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Original Article

New method for dependence assessment in human reliability analysis based on linguistic hesitant fuzzy information

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A B S T R A C T

Human reliability analysis (HRA) is a proactive approach to model and evaluate human systematic errors, and has been extensively applied in various complicated systems. Dependence assessment among human errors plays a key role in the HRA, which relies heavily on the knowledge and experience of experts in real-world cases. Moreover, there are ofthen different types of uncertainty when experts use linguistic labels to evaluate the dependencies between human failure events. In this context, this paper aims to develop a new method based on linguistic hesitant fuzzy sets and the technique for human error rate prediction (THERP) technique to manage the dependence in HRA. This method handles the linguistic assessments given by experts according to the linguistic hesitant fuzzy sets, determines the weights of influential factors by an extended best-worst method, and confirms the degree of dependence between successive actions based on the THERP method. Finally, the effectiveness and practicality of the presented linguistic hesitant fuzzy THERP method are demonstrated through an empirical healthcare dependence analysis.

1. Introduction

Human error is the key factor causing a wide range of undesired consequences in various industrial facilities [1,2]. As a part of probabilistic safety assessment, human reliability analysis (HRA) is a proactive approach for identifying, quantifying, and decreasing the human errors in human-machine systems [3,4]. It is aimed to analyze vulnerabilities within tasks and operations, understand error cycle and shaping factors, quantify potential errors, and finally, give guidance to improve reliability of a system [5]. HRA addresses the impact of people performance on system risk, which includes the assessment of human failure events (HFEs) and related impacts on the structures, systems, and components of complex facilities [6]. Via the HRA, safety engineers can enhance human-centered and error-tolerant design to make high-risk systems inherently suited to operation by humans [7]. Over the last decades, HRA has gained a large amount of attention and has been extensively utilized to reduce the incidents or accidents linked with human errors in different industries, including the nuclear [8–10], aerospace [11], chemical [12], healthcare [13], and other safety-critical industries [14–16].

Dependence assessment among HFEs is a pivotal component to avoid underestimation of the risk in HRA [17,18], which is defined as assessing the effect of operator task failure on the probability of sequential task failures [19,20]. When there is a dependency between two tasks, the probability of a continuous task failure is higher if a worker fails on the previous task [21,22]. Normally, the result of dependency assessment is a conditional human error probability (CHEP), assuming that the previous task failed [20,23]. In the literature, different methods have been suggested for assessing the dependence between HFEs in HRA [24–26]. One of the most widely used dependence assessment method in HRA is the technique for human error rate prediction (THERP). The advantages of the method can be analyzed from two aspects [22,27,28]: (1) It suggests five dependence levels, i.e., zero dependence, low dependence, moderate dependence, high dependence, and complete dependence, and provides guidelines for assigning the dependence degree between two tasks on the basis of multiple factors. (2) For different dependence degrees, a modified formula is given to obtain the CHEP which denotes the effect of one task

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failure on the probability of continuous task failure.

In THERP, the assessment of dependence is essentially a highly subjective process based on experts' judgments [17,22]. In the real world, it is often difficult for HRA experts to apply crisp values to describe the dependence levels between consecutive human actions. Moreover, experts tend to uses linguistic terms like "high" and "low" to express the dependence assessment information of successive actions [23,29]. The linguistic hesitant fuzzy sets (LHFSs) proposed by Meng et al. [30] is a new and effective vague information representation method. It integrated the advantages of hesitant fuzzy sets with linguistic fuzzy sets to concretize the complexity of an uncertain environment [31]. As a result, the LHFSs allow several possible linguistic numbers to represent the membership degree of an element to a set [32], and are considered as a useful way to express fuzzy and uncertain information given by decision makers [33]. In view of these characteristics, the LHFSs have been utilized to deal with ambiguity and uncertainty in different decision-making problems, such as E-learning website evaluation [34], energy project risk assessment [35], renewable energy mode choice [36], surrounding rock stability evaluation [37], and intelligent transportation system selection [38]. Therefore, the LHFSs can be an effective and powerful method to evaluate ambiguity and uncertainty information in the process of dependence assessment among human errors.

Based on the above, a dependence assessment method on the basis of the LHFSs and THERP is introduced in this paper to determine the dependence levels between consecutive human actions. To sum up, this research makes the following important contributions to the HRA literature: First, the LHFSs are used to handle the ambiguity and complex evaluation information of experts about consecutive actions. Second, an extended best-worst method (BWM) is applied for the purpose of obtaining the weights of influential factors according to an optimization model. Third, an improved THERP method is proposed to compute the overall dependence levels between consecutive operator actions. To this end, the remainder of this article is organized as follows: The related researches on dependence assessment in HRA and risk assessment using the BWM method are reviewed in Section 2. The basic concepts associated with the LHFSs are briefly given in Section 3. Section 4 presents an extended THERP method to assess the dependency of HFEs in a linguistic hesitant fuzzy environment. In Section 5, the proposed linguistic hesitant fuzzy THERP (LHF-HERP) method is demonstrated by a healthcare dependence analysis case study. Finally, we summarize the research and look into future development directions in Section 6.

2. Literature review

2.1. Dependence assessment in HRA

Dependence analysis evaluates the impact of worker's failure to conduct a task on the failure probability of follow-on tasks. Over the years, dependence analysis has become an increasingly important area of study and many dependence assessment methods have been presented for determining the dependence between successive actions. For instance, Zio et al. [20] presented a framework based on fuzzy expert system for the evaluation of the dependence between two successive tasks. Podofillini et al. [17] proposed a method for dependence assessment that captures the rules used by experts to assess dependence levels among human actions. Su et al. [22] developed a computational model based on Dempster-Shafer evidence theory and analytic hierarchy process (AHP) method to handle the dependence in HRA. To improve the method in Ref. [22], Chen et al. [21] suggested an evidential AHP dependence assessment method, Guo et al. [28] applied evidence credibility decay model (ECDM) to assess the dependence between human tasks, Zhou et al. [39] introduced a dependence assessment model based on D numbers and AHP, and Zheng and Deng [27] proposed a dependence assessment method based on ECDM and induced OWA operator. An evidential network approach extended by belief rules and uncertainty measures was proposed in Ref. [40] to manage dependence assessment in HRA. A large group approach based on interval 2- tuple linguistic variables and cluster analysis method was put forward in Ref. [23] to assess the dependence between tasks in HRA. Recently, Jiang et al. [29] assessed the dependence between tasks by a Z-network model based on Bayesian network and Z-numbers. Wang et al. [41] evaluated the dependences between performance shaping factors through moderating and mediating effect analysis. Zhang et al. [42] handled the uncertainty and traceability of dependence assessment by using belief rules and interval belief distribution.

2.2. Risk assessment using the BWM method

The BWM proposed by Rezaei [43] is a highly effective decision-making method with higher consistency. It has been extended and employed to tackle with various risk assessment problems since its introduction. For example, Zarei et al. [44] integrated D number theory, BWM, and dynamic Bayesian network to analyze the risk of hydrogen infrastructures. Yazdi et al. [45] combined decision-making trial and evaluation laboratory (DEMATEL) method with BWM and Bayesian network for safety management in the high-tech industry. Nasirzadeh et al. [46] used systems dynamics and BWM for the investment analysis in privatization of a drilling company. Liu et al. [47] combined BWM with an improved alternative queuing method for occupational health and safety risk assessment. Moktadir et al. [48] proposed a Pareto-based BWM to investigated the risk factors in sustainable supply chain management of the leather industry. Kumar et al. [49] applied a fuzzy BWM to identify risk mitigation strategies in perishable food supply chains during the COVID-19 pandemic. Yazdi et al. [50] proposed an intuitionistic fuzzy BWM with the consideration of democratic and autocratic decision making styles for failure mode and effect analysis (FMEA). Rostamabadi et al. [51] incorporated Bayesian network with fuzzy BWM for the dynamic safety analysis of process systems. In addition, many other extensions of the BWM have been developed for construction safety risk assessment [52], ergonomic risk assessment [53], and machine tool risk analysis [54].

As reviewed previously, many models and methods have been proposed for managing the dependence assessment between HFEs. Among them, both fuzzy logic and evidence theory have been widely utilized to handle the subjective dependence assessments of experts. Nevertheless, these methods have limitations in linguistic assessments, and are incapable of reflect the inconsistency and hesitancy of experts. On the other hand, the normal BWM has been employed or extended for risk assessment and safety analysis in a variety of fields. However, there is not a study on the application of BWM to address the dependence assessment problem in HRA. Considering these research gaps, we develop a new computational model that integrates the LHFSs with an extended BWM in this study for the dependence assessment among human errors in HRA.

3. Preliminaries

3.1. Linguistic hesitant fuzzy sets

The theory of LHFSs was initially presented by Meng et al. [30] to deal with the qualitative preferences of experts and express their hesitancy, uncertainty and inconsistency.

Definition 1. [30]. Suppose that there is a linguistic term set $S = \{s_0, s_1, ..., s_{t-1}\}$, an LHFS on S is a set, whose element is a combination of linguistic term $S_{\theta(i)}$ and its membership degrees $lh(s_{\theta(i)})$, represented by

$$LH = \{(s_{\theta(i)}, lh(s_{\theta(i)}))|s_{\theta(i)} \in S\} \quad (1)$$

where $lh(s_{\theta(i)}) = \{r_1, r_2, \ldots, r_{m_i}\}$ is a set of m_i values in [0, 1] indicating the possible membership degrees of $s_{\theta(i)} \in S$.

Definition 2. [30]. Suppose that LH_1 and LH_2 are any two LHFSs, then their operation rules can be defined as follows:

$$LH_1 \oplus LH_2 = \bigcup_{(s_{\theta(i)}, lh(s_{\theta(i)})) \in LH_1, (s_{\theta(j)}, lh(s_{\theta(j)})) \in LH_2} \left\{ \left(S_{\theta(i)+\theta(j)}, \bigcup_{r_i \in lh(s_{\theta(i)}), r_j \in lh(s_{\theta(j)})} 1-(1-r_i)(1-r_j) \right) \right\}$$

$$LH_1 \otimes LH_2 = \bigcup_{(s_{\theta(i)}, lh(s_{\theta(i)})) \in LH_1, (s_{\theta(j)}, lh(s_{\theta(j)})) \in LH_2} \left\{ \left(S_{\theta(i)\theta(j)}, \bigcup_{r_i \in lh(s_{\theta(i)}), r_j \in lh(s_{\theta(j)})} r_i r_j \right) \right\}$$

$$\lambda LH_1 = \bigcup_{(s_{\theta(i)}, lh(s_{\theta(i)})) \in LH_1} \left\{ \left(S_{\lambda\theta(i)}, \bigcup_{r_i \in lh(s_{\theta(i)})} 1-(1-r_i)^{\lambda} \right) \right\}, \lambda \in [0, 1]$$

$$LH_1{}^{\lambda} = \bigcup_{(s_{\theta(i)}, lh(s_{\theta(i)})) \in LH_1} \left\{ \left(S_{\theta(i)^{\lambda}}, \bigcup_{r_i \in lh(s_{\theta(i)})} r_i \right) \right\}, \lambda \in [0, 1]$$

where $r_i \in lh(s_{\theta(i)})(i = 1, 2, ..., m_i)$ and $r_j \in lh(s_{\theta(j)})(i = 1, 2, ..., m_j)$ denote the ith and the jth linguistic term possible membership degrees in $lh(s_{\theta(i)})$ and $lh(s_{\theta(j)})$, respectively.

Definition 3. [30]. Let $LH = \{(s_{\theta(i)}, lh(s_{\theta(i)}))|s_{\theta(i)} \in S, i = 1, 2, ..., m\}$ be an LHFS. Then its expectation function and variance function can be computed by

$$E(LH) = \frac{1}{|index(LH)|} \left(\sum_{\theta(i) \in index(LH)} \frac{\theta(i)}{|lh(s_{\theta(i)})|} \sum_{r \in lh(s_{\theta(i)})} r \right) \quad (2)$$

$$V(LH) = \frac{1}{|index(LH)|} \left(\sum_{\theta(i) \in index(LH)} \left(\frac{\theta(i)}{|lh(s_{\theta(i)})|} \sum_{r \in lh(s_{\theta(i)})} r - E(LH) \right)^2 \right) \quad (3)$$

where $|lh(s_{\theta(i)})|$ is the count of real numbers in $lh(s_{\theta(i)})$, and $|index(LH)|$ is the cardinality of $index(LH)$; $index(LH) = \{\theta(i)|(s_{\theta(i)}, lh(s_{\theta(i)})) \in LH, s_{\theta(i)} \in S, lh(s_{\theta(i)}) \neq \{0\}\}$.

Definition 4. [30]. For any two LHFSs $LH_1 = \{(s_{\theta(i)}, lh(s_{\theta(i)}))|s_{\theta(i)} \in S, i = 1, 2, ..., m_1\}$ and $LH_2 = \{(s_{\theta(i)}, lh(s_{\theta(i)}))|s_{\theta(i)} \in S, i = 1, 2, \ldots, m_2\}$, their comparison rules are explained as follows:

(1) If $E(LH_1) > E(LH_2)$, then $LH_1 > LH_2$;
(2) If $E(LH_1) = E(LH_2)$, then
  (a) if $V(LH_1) < V(LH_2)$, then $LH_1 > LH_2$;
  (b) if $V(LH_1) = V(LH_2)$, then $LH_1 = LH_2$.

Definition 5. [30,38]. Let $LH_i(i = 1, 2, ..., n)$ be a set of LHFSs and $w = (w_1, w_2, ..., w_n)$ is the associated weighting vector with $w_j \in [0, 1]$ and $\sum_{j=1}^{n} w_j = 1$. Then the linguistic hesitant fuzzy weighted averaging (LHFWA) operator is defined as:

$$\text{LHFWA}(LH_1, LH_2, ..., LH_n) = \bigcup_{(s_{\theta(1)}, lh(s_{\theta(1)})) \in LH_1, \cdots (s_{\theta(n)}, lh(s_{\theta(n)})) \in LH_n} \times \left(s_{\sum_{j=1}^{n} w_j \theta(j)}, \bigcup_{r_1 \in lh(s_{\theta(1)}), \cdots, r_n \in lh(s_{\theta(n)})} \left(1 - \prod_{j=1}^{n} (1-r_j)^{w_j} \right) \right). \quad (4)$$

Definition 6. [38]. Let $S = \{s_0, s_1, \ldots, s_{t-1}\}$ be a linguistic term set, $LH_1 = \{(s_{\theta(i)}, lh(s_{\theta(i)}))|s_{\theta(i)} \in S, i = 1, 2, ..., m_1\}$ and $LH_2 = \{(s_{\theta(i)}, lh(s_{\theta(i)}))|s_{\theta(i)} \in S, i = 1, 2, ..., m_2\}$ be two LHFSs, $f(s_i) = \frac{i}{t-1}$ be an extended scale function. Then, the distance between LH_1 and LH_2 can be computed by

$$d(LH_1, LH_2) = \frac{1}{2} \left[\frac{1}{m_1} \sum_{(s_{\theta(i)}, lh(s_{\theta(i)})) \in LH_1} \min_{(s_{\theta(j)}, lh(s_{\theta(j)})) \in LH_2} \left| \frac{\frac{f(s_{\theta(i)})}{|lh(s_{\theta(i)})|} \left(\sum_{i=1}^{|lh(s_{\theta(i)})|} i r_i \right)}{\sum_{j=1}^{|lh(s_{\theta(j)})|} j} - \frac{\frac{f(s_{\theta(j)})}{|lh(s_{\theta(j)})|} \left(\sum_{j=1}^{|lh(s_{\theta(j)})|} j r_j \right)}{\sum_{i=1}^{|llh(s_{\theta(i)})|} i} \right| \right.$$
$$\left. + \frac{1}{m_2} \sum_{(s_{\theta(j)}, lh(s_{\theta(j)})) \in LH_2} \min_{(s_{\theta(i)}, lh(s_{\theta(i)})) \in LH_1} \left| \frac{\frac{f(s_{\theta(j)})}{|lh(s_{\theta(j)})|} \left(\sum_{j=1}^{|lh(s_{\theta(j)})|} j r_j \right)}{\sum_{i=1}^{|lh(s_{\theta(i)})|} i} - \frac{\frac{f(s_{\theta(i)})}{|lh(s_{\theta(i)})|} \left(\sum_{i=1}^{|lh(s_{\theta(i)})|} i r_i \right)}{\sum_{j=1}^{|lh(s_{\theta(j)})|} j} \right| \right]. \quad (5)$$

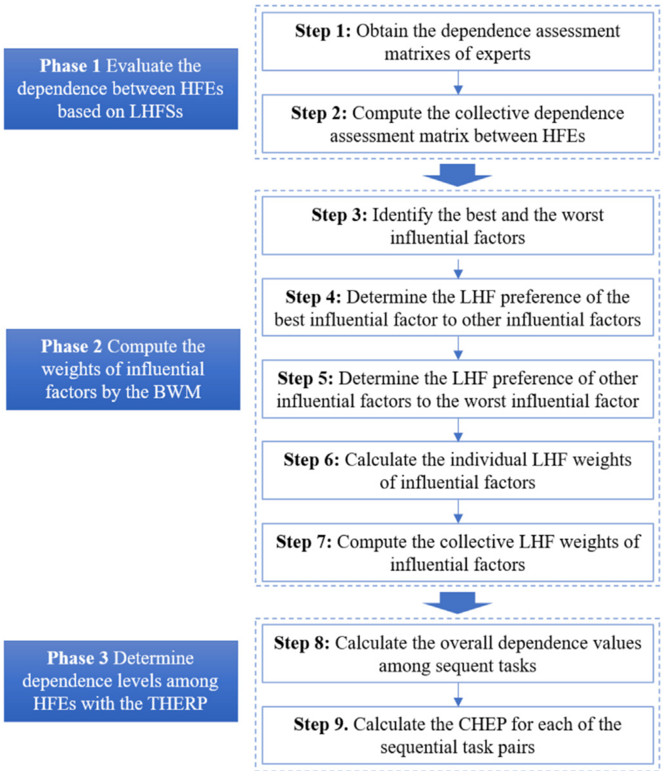

Fig. 1. Flowchart of the proposed dependence assessment method.

4. The proposed dependence assessment method

In the section, we propose a new dependence assessment methodology using LHFSs and THERP to deal with the dependency in HRA. The method is made up of three phases, i.e., evaluating the dependence between HFEs based on the LHFSs, computing the weights of influential factors by the BWM, and determining dependency levels among human operations in line with the THERP. Fig. 1 shows the graphical based framework of the proposed LHF-HERP method.

For a dependence assessment problem in HRA, we assume that n influencing factors $IF_j(j=1,2,...,n)$ are considered and assessed by l domain experts $E_k(k=1,2,...,l)$ for m pairs of consecutive sequential tasks $ST_i(i=1,2,...,m)$. Each expert E_k is assigned a weight $\lambda_k>0(k=1,2,...,l)$ satisfying $\sum_{k=1}^{l}\lambda_k=1$ to reflect his/her relative importance in the dependence assessment process. In what follows, the presented dependence assessment method to obtain the level of dependency between successive tasks is explained in detail.

4.1. Evaluate the dependence between HFEs based on LHFSs

Step 1. Obtain the dependence assessment matrixes of experts

In the proposed method, linguistic expressions are assumed to be adopted by experts to express their assessment between the m pairs of sequent tasks with respect to each influential factor. After transforming into LHFSs, a dependence assessment matrix for the kth expert can be constructed as $\tilde{R}^k=[\tilde{r}_{ij}^k]_{m\times n}(k=1,2,...,l)$, where $\tilde{r}_{ij}^k=({s^k}_{\theta(ij)},lh({s^k}_{\theta(ij)}))$ is the linguistic hesitant fuzzy evaluation of the ith sequential task pair concerning the jth influential factor based on the linguistic term set $S=\{s_0,s_1,...,s_{t-1}\}$.

Step 2. Compute the collective dependence assessment matrix between HFEs

In this step, the LHFWA operator is used to aggregate the individual opinions of experts to obtain the collective dependence assessment matrix $\tilde{R}=[\tilde{r}_{ij}]_{m\times n}$, in which $\tilde{r}_{ij}=(s_{\theta(ij)},lh(s_{\theta(ij)}))$ is determined by

$$\tilde{r}_{ij}=\text{LHFWA}\left(\tilde{r}_{ij}^1,\tilde{r}_{ij}^2,...,\tilde{r}_{ij}^k\right)=\cup_{(s_{\theta(1)},lh(s_{\theta(1)}))\in\tilde{r}_{ij}^1,...,(s_{\theta(k)},lh(s_{\theta(k)}))\in\tilde{r}_{ij}^k}$$
$$\times\left(s_{\sum_{k=1}^{l}\lambda_k\theta_k},\cup_{r_1\in lh(s_{\theta(1)}),...,r_k\in lh(s_{\theta(k)})}\left(1-\prod_{k=1}^{l}(1-r_k)^{\lambda_k}\right)\right). \tag{6}$$

4.2. Compute the weights of influential factors by the BWM

The BWM first proposed by Rezaei [43] is an efficient weighting method with smaller amount comparisons from experts and higher consistency in results. It calculates the weights of criteria by using two vectors that are compared in pairs. In this study, we extend the BWM with LHFSs for the weight calculation of influential factors.

Step 3. Identify the best and the worst influential factors

For the n considered influential factors $IF_j(j=1,2,...,n)$, every expert E_k should give the best (most important) influential factor IF_B^k and the worst (least important) influential factor IF_W^k from his or her point of view.

Step 4. Determine the linguistic hesitant fuzzy (LHF) preference of the best influential factor to other influential factors

The preferences of the best influential factor to each of the others can be evaluated by experts utilizing the linguistic term set $S'=\{s'_1,s'_2,...,s'_{t-1}\}$. The obtained LHF best-to-others vector of E_k is represented as

$$\tilde{F}_B^k=\left(\tilde{f}_{B1}^k,\tilde{f}_{B2}^k,...,\tilde{f}_{Bn}^k\right)(k=1,2,...,l), \tag{7}$$

where $\tilde{f}_{Bj}^k=\{(s_{\theta(Bj)}^k,r_{Bj}^k)\}$ indicates the expert's LHF assessment of the best influential factor IF_B^k over the other influential factors.

Step 5. Determine the LHF preference of other influential factors to the worst influential factor

By utilizing the linguistic term set S', the LHF others-to-worst vector of E_k is expressed as

$$\tilde{F}_W^k=\left(\tilde{f}_{1W}^k,\tilde{f}_{2W}^k,...,\tilde{f}_{nW}^k\right)(k=1,2,...,l) \tag{8}$$

where $\tilde{f}_{jW}^k=\{(s_{\theta(jW)}^k,r_{jW}^k)\}$ represents the kth expert's LHFS preference of the other influential factors over the worst influential factor IF_W^k.

Step 6. Calculate the individual LHF weights of influential factors

In this step, an optimization model is established by minimizing the distances $d(\tilde{w}_B^k,\tilde{f}_{Bj}^k\tilde{w}_j^k)$ and $d(\tilde{w}_j^k,\tilde{f}_{jW}^k\tilde{w}_W^k)$ as follows:

Table 1
HRA of the blood transfusion process.

Sequential tasks	Actions	HFEs	Causes of HFEs
ST_1	Preoperative assessment	Insufficient preoperative assessment of the blood product requirement	Incorrect assessment of the potential blood loss
ST_2	Request form filling	Inadequate and/or incorrect clinical information on application form	Incorrect/incomplete application form
ST_3	Transfusion preparation	Too long preparation time before injection	It takes too long to deliver blood products to clinics
ST_4	Transfusing blood component	Inappropriate timing of transfusion	Inappropriate transfusion time
	Transfusion monitoring	Transfusion reactions occur in the transfusion	Patients are not monitored in the transfusion

Table 2
Anchor points for the three influential factors.

Time relationship	Task relatedness	Similarity of performers	Dependence level
Tasks are widely separated in time, ≥ 8 h	Tasks are unrelated	No similarity of performers is present between tasks	ZD
Tasks are moderate farness in time, 30 min-1 hr	Tasks are slightly related	Tasks are accomplished by different teams	LD
Closeness in time is not relevant in the dependence assessment, 20–30 min	Tasks are moderately related	Tasks are accomplished by different individuals with same qualification	MD
Tasks are moderate close in time, 5–20 min	Tasks are highly related	Tasks are accomplished by the Same team	HD
Tasks are strong close in time, ≤ 5 min	Tasks are closely related	Tasks are accomplished by the same individual	CD

Table 3
Dependence assessments for the sequential tasks.

Experts	Influential factors	Sequent tasks			
		ST_1	ST_2	ST_3	ST_4
E_1	Time	MD	LD	MD	LD-MD
	Task	HD	LD	HD	LD
	Performer	HD	ZD	HD	HD
E_2	Time	LD	LD-MD	HD	LD
	Task	LD	MD	HD	MD
	Performer	MD-HD	HD	MD	MD
E_3	Time	MD-HD	LD	HD	ZD
	Task	HD	CD	CD	CD
	Performer	HD	HD-CD	HD-CD	MD-HD
E_4	Time	LD	MD	LD	LD
	Task	MD	HD-CD	MD	MD
	Performer	LD	MD	LD	MD
E_5	Time	LD-MD	LD	MD	LD
	Task	MD	MD	LD	MD
	Performer	LD	LD	LD	LD

$$\min \xi^k$$
$$s.t. \begin{cases} \left|\tilde{f}\left(s^k_{\theta(B)}\right) r^k_B - \tilde{f}\left(s^k_{\theta^k(Bj)\theta^k(j)}\right) r^k_{Bj} r^k_j\right| \le \xi^k \\ \left|\tilde{f}\left(s^k_{\theta(j)}\right) r^k_j - \tilde{f}\left(s^k_{\theta^k(jW)\theta^k(W)}\right) r^k_{jW} r^k_W\right| \le \xi^k \\ \sum_{j=1}^n E\left(\tilde{w}^k_j\right) = 1 \\ E\left(\tilde{w}^k_j\right) \ge 0,\ \text{for } j = 1, 2, ..., n \end{cases} \tag{9}$$

where $\tilde{w}^k_B = \{(s^k_{\theta(B)}, r^k_B)\}$ and $\tilde{w}^k_j = \{(s^k_{\theta(j)}, r^k_j)\}$ for $j = 1, 2, ..., n$, and $\tilde{w}^k_W = \{(s^k_{\theta(W)}, r^k_W)\}$.

Based on the definition of absolute values [36], model (9) is equivalent to the following form

Table 4
Dependence assessment matrixes for the four pairs of tasks.

Experts	Influential factors	Sequent tasks			
		ST_1	ST_2	ST_3	ST_4
E_1	Time	$\{(s_2,0.3,0.5)\}$	$\{(s_1,0.5)\}$	$\{(s_2,0.5)\}$	$\{(s_1,0.7), (s_2,0.1)\}$
	Task	$\{(s_3,0.4)\}$	$\{(s_1,0.4)\}$	$\{(s_3,0.5,0.8)\}$	$\{(s_1,0.1)\}$
	Performer	$\{(s_3,0.2)\}$	$\{(s_0,0.5)\}$	$\{(s_3,0.4)\}$	$\{(s_3,0.2,0.4)\}$
E_2	Time	$\{(s_1,0.6)\}$	$\{(s_1,0.1), (s_2,0.2)\}$	$\{(s_3,0.2,0.4)\}$	$\{(s_1,0.8)\}$
	Task	$\{(s_1,0.4)\}$	$\{(s_1,0.2)\}$	$\{(s_3,0.3)\}$	$\{(s_1,0.5)\}$
	Performer	$\{(s_2,0.7), (s_3,0.2)\}$	$\{(s_3,0.1)\}$	$\{(s_2,0.3,0.4)\}$	$\{(s_2,0.8)\}$
E_3	Time	$\{(s_2,0.2), (s_3,0.4)\}$	$\{(s_1,0.3)\}$	$\{(s_3,0.4)\}$	$\{(s_0,0.6)\}$
	Task	$\{(s_3,0.3,0.4)\}$	$\{(s_4,0.5)\}$	$\{(s_4,0.7)\}$	$\{(s_4,0.7)\}$
	Performer	$\{(s_3,0.2,0.7)\}$	$\{(s_3,0.2), (s_4,0.3)\}$	$\{(s_3,0.1), (s_4,0.2)\}$	$\{(s_2,0.8), (s_3,0.4)\}$
E_4	Time	$\{(s_1,0.5)\}$	$\{(s_2,0.4,0.5)\}$	$\{(s_1,0.6)\}$	$\{(s_1,0.5)\}$
	Task	$\{(s_2,0.3,0.4)\}$	$\{(s_3,0.5), (s_4,0.8)\}$	$\{(s_2,0.1)\}$	$\{(s_2,0.3)\}$
	Performer	$\{(s_1,0.2)\}$	$\{(s_2,0.5,0.6)\}$	$\{(s_1,0.3)\}$	$\{(s_2,0.6)\}$
E_5	Time	$\{(s_1,0.6)\}$	$\{(s_1,0.5)\}$	$\{(s_2,0.1), (s_3,0.3)\}$	$\{(s_1,0.3)\}$
	Task	$\{(s_2,0.5)\}$	$\{(s_2,0.2)\}$	$\{(s_1, 0.4)\}$	$\{(s_2,0.5,0.6)\}$
	Performer	$\{(s_1,0.6)\}$	$\{(s_1,0.7)\}$	$\{(s_1,0.7)\}$	$\{(s_1,0.1)\}$

Table 5
The collective dependency assessment matrix.

Sequent tasks	Influential factor		
	IF_1	IF_2	IF_3
ST_1	{($s_{1.45}$,0.44,0.47), ($s_{1.75}$,0.49,0.51)}	{($s_{2.25}$,0.37,0.39, 0.40,0.42)}	{($s_{2.1}$,0.41,0.56), ($s_{2.3}$,0.28,0.46)}
ST_2	{($s_{1.2}$,0.35,0.36), ($s_{1.4}$,0.37,0.38)}	{($s_{2.45}$,0.39), ($s_{2.65}$,0.49)}	{($s_{2.05}$,0.40,0.42), ($s_{2.35}$,0.42,0.45)}
ST_3	{($s_{2.3}$,0.39,0.43), ($s_{2.5}$,0.42,0.45)}	{($s_{2.8}$,0.65,0.69)}	{($s_{2.1}$,0.35,0.37), ($s_{2.4}$,0.37,0.39)}
ST_4	{($s_{0.7}$,0.62), ($s_{0.9}$,0.55)}	{($s_{2.25}$,0.50,0.52)}	{(s_2,0.65,0.66), ($s_{2.3}$,0.51,0.53)}

Table 6
The best and the worst influential factors identified.

Experts	The best influential factors	The worst influential factors
E_1	Time (IF_1)	Task (IF_2)
E_2	Task (IF_2)	Time (IF_1)
E_3	Performer (IF_3)	Task (IF_2)
E_4	Task (IF_2)	Performer (IF_3)
E_5	Performer (IF_3)	Time (IF_1)

Table 7
LHF best-to-others vectors of the five experts.

Experts	Best influential factor	Other influential factors		
		IF_1	IF_2	IF_3
E_1	IF_1	{(s'_1,1.0)}	{(s'_5,0.4)}	{(s'_2,0.8)}
E_2	IF_2	{(s'_4,0.5)}	{(s'_1,1.0)}	{(s'_2,0.4)}
E_3	IF_3	{(s'_2,0.6)}	{(s'_4,0.2)}	{(s'_1,1.0)}
E_4	IF_2	{(s'_3,0.3)}	{(s'_1,1.0)}	{(s'_3,0.4)}
E_5	IF_3	{(s'_4,0.3)}	{(s'_3,0.5)}	{(s'_1,1.0)}

Table 8
LHF others-to-worst vector of the five experts.

Experts	Worst influential factor	Other influential factors		
		IF_1	IF_2	IF_3
E_1	IF_2	{(s'_5,0.6)}	{(s'_1,1.0)}	{(s'_3,0.4)}
E_2	IF_1	{(s'_1,1.0)}	{(s'_4,0.1)}	{(s'_2,0.7)}
E_3	IF_2	{(s'_4,0.5)}	{(s'_1,1.0)}	{(s'_4,0.8)}
E_4	IF_3	{(s'_3,0.2)}	{(s'_4,0.8)}	{(s'_1,1.0)}
E_5	IF_1	{(s'_1,1.0)}	{(s'_3,0.5)}	{(s'_4,0.4)}

$$\min \xi^k$$
$$s.t.\begin{cases} \tilde{f}\left(s^k_{\theta(B)}\right)r^k_B - \xi^k \le \tilde{f}\left(s^k_{\theta^k(Bj)\theta^k(j)}\right)r^k_{Bj}r^k_j \\ \tilde{f}\left(s^k_{\theta(B)}\right)r^k_B + \xi^k \le \tilde{f}\left(s^k_{\theta^k(Bj)\theta^k(j)}\right)r^k_{Bj}r^k_j \\ \tilde{f}\left(s^k_{\theta(j)}\right)r^k_j - \xi^k \le \tilde{f}\left(s^k_{\theta^k(jW)\theta^k(W)}\right)r^k_{jW}r^k_W \\ \tilde{f}\left(s^k_{\theta(j)}\right)r^k_j + \xi^k \le \tilde{f}\left(s^k_{\theta^k(jW)\theta^k(W)}\right)r^k_{jW}r^k_W \\ \sum_{j=1}^n E\left(\tilde{w}^k_j\right) = 1 \\ E\left(\tilde{w}^k_j\right) \ge 0, \text{ for } j = 1,2,\dots,n \end{cases} \tag{10}$$

By solving model (10), the LHF weights of influential factors determined from E_k can be obtained as $\tilde{w}^k = \left(\tilde{w}^k_1, \tilde{w}^k_2, \dots, \tilde{w}^k_n\right)^T$.

Step 7. Compute the collective LHF weights of influential factors

By using the LHFWA operator, the collective LHF weights of influential factors $\tilde{w}_j$ for $j = 1,2,\dots,n$ can be derived via the following equation:

$$\tilde{w}_j = \mathrm{LHFWA}\left(\tilde{w}^1_j, \tilde{w}^2_j, \dots, \tilde{w}^l_j\right) = \bigcup_{\left(s^1_{\theta(j)}, lh\left(s^1_{\theta(j)}\right)\right)\in w^1_j, \cdots \left(s^1_{\theta(j)}, lh\left(s^l_{\theta(j)}\right)\right)\in w^l_j} \times\left(s_{\sum_{k=1}^l \lambda_k \theta^k(j)}, \bigcup_{r^1_j \in lh\left(s^1_{\theta(j)}\right),\cdots,r^l_j\in lh\left(s^l_{\theta(j)}\right)} \left(1-\prod_{k=1}^l \left(1-r^k_j\right)^{\lambda_k}\right)\right). \tag{11}$$

4.3. Determine dependence levels among HFEs with the THERP

THERP provides a modification formula to calculate the CHEP which reveals the influence of the failure of one task on the failure probabilities of subsequent task according to five dependence levels. In this stage, a modified THERP method on the basis of LHFSs is proposed to compute the CHEP for each pair of sequent tasks based on the collective dependence assessment matrix $\tilde{R}$.

Step 8. Calculate the overall dependence values among sequent tasks

By using the LHFWA operator, the overall dependence values between sequent task pairs $ST_i (i = 1,2,\dots,m)$ are calculated as

$$OD_i = \mathrm{LHFWA}\left(\tilde{r}_{i1}, \tilde{r}_{i2}, \dots, \tilde{r}_{in}\right) = \cup_{(s_{\theta(1)}, lh(s_{\theta(1)}))\in\tilde{r}_{i1},\dots,(s_{\theta(n)}, lh(s_{\theta(n)}))\in\tilde{r}_{in}} \times\left(s_{\sum_{j=1}^n w_j\theta_j}, \cup_{r_1\in lh(s_{\theta(1)}),\dots,r_n\in lh(s_{\theta(n)})}\left(1-\prod_{j=1}^l\left(1-r_j\right)^{w_j}\right)\right). \tag{12}$$

where w_j is the weight of the jth influential factor determined by $w_j = E(\tilde{w}_j)/\sum_{j=1}^n E(\tilde{w}_j)$, for $j = 1,2,..,n$.

Step 9. Calculate the CHEP for each of the sequential task pairs

At last, the CHEP $P(B_i|A_i)$ of the pair of sequential tasks ST_i is determined by

$$P(B_i|A_i) = OD_i \times P_{s_i}(B_i|A_i) \tag{13}$$

$$P_{s_i}(B_i|A_i) = \frac{1+\zeta_i \times P_{B_i}}{\zeta_i + 1} \tag{14}$$

where P_{B_i} is the failure probability of task B_i and ζ_i is an identifier acquired on the basis of the linguistic term set S. For instance, if five levels are included in S, then ζ_i can be a set of ∞, 19, 6, 1, 0 [19,20].

5. Case study

In this section, a practical dependence assessment example of

Table 9
Overall dependence values among sequent tasks.

Sequent tasks	OD_i
ST_1	{($s_{2.04}$,0.39,0.40,0.40,0.41,0.41,0.41,0.42,0.42,0.42,0.45,0.46,0.46,0.47,0.47,0.47,0.48), ($s_{2.11}$,0.35,0.36,0.36,0.37,0.37,0.37,0.38,0.38,0.42,0.42,0.42,0.43,0.43,0.44,0.44,0.44), ($s_{2.10}$,0.41,0.42,0.42,0.42,0.42,0.43,0.43,0.44,0.47,0.47,0.47,0.48,0.48,0.48,0.49,0.49), ($s_{2.12}$,0.37,0.37,0.37,0.37,0.38,0.38,0.38,0.39,0.43,0.44,0.44,0.44, 0.44, 0.44, 0.44,0.45)}
ST_2	{($s_{2.07}$,0.39,0.39,0.40,0.40), ($s_{2.18}$,0.40,0.40,0.40,0.40), ($s_{2.16}$,0.43,0.43,0.44,0.44), ($s_{2.27}$,0.44,0.44,0.45,0.45), ($s_{2.11}$,0.39,0.40,0.40,0.40), ($s_{2.21}$,0.40,0.40,0.40,0.41), ($s_{2.20}$,0.43,0.44,0.44,0.45), ($s_{2.30}$,0.44,0.45,0.45,0.45)}
ST_3	{($s_{2.46}$,0.46,0.52,0.52,0.53,0.54,0.54,0.54,0.55), ($s_{2.56}$,0.52,0.53,0.53,0.53,0.54,0.55,0.55,0.55), ($s_{2.49}$,0.52,0.53,0.53,0.53,0.54,0.55,0.55,0.55), ($s_{2.60}$,0.53,0.53, 0.53,0.54,0.55,0.55, 0.55,0.56)}
ST_4	{($s_{1.86}$,0.58, 0.58,0.59, 0.59), ($s_{1.97}$,0.53, 0.53,0.54, 0.55), ($s_{1.90}$,0.57,0.57,0.57,0.58), ($s_{2.01}$,0.51,0.52,0.52,0.53)}

Table 10
CHEPs between sequential tasks.

Sequential tasks	$P(A_i \| B_i)$	$E(P(A_i \| B_i))$
ST_1	{($s_{0.33}$,0.90,0.90,0.90,0.90,0.91,0.91,0.91,0.92,0.92,0.92,0.92,0.92,0.92,0.92,0.92,0.92), ($s_{0.34}$,0.91,0.91,0.91,0.91,0.91,0.92,0.92,0.92,0.93,0.93,0.93,0.93,0.93,0.93,0.93,0.93), ($s_{0.34}$,0.90,0.90,0.90,0.90,0.90,0.90,0.90,0.90,0.91,0.91,0.91,0.92,0.92,0.92,0.92,0.92), ($s_{0.34}$,0.91,0.91,0.91,0.91,0.91,0.91,0.91,0.91,0.92,0.93,0.93,0.93,0.93,0.93,0.93,0.93)}	0.313
ST_2	{($s_{0.35}$,0.92,0.92,0.92,0.92), ($s_{0.37}$,0.92,0.92,0.92,0.92), (s0.37,0.91,0.91,0.91,0.91), ($s_{0.39}$,0.90,0.90,0.91,0.91), ($s_{0.36}$,0.92,0.92,0.92,0.92), ($s_{0.38}$,0.91,0.92,0.92,0.92), ($s_{0.37}$,0.90,0.91,0.91,0.91), ($s_{0.39}$,0.90,0.90,0.90,0.91)}	0.340
ST_3	{($s_{0.59}$,0.83,0.83,0.83,0.83,0.83,0.84,0.84,0.86), ($s_{0.61}$,0.83,0.83,0.83,0.83,0.83,0.83,0.83,0.84), ($s_{0.60}$,0.83,0.83,0.83,0.83,0.83,0.83,0.83,0.84), ($s_{0.62}$, 0.82,0.83,0.83, 0.83,0.83,0.83,0.83, 0.83)}	0.503
ST_4	{($s_{0.26}$,0.88, 0.88,0.89, 0.89), ($s_{0.28}$,0.89,0.90, 0.90,0.90), ($s_{0.27}$,0.89,0.89,0.89,0.89), ($s_{0.28}$,0.90,0.90,0.90,0.90)}	0.243

blood transfusion process is given to reveal the feasibility and effectiveness of our proposed methodology.

5.1. Problem description

Blood transfusion is an important means of modern medical treatment, which plays an important role in saving lives and reducing incidence in the clinical medicine field. However, it may bring risks to patients and cause a series of infectious and immunological diseases. As a result, safer blood transfusion practices have been considered to minimize the risk of human errors during transfusions. In this study, the proposed dependence assessment method was used to analyze HFEs during the blood transfusion process. Initially, 19 possible human errors were determined in the blood transfusion through brainstorming sessions [55,56]. Among them, four pairs of sequential tasks indicated as $ST_i (i = 1, 2, 3, 4)$ are taken into consideration for further discussion. Table 1 shows that the transfusion procedures, the human errors that can occur and their effects.

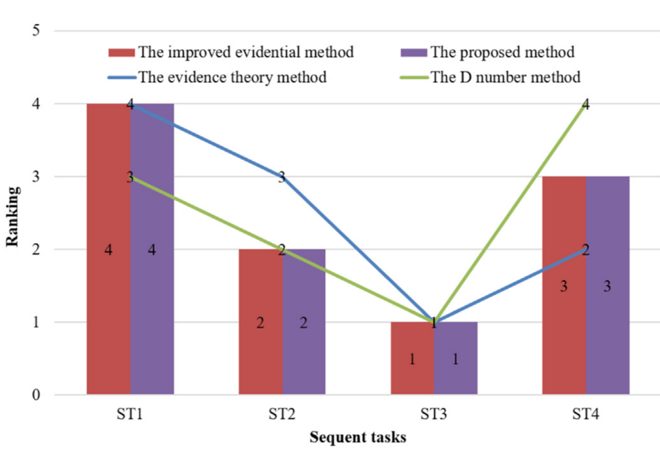

Fig. 2. Dependence rankings with different dependence assessment methods.

To obtain dependence levels between the successive actions, five HRA experts (E_1, E_2, E_3, E_4, and E_5) from a university teaching hospital were invited for the dependence assessment. These experts are from different departments in the hospital including blood transfusion departments, logistics system, as well as quality control departments. In view of their different backgrounds and professional fields, the five experts are allocated different weights to reflect their importance in the HRA process, i.e., $\lambda_1 = 0.15$, $\lambda_2 = 0.20$, $\lambda_3 = 0.30$, $\lambda_4 = 0.20$, and $\lambda_5 = 0.15$. In this case study, three influencing factors, time relationship (IF_1), task relatedness (IF_2), and similarity of performers (IF_3) are considered. Time relationship is to evaluate the time relationship among human actions. Task relatedness is made up of similarity of cues and similarity of goals, and it is to evaluate the functional relationships among human actions. Besides, similarity of performers is to evaluate human's status, training, responsibility, and many other social and psychological factors.

The linguistic term set S is used by the HRA experts to indicate their judgments on the dependence between sequential actions.

$$S = \left\{ \begin{array}{l} s_o = Zero\,Dependence\,(ZD), s_1 = Low\,Dependence\,(LD), \\ s_2 = Moderate\,Dependence\,(MD), s_3 = High\,Dependence\,(HD), \\ s_4 = Complete\,Dependence\,(CD) \end{array} \right\}$$

For every influential factor, anchor points corresponding to the above five dependency levels are demonstrated in Table 2 [20,23]. Table 3 shows the qualitative dependence assessments of the four pairs of sequential tasks against each influencing factor given by the HRA experts.

5.2. Implementation results

Next, the presented LHF-HERP method was adopted to assess the dependency levels between the four pairs of consecutive actions.

Step 1. By transforming the linguistic dependence assessments of experts into LHFSs, the dependence assessment matrixes

$\tilde{R}^k = [\tilde{r}^k_{ij}]_{4\times 3}(k = 1, 2, ..., 5)$ are obtained and presented in Table 4.

Step 2. By applying Eq. (6), the collective dependency assessment matrix $\tilde{R} = [\tilde{r}_{ij}]_{4\times 3}$ is derived as shown in Table 5.

Step 3. The best and the worst influential factors, IF^k_B and $IF^k_W(k = 1, 2, ..., 5)$, determined by the five HRA experts are displayed in Table 6.

Step 4. By using the linguistic term set $S' = \{s'_1 =$ Equally important, $s'_2 =$ Weakly important, $s'_3 =$ Fairly important, $s'_4 =$ Very important, $s'_5 =$ Absolutely important$\}$, the LHF best-to-others vectors of the five experts $\tilde{F}^k_B(k = 1, 2, ..., 5)$ are displayed in Table 7.

Step 5. Similarly, the LHF others-to-worst vector of of the five experts $\tilde{F}^k_W(k = 1, 2, ..., 5)$ are shown in Table 8.

Step 6. Via Eq. (9), five linear optimization models are built for obtaining the LHF weights of the three influential factors with respect each expert $\tilde{w}^k(k = 1, 2, ..., 5)$. For example, the linear optimization model concerning E_1 is constructed as:

$$\min \xi^1$$
$$s.t.\begin{cases} \left|\tilde{f}\left(s^1_{\theta(1)}\right)r^1_1 - \tilde{f}\left(s^1_{\theta^1(1j)\theta^1(j)}\right)r^1_{1j}r^1_j\right| \le \xi^1, j = 1, 2, 3. \\ \left|\tilde{f}\left(s^1_{\theta(j)}\right)r^1_j - \tilde{f}\left(s^1_{\theta^1(j2)\theta^1(2)}\right)r^1_{j2}r^1_2\right| \le \xi^1, j = 1, 2, 3. \\ \theta^1(1)r^1_1 + \theta^1(2)r^1_2 + \theta^1(3)r^1_3 = 1, \\ \theta^1(j)r^1_j \ge 0,\ j = 1, 2, 3. \end{cases}$$

By solving the programming model, the optimal influential factor weights provided by E_1 are determined as: $\tilde{w}^1 = (\{(s'_{0.427}, 0.269)\}\{(s'_{0.763}, 0.528)\}\{(s'_{0.591}, 0.584)\})$.

Step 7. Via Eq. (11), the collective LHF weights of influential factors are computed as: $\tilde{w} = (\{(s'_{0.422}, 0.452)\}, \{(s'_{0.601}, 0.754)\}, \{(s'_{0.583}, 0.611)\})$.

Step 8. Using Eq. (12), the overall dependence values among sequent tasks $ST_i(i = 1, 2, ..., 4)$ are obtained as shown in Table 9.

Step 9. Based on Eqs. (13) and (14), the CHEP for each of the four sequential task pairs are determined as shown in Table 10. Note that the failure probability P_{B_i} of task B_i is assumed to be 0.01 for $i = 1, 2, 3, 4$. As shown in Table 10, the third pair of sequential tasks has the highest CHEP in this case study.

5.3. Comparative analysis

A comparative analysis with existing dependence assessment methods is performed in this section to validate the rationality of the presented approach. The same illustrative example is solved by the evidence theory method [22], the modified evidential method [21], and the D number method [39]. According to these dependence assessment methods, the relative dependency rankings for the four pairs of sequential tasks are derived and pictured in Fig. 2.

From Fig. 2, it can be observed that ST_1 has the highest dependency level according to all the four dependence assessment methods. By using the modified evidential method, the D number method and the proposed method, the top two highly dependent sequential tasks are the same, i.e., ST_3 and ST_2. Besides, the improved evidence theory method, the modified evidential method, and the proposed method produces the same lowest dependency level for the sequential task ST_1. The result coincides with the experts' feedback that the HFE of "transfusion cannot be completed within the appropriate time" is largely rely on the failure on its preceding task "preparation time before injection is too long". These prove the feasibility and effectiveness of our proposed LHF-HERP model.

On the other hand, there are some differences between the dependency ranking results determined through the proposed method and those obtained with the evidence theory method (for ST_2 and ST_4) and the D number method (for ST_1 and ST_4). The main reasons of these discrepancies can be attributed to the following aspects: (1) The compared methods applied evidence theory or D numbers to evaluate the dependence levels of human operations. Both the two methods have the limitations in handling the hesitancy, inconsistency and uncertainty of dependence assessments provided by experts. (2) The compared methods used Delphi method or AHP for the weight calculation of influential factors. For the Delphi method, the opinions of authority may influence the opinions of others. The AHP needs a lot of pairwise comparisons and is enormously complex and time-consuming when there are too many influential factors. (3) The compared methods obtained the dependence probability of human operations on the basis of the belief assignments or D number's combination rule. Both the two methods cannot capture the probabilistic linguistic judgments of experts on the dependence degrees between successive actions.

5.4. Managerial implications

Some managerial implications are as well achieved in this study. Considering the research findings obtained, the proposed dependence assessment model can help hospital managers to improve patient care and safety in the blood transfusion process. Some specific managerial implications of this study are listed as follows. First, the proposed model is performed in the linguistic hesitant fuzzy environment, wherein experts can express their opinions flexibly and realistically. In this way, the proposed model is able to provide a convenient and flexible technique to gather more comprehensive and accurate dependence information between successive tasks in practical situations. Second, an extended BWM is employed to derive the weights of influential factors. By using this method, the proposed model needs fewer judgments from experts and reduces the inconsistency of pairwise comparisons. This makes the computed weights of influential factors more rational in the dependence analysis process. Finally, based on an extended THERP method, the proposed model provides a modification formula to calculate CHEP which reveals the influence of the failure of one task on the failure probability of subsequent task. Therefore, the LHF-THERP method being proposed in this study can provide valuable dependence assessment information for managers so that proactive and reactive measures can be taken to minimize the risk of human errors in practical applications.

6. Conclusions

In this paper, we introduced an LHF-THERP method for the purpose of assessing the dependency among HFEs in HRA. To express experts' qualitative preferences, the LHFSs are used to address the qualitative dependence assessments of experts as well as reflect their hesitancy and uncertainty. An extended BWM is proposed to compute the weights of influential factors. A modified THERP method is utilized for calculating the dependence levels of sequential tasks. Finally, a practical blood example regarding transfusion dependence analysis is presented to demonstrate the applicability and efficiency of the proposed LHF-THERP method. The results indicate that the new dependence assessment method proposed in this study can not only deal with experts' uncertain knowledge flexibly, but also offer a reasonable and reliable dependence probability result of human actions in HRA.

For the future research, some attempts can be made to address the limitations of this study. First, the presented method is restricted to a small group of experts. In the future, an approach to solve the dependence assessment problem in a large group environment may be needed. Second, experts often have diverse experience and knowledge, and thus it is inevitable to have conflicting opinions in the HRA process. Therefore, we call for further investigation especially using consensus methods to improve the group consistency in HRA. Third, the proposed approach on the basis of LHFSs and THERP requires many computations to acquire the CHEP. Thus, a computer-based application system can be developed to facilitate the implementation of the presented dependency assessment method in real world situations.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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