01	3.40E-02	3.06E-02	7.25E-03	9.87E-04
2	9.10E-01	6.27E-02	1.41E-02	6.35E-03	6.37E-03
3	9.52E-01	2.19E-02	2.23E-02	2.24E-03	1.91E-03
4	9.08E-01	5.38E-02	3.54E-02	1.57E-03	1.07E-03
5	8.86E-01	6.80E-02	3.54E-02	5.97E-03	4.43E-03
6	9.66E-01	1.43E-02	1.44E-02	4.79E-03	8.37E-04
7	9.59E-01	1.69E-02	1.71E-02	5.93E-03	1.06E-03

Another important result produced by the risk model is the probability distribution of the construction accident. As indicated in Table 11, based on the expert’s opinions, the probability of no accident generated by the risk model varies from 0.866 to 0.966. Also, the result indicted that the probability

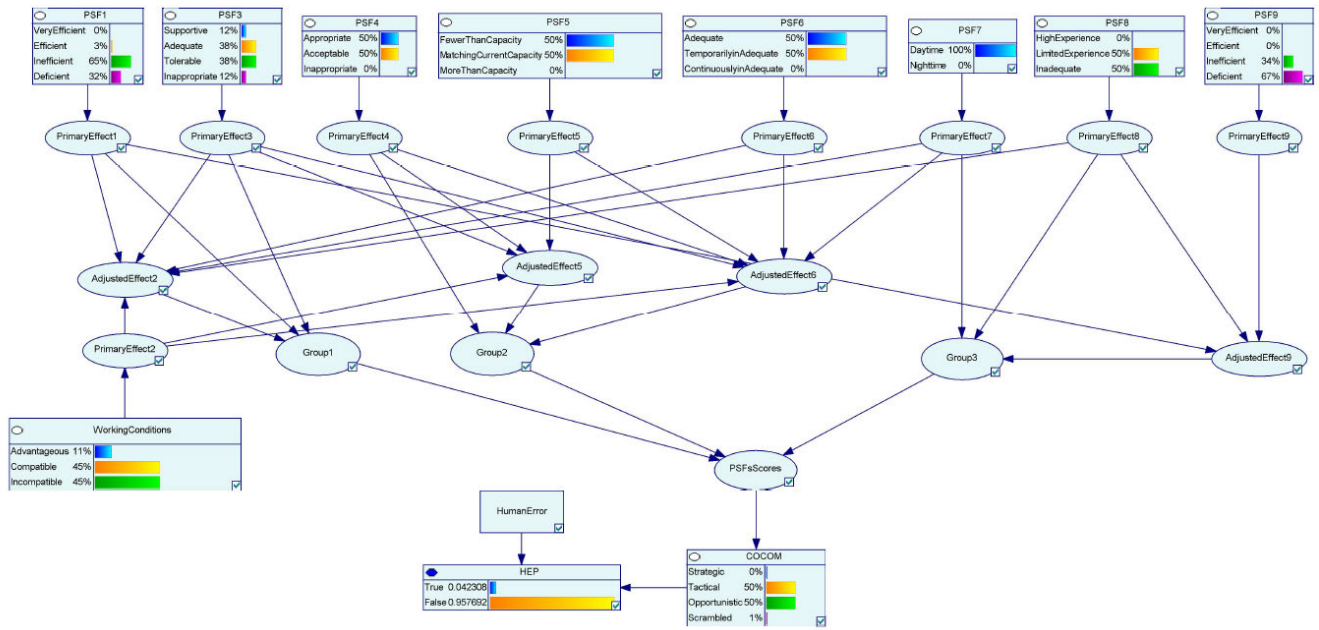


FIGURE 14. The calculation result of HEP based on the expert 1’s evaluation result.

of the ordinary accident and the severe accident is considered very close in the opinion of most experts. This is consistent with the fact that the severity of the accident (3 fatalities) has eventually been attributed to the severe accident (3-9 fatalities) but very close to the ordinary accident (1-2 fatalities).

VI. PRACTICAL IMPLICATION

This study has demonstrated the applicability of the HRA in the risk analysis of construction safety. The HRA method, such as the CREAM, offers a systematic framework for analysing the human errors in a specific operation. The major phases in HRA include identifying the PSFs in the scenario, modelling the PSFs’ effects on the human performance and quantifying the HEP. Following this analysis process, the human errors and the scenario that leading the error in the construction work can be identified and analysed. The major practical implications for our study includes the following aspects:

Firstly, in the construction safety, the workers’ performance should be put into a comprehensive and inter-correlated analytical framework. The neglect of the human factor or analysis this factor in an isolated way may lead to an incomplete, biased or even misleading awareness of the accident event. The causal reasoning in our study reveals the important factors (PSFs) and their influences on the worker performance. With offering the task context, the human-centered analysis helps to infer the prior probability for the human error and the accident in the construction work. Also, the important factors (PSFs) in the context can be recognized and analyzed. All these can offer guidance and support to the construction safety management practice.

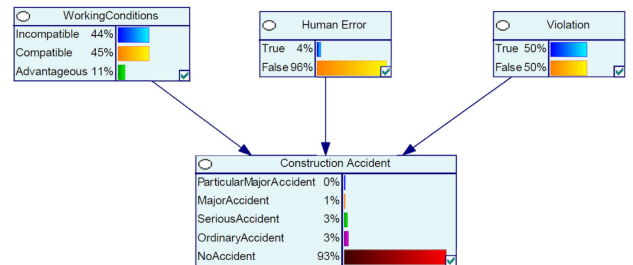


FIGURE 15. The calculated probability distribution of the construction accident based on the expert 1’s judgement.

Specifically, it helps the relevant personal to understand the various factors involved in the construction safety issue and take targeted actions on the critical factors.

Secondly, it is paramount that HRA being implemented during the conduction of the construction engineering. Currently, the automation technology in construction such as UAV has eased human burden in most tasks. In the meantime, the interactions between construction worker and advanced machine are becoming more frequent and critical. For those high safety demanding tasks, the HRA offers a well-developed analytical framework to predict and analysis the potential human errors. The results produced by the HRA not only offers a more comprehensive view on the industrial system reliability but also guides the future accident management. Our finding suggests that the operation task in the construction activity requires a great deal of cognitive resources. For example, the workers are tended to fall into the opportunistic control mode and make perceptual errors such as failing to follow the safety procedure in a sudden fire

case. One way to increase the worker's awareness of the task context is to make plan before a specific operation and reduce the time constraint in the task.

## VII. CONCLUSION AND FUTURE WORK

In this study, a human-centered risk model was developed for quantifying the HEP and the probability of the accident in the construction work. The approach is based on the a fuzzy BNN version of the CREAM that models the PSFs' effects on the human error and the construction accident. To build the model, it starts with collecting the expert's opinions. The experts have to offer their own judgements of the PSFs' effects. These judgements are represented as the membership degree for different fuzzy sets in each PSF. In this process, with introducing the concept as IFS, the uncertainties in the expert's judgement are considered from both the objective and the subjective perspective. The expert's judgements are adjusted with combining the uncertainty into the membership degree. The adjusted results, which are the possibility distributions to the fuzzy sets, are firstly convert to the MA and then to the probability distributions. These prior probability distributions of PSFs are input into the BNN for inferences.

In the risk model, the structure of the BNN follows the definitions in the CREAM, which determines the human error with nine PSFs. Also, each reasoning process in the CREAM is transferred into a local BNN. Eventually, a BNN modelling the PSFs' probabilistic influence on the human error can be achieved. To adapt the BNN to analysis the scenarios in the construction accident, two modifications have been made. Firstly, the PSF as the working condition is given a much broader definition. In this definition, all the mechanical, physical and environmental factors having direct effects on the construction safety are considered as the working condition. Secondly, beside the unintentional human error, the violation is considered as another type of the unsafe act of the construction worker. In the model, the violation is defined as the deliberate deviations from the safe operation in the construction and should be evaluated separately. However, there are also certain limitations in this study and future work should be performed:

Firstly, although the CREAM has been proved as a generic HRA method and used in various engineering fields, the application of this method should guarantee the fitness to the current situation. Actually, differed from most engineering projects, the conditions at the construction sites can be very rough and the mobility of the worker is strong. Enormous challenges are left to the construction safety management and the risk may rise for those most simple operations in the construction work. Thusly, in the construction work, the PSFs and their interactive effects on the human performance should be further adjusted based on the existed definitions and rules in the HRA. A limitation of this study is lack of the qualitative analysis of the potential risk factors in the construction work. Referring to this limitation, a general evaluation on the task scenario should be firstly performed before applying the HRA for the construction safety.

Secondly, as the statics scarcity on the human factors in the construction accident, the risk model in this study takes the expert judgements as the input. In the case study, the model has proved to be able to incorporate the expertise on the scenario and produce meaningful result for a specific task. Nevertheless, due to the lack of relative data, there is no demonstration of the accuracy of this model for real-world predictions. To cope with the data scarcity of the human factor in the construction work, it is necessary and important for researchers to adopt new approaches as simulations and experiments to gather data of human performance while performing the HRA for the construction safety.

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