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An Integrated CREAM for Human Reliability Analysis Based on Consensus Reaching Process under Probabilistic Linguistic Environment

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Abstract: Human reliability analysis (HRA) is widely used to evaluate the impact of human errors on various complex human–machine systems for enhancing their safety and reliability. Nevertheless, it is hard to estimate the human error probability (HEP) in reality due to the uncertainty of state assessment information and the complex relations among common performance conditions (CPCs). In this paper, we aim to present a new integrated cognitive reliability and error analysis method (CREAM) to solve the HRA problems under probabilistic linguistic environment. First, the probabilistic linguistic term sets (PLTSs) are utilized to handle the uncertain task state assessments provided by experts. Second, the minimum conflict consensus model (MCCM) is employed to deal with conflict task state assessment information to assist experts reach consensus. Third, the entropy weighting method is used to determine the relative objective weights of CPCs. Additionally, the CPC effect indexes are introduced to assess the overall effect of CPCs on performance reliability and obtain the HEP estimation. Finally, the reliability of the proposed CREAM is demonstrated via a healthcare practical case. The result shows that the new integrated CREAM can not only effectively represent experts' uncertain task state assessments but also determine more reliable HEP estimation in HRA.

Keywords: human reliability analysis; human error probability; cognitive reliability and error analysis method (CREAM); probabilistic linguistic term set (PLTS); consensus reaching process

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1. Introduction

Over recent decades, human reliability is becoming more significant to the safety and reliability of complex engineering systems [1,2]. Human reliability analysis (HRA) is a systematic methodology used to quantify the influence of human errors on human–machine systems [3,4]. It can not only realistically assess human errors, but also provide a fundamental platform for testing previously overlooked error mechanisms [5,6]. The cognitive reliability and error analysis method (CREAM), as one of the second-generation HRA methods, can quantify the impact of context environment on the behavioral reliability of personnel [7]. The CREAM can estimate human errors, determine their error mechanisms based on human activities, and emphasize the importance of the working environment on human reliability [8,9]. In recent years, the CREAM has been applied to a variety of fields to improve the safety and reliability of socio-technical systems, including the building construction [8], the nuclear power plant [10], the offshore platform operation [11], and the crude oil cargo discharging operation [12].

In the CREAM, the qualitative opinions from experts are converted into quantitative human failure analysis results for the human error probability (HEP) estimation [13–15]. This method allows for the retrospective analysis of historical events as well as a prospective analysis of high-risk systems. Normally, it provides an approximation analysis and determines the error rate intervals of human error events via four control modes due to the lack of sufficient failure data [16,17]. However, as indicated by many researchers, the traditional CREAM has several shortcomings in practical applications [10,15,18]. For example, the judgment criteria for experts' assessment are vague; all common performance conditions (CPCs) are treated as the same weight, and their different impacts on human performance reliability are not considered. Besides, failure rate intervals of HFP values obtained by the traditional CREAM are unacceptably wide and cannot be used for the initial screening of human error events [19].

Normally, multiple experts are involved in the state assessments of human tasks in solving HRA problems [8,12]. Nevertheless, due to the increasing complexity of real-world human error events, the numerical values adopted in the traditional CREAM are insufficient to express experts' uncertain assessments in the real world [16,20]. Moreover, domain experts prefer to express their judgments by using linguistic terms because they are convenient to use [15]. To effectively capture the linguistic information of decision makers, the probabilistic linguistic term sets (PLTSs) were proposed by Pang et al. [21] by describing an alternative with several linguistic terms and assigning different probability values to them. Compared to other linguistic computing methods, the PLTSs can represent decision-makers' assessments much closer to reality and avoid the loss of original linguistic information to the greatest extent [22,23]. In recent years, the PLTSs have attracted widespread attention from researchers and have been employed to solve various decision-making problems, such as knowledge representation [24], online product ranking [25], occupational health risk assessment [26], film classification [27], and drug value assessment [28].

As a multidisciplinary team activity, the HRA is mainly based on experts' experience and knowledge to drive HEP estimations [10,13]. In some situations, the task state assessments given by experts may conflict because they have different educational backgrounds, knowledge structures, and understanding of HRA problems [5]. Thus, a consensus-reaching process should be used to achieve a solution with a high level of consensus and ensure the effective human error quantification of systems [15]. Besides, experts may exhibit non-cooperative behaviors such as making only minor modifications in the consensus-based group HRA problems. These noncooperative behaviors will lead to high intra-group conflicts and low consensus efficiency. To derive a consensual solution, the minimum conflict consensus model (MCCM) was proposed in [29] by considering the noncooperative behaviors of decision-makers. It can coordinate different assessments provided by decision-makers, alleviate the conflicts among decision-makers, and provide an effective consensus-reaching mechanism [30]. In MCCM, only the decision-makers' information with a low consensus level will be adjusted, which can retain the original assessments of decision-makers to the greatest extent. Thus, it is significant to use the MCCM to promote expert consensus and obtain acceptable HEP estimations in the CREAM.

Taking advantage of the PLTSs and the MCCM, the paper aims to develop a new integrated CREAM to estimate the HEPs in human error activities. This paper provided the following valuable contributions to the current HRA methods: First, the PLTSs are introduced to represent the task state assessment information of experts accurately by taking the ambiguity and hesitation of task state assessment information into account. Second, to minimize experts' conflict task state assessments, the MCCM is employed to assist individual experts in reaching a consensus. Third, the entropy weighting method is introduced in the CREAM model to obtain the relative weights of CPCs. In addition, for the HEP estimation, the CPC effect indexes are adopted to measure how CPCs influence the human activities' performance reliability quantitatively. Finally, the feasibility and practicality of the proposed CREAM are verified by an example of the polymerase chain reaction (PCR) detector operation.

The rest of the paper is structured as follows. Section 2 provides an overview of the relevant studies on the CREAM. Section 3 is concerned with the basic theories associated with the PLTSs. Section 4 proposes a new CREAM by integrating the PLTSs with the MCCM. In Section 5, a practical case is presented to demonstrate the applicability and effectiveness of the CREAM proposed in this paper. Section 6 concludes this paper and makes recommendations for future research.

2. Literature Review

In the literature, a variety of improved CREAMs have been developed to handle the uncertain task state assessment information in HRA. For example, Sezer et al. [12] suggested a modified CREAM for the quantitative analysis of human errors, in which fuzzy sets were used to manage the uncertainty and ambiguity of CPCs. Shi et al. [15] proposed an improved CREAM based on linguistic D numbers with the decision-making trial and evaluation laboratory-based analytic network process (DANP) approach to assess human factor reliability. Li et al. [8] combined CREAM with fuzzy theory and Bayesian network to transform experts' fuzzy task state assessments into conditional probabilities and calculate the HEPs of building construction work at height. Elidolu et al. [31] designed a fuzzy bow-tie CREAM to quantify failure probabilities of explosion and fire accidents on tanker vessels. Abbassinia et al. [32] integrated Bayesian networks and fuzzy CREAM to put forward a dynamic model to estimate the HEP in emergencies. Ahn and Kurt [33] constructed a CREAM by integrating Bayesian networks and evidential reasoning methods to analyze human reliability in emergency response to engine room fires on ships. Yu et al. [11] improved the traditional CREAM through Z-number-based grey relation analysis (GRA) and Z-number-based best-worst method. Besides, Ung [34] utilized a fuzzy Bayesian network-based CREAM to handle the uncertainty of experts' task state evaluations in oil tanker collision tasks and Lee et al. [35] applied a Bayesian network-based fuzzy CREAM to address the uncertainty in the collected data for fishing vessels.

Recently, it has become a trend to quantify the weights of CPCs in solving complex HRA problems. For instance, Bafandegan Emroozi et al. [18] developed a CREAM that takes into consideration the costs associated with enhancing CPCs and assigns weights to CPCs with the Bayesian best-worst method. Zhang et al. [36] proposed a modified CREAM to estimate the HEP in advanced control rooms and computed the correlative and important weights of CPCs for different cognitive functions. Chen et al. [37] introduced an extended CREAM model for the high-speed train operation, in which the weights of CPCs were determined by analytic network process (ANP), and the uncertain CPC information was expressed via interval type-2 fuzzy sets. Chen et al. [38] adopted a triangular fuzzy number to quantify the fuzzy semantics of CPCs and constructed a Bayesian network model to compute the weights of CPCs for the manned submersible diving process. Wang et al. [39] provided a weighted fuzzy CREAM to estimate HEP in subway construction, in which the multiple correlation analysis and evidence theory were used to compute the weights of CPCs. Bafandegan Emroozi and Fakoor [40] proposed a modified CREAM for financial services, employed the DANP to weight CPCs, and examined various impacts of work condition factors on CPCs. Lin et al. [10] presented an improved CREAM for quantifying human reliability and applied the hesitant fuzzy matrix to determine the weights of CPCs on the steam generator tubes of nuclear power plants. Yao et al. [20] used the fuzzy CREAM for HRA in the digital main control room of nuclear power plants and determined the CPC weights by the analytic hierarchy process (AHP) method.

The above literature review indicated that many approaches have been proposed to address the uncertainty of task state assessments elicited from experts and obtain the CPC weights in CREAM. Nevertheless, there are some limitations associated with the CREAMs in literature. First, due to the complexities of practical HRA problems, the current methods are ineffective in capturing the probabilistic linguistic task state judgments of experts. Second, conflict task state assessment information is not considered in previous studies, but a consensus-reaching process is needed for HRA because of the different educational backgrounds and experiences of experts. To fill these research gaps, this paper develops an improved CREAM for HRA by integrating the PLTSs and the MCCM for describing experts' uncertain task state assessments and alleviating the conflicts among experts to reach a consensus.

3. Preliminaries

The PLTSs were proposed by Pang et al. [21] to deal with the complexity and uncertainty of linguistic information.

Definition 1 **[41].** *Let* $S = \{s_i | i = 0, 1, \ldots, 2t\}$ *be a totally ordered and finite discrete term set,* s_i *be a possible value of a linguistic variable, then the linguistic term set* S *satisfies the following properties:*

(1) *The set is ordered as:* $s_i \geq s_j$ *if* $i \geq j$*;*
(2) *The negation operator is defined as:* $neg(s_i) = s_j$*, where* $i + j = \tau$*.*

Definition 2 **[21].** *Let* $S = \{s_i | i = 0, 1, \ldots, 2t\}$ *be a linguistic term set, a PLTS can be defined as:*

$$L(p) = \left\{ L^{(\mu)}\left(p^{(\mu)}\right) | L^{(\mu)} \in S,\ p^{(\mu)} \geq 0,\ \mu = 1, 2, \ldots, \#L(p),\ \sum_{\mu=1}^{\#L(p)} p^{(\mu)} \leq 1 \right\}, \quad (1)$$

where $L^{(\mu)}\left(p^{(\mu)}\right)$ *is the linguistic term* $L^{(\mu)}$ *related to the probability* $p^{(\mu)}$*, and* $\#L(p)$ *is the number of all different linguistic terms in* $L(p)$*.*

Definition 3 **[21].** *Given a PLTS* $L(p) = \left\{ L^{(\mu)}\left(p^{(\mu)}\right) \middle| \mu = 1, 2, \ldots, \#L(p) \right\}$*, and* $r^{(\mu)}$ *is the subscript of the linguistic term* $L^{(\mu)}$*.* $L(p)$ *is an ordered PLTS if and only if the arrangement of linguistic terms* $L^{(\mu)}\left(p^{(\mu)}\right)(\mu = 1, 2, \ldots, \#L(p))$ *is organized in descending order based on the values of* $r^{(\mu)} p^{(\mu)} (\mu = 1, 2, \ldots, \#L(p))$*.*

Definition 4 **[21].** *Given a PLTS* $L(p)$ *with* $\sum_{\mu=1}^{\#L(p)} p^{(\mu)} < 1$*, then the normalized PLTS* $\dot{L}(p)$ *is defined by*

$$\dot{L}(p) = \left\{ L^{(\mu)}\left(\dot{p}^{(\mu)}\right) \middle| \mu = 1, 2, \ldots, \#L(p) \right\}, \quad (2)$$

where $\dot{p}^{(\mu)} = p^{(\mu)} / \sum_{\mu=1}^{\#L(p)} p^{(\mu)}$*, for all* $\mu = 1, 2, \ldots, \#L(p)$*.*

Definition 5 **[26].** *Let* $S = \{s_i | i = 0, 1, \ldots, 2t\}$ *be a linguistic term set and* $L(p) = \left\{ L^{(\mu)}\left(p^{(\mu)}\right) | L^{(\mu)} \in S,\ p^{(\mu)} \geq 0,\ \mu = 1, 2, \ldots, \#L(p),\ \sum_{\mu=1}^{\#L(p)} p^{(\mu)} \leq 1 \right\}$ *be a PLTS, then the linguistic scale function is defined by*

$$f(s_i) = \begin{cases} \frac{a^t - a^{t-i}}{2a^t - 2}, & i = 0, 1, \ldots, t, \\ \frac{a^t + a^{i-t} - 2}{2a^t - 2}, & i = t+1, t+2, \ldots, 2t, \end{cases} \quad (3)$$

where a *is the degree of preference and can be obtained by* $a = \sqrt[3]{9}$*.*

Definition 6 **[26].** *Let* $L(p) = \left\{ L^{(\mu)}\left(p^{(\mu)}\right) | \mu = 1, 2, \ldots, \#L(p) \right\}$ *be a PLTS and* $r^{(\mu)}$ *is the subscript of the linguistic term* $L^{(\mu)}$*. Then the score of* $L(p)$ *is defined as:*

$$S(L(p)) = \sum_{\mu=1}^{\#L(p)} f(s_i) p^{(\mu)} / \sum_{\mu=1}^{\#L(p)} p^{(\mu)}, \quad i = 0, 1, \ldots, 2t. \quad (4)$$

Definition 7 **[21].** *Let* $L_1(p)$ *and* $L_2(p)$ *be two ordered PLTSs,* $L_1(p) = \{L_1{}^{(\mu)}\left(p_1{}^{(\mu)}\right)|\mu = 1,2,\ldots,\#L_1(p)\}$ *and* $L_2(p) = \left\{L_2{}^{(\mu)}\left(p_2{}^{(\mu)}\right)|\mu = 1,2,\ldots,\#L_2(p)\right\}$. *Then:*

(1) $L_1(p) \oplus L_2(p) = \cup_{L_1{}^{(\mu)}\in L_1(p), L_2{}^{(\mu)}\in L_2(p)}\left\{p_1{}^{(\mu)}L_1{}^{(\mu)} \oplus p_2{}^{(\mu)}L_2{}^{(\mu)}\right\}$;

(2) $L_1(p) \otimes L_2(p) = \cup_{L_1{}^{(\mu)}\in L_1(p), L_2{}^{(\mu)}\in L_2(p)}\left\{(L_1{}^{(\mu)})^{p_1{}^{(\mu)}} \otimes (L_2{}^{(\mu)})^{p_2{}^{(\mu)}}\right\}$;

(3) $\lambda L(p) = \cup_{L^{(\mu)}\in L(p)}\lambda p^{(\mu)}L^{(\mu)},\ \lambda \geq 0$;

(4) $(L(p))^{\lambda} = \cup_{L^{(\mu)}\in L(p)}\left\{\left(L^{(\mu)}\right)^{\lambda p^{(\mu)}}\right\}$.

where $L_1{}^{(\mu)}$ *and* $L_2{}^{(\mu)}$ *are the* μ*th linguistic terms in* $L_1(p)$ *and* $L_2(p)$*,* $p_1{}^{(\mu)}$ *and* $p_2{}^{(\mu)}$ *are the probabilities of the* μ*th linguistic terms in* $L_1(p)$ *and* $L_2(p)$*, respectively.*

Definition 8 **[42].** *Let* $S = \{s_i|i = 0,\ 1,\ \ldots,\ 2t\}$ *be a linguistic term set and* $\dot{L}(p) = \{L^{(\mu)}\left(\dot{p}^{(\mu)}\right)|\mu = 1,2,\ldots,\#L(p)\}$ *be a normalized PLTS, then its linguistic term vector* α *is denoted by*

$$\alpha = (a_1, a_2, \ldots, a_{2t+1})^T, \tag{5}$$

$$a_i = \begin{cases} 1,\ i-(t+1) \in r^{(\mu)} \\ 0,\ i-(t+1) \notin r^{(\mu)} \end{cases} \tag{6}$$

and its probability vector β *is defined as:*

$$\beta = (b_1, b_2, \ldots, b_{2t+1})^T, \tag{7}$$

$$b_j = \begin{cases} \dot{p}^{(\mu)},\ j-(t+1) \in r^{(\mu)}, \\ 0,\ j-(t+1) \notin r^{(\mu)}. \end{cases} \tag{8}$$

Definition 9 **[42].** *Let* $S = \{s_i|i = 0,\ 1,\ \ldots,\ 2t\}$ *be a linguistic term set,* $\dot{L}_1(p) = \{L_1{}^{(\mu)}\left(\dot{p}_1{}^{(\mu)}\right)|\mu = 1,2,\ldots,\#L_1(p)\}$ *and* $\dot{L}_2(p) = \left\{L_2{}^{(\mu)}\left(\dot{p}_2{}^{(\mu)}\right)|\mu = 1,2,\ldots,\#L_2(p)\right\}$ *be two normalized PLTSs, then the relative repetition degree* δ *and the diversity degree* μ *between* $\dot{L}_1(p)$ *and* $\dot{L}_2(p)$ *are computed by*

$$\delta = (2t+1)\frac{\alpha_1{}^T\alpha_2}{\max\{\#L_1(p), \#L_2(p)\}} \tag{9}$$

$$v = \frac{\|\beta_1 - \beta_2\|}{2} = \frac{\sqrt{(\beta_1-\beta_2)^T(\beta_1-\beta_2)}}{2} \tag{10}$$

Definition 10 **[42].** *Let* $\dot{L}_1(p)$ *and* $\dot{L}_2(p)$ *be two normalized PLTSs, then the distance measure between them is defined as:*

$$d\left(\dot{L}_1(p), \dot{L}_2(p)\right) = \begin{cases} \frac{v}{\delta},\ \alpha_1{}^T\alpha_2 \neq 0, \\ 1,\ \alpha_1{}^T\alpha_2 = 0. \end{cases} \tag{11}$$

Definition 11 **[43].** *Let* $S = \{s_i|i = 0,\ 1,\ \ldots,\ 2t\}$ *be a linguistic term set, then the entropy of* s_i *is computed by*

$$E(s_i) = \sin\frac{\pi}{2}\left(\frac{i+t}{2t}\right) + \sin\frac{\pi}{2}\left(\frac{-i+t}{2t}\right) - 1 \tag{12}$$

Definition 12 [44]. *Let* $L(p) = \left\{L^{(\mu)}\left(p^{(\mu)}\right)|\mu = 1,2,\ldots,\#L(p)\right\}$ *be a PLTS, then the entropy of* $L(p)$ *can be calculated by*

$$E(L(p)) = \sum_{i=1}^{\#L(p)} p_i[E(s_i)]. \tag{13}$$

4. The Proposed CREAM

This section proposes a new CREAM by combining the PLTSs and the MCCM to calculate the HEPs of different human tasks. The proposed CREAM involves four stages: (1) aggregating the individual state assessments of experts; (2) achieving expert consensus via the MCCM; (3) calculating the weights of CPCs with the entropy weighting method; (4) identifying the HEPs of tasks according to the CPC effect indexes.

For an HRA problem, l experts $E_k(k = 1,2,\ldots,l)$ are engaged to assess the states of m tasks $T_i(i = 1,2,\ldots,m)$ regarding n CPCs $C_j(j = 1,2,\ldots,n)$. Let $L_k = \left[{L_{ij}}^k(p)\right]_{m\times n}$ be the probabilistic linguistic state assessment matrix of the kth expert, where ${L_{ij}}^k(p) = \left\{{L_{ij}}^{k(\mu)}\left({p_{ij}}^{k(\mu)}\right)|\mu = 1,2,\ldots,\#{L_{ij}}^k(p)\right\}$ is the PLTS denotes the state assessment of expert E_k. Next, a step-by-step procedure of the proposed CREAM is explained.

Stage 1: Aggregate the individual state assessments of experts.

In this stage, the individual state assessments of experts are aggregated to derive the collective probabilistic linguistic state assessments of tasks.

Step 1: Calculate the conflict degrees among experts.

The conflict measurement method is proposed by Yuan et al. [29] based on task conflict and relationship conflict. The conflict degree γ_{kh} between expert E_k and expert E_h is calculated by

$$\gamma_{kh} = d(L_k, L_h) \times |t_{kh} - t_{hk}|, \tag{14}$$

where t_{kh} is the trust degree of expert E_k on expert E_h obtained by the expert E_k. Note that t_{kh} satisfies $0 \le t_{kh} \le 1$; $t_{kh} = 1$ indicates that expert E_k completely trusts expert E_h, $t_{kh} = 0$ means that expert E_k does not trust expert E_h at all.

Step 2: Compute the individual conflict degree of each expert.

The conflict degree γ_k of expert E_k is computed by

$$\gamma_k = \sum_{h=1,h\neq k}^{l} \gamma_{kh}. \tag{15}$$

Step 3: Obtain the relative weights of experts.

The weight λ_k of expert E_k can be calculated by

$$\lambda_k = \frac{1/\gamma_k}{\sum_{k=1}^{l} 1/\gamma_k}. \tag{16}$$

Step 4: Determine the collective probabilistic linguistic state assessment matrix.

The collective probabilistic linguistic state assessment matrix $L = \left[L_{ij}(p)\right]_{m\times n}$ can be obtained by

$$L_{ij}(p) = \sum_{k=1}^{l} \lambda_k {L_{ij}}^k(p). \tag{17}$$

Stage 2: Achieve expert consensus via the MCCM.

In this stage, the MCCM with the budget constraint [29] is used to modify experts' judgments and reach the consensus process.

Step 5: Measure experts' individual consensus level.

The individual consensus level Cl_k of expert E_k is computed by

$$Cl_k = 1 - d(L, L_k) \tag{18}$$

where $0 \leq Cl_k \leq 1$.

The consensus level of experts is acceptable if $Cl_k \geq \phi(k = 1, 2, \ldots, l)$, where ϕ is the consensus threshold. Note that the consensus threshold ϕ can be determined by experts based on their experiences directly or by the methods suggested in previous studies [5,45,46]. If $Cl_k < \phi(k = 1, 2, \ldots, l)$, a consensus-reaching process is implemented to arrive at a consensus regarding experts' state assessments.

Step 6: Obtain the final adjusted state assessment matrix L^*.

A consensus budget B is determined and the MCCM with the budget constraint is constructed as:

$$\begin{aligned} &\min z = \sum_{k=1}^{l-1} \sum_{h=k+1}^{l} \gamma^*{}_{kh} \\ &s.t. \begin{cases} Cl^*{}_k \geq \phi, \\ \sum_{k=1}^{l} c_k \times d(L_k, L^*{}_k) \leq B \\ k \in 1, 2, \ldots, l, \end{cases} , \end{aligned} \tag{19}$$

where z is the total conflict degree of experts, $Cl^*{}_k$ is the adjusted individual consensus level of expert E_k, c_k is the unit adjustment cost of expert E_k, $L^*{}_k$ is the optimally adjusted state assessment matrix of expert E_k. By solving model (19), the final adjusted state assessment matrix L^* can be obtained.

Stage 3: Calculate the weights of CPCs by using the entropy weighting method.

In this stage, the entropy weighting method [47] is used to derive the relative weights of CPCs.

Step 7: Establish the probabilistic linguistic entropy matrix E.

Based on the final adjusted state assessment matrix L^*, the probabilistic linguistic entropy matrix $E = \left[E\left(L^*{}_{ij}(p)\right)\right]_{m \times n}$ can be determined as

$$E = \begin{bmatrix} E(L^*{}_{11}(p)) & E(L^*{}_{12}(p)) & \cdots & E(L^*{}_{1m}(p)) \\ E(L^*{}_{21}(p)) & E(L^*{}_{22}(p)) & \cdots & E(L^*{}_{2m}(p)) \\ \vdots & \vdots & \ddots & \vdots \\ E(L^*{}_{n1}(p)) & E(L^*{}_{n2}(p)) & \cdots & E(L^*{}_{nm}(p)) \end{bmatrix} \tag{20}$$

Step 8: Calculate the normalized probabilistic linguistic entropy matrix E'.

The normalized probabilistic linguistic entropy matrix $E' = \left[E_{ij}{}'\right]_{m \times n}$ is obtained by

$$E_{ij}{}' = \frac{E\left(L^*{}_{ij}(p)\right)}{\max_{1 \leq i \leq m}\left\{E\left(L^*{}_{ij}(p)\right)\right\}}. \tag{21}$$

Step 9: Calculate the importance weights of CPCs.

Finally, the importance weights of CPCs $w = (w_1, w_2, \ldots w_n)$ can be calculated by

$$w_j = \frac{1 - \sum_{i=1}^{m} E_{ij}{}'}{n - \sum_{i=1}^{m} \sum_{j=1}^{n} E_{ij}{}'}, \; j = 1, 2, \ldots, n. \tag{22}$$

Stage 4: Compute the HEPs of tasks based on the CPC effect indexes.

The CPCs present a systematic framework to describe the expected performance conditions in human error problems. The CPC effect indexes assess the overall influence of CPCs quantitatively on human reliability. In this stage, the CPC effect indexes [24] are used for HEP estimation.

Step 10: Compute the CPC effect indexes of tasks.

According to the final adjusted state assessment matrix L^* and the weights of CPCs w, the CPC effect index ψ_i of the task T_i is computed by

$$\psi_i = \sum_{j=1}^{n} \frac{S\left(L_{ij}{}^*(p)\right) - f(s_t)}{f(s_t)} n w_j, \tag{23}$$

where s_t is the middle linguistic term of S, which implies that the CPCs have no significant effect on human reliability of human error activities.

Step 11: Calculate the HEPs of different tasks.

A natural logarithm function can represent the correlation between HEPs and CPC effect indexes [48]. For the task T_i, the HEP_i can be represented as:

$$HEP_i = HEP_0 \times e^{\delta \psi_i}, \tag{24}$$

where the constant coefficients HEP_0 and δ are calculated by the upper and lower bounds of the CPC effect indexes and HEP estimations. Based on the correspondence between control modes and the probability of action failure, it is appropriate to let $HEP_{\min} = 0.00005$ and $HEP_{\max} = 1.0$ [49]. In this study, $HEP_0 = 7.07 \times 10^{-3}$ and $\delta = -4.9517$, and thus the HEP for the task T_i can be represented as:

$$HEP_i = 7.07 \times 10^{-3} \times e^{-4.9517\psi_i}. \tag{25}$$

5. Case Study

In this section, an example of the PCR detector operation process [50] is provided to illustrate the effectiveness of the CREAM being proposed in this paper.

5.1. Implementation and Results

As the demand for healthcare services increases, the use of PCR detectors has grown rapidly in recent years. The PCR detector operation process involves four tasks: (1) selecting an appropriate condition for the sample (T1); (2) setting up the condition and starting preincubation (T2); (3) changing the condition according to specific requirements (T3); (4) diagnosing and responding to the results (T4). PCR detectors can reduce the burden on healthcare staff and significantly improve diagnostic efficiency and accuracy. Due to the particularity of PCR tests, the reliability of PCR detectors can be affected by many factors, such as working conditions, healthcare staff's states, and training and experience of healthcare staff. Thus, it is vital to implement the proposed CREAM to qualify the reliability of the PCR detector operation process.

In this case example, nine CPCs are considered in the PCR detector operation process. Five experts from different departments formed an HRA expert panel to assess the states of the tasks via an online questionnaire system. These experts include a medical laboratory technologist, a pathologist, an infectious disease physician, a clinical researcher, and a molecular biologist. The CPCs and their corresponding linguistic terms of the operation process are listed in Table 1. For the expert E_1, the probabilistic linguistic state assessment matrix $L_1 = \left[L_{ij}{}^1(p)\right]_{4\times 9}$ is obtained as shown in Table 2. The trust degree matrix of experts is exhibited as:

$$T = \begin{bmatrix} 1.0 & 0.2 & 0.3 & 0.6 & 0.3 \\ 0.5 & 1.0 & 0.5 & 0.5 & 0.6 \\ 0.4 & 0.3 & 1.0 & 0.4 & 0.6 \\ 0.6 & 0.4 & 0.3 & 1.0 & 0.3 \\ 0.5 & 0.6 & 0.2 & 0.4 & 1.0 \end{bmatrix}.$$

Table 1. The considered CPCs and linguistic terms of operation process.

CPCs	States	Effects
Proper organization (C_1)	s_0: Deficient s_1: Inefficient s_2: Efficient s_3: Quite efficient s_4: Very efficient	Reduced Reduced Not significant Improved Improved
Working conditions (C_2)	s_0: Incompatible s_1: Compatible s_2: Advantageous	Reduced Not significant Improved
Appropriate Man-machine Interface (MMI) and operational support (C_3)	s_0: Very inappropriate s_1: Inappropriate s_2: Tolerable s_3: Adequate s_4: Supportive	Reduced Reduced Not significant Improved Improved
Available procedures and plans (C_4)	s_0: Inappropriate s_1: Acceptable s_2: Appropriate	Reduced Not significant Improved
Number of simultaneous goals achieved (C_5)	s_0: Far beyond actual capacity s_1: More than actual capacity s_2: Matching current capacity s_3: Fewer than actual capacity s_4: Far fewer than actual capacity	Reduced Reduced Not significant Improved Improved
Available time (C_6)	s_0: Continuously inadequate s_1: Temporarily inadequate s_2: Adequate	Reduced Reduced Improved
Fatigue and distraction (C_7)	s_0: High s_1: Acceptable s_2: Low	Reduced Not significant Improved
Adequate training and preparation (C_8)	s_0: Inadequate s_1: Adequate, limited experience s_2: Adequate, high experience	Reduced Not significant Improved
Quality of crew collaboration (C_9)	s_0: Deficient s_1: Inefficient s_2: Efficient s_3: Quite efficient s_4: Very efficient	Reduced Reduced Not significant Improved Improved

Table 2. Task state assessment matrix of expert E_1.

Tasks	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
T_1	$\{s_1(0.40), s_2(0.60)\}$	$\{s_1(0.50), s_2(0.50)\}$	$\{s_2(0.35), s_4(0.65)\}$	$\{s_0(0.50), s_1(0.50)\}$	$\{s_0(0.30), s_1(0.70)\}$	$\{s_0(0.40), s_2(0.60)\}$	$\{s_1(0.85), s_2(0.15)\}$	$\{s_1(0.80), s_2(0.20)\}$	$\{s_1(0.90), s_2(0.10)\}$
T_2	$\{s_3(0.42), s_4(0.58)\}$	$\{s_1(0.38), s_2(0.62)\}$	$\{s_1(0.35), s_2(0.65)\}$	$\{s_0(0.23), s_1(0.77)\}$	$\{s_2(0.70), s_4(0.30)\}$	$\{s_0(0.68), s_2(0.32)\}$	$\{s_1(0.78), s_2(0.22)\}$	$\{s_1(0.80), s_2(0.20)\}$	$\{s_3(0.85), s_4(0.15)\}$
T_3	$\{s_1(0.60), s_2(0.40)\}$	$\{s_1(0.55), s_2(0.45)\}$	$\{s_1(0.30), s_2(0.70)\}$	$\{s_1(0.40), s_2(0.60)\}$	$\{s_0(0.65), s_2(0.35)\}$	$\{s_1(0.80), s_2(0.20)\}$	$\{s_1(0.15), s_2(0.85)\}$	$\{s_1(0.20), s_2(0.80)\}$	$\{s_1(0.30), s_2(0.70)\}$
T_4	$\{s_1(0.48), s_2(0.52)\}$	$\{s_1(0.30), s_2(0.70)\}$	$\{s_1(0.40), s_2(0.60)\}$	$\{s_0(0.70), s_2(0.30)\}$	$\{s_2(0.66), s_4(0.34)\}$	$\{s_1(0.30), s_2(0.70)\}$	$\{s_1(0.80), s_2(0.20)\}$	$\{s_1(0.75), s_2(0.25)\}$	$\{s_1(0.17), s_2(0.83)\}$

Next, the proposed CREAM is utilized for estimating the HEPs of tasks in the PCR detector operation.

Step 1: Via Equation (14), the conflict degrees among experts are calculated and presented in Table 3.

Table 3. The conflict degrees among experts.

Tasks	E_1	E_2	E_3	E_4	E_5
E_1	0.000	0.011	0.004	0.000	0.012
E_2	0.011	0.000	0.010	0.004	0.000
E_3	0.004	0.010	0.000	0.003	0.019
E_4	0.000	0.004	0.003	0.000	0.006
E_5	0.012	0.000	0.019	0.006	0.000

Step 2: Through Equation (15), the individual conflict degrees of experts are acquired as: $\gamma_1 = 0.0265,\ \gamma_2 = 0.0237,\ \gamma_3 = 0.0356,\ \gamma_4 = 0.0130,\ \gamma_5 = 0.0376$.

Step 3: Via Equation (16), the weights of experts are yielded as: $\lambda_1 = 0.178$, $\lambda_2 = 0.200$, $\lambda_3 = 0.133,\ \lambda_4 = 0.363,\ \lambda_5 = 0.126$.

Step 4: By Equation (17), the collective probabilistic linguistic state assessment matrix $L = \left[L_{ij}(p)\right]_{4\times 9}$ is obtained as shown in Table 4.

Table 4. The collective probabilistic linguistic state assessment matrix L.

Tasks	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
T_1	$\{s_1(0.26), s_2(0.66), s_3(0.08)\}$	$\{s_0(0.04), s_1(0.61), s_2(0.35)\}$	$\{s_0(0.04), s_2(0.29), s_4(0.67)\}$	$\{s_0(0.28), s_1(0.69), s_2(0.03)\}$	$\{s_0(0.19), s_1(0.75), s_2(0.06)\}$	$\{s_0(0.34), s_1(0.05), s_2(0.61)\}$	$\{s_1(0.78), s_2(0.22)\}$	$\{s_0(0.10), s_1(0.80), s_2(0.10)\}$	$\{s_1(0.84), s_2(0.16)\}$
T_2	$\{s_3(0.63), s_4(0.37)\}$	$\{s_1(0.31), s_2(0.69)\}$	$\{s_1(0.25), s_2(0.75)\}$	$\{s_0(0.21), s_1(0.79)\}$	$\{s_2(0.73), s_3(0.10), s_4(0.17)\}$	$\{s_0(0.59), s_1(0.06), s_2(0.35)\}$	$\{s_1(0.75), s_2(0.25)\}$	$\{s_0(0.10), s_1(0.78), s_2(0.12)\}$	$\{s_3(0.77), s_4(0.23)\}$
T_3	$\{s_1(0.38), s_2(0.62)\}$	$\{s_1(0.68), s_2(0.32)\}$	$\{s_1(0.20), s_2(0.80)\}$	$\{s_1(0.45), s_2(0.55)\}$	$\{s_0(0.68), s_2(0.32)\}$	$\{s_0(0.03), s_1(0.76), s_2(0.21)\}$	$\{s_1(0.18), s_2(0.82)\}$	$\{s_1(0.29), s_2(0.71)\}$	$\{s_1(0.40), s_2(0.60)\}$
T_4	$\{s_1(0.38), s_2(0.62)\}$	$\{s_1(0.31), s_2(0.69)\}$	$\{s_1(0.30), s_2(0.70)\}$	$\{s_0(0.73), s_2(0.27)\}$	$\{s_2(0.72), s_3(0.16), s_4(0.12)\}$	$\{s_1(0.32), s_2(0.68)\}$	$\{s_1(0.76), s_2(0.24)\}$	$\{s_0(0.11), s_1(0.74), s_2(0.15)\}$	$\{s_1(0.18), s_2(0.82)\}$

Step 5: Based on Equation (18), the individual consensus levels of experts are derived as: $Cl_1 = 0.980,\ Cl_2 = 0.977,\ Cl_3 = 0.974,\ Cl_4 = 0.984,\ Cl_5 = 0.961$. The consensus threshold ϕ is set as ϕ= 0.95 in this example, which is determined by the moderator to ensure obtaining results with a high level of consensus. As the consensus level of the fifth expert Cl_5 is smaller than the threshold ϕ, Step 6 is executed.

Step 6: Based on the MCCM (19), the unit adjustment costs of experts are obtained as: $c_1 = 2.5,\ c_2 = 3.5,\ c_3 = 2,\ c_4 = 1.5,\ c_5 = 2$ and the moderator sets the consensus budget constraint as $B = 1.5$. The optimally adjusted state assessment matrix of the fifth expert $L_5{}^* = \left[L_{ij}{}^{*^5}(p)\right]_{4\times 9}$ is obtained by adjusting six elements of the task state assessment matrix L_5. The final adjusted state assessment matrix $L^* = \left[L_{ij}{}^*(p)\right]_{4\times 9}$ is determined as shown in Table 5. Therefore, the experts' individual consensus levels are derived as: $Cl_1 = 0.980,\ Cl_2 = 0.976,\ Cl_3 = 0.974,\ Cl_4 = 0.985,\ Cl_5 = 0.965$, satisfying $Cl_k \geq \phi(k = 1,2,\ldots,5)$.

Table 5. The final adjusted state assessment matrix L^*.

Tasks	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
T_1	$\{s_1(0.26), s_2(0.66), s_3(0.08)\}$	$\{s_0(0.04), s_1(0.61), s_2(0.35)\}$	$\{s_0(0.04), s_2(0.29), s_4(0.67)\}$	$\{s_0(0.28), s_1(0.69), s_2(0.03)\}$	$\{s_0(0.19), s_1(0.75), s_2(0.06)\}$	$\{s_0(0.34), s_1(0.05), s_2(0.61)\}$	$\{s_1(0.78), s_2(0.22)\}$	$\{s_0(0.10), s_1(0.80), s_2(0.10)\}$	$\{s_1(0.84), s_2(0.16)\}$
T_2	$\{s_3(0.60), s_4(0.40)\}$	$\{s_1(0.31), s_2(0.69)\}$	$\{s_1(0.25), s_2(0.75)\}$	$\{s_0(0.21), s_1(0.79)\}$	$\{s_2(0.73), s_3(0.10), s_4(0.17)\}$	$\{s_0(0.59), s_1(0.06), s_2(0.35)\}$	$\{s_1(0.75), s_2(0.25)\}$	$\{s_0(0.10), s_1(0.78), s_2(0.12)\}$	$\{s_3(0.77), s_4(0.23)\}$
T_3	$\{s_1(0.38), s_2(0.62)\}$	$\{s_1(0.66), s_2(0.34)\}$	$\{s_1(0.18), s_2(0.82)\}$	$\{s_1(0.47), s_2(0.53)\}$	$\{s_0(0.68), s_2(0.32)\}$	$\{s_0(0.03), s_1(0.76), s_2(0.21)\}$	$\{s_1(0.18), s_2(0.82)\}$	$\{s_1(0.29), s_2(0.71)\}$	$\{s_1(0.40), s_2(0.60)\}$
T_4	$\{s_1(0.40), s_2(0.60)\}$	$\{s_1(0.31), s_2(0.69)\}$	$\{s_1(0.30), s_2(0.70)\}$	$\{s_0(0.73), s_2(0.27)\}$	$\{s_2(0.72), s_3(0.16), s_4(0.12)\}$	$\{s_1(0.33), s_2(0.67)\}$	$\{s_1(0.76), s_2(0.24)\}$	$\{s_0(0.11), s_1(0.74), s_2(0.15)\}$	$\{s_1(0.18), s_2(0.82)\}$

Step 7: Using Equation (20), the probabilistic linguistic entropy matrix $E = \left[E\left({L^*}_{ij}(p)\right)\right]_{4\times 9}$ is determined as listed in Table 6.

Table 6. The probabilistic linguistic entropy matrix E.

Tasks	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
T_1	0.378	0.253	0.120	0.286	0.255	0.021	0.323	0.331	0.324
T_2	0.184	0.128	0.387	0.327	0.333	0.025	0.311	0.323	0.236
T_3	0.373	0.273	0.395	0.195	0.132	0.315	0.075	0.120	0.371
T_4	0.371	0.128	0.382	0.000	0.347	0.137	0.315	0.306	0.395

Step 8: Applying Equation (21), the normalized probabilistic linguistic entropy matrix $E' = \left[{E_{ij}}'\right]_{4\times 9}$ is displayed in Table 7.

Table 7. The normalized probabilistic linguistic entropy matrix E'.

Tasks	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
T_1	1.000	0.924	0.304	0.873	0.735	0.066	1.000	1.000	0.821
T_2	0.488	0.470	0.981	1.000	0.959	0.079	0.962	0.975	0.599
T_3	0.989	1.000	1.000	0.595	0.382	1.000	0.231	0.363	0.940
T_4	0.983	0.470	0.967	0.000	1.000	0.434	0.974	0.925	1.000

Step 9: Based on Equation (22), the weights of CPCs are calculated as: $w_1 = 0.141$, $w_2 = 0.106$, $w_3 = 0.129$, $w_4 = 0.084$, $w_5 = 0.119$, $w_6 = 0.033$, $w_7 = 0.124$, $w_8 = 0.129$, $w_9 = 0.135$.

Step 10: Via Equation (23), the effect indexes of the four tasks are yielded as: $\psi_1 = 0.294$, $\psi_2 = 2.191$, $\psi_3 = 1.408$, $\psi_4 = 0.659$.

Step 11: By Equations (24) and (25), the HEPs for the four tasks are obtained as: $HEP_1 = 8.60 \times 10^{-3}$, $HEP_2 = 3.26 \times 10^{-3}$, $HEP_3 = 4.86 \times 10^{-3}$, $HEP_4 = 7.14 \times 10^{-3}$.

5.2. Comparison Analysis

To demonstrate the effectiveness of the proposed CREAM, this section carries out a comparative analysis based on the above case study. In the traditional CREAM method, the context influence index CREAM (CII-CREAM) [51], the evidential reasoning CREAM (ER-CREAM) [52], the hesitant fuzzy matrix CREAM (HFM-CREAM) [10], and the modified CREAM [48] are chosen in this case study. Table 8 presents the priority of the four tasks in the PCR detector operation process based on the listed approaches.

Table 8. Ranking results of tasks obtained by different approaches.

Tasks	The Traditional CREAM	The CII-CREAM	The HFM-CREAM	The ER-CREAM	The Modified CREAM	The Proposed CREAM
Task 1	1	4	1	1	1	1
Task 2	1	1	4	4	4	4
Task3	1	2	3	3	3	3
Task 4	1	3	2	2	2	2

From Table 8, it can be seen that T_3 ranks third via the proposed CREAM, the HFM-CREAM, the ER-CREAM, and the modified CREAM. Besides, except for the CII-CREAM, the other four methods place T_4 in second place. Furthermore, the priority of tasks obtained by the proposed CREAM is identical to the results determined by the HFM-CREAM, the ER-CREAM, and the modified CREAM. These results imply the availability and practicality of the proposed CREAM.

However, Table 8 shows that the ranking results of the task for the PCR detector operation process obtained by the traditional CREAM, the CII-CREAM, and the proposed CREAM are not the same. Inconsistent outcomes may be attributable to the following reasons: First, the numerical information utilized in the traditional CREAM and the CII-CREAM cannot express task state assessments accurately. As a result, the original state assessment information given by experts may be missed in HRA. Second, the importance weights of CPCs are considered to be the same. This may not be in line with practical situations for a real application of CREAM. Furthermore, the HFP values obtained by the traditional CREAM are intervals that are unacceptably wide and cannot be used for the initial screening of human error events.

Moreover, the HEP ranking outcomes derived from the proposed CREAM and the CII-CREAM are different. Specifically, T_1 is situated first by the proposed CREAM but is in the fourth position with the CII-CREAM. In addition, T_2 occupies the fourth position by using the proposed CREAM. But by the CII-CREAM, T_2 stands in the first place. These inconsistent results may be explained by the following points: First, the PLTSs are not used in the CII-CREAM, which cannot express the uncertain assessments of experts accurately and reflect the probabilistic information effectively. Second, the CPCs are treated as the same weight in the CII-CREAM, and the interactions between CPCs are not considered. Third, the CII-CREAM uses the performance influence index to quantify the overall impact of CPCs in solving HRA problems, which cannot realize the continuity of HEPs.

The comparison of different approaches is further analyzed via the aggregation technique [15] to validate the proposed CREAM model. The optimal method is expected to produce results that closely match the aggregate ranking. Table 9 presents the HEP ranking matrix for four operational tasks, where the entries indicate the frequency of each task assigned to different rankings. Subsequently, Table 10 displays the smoothing of task assignments on rankings based on the results computed through the aggregation technique. From Table 10, the linear programming model is constructed to determine the optimal rankings:

$$\max \textstyle\sum_{i=1}^{4} \sum_{k=1}^{4} M_{ik} \times \frac{4^2}{k} \times N_{ik}$$
$$s.t. \begin{cases} \sum\limits_{k=1}^{4} N_{ik} = 1 i = 1,2,3,4, \\ \sum\limits_{i=1}^{4} N_{ik} = 1 k = 1,2,3,4, \end{cases}$$

where N_{ik} is equal to 0 or 1 for all i and k. By solving the model above, the optimal ranking of four operational tasks in the case study is determined as $T_1 > T_4 > T_3 > T_2$, which is identical to the ranking results calculated by the proposed CREAM model. Thus, the proposed CREAM model provides a more logical and credible HEP ranking in the specified application.

Table 9. Total times tasks assigned to different rankings.

Tasks	Ranking			
	1	**2**	**3**	**4**
T_1	5	0	0	1
T_2	1	1	0	4
T_3	0	1	5	0
T_4	0	4	1	1

Table 10. Smoothing of task assignments on rankings (M_{ik}).

Tasks	Ranking			
	1	**2**	**3**	**4**
T_1	5	5	5	6
T_2	1	2	2	6
T_3	0	1	6	6
T_4	0	4	5	6

From the analyses above, it can be concluded that a more accurate and reliable HEP ranking result for the PCR detector operation process can be obtained by employing the CREAM proposed in this paper. Compared with extant approaches, the proposed CREAM has the following advantages: First, via the PLTSs, the proposed CREAM can consider the probability of linguistic term sets, accurately describe the uncertain linguistic evaluations of experts, and retain the original assessment information as much as possible. Second, with the MCCM, the proposed CREAM can minimize conflicts among experts and assist experts with different opinions to achieve a consensus. As a result, the proposed CREAM can address the limitations associated with the traditional CREAM and provide a more reasonable estimation of the HEPs.

6. Conclusions

In this paper, we develop a new integrated CREAM by combining the PLTSs and the MCCM to assess the task states of human error activities and estimate the probabilities of human error problems. The PLTSs are adopted to represent experts' ambiguous linguistic judgments on the task states of human error activities. The MCCM with the budget constraint is employed to assist different experts in reaching consensus. In addition, the entropy weighting method is introduced to derive the relative weights of CPCs based on the task state assessments given by experts in a probabilistic linguistic context. Finally, an example concerning the PCR detector operation is implemented to demonstrate the reliability and applicability of the CREAM proposed in this study. The results show that the proposed CREAM can not only handle the uncertain linguistic task state assessments elicited from experts, but also support experts agreeing and obtaining reliable HEP estimations of tasks in HRA.

In further studies, the following improvements for the proposed CREAM are suggested. First, the environmental factors in practical HRA problems may change over time. It is interesting to develop a dynamic HRA approach to solve this problem in the future. Second, the entropy weighting method used in this study is an objective weighting approach. Future research can apply a combination weighting method for assessing the CPC weights based on the subjective judgments of experts and objective CPC data. Besides, the calculations of the proposed CREAM are long, and it may be impossible to follow and check in solving practical HRA problems. Therefore, it is important to develop a web-based HRA software system to automate the implementation of the proposed CREAM in future work.

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Abbreviations

AHP	Analytic hierarchy process
ANP	Analytic network process
CPCs	Common performance conditions
CII-CREAM	Context influence index CREAM
CREAM	Cognitive reliability and error analysis method
DANP	Decision-making trial and evaluation laboratory-based analytic network process
ER-CREAM	Evidential reasoning CREAM
GRA	Grey relation analysis
HEP	Human error probability
HFM-CREAM	Hesitant fuzzy matrix CREAM
HRA	Human reliability analysis
MCCM	Minimum conflict consensus model
PCR	Polymerase chain reaction
PLTSs	Probabilistic linguistic term sets

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