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Human error probability evaluation based on reference task using intuitionistic fuzzy theory

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A R T I C L E I N F O

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A B S T R A C T

Human Reliability Analysis (HRA) is a critical issue for addressing human error in system reliability. There are numerous tasks for which human factors-related data are not available, rendering expert knowledge the only basis for assessing such tasks. However, the knowledge obtained from experts is subject to ambiguity and vagueness, which affects the usability of the assessment results. To overcome this challenge, in this paper a reference task based HRA method is proposed and the intuitionistic fuzzy set (IFS) is adopted because of its advantage of being able to handle ambiguous information. Firstly, to analyze the human error probability (HEP) of the target task, a reference task-based human error analysis model is introduced. Two solutions are provided: calculating the performance shaping factors (PSFs) distance between the reference task and the target task and establishing a quantitative relationship between PSFs and HEP. Secondly, the PSFs evaluation and inference methods based on triangular intuitionistic fuzzy numbers (TIFNs) are developed. Finally, the effectiveness and consistency of the two solutions of TIFN-HRA are demonstrated through a spaceflight refueling mission analysis. The distances between the results of the two solutions and the expert linguistic are compared and both results have the shortest distance to “Low”. However, solution I is simpler and the result is clearer.

1. Introduction

In recent years, the number of accidents due to technical failures decreases due to the development and progress in terms of redundancy and protection, which have made system more reliable (Zhan et al., 2019). However, the reliability of human, a significant component of system reliability, has not been effectively guaranteed. Despite difficulties in obtaining accurate data, it is estimated that nearly 60 %~90 % of errors can be attributed to human factors, either directly or indirectly (Kelly & Efthymiou, 2019; Schiraldi, 2013). Therefore, the role of human should be considered in accident dynamics to ensure effective prevention of hazardous events (Jo & Lee, 2024).

In order to reduce the risk caused by Human factors, the research on Human Reliability Analysis (HRA), a proactive method to identify, quantify, and reduce the human error probability (HEP) in human–machine system (Hou et al., 2021), has emerged. With the introduction of HRA by (Swain & Guttmann, 1983) in the field of nuclear engineering, various methods, theories and models for HRA have been gradually developed and perfected, and theoretical studies and model applications have been carried out by experts in other fields such as transportation (Chen et al., 2021), marine engineering (Uflaz et al., 2023), aerospace industry (DeMott & Bigler, 2017), and chemical industry (Aliabadi, 2021). Through decades of efforts, more than 35 HRA techniques are developed, such as, Technique For Human Error Rate Prediction (THERP) (Zimolong, 1992), Success Likelihood Index Method (SLIM) (Vestrucci, 1988), Standardized Plant Analysis Risk-Human reliability analysis (SPAR-H) (Gertman et al., 2005), Cognitive Reliability and Error Analysis Method (CREAM) (Hollnagel, 1998). In these widely-applied HRA methods, a prevalent perspective suggests that human errors stem from the context surrounding human task execution. Performance shaping factors (PSFs) serve as tools to define the human context, encapsulating all elements influencing human behavior (Pan & Wu, 2018). HRA methods are dedicated to establishing human error models that describe the relationship between PSFs and HEP. Furthermore, due to the scarcity of HRA data, expert knowledge plays a significant role in quantifying HEP (Tu et al., 2015). However, owing to the inherent ambiguity and uncertainty in human knowledge, although not entirely impossible, it is challenging for experts to provide precise probability

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values (Shen et al., 2016). Therefore, addressing the uncertainty associated with expert knowledge is another concern of HRA community.

The existing human error models primarily leverage the fact that PSFs directly influence HEP. They employ functions to map PSFs onto HEP, representing a classic research paradigm (Wang et al., 2023). However, the generalization capability of such functional relationships is limited, particularly when applied to human operational tasks in novel domains. This paper introduces an alternative research paradigm, as illustrated in Fig. 1, namely a reference task based human error model. Unlike directly establishing a mathematical representation between PSFs and HEP, this model utilizes relevant information from reference task to assess human error in target task. In addressing the uncertainty quantification issue in HRA, fuzzy sets (FS) theory (Zadeh, 1965) has been employed to tackle the uncertainty and ambiguity in expert knowledge. However, such an approach may be inadequate in handling uncertainty in human cognitive functions such as reasoning and hesitation. A potential solution to this issue lies in intuitionistic fuzzy sets (IFS) (Atanassov & Atanassov, 1999). As an extension of FS, IFS not only considers the membership degrees of expert opinions but also takes into account non-membership degrees and hesitancy, effectively capturing the uncertainty and ambiguity of human knowledge. Therefore, this study develops a method based on IFS for quantifying HEP.

The aim of this paper is to evaluate the HEP of the target task using the information of reference task, while incorporating IFS theory to address the uncertainty associated with expert knowledge in the quantification process of HRA. The main contributions of this study are as follows:

(1) A reference task based human error model is proposed, which offers two solutions for assessing the HEP of the target task. In this model, the reference task is a task similar to the target task (the task under evaluation), with known PSFs and HEP.
(2) The IFS theory is utilized to address the uncertainty in expert knowledge during the quantification process of HRA, introducing a novel method termed TIFN-HRA.
(3) The TIFN-HRA method is employed to quantify the two solutions within the proposed human error model: considering the PSFs distance and establishing a quantitative relationship between PSFs and HEP. The effectiveness and feasibility of this approach are validated using a space refueling task as a case study.

The remaining organization of this paper is as follows. Section 2 reviews the literature concerning HRA. Section 3 will detail the proposed human error model and the TIFN-HRA method. Section 4 validates the effectiveness and feasibility of this method using a space refueling task as an example. Section 5 discusses the research findings, while Section 6 concludes the paper and suggests future directions for improvement.

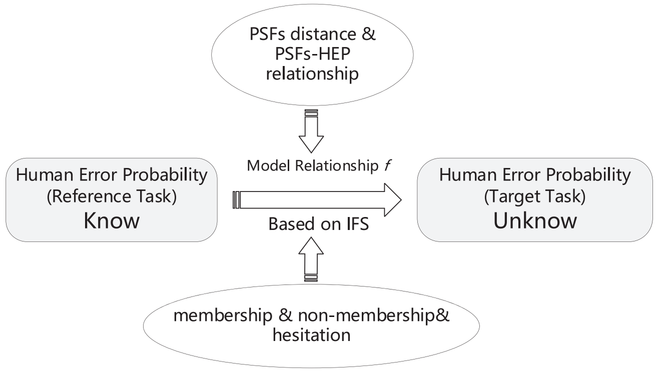

Fig.1. Research ideas.

2. Literature review

Human error is an important factor leading to the overall risk of safety–critical systems (Zhao, 2022). The focus of this study lies in establishing a novel human error model and devising methods to address the uncertainty in expert knowledge during HRA quantification. Simultaneously, given its paramount importance in contributing to human error, existing research has consistently evaluated HRA by quantifying the PSF. Therefore, in addition to providing a brief overview of the evolution of HRA methods and PSF categorization, it is crucial to comprehensively review human error models and quantification methods within HRA.

2.1. Evolution of HRA methods

Various HRA methods have been proposed over time to enhance human reliability. These methods can be categorized by generation. The first-generation HRA methods encompass THERP (Zimolong, 1992), Human Cognitive Reliability (HCR) (Apostolakis et al., 1988) and SLIM (Vestrucci, 1988). These methods notably lack consideration for the influence of human cognitive activities, and their calculation of HEP mirrors that of equipment failures. Consequently, the first-generation HRA methods fail to address the exploration of human error mechanisms. The second-generation of HRA methods emerged in the 1990 s and are currently undergoing further development. Representative methods include the CREAM (Hollnagel, 1998), a technique for human error analysis (ATHEANA) (Cooper et al., 1996), and the accident dynamics simulator – information, decision, action in crew context (ADS-IDAC) (Chang & Mosleh, 2007). These methods incorporate cognitive models of human behavior into HRA approaches, aiming to elucidate the mechanisms underlying human errors. With the rapid advancement of computer technology, HRA methods such as ADS-IDAC have employed simulation techniques to predict human error. These methods are referred to as third-generation or next-generation HRA methods (Coyne, 2009). Regardless of the generation of HRA method, they all strive to construct a human error model elucidating the mechanisms by which PSFs influence HEP. Additionally, emphasis has been placed on the accuracy and credibility of HRA quantification.

2.2. PSF categorization

Definitions of PSF differ between HRA methods. Swain divides PSFs into three broad categories: external PSFs, stressor PSFs, and internal PSFs in THERP approach, where external PSFs also include situational characteristics, operational and task instructions, and task and equipment characteristic, stressor PSFs include psychological stress and physiological stress, and internal PSFs include organismal factors (Swain & Guttmann, 1983). The CREAM approach categorizes factors that influence human performance into nine types named common performance conditions (CPCs) (Hollnagel, 1998). In the Technique for the Retrospective and Predictive Analysis of Cognitive Errors (TRACEr) approach, PSFs are divided into human factors, information/communication factors, ability/training factors, internal/external environmental factors, organizational factors, and other factors (Said & Noor, 2013). Due to the significant impact of PSFs and the variability in its interpretation, this study begins by systematically categorizing PSFs as all contextual factors that contribute to or result in human errors during the interaction between human and the task (Pan & Wu, 2018).

Based on the discussion above, PSFs are organized and summarized into five categories in this study: environmental factors, equipment factors, task factors, team and organizational factors, and personal factors, as shown in Table 1.

2.3. Human error models in HRA

The challenge of human error model is to establish the relationship

Table 1
Categorization of PSFs.

PSFs Category	PSFs
Environmental	Working hours, Climate, Temperature
Equipment	Equipment Availability, Maintenance equipment availability
Task	Operation program availability, Operation program availability, Number of simultaneous operation tasks
Team and organizational	Information Adequacy, Information Accuracy, Training, Organizational Culture, Organizational Structure, Available times, Supervision
Personal	Cognitive factors, Physiological factors, Psychological factors, Stress, Experience, Age

between PSFs and HEP, aiming to describe the mechanisms underlying human errors. Specifically, these models provide a foundational framework for the quantification methods of HRA (Hou et al., 2021), which can be categorized into three main types: parameter-based models, cognitive-behavioral models, and computer simulation models.

Parameter-based models, rooted in system parameters, primarily focus on the task level of human error mechanisms. They address the HEP from a global and systemic perspective, linking PSFs to HEP through implicit functions (Apostolakis et al., 1988; Vestrucci, 1988; Zimolong, 1992). This approach parallels the analysis methods for equipment failure probabilities. The first-generation HRA methods commonly employ parameter-based models, such as THERP and HCR.

In cognitive-behavioral models, the modulation of PSFs on HEP starts to delve into human cognitive activities and even cognitive functions (Cooper et al., 1996; Hollnagel, 1998). Among these, the most representative is the Contextual Control Model (COCOM) provided by the CREAM. COCOM assesses operator control using four cognitive control modes: Scrambled, Opportunistic, Tactical, and Strategic, categorized based on the evaluation levels of nine CPCs representing the context influencing human error. Despite significant progress compared to parameter-based models, cognitive-behavioral models lack sufficient theoretical and experimental foundations, and none of these methods has yet established a comprehensive underlying causal mechanism model linking PSFs and HEP.

With the assistance of computer simulation technology, the next-generation HRA methods can simulate human cognitive activities in specific task context through computers (Chang & Mosleh, 2007; Li & Mosleh, 2019). In these methods, human error models are closely linked with simulation programs, enabling more accurate HEP by adjusting simulation task context. A representative approach is ADS-IDAC. However, these approaches face significant challenges in describing uncertainty, particularly regarding human cognitive ambiguity.

2.4. Quantification methods of HRA

HRA is a domain characterized by scarcity of data. In practice, although methodologies vary depending on tasks being addressed, these methods all aim to quantify HEP under conditions of uncertainty. Currently, Bayesian networks-based methods and fuzzy-based approaches are highly favored by HRA researchers.

Bayesian Networks (BNs) possess the capability to model complex relationships among influencing factors. Moreover, their ability to integrate multiple sources of information enables researchers to develop HRA models with stronger cognitive theoretical and empirical foundations (Mkrtchyan et al., 2015). Additionally, BNs are regarded as a method for handling data scarcity and multiple data sources, thus their utilization in quantifying HRA has steadily increased over the past decade (Li et al., 2012; Shirley et al., 2020; Zhao, 2022). BNs can integrate traditional fault tree and event tree models and capture the probabilistic relationships between PSFs and HEP. Despite numerous advantages, however, BNs may encounter limitations in handling expert knowledge within a probabilistic framework, as they require experts to provide precise probability values and may not adequately account for the vagueness and uncertainty in expert knowledge.

Zadeh's (Zadeh, 1965) FS theory has been utilized as an effective tool for addressing uncertainty and ambiguity, achieving significant success in the field of HRA. Table 2 summarizes some of the latest HRA methods using fuzzy approaches. For instance, (Konstandinidou et al., 2006) integrated FS theory with CREAM methods to determine the HEP based on the data acquired from experts. (Ung, 2015) applied a weighted fuzzy CREAM method considering the importance of PSFs to obtain HEP in the HRA of maritime transportation. In another study, (Li et al., 2010) proposed a new Fuzzy Human Error Risk Assessment Methodology (FHERAM) to measure the importance of human errors in risk analysis. (Casamirra et al., 2009) integrates fault tree analysis, HEART and fuzzy set theory to analyze the probability of human error in irradiation process.

The classical FS theory assigns a degree of membership to each element in a set to indicate the degree of belongingness to that set. This leads to an "either/or" representation in the universe of discourse. However, there is hesitation in the linguistics of the experts due to personal errors and lack of knowledge. In other words, the membership degree and non-membership degree of human natural language are not complementary, which is noted in the theory of intuitionistic fuzzy set developed by (Atanassov & Atanassov, 1999). As an extend to classical fuzzy set, IFS suggest that non-membership is not always equal to one minus the degree of membership, providing a robust solution to the situation when human language is "neither/nor" (uncertainty, hesitation neutral) (Aliabadi, 2021). Therefore, IFS theory with triangular intuitionistic fuzzy number (TIFN) is adopted as the method of quantifying HEP in this study.

3. Material and methods

This section presents a reference task based human error model and a HRA quantification method named TIFN-HRA based on IFS theory.

3.1. A reference task based human error model

The relationship between PSFs and HEP is an indispensable part of research on the HRA model, however, this relationship is difficult to quantify explicitly. For example, in the information-processing model proposed by Wickens, although it is known that there is a connection between the influencing factors and actions, it is difficult to characterize the exact form of the connection and express it quantitatively as a function (Wickens et al., 2021).

Existing research has indicated that human behavior and performance are highly complex and challenging to measure directly (Pan & Wu, 2018). Therefore, in HRA, most studies focus on identifying and quantifying PSFs to infer HEP. In this paper, the influence of PSFs on HEP should be divided into two parts: 1) PSFs level (the level of the PSFs itself), and 2) PSFs weight (the importance of PSFs to HEP). This

Table 2
Some Fuzzy-HRA methods.

Methods	Applications
Fuzzy-CREAM	Human error in maintenance tasks of a chemical plant (Konstandinidou et al., 2006)
FHERAM	Crew reliability in the maritime field (Ung, 2015)
	Human reliability in ship cabin fire emergency response (Ahn & Kurt, 2020)
	Human errors in risk analysis (Li et al., 2010)
	Human reliability assessment for medical devices (Lin et al., 2014)
Fuzzy-FMEA	
Fuzzy-SPAR-H	Human reliability during emergency response drill for man overboard on ships (Ahn et al., 2022)
IT2FS-SLIM	Human error in maritime transportation (Erdem & Akyuz, 2021)
Fuzzy-BN-CREAM	Human error in oil tank collision (Ung, 2019)
Fuzzy- HEART	Human error in irradiation process (Casamirra et al., 2009)

introduces a novel concept into HEP evaluation, suggesting that the HEP of a target task can be estimated by leveraging the distance between the PSFs of the reference task and the target task.

Hence, with reference to a previous study (Tyagi & Akram, 2013), this study proposes a reference task based human error model. An innovative solution is proposed to evaluate the HEP of the target task based on the distance between PSFs of reference task and target task, while considering expert credibility.

The proposed model is built upon the following assumptions:

Assumption 1. *PSFs of the same type can have different effects on tasks depending on the context.*

Assumption 2:. *The distance relationship between the PSFs of the reference task and the target task is believed to be consistent with the distance relationship between their corresponding HEPs.*

Assumption 3:. *The quantitative relationship between the PSFs and HEP in the reference task can be mapped to the target task.*

The motivation of this article is to infer the HEP of the target task from the information of the reference task. However, the reference task and the target task are almost impossible to be identical. Otherwise, the contexts of these two tasks would be the same (i.e., the types and measurement of PSFs are the same), and their HEPs would also be equal. Therefore, our research implies an assumption that the same type of PSFs can be used to measure different tasks. In other words, the premise of this analysis is that the key types of PSFs between the reference and target tasks should be fundamentally similar. Before assessing the HEP of the target task, relevant PSFs for the task context should be identified based on historical statistical data or expert assessment.

With the discussion above, this study provides two solutions to establish the link between the reference task and the target task (quantitative relationship f). Solution I: Calculating the distance of PSFs between the reference task and the target task. Solution II: Establishing a quantitative relationship between PSFs and HEP in the reference task, as shown in Fig. 2.

3.1.1. Solution I:Calculating the PSFs distance

Since the reference task selected is highly similar to the target task, it is feasible and plausible to conduct a distance analysis at the level of PSFs. Depending on assumption 2, the distance relationship between the PSFs of the target task and the reference task in this study is consistent with the distance relationship between their HEP. This means that the HEP of the target task can be determined once the PSFs distance is assessed. Fig. 3 illustrates the concept of calculating the PSFs distance to evaluate the HEP of the target task.

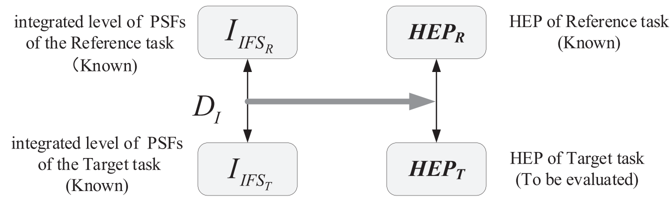

Fig.3. The concept of calculating PSFs distance (where D_I represents the PSFs distance, I_{IFS_R} and I_{IFS_T} represent the integrated evaluation results of the PSFs for the reference task and the target task, respectively., HEP_R and HEP_T represents the HEP of reference task and target task, respectively.).

3.1.2. Solution II: Establishing a quantitative relationship between PSFs-HEP

Most current HRA methods acknowledge that PSFs play a critical role in affecting HEP, (Xing Pan & Wu, 2020) summarized the role of PSFs in the perceived error quantification process and proposed that PSFs consist of personal factors and external factors, which collectively constitute the task context. Therefore, HEP can be considered as being determined by the task context, which is characterized and evaluated by PSFs.

Assuming that the operators involved in the reference task and the target task are the same, so the quantitative relationship between the external PSFs and HEP in the reference task is equally applicable to the

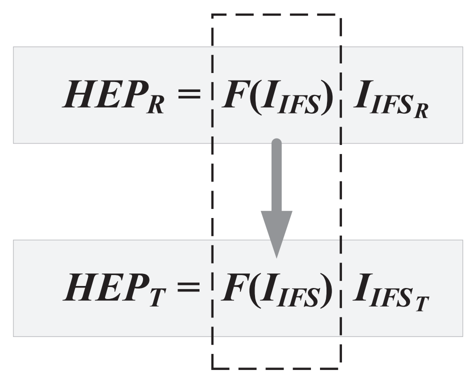

Fig.4. The concept of establishing a quantitative PSFs-HEP relationship.

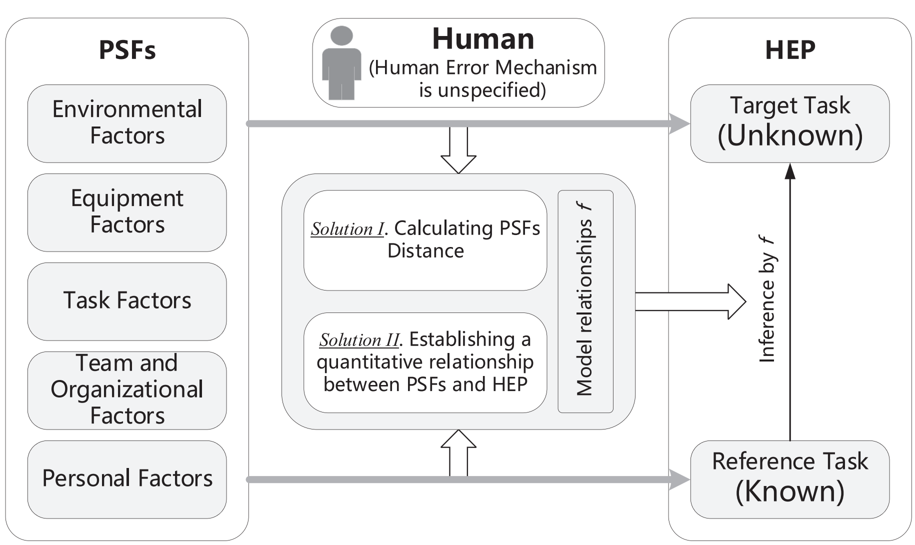

Fig.2. The reference task-based human error analysis model.

target task (assumption 3). Fig. 4 indicates the concept of establishing a PSFs-HEP quantitative relationship to assess the HEP of the target task. Where $F(I_{IFS})$ represents the quantitative relationship between PSFs and HEP, I_{IFS} represents the comprehensive assessment result of PSFs.

3.2. Intuitionistic fuzzy set

Building upon the two solutions, it's crucial to note that assessing HEP in a target task necessitates expert input. This study aims to address the uncertainty inherent in expert knowledge by employing the IFS theory, which will be elucidated further below.

3.2.1. Definitions, rules and properties

The IFS can be represented as follows (Atanassov & Atanassov, 1999; Yazdi, 2018).

Definition 1. *Intuitionistic Fuzzy Set.*

Suppose X is a given discourse domain, where X:[0,1] and $x \in X$, then IFS A on X is expressed by:

$$A = \{\langle x, \mu_A(x), \nu_A(x)\rangle | x \in X\} \tag{1}$$

where $\mu_A(x) \in [0,1]$ and $\nu_A(x) \in [0,1]$ denote membership and non-membership, respectively, and:

$$0 \leqslant \mu_A(x) + \nu_A(x) \leqslant 1 \tag{2}$$

$\pi_A(x) = 1 - \mu_A(x) - \nu_A(x)$ is also introduced as hesitation degree (Intuitionistic index) of whether x belongs to A or not, which always equals 0 in classical fuzzy set.

Definition 2. *Intuitionistic Fuzzy Number.*

An ordered pair $\langle \mu_A(x), \nu_A(x)\rangle$ from an IFS $A = \{\langle x, \mu_A(x), \nu_A(x)\rangle | x \in X\}$ is called intuitionistic fuzzy numbers (IFN) if it follows:

(i) (i)$\mu_A(x)$ must be convex and $\nu_A(x)$ must be concave, if and only if they satisfy following functions (Tyagi & Akram, 2013):

$$\mu_A(\lambda x_1 + (1-\lambda)x_2) \leqslant \lambda\mu_A(x_1) + (1-\lambda)\mu_A(x_2) \tag{3}$$

$$\nu_A(\lambda x_1 + (1-\lambda)x_2) \geqslant \lambda\nu_A(x_1) + (1-\lambda)\nu_A(x_2) \tag{4}$$

where $\lambda \in [0,1]$ and $\forall x_1, x_2 \in X$.

(ii) (ii)An IFS is normalized if and only if $\exists x_0 \in X$,which makes $\mu_A(x_0) = 1$ and $\nu_A(x_0) = 0$.
(iii) (iii)Support $S(A) = \{x \in E : \nu_A(x) < 1\}$ is bounded.
(iv) (iv)$\mu_A(x)$ is upper semi-continuous and $\nu_A(x)$ is lower semi-continuous.

Assuming that A and B are IFSs on a given domain X, the following properties and rules exist (Atanassov, 1994):

Rule 1:$A \cap B = \{\langle x, \mu_A(x) \wedge \mu_B(x), \nu_A(x) \vee \nu_B(x)\rangle | \forall x \in X\}$;
Rule 2:$A \cup B = \{\langle x, \mu_A(x) \vee \mu_B(x), \nu_A(x) \wedge \nu_B(x)\rangle | \forall x \in X\}$;
Rule 3:$\overline{A} = \{\langle x, \nu_A(x), \mu_A(x)\rangle | \forall x \in X\}$;

Property 1. $A \subseteq B \Leftrightarrow$ *ifandonlyif* $(\forall x \in X)(\mu_A(x) \leqslant \mu_B(x) \& \nu_A(x) \geqslant \nu_B(x))$;

Property 2:. $A = B \Leftrightarrow$ *ifandonlyif* $(\forall x \in X)(\mu_A(x) = \mu_B(x) \& \nu_A(x) = \nu_B(x))$;

Where $\mu_A(x) \wedge \mu_B(x) = \min(\mu_A(x), \mu_B(x)), \nu_A(x) \vee \nu_B(x) = \max(\nu_A(x), \nu_B(x))$.

The three rules give the operational forms of the membership and non-membership functions under the conditions of intersecting, merging, and taking the inverse operation among IFSs, respectively.

3.2.2. TIFN and arithmetic rules

In this study, triangular intuitionistic fuzzy sets (TIFNs) are used for the evaluation and inference of PSFs. A TIFN is an IFN that considers both membership and non-membership functions, represented as follows:

$$\mu_A(x) = \begin{cases} \dfrac{x-a_1}{a_2-a_1}, a_1 \leqslant x < a_2 \\ \dfrac{a_3-x}{a_3-a_2}, a_2 \leqslant x < a_3 \\ 0, \text{otherwise} \end{cases} \tag{5}$$

$$\nu_A(x) = \begin{cases} \dfrac{b_1-x}{b_2-b_1}, _1 b_1 \leqslant x < b_2 \\ \dfrac{x-b_2}{b_3-b_2}, b_2 \leqslant x < b_3 \\ 0, \text{otherwise} \end{cases} \tag{6}$$

where $b_1 \leqslant a_1 \leqslant a_2(b_2) \leqslant a_3 \leqslant b_3$, and when $\mu_A(x_i) = \nu_A(x_i)$, there exists $\mu_A(x_i)$, $\nu_A(x_i) < 0.5$. TIFN can then be illustrated as $A = (a_1, a_2, a_3; b_1, b_2, b_3)$. Fig. 5 gives a schematic representation of a TIFN.

To represent the quantified relationship of the PSFs and HEP, a TIFN-based inference method is established as below.

Assume that $M = (m_1, m_2, m_3; n_1, n_2, n_3)$ and $T = (t_1, t_2, t_3; s_1, s_2, s_3)$, then for the operation between TIFNs is defined as follows (Atanassov, 1994; Dengfeng & Chuntian, 2002).

1) $\delta \times M = (\delta m_1, \delta m_2, \delta m_3; \delta n_1, \delta n_2, \delta n_3)$, and the result is still a TIFN.

   Where δ is a constant and$\delta > 0$.

2) $M \oplus T = (m_1 + t_1, m_2 + t_2, m_3 + t_3; n_1 + s_1, n_2 + s_2, n_3 + s_3)$, and the result is still a TIFN.
3) $M \otimes T = (m_1t_1, m_2t_2, m_3t_3; n_1s_1, n_2s_2, n_3s_3)$, and the result is still a TIFN.

Moreover, in order to solve intuitionistic fuzzy relations among TIFNs, certain functions need to be employed.

3.2.3. Relation function between two TIFNs

The relation function between two TIFNs represents the mapping relationship between input and output in the IFS system. Define D as an intuitionistic fuzzy(IF) relation from M to T:

$$D = M \cap T = \{\langle (x,y), \mu_D(x,y), \nu_D(x,y)\rangle | x \in M, y \in T\} \tag{7}$$

Then there exist $\mu_D(x,y) = \mu_M(x) \wedge \mu_T(y)$ and $\nu_D(x,y) = \nu_M(x) \vee \nu_T(y)$.

When the IFS M and the intuitionistic fuzzy relation D are known, the IFS T can be calculated by the following equations (Tyagi & Akram, 2013):

$$\mu_T(y) = \bigvee_x [\mu_M(x) \wedge \mu_D(x,y)] \tag{8}$$

$$\nu_T(y) = \bigwedge_x [\nu_M(x) \vee \nu_D(x,y)] \tag{9}$$

3.2.4. Distance between two TIFNs

The measurement of IFS distance is an important part of the expert-based IFS system. The distance between two continuous and discrete TIFNs can be calculated by Eqs. (10) and (11), respectively, which contain three parameters: membership, non-membership, and intuitionistic index. The traditional Euclidean distance (Szmidt & Kacprzyk, 2000) considers the Intuitionistic index ($\pi(x)$) equally with the membership degree ($u(x)$) and the non-membership degree ($\nu(x)$), which is somewhat unreasonable. Because the Intuitionistic index ($\pi(x)$) is an important parameter that represents the degree of hesitation of experts, it needs to be corrected.

$$d(M,T) = \sqrt{\frac{1}{2(b-a)}\int_a^b \left[(\mu_M(x) - \mu_T(x))^2 + (\nu_M(x) - \nu_T(x))^2 + \rho(\pi_M(x) - \pi_T(x))^2\right]} \quad (10)$$

$$d(M,T) = \sqrt{\frac{1}{2n}\sum_{i=1}^{n}\left[(\mu_M(x_i) - \mu_T(x_i))^2 + (\nu_M(x_i) - \nu_T(x_i))^2\right) + \rho\left(\pi_{I_B}(x_i) - \pi_{I_A}(x_i)\right)^2]} \quad (11)$$

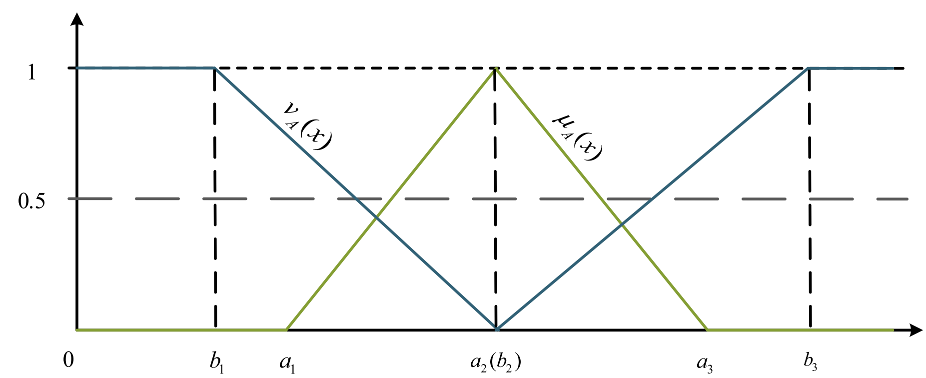

Fig.5. Membership and non-membership functions of a TIFN.

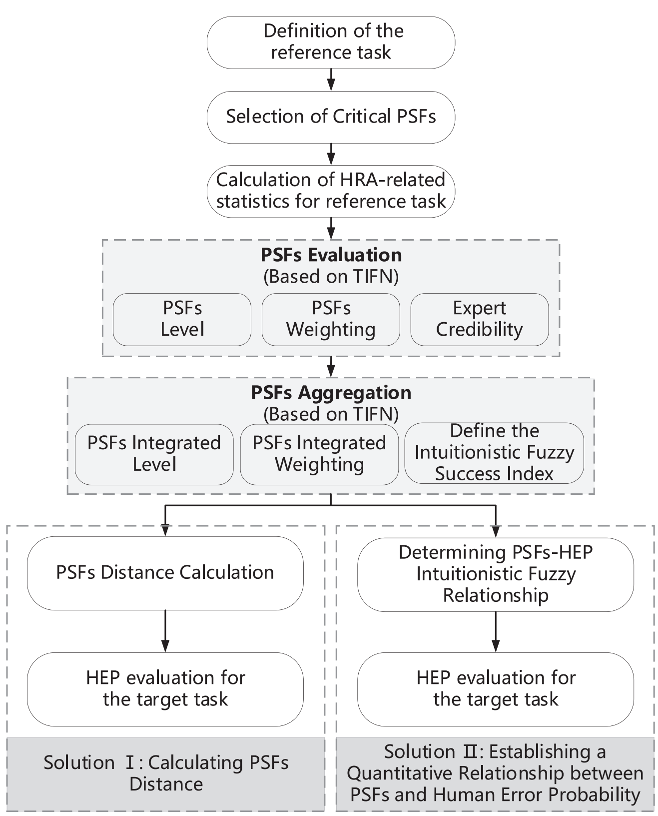

Fig.6. The detailed algorithm of TIFN-HRA methodology.

where a and b are constants and $0 < a < b$, $[a, b]$ is the interval over which membership functions and non-membership functions need to be integrated. ρ is a correction coefficient, and $\rho \in [0,1]$. When $\rho = 0$, the influence of $\pi(x)$ on distance is ignored. When $\rho = 1$, Eq. (11) becomes the traditional Euclidean distance. The Intuitionistic index $\pi(x)$ contains both membership and non-membership information. In the absence of any other prior information, we take $\rho = 0.5$ to represent the maximum uncertainty in hesitation.

3.3. The proposed TIFN-HRA

Grounded in the analysis of the human error model discussed earlier and the IFS theory introduced, we present a novel method named TIFL-HRA for effectively evaluating HEP in a target task. The routine steps of the integrated TIFN-HRA method are summarized as follows (Fig. 6).

Step 1: Definition of the reference task.

The goal of this paper is to evaluate the HEP of target task using a reference task with known data. Therefore, the first step is to find a reference task which is highly similar to the target task.

Step 2: Selection of critical PSFs.

The proposed methodology begins with the selection of PSFs. Given the large number of PSFs that exist in reality, it is important to identify

Table 3
Expert Credibility Value and Judgment Basis.

No.	Level	Judgment basis	values
1	Very Believable (*VB*)	10 years or more of work experience or a PhD	1.0
2	Believable (*B*)	5–10 years of work experience or a master's degree	0.9
3	Relative Believable (*RB*)	Less than 5 years of work experience or a bachelor's degree	0.8

those that have the greatest influence on HEP. While some PSFs may have a negligible effect, others may be critical and contribute significantly to overall performance. Therefore, it is essential to accurately identify and prioritize these critical PSFs.

Step 3: Calculation of HRA-related statistics for reference task.

In this step, statistics on HRA-related data for the reference task are calculated.

Step 4: PSFs evaluation based on TIFN.

The goal of this step is to perform the evaluation of PSFs (for both the reference task and the target task) with TIFNs, including the expert credibility, the evaluation of PSFs level and PSFs weight.

(1) Expert credibility evaluation

It is necessary to assess the credibility of the experts (the importance of the expert's evaluations in the universe of discourse), because the credibility of their assessments varies depending on the expert's knowledge level (Zhang et al., 2016). The credibility of experts is divided into three levels in this study $C = \{$Relative Believable (RB), Believable (B), Very Believable (VB)$\}$. Table 3 illustrates the criteria of determining the expert credibility and the values of each level of credibility.

(2) PSF level evaluation

PSF level represents the level of its own. In this study, there are five levels for PSFs, which are defined as $L = \{$Very Poor (VP), Poor(P), Medium(M), Good(G), Very Good (VG)$\}$. For example, comparable to the concept of CPCs in CREAM, the PSF level in this study is gauged relative to its influence on HEP. When the PSF exhibits a "Very good" level, it exerts a favorable influence on HEP, thereby enhancing human performance; conversely, at a "Very poor" PSF level, it bears a detrimental effect on HEP, potentially escalating the likelihood of human error occurrence.

The PSF level is determined by expert linguistic and subsequently translated into TIFN.

The TIFN representing expert linguistic is given by the following equation in terms of Very Poor (VP):

$$VP = \frac{1}{m} \times \left(\widetilde{E_1} + \widetilde{E_2} + \ldots + \widetilde{E_m}\right) \tag{12}$$

where $\widetilde{E}_i (i = 1, 2, \ldots, m)$ is the TIFN given by the i^{th} expert, m is the number of experts.

(3) PSFs weight evaluation

Different PSFs have different effects on the human error, and considering the importance of the PSFs means considering the weight of each PSF for the task. The weight of PSFs in this study is divided into five levels $W = \{$Very Unimportant (VU), Unimportant(U), Fair(F), Important(I), Very Important (VI)$\}$. Similarly, PSFs weights are given by experts linguistic and transformed into TIFNs.

Step 5: PSFs aggregation based on TIFN.

This step is the process of aggregating several TIFNs into a single TIFN, and ultimately obtaining the integrated level and integrated weight of PSFs.

(1) Integrated level of PSFs

The integrated level of each PSF $I_t, t = 1, 2, \ldots, n$ is represented as below:

$$I_t = \frac{1}{m} \times [(c_1 \times I_{t1}) \oplus (c_2 \times I_{t2}) \oplus \cdots \oplus (c_m \times I_{tm})] \tag{13}$$

where I_{ti} represents the i^{th} expert's assessment of the t^{th} PSF level, and I_{ti} corresponds to a TIFN in L. c_i represents i^{th} expert's credibility, n is the number of PSFs and m is the number of experts. According to the aggregation algorithm mentioned in 3.2.2, the result of the calculation is still a TIFN, from which we can obtain the integrated level of each PSF.

(2) Integrated weight of PSFs

Similar to the aggregation process of the PSF level, the aggregation of the PSF weight $W_t, i = 1, 2, \ldots, n$ is the integration of each expert's evaluation of the importance of the PSF by considering the expert credibility c_i, which is represented as below.

$$W_t = \frac{1}{m} \times [(c_1 \times W_{t1}) \oplus (c_2 \times W_{t2}) \oplus \cdots \oplus (c_m \times W_{tm})] \tag{14}$$

where W_{ti} represents the i^{th} expert's assessment of the t^{th} PSF weight. Similarly, it can be seen that the result of the calculation is still a TIFN, which gives the integrated weight of each PSF.

(3) Definition of the IFS index

In order to make a comprehensive assessment of each PSF, this study defined the Intuitionistic fuzzy success index (I_{IFS}) as a comprehensive assessment result of the PSFs, which contains the weights of the PSF, the levels of the PSFs, and the credibility of the expert. I_{IFS} can be obtained by aggregating the integrated level and integrated weight of the PSFs, and the equation is as follows:

$$I_{IFS} = \frac{1}{n} \times [(W_1 \otimes I_1) \oplus (W_2 \otimes I_2) \oplus \cdots \oplus (W_n \otimes I_n)] \tag{15}$$

Step 6: Solution I: Calculation of the PSF distance.

The goal of this step is to assess the HEP of the target task by calculating the distance of PSFs.

Step 6–1: PSFs distance calculation

Following the assessment of the PSFs for both the target and reference tasks, the comprehensive assessment results for each PSF must be compared. Specifically, if the level of a PSF (I_{IFS_T}) in the target task is higher, it suggests that the PSF will have a more positive impact on the target task and hence, a lower HEP.

Suppose that the integrated evaluation result of a PSF for the reference task is I_{t_R}, and that for the target task is I_{t_A}. In this context, the distance between the two tasks for the t^{th} PSF can be expressed as follows using Eq. (10):

$$d_{I_t}(I_{t_R}, I_{t_T}) = \sqrt{\frac{1}{2(b-a)} \int_a^b \left[\left(\mu_{I_{tR}}(x) - \mu_{I_{t_A}}(x)\right)^2 + \left(\nu_{I_{t_R}}(x) - \nu_{I_{t_A}}(x)\right)^2 + \rho\left(\pi_{I_{t_R}}(x) - \pi_{I_{t_A}}(x)\right)^2 \right]} \tag{16}$$

The integrated distance of all PSFs is:

$$D_I = \frac{1}{n} \times [(d_{I_1} \times W_1) \oplus (d_{I_2} \times W_2) \oplus \cdots \oplus (d_{I_n} \times W_n)] \tag{17}$$

where n is the number of PSFs.

According to the aggregation algorithm, the result of the calculation is still a TIFN.

Step 6–2: HEP evaluation for the target task.

As the HEP of the reference task HEP_R is known and represented in the form of TIFN, it can be calculated as:

$$\begin{cases} HEP_T = HEP_R + D_I \otimes HEP_R I_{IFS_R} > I_{IFS_T} \\ HEP_T = HEP_R - D_I \otimes HEP_R I_{IFS_R} < I_{IFS_T} \end{cases} \quad (18)$$

Step 7: Solution II: Establishment of a quantitative relationship between PSFs and HEP.

The goal of this step is to assess the HEP of the target task by establishing a quantitative relationship between PSFs and HEP.

Step 7–1: Determining the PSF-HEP intuitionistic fuzzy relationship.

It is assumed that the HEP of the reference task HEP_R can be determined and reflected in the form of TIFN as shown below:

$$HEP_R = (r_1, r_2, r_3; e_1, e_2, e_3)$$

Then, on this basis, the IF relationship between HEP_R and I_{IFS_R} can be determined.

Fuzzy logic and fuzzy approximate inference are useful for the process of deriving imprecise conclusions from an imprecise set of data, and this study extends the concept of fuzzy logic to intuitionistic fuzzy logic. In the conditional propositions and integrated inference rules, the reference task-related indicators are evaluated using TIFN to establish an intuitionistic fuzzy relationship F between I_{IFS_R} and HEP_R. The conditional statement is "if I_{IFS_R}, then HEP_R", where I_{IFS_R} is the cause event and HEP_R is the result event. The elements in the fuzzy relation F represent the possibility of mapping from the intuitionistic fuzzy success index I_{IFS_R} to the human error probability HEP_R.

Let $E_{I_{IFSR}}$ and E_R represent the set of discrete elements on the intuitionistic fuzzy success index I_{IFS_R} and the HEP_R, respectively, defined as $E_{I_{IFSR}} = \{x_{I_1}, x_{I_2}, \cdots, x_{I_\alpha}\}$, $E_R = \{x_{R_1}, x_{R_2}, \cdots, x_{R_\beta}\}$, where α, β are finite certain integers. An intuitionistic fuzzy relation F is an intuitionistic fuzzy set on $E_{I_{IFSR}} \cap E_R$ and its elements are element pairs consisting of elements corresponding to $E_{I_{IFSR}}$ and E_R, respectively. Given that the element pairs on F is (x, z), the membership function and the non-membership function of F can be defined as Eq. (19) and Eq. (20), respectively.

$$\mu_F(x,z) = \{\mu_{I_{IFSR}}(x) \wedge \mu_R(z)\} \quad (19)$$

$$\nu_F(x,z) = \{\nu_{I_{IFSR}}(x) \vee \nu_R(z)\} \quad (20)$$

Based on (19) and (20), the membership and non-membership matrices about F can be acquired, and the IF relation F is established.

Step 7–2: HEP evaluation for the target task.

The relationship between PSFs and HEP for the target task considered in this study is the same as the relationship in the reference task. Because the IF relationship F between I_{IFS_R} and HEP_R has been determined (the membership and non-membership matrixes of F have been established), we can find the set of discrete elements on the IF relation F corresponding to the I_{IFS_T} and then identify the set of discrete elements on HEP of the target task.

Therefore, according to the Eqs. (8) and (9), and from the evaluation results of the known I_{IFS_T} and the IF relationship F obtained from the reference task, the HEP of the target task can be calculated as follows:

$$\mu_{HEP_T}(z) = \bigvee_x \left[\mu_{I_{IFS_T}}(x) \wedge \mu_F(x,z)\right] \quad (21)$$

$$\nu_{HEP_T}(z) = \bigwedge_x \left[\nu_{I_{IFS_T}}(x) \vee \nu_F(x,z)\right] \quad (22)$$

where Eq. (21) means: the membership degree $\mu_{HEP_T}(z)$ of HEP_T takes the maximum value among the minimum values between the membership degree $\mu_{I_{IFST}}(x)$ of all I_{IFS_T} and the membership degree matrix $\mu_F(x,z)$ of F.

Finally, HEP_T with discrete element pairs as set elements can be obtained and shown as below:

$$HEP_T = \{(x_1, \mu_{x_1}, \nu_{x_1}), (x_2, \mu_{x_2}, \nu_{x_2}), \cdots (x_n, \mu_{x_n}, \nu_{x_n})\}$$

4. Case study

4.1. Background

Human factors play a crucial role in various phases of spaceflight, ranging from design and implementation to launch and maintenance. Studies have demonstrated that human error is the primary cause of hazardous incidents in the spaceflight launch field(Forsbacka & Helton, 2023; Pan et al., 2022), and can even lead to catastrophic consequences sometimes, such as core equipment damage or even personnel injury. Therefore, in order to improve the reliability of the entire launch mission, the HEP must be fully considered in advance (Calhoun et al., 2013). HRA of space refueling missions can provide a decision basis for the analysis, measurement and prevention of human errors during space launch.

In this study, the refueling task in the spaceflight launch process is selected as a specific object of study, and a simulation experiment is designed as a reference task to analyze the HEP of the refueling task.

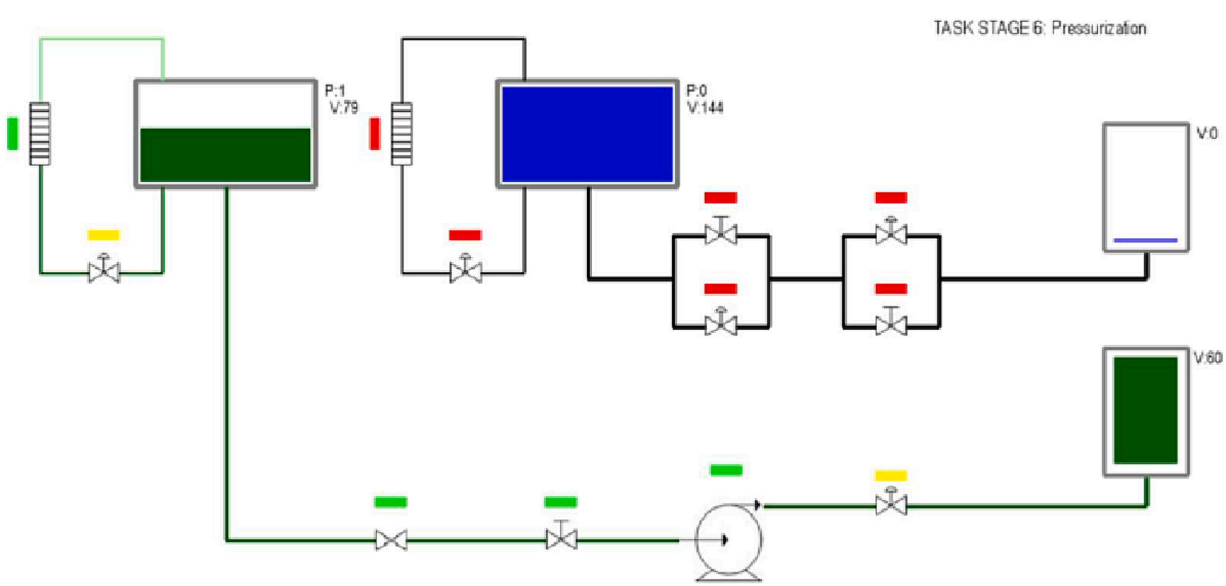

Fig.7. Interface of the spaceflight refueling mission simulation experiment.

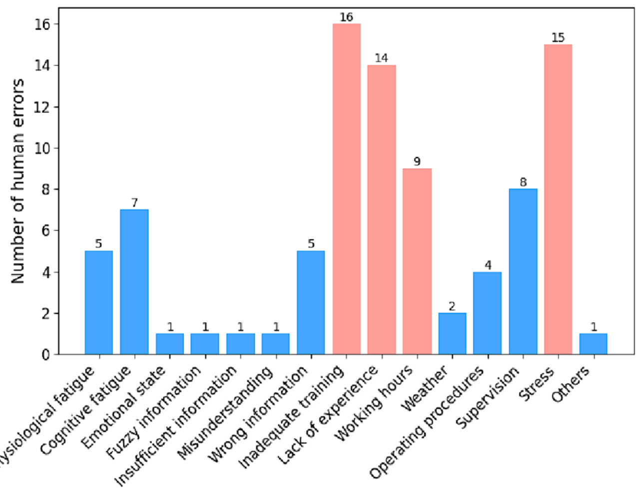

Fig.8. PSFs in spaceflight fuel refueling missions.

Table 4
Description of the PSFs.

PSFs	Description
Training (T)	PSF relates to team and organizations, which offers guidance and skill-building for people to improve task performance and minimize human errors.
Experience(E)	PSFs that impact personal competence involve honing intuitive understanding and skills through practice, encountering situations, and learning from successes and failures.
Stress (S)	PSF influencing timely completion of collective actions safely, primarily shaped by initiators' perceptions of consequences for task non-completion.
Working hours (WH)	PSF related to the environment. The duration and scheduling of working hours, which affect individuals' cognitive abilities, fatigue levels, and overall productivity, are crucial factors.

4.2. HEP during spaceflight refueling mission

4.2.1. Preliminary

Step 1: Definition of the reference task.

To assess the HEP of the target task, this study utilizes human factor experiment as a reference task for the spaceflight refueling mission. Based on field investigation conducted at the space launch site, relevant information pertaining to the equipment and the refueling process was collected. Using this information, the refueling task was decomposed into 13 specific steps, with each step consisting of a certain number of actions. A simulation program was then developed to capture various actions of the operator and compare them with the set error judgment criteria to detect any human errors. Fig. 7 illustrates the interface of the refueling simulation experiment.

Step 2: Selection of critical PSFs.

By conducting field investigation and collecting data at a spaceflight launch site, we analyzed accident reports from four years (2004, 2008, 2011, and 2012) to obtain the number of human errors and identify the primary influencing factors, as depicted in Fig. 8.

Among the various PSFs associated with the spaceflight launch mission, four factors are found to have a significant impact on human errors in the space refueling mission, namely training (T), experience (E), stress (S), and working hours (WH). It's important to note that, even though supervision appears to have a similar impact as working hours, expert indicates that its effect might be relatively minor. This is because it's less common and has less influence in practice compared to working hours. These PSFs correspond to team and organizational factors, personal factors, and environmental factors, respectively, as described in Section 2.1. Consequently, this case study focuses on analyzing these four PSFs, which are described in detail in Table 4.

Step 3: HRA-related statistics for reference task.

According to the human factor experiment based on the space refueling mission and the analysis of the experimental data, the probability interval of human error probability is [0.044,0.116] (Pan et al., 2020). Subsequently, similar to the approach for obtaining TIFNs used to represent expert linguistics, we can get the TIFN of the reference task as $HEP_R = [0.044, 0.08, 0.116; 0.014, 0.08, 0.146]$ with the expert's suggestion.

Table 5
Expert Credibility Evaluation.

Experts	Judgement basis	Credibility
E_1	Expert 1 has a master's degree and have 6 years work experience in aerospace field.	0.9
E_2	Expert 2 has a PhD degree and work for 15 years in the field of reliability of space refueling systems.	1.0
E_3	Expert 3 has a master's degree and work for 8 years in the field of safety management of space refueling systems.	0.9
E_4	Expert 4 has a bachelor's degree and work for 2 years in the field of safety management of space refueling systems.	0.8
E_5	Expert 5 has a master's degree and work for 9 years in the field of reliability of space refueling systems.	0.9

Table 6
Reference task PSFs level evaluation.

PSFs	Experts				
	E_1	E_2	E_3	E_4	E_5
Training	*M*	*G*	*M*	*M*	*G*
Experience	*M*	*M*	*M*	*G*	*G*
Stress	*P*	*VG*	*VP*	*G*	*G*
Working hours	*VG*	*G*	*VG*	*M*	*P*

Table 7
TIFN for each level of PSFs.

Levels	TIFN values
VP	(0.58, 0.64, 0.68; 0.57, 0.64, 0.70)
P	(0.66, 0.72, 0.77; 0.64, 0.72, 0.79)
M	(0.73, 0.78, 0.84; 0.71, 0.78, 0.86)
G	(0.80, 0.86, 0.90; 0.79, 0.86, 0.92)
VG	(0.85, 0.92, 0.97; 0.82, 0.92, 1.00)

4.2.2. PSF evaluation and aggregation based on TIFN

Step 4:PSF evaluation based on TIFN.

(1) Expert credibility evaluation

After considering the experts' experience and education, the credibility and detailed information of the experts are obtained in Table 5.

(2) PSFs level evaluation

The evaluation of the four PSFs by experts for the reference task are listed in Table 6 below.

Table 7 gives the TIFN for each level of PSF by expert evaluation.

At the same time, PSFs levels for target tasks are also given by expert

Table 8
Target task PSFs influence level assessment.

PSFs	Experts				
	E_1	E_2	E_3	E_4	E_5
Training	*G*	*VG*	*VG*	*G*	*G*
Experience	*G*	*M*	*G*	*VG*	*M*
Stress	*M*	*VG*	*G*	*M*	*VG*
Working hours	*VG*	*G*	*VG*	*G*	*M*

Table 9
TIFN for each weight of PSFs.

Levels	TIFN values
VU	(0.33, 0.42, 0.51; 0.31, 0.42, 0.53)
U	(0.45, 0.56, 0.66; 0.42, 0.56, 0.68)
F	(0.62, 0.70, 0.78; 0.59, 0.70, 0.81)
I	(0.72, 0.81, 0.89; 0.68, 0.81, 0.93)
VI	(0.85, 0.92, 0.97; 0.82, 0.92, 1.00)

Table 10
PSFs weight evaluation.

PSFs	Experts				
	E_1	E_2	E_3	E_4	E_5
Training	*VI*	*I*	*VI*	*I*	*F*
Experience	*F*	*I*	*VI*	*F*	*U*
Stress	*I*	*VI*	*I*	*U*	*I*
Working hours	*F*	*F*	*U*	*I*	*F*

Table 11
TIFN of each PSF integrated influence level of reference task.

PSFs	TIFN values
I_{T_R}	(0.6836, 0.7324, 0.7788; 0.6694, 0.7324, 0.7968)
I_{E_R}	(0.6808, 0.7292, 0.7764; 0.6662, 0.7292, 0.7944)
I_{S_R}	(0.6652, 0.7212, 0.7610; 0.6504, 0.7212, 0.7810)
I_{WH_R}	(0.7016, 0.7576, 0.8022; 0.6820 0.7576, 0.8238)

Table 12
TIFN of each PSF integrated influence level of target task.

PSFs	TIFN values
I_{T_T}	(0.7390, 0.7968, 0.8366; 0.7224, 0.7968, 0.8584)
I_{E_T}	(0.7014, 0.7532, 0.7984; 0.6854, 0.7532, 0.8180)
I_{S_T}	(0.7152, 0.7696, 0.8162; 0.6952, 0.7696, 0.8380)
I_{WH_T}	(0.7254, 0.7812, 0.8244; 0.7074, 0.7812, 0.8460)

Table 13
TIFN of the integrated weight of each PSF.

PSFs	TIFN values
W_T	(0.6768, 0.7488, 0.8100; 0.6462, 0.7488, 0.8406)
W_E	(0.5888, 0.6664, 0.7366; 0.5598, 0.6664, 0.7638)
W_S	(0.6308, 0.7110, 0.7802; 0.5984, 0.7110, 0.8110)
W_{WH}	(0.5434, 0.6224, 0.6980; 0.5148, 0.6224, 0.7248)

assessment, and the results are listed in Table 8.

(3) PSFs weight evaluation

Table 9 gives the TIFN for each weight level of PSFs by expert evaluation.

The weight of each PSF is evaluated by experts and shown in Table 10 below.

Step 5: PSF aggregation based on TIFN.

On the basis of the evaluation results of the PSFs, the aggregation of the PSFs of the reference task and the target task are performed.

(1) Integrated level of PSFs

According to Eq. (13), the integrated TIFN of each PSF can be obtained.

For the reference task, the integrated evaluation results for each PSF are shown in Table 11.

For instance, the TIFN of the "Training" of the reference task can be calculated as follows:

$$I_{T_R} = \frac{1}{5} \times [(c_1 \times M) \oplus (c_2 \times G) \oplus (c_3 \times M) \oplus (c_4 \times M) \oplus (c_5 \times G)]$$
$$= (0.6836, 0.7324, 0.7788; 0.6694, 0.7324, 0.7968)$$

For the target task, the combined evaluation results of each PSF are shown in Table 12.

(2) Integrated weight of PSFs

According to Eq. (14), the TIFNs of the integrated weight of each PSF can be obtained (Table 13).

For instance, the TIFN of the integrated weight of "Training" can be calculated as follows:

$$W_T = \frac{1}{5} \times [(c_1 \times VI) \oplus (c_2 \times I) \oplus (c_3 \times VI) \oplus (c_4 \times I) \oplus (c_5 \times F)]$$
$$= (0.6768, 0.7488, 0.8100; 0.6462, 0.7488, 0.8406)$$

(3) Intuitionistic fuzzy success index

To compare PSFs levels more intuitively between the reference task and the target task, it is first necessary to determine the intuitionistic fuzzy success index, which is an integrated level of all PSFs. In accordance with the results of integrated level and integrated weight of the PSFs and Eq. (15), aggregation can be performed to obtain the intuitive fuzzy success index of the reference task and the target task as:

$$I_{IFS_R} = \frac{1}{4} \times [(W_T \otimes I_{T_R}) \oplus (W_E \otimes I_{E_R}) \oplus (W_P \otimes I_{P_R}) \oplus (W_{WH} \otimes I_{WH_R})]$$
$$= (0.4161, 0.5047, 0.5891; 0.3864, 0.5047, 0.6268)$$

$$I_{IFS_T} = \frac{1}{4} \times [(W_T \otimes I_{T_T}) \oplus (W_E \otimes I_{E_T}) \oplus (W_P \otimes I_{P_T}) \oplus (W_{WH} \otimes I_{WH_T})]$$
$$= (0.4396, 0.5330, 0.6195; 0.4077, 0.5330, 0.6598)$$

The I_{IFS_R} and I_{IFS_T} are still TIFNs.

4.2.3. *Evaluation of the HEP of the target task*

Step 6: Solution I: Calculating the PSFs distance.

(1) PSFs distance calculation

According to Eq. (16), the distance between each PSF of the target

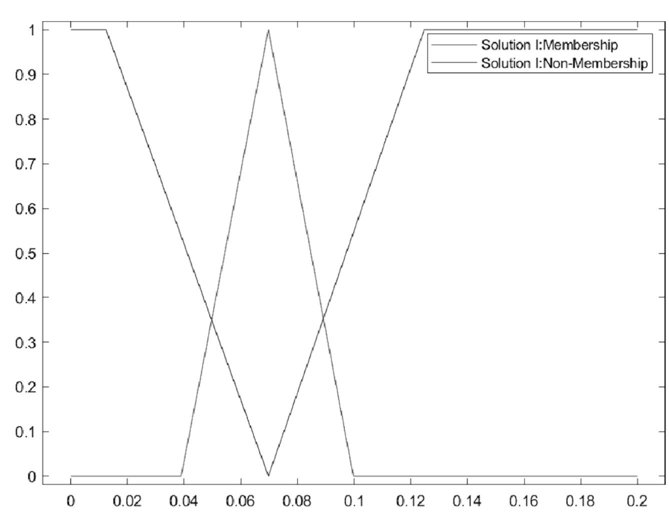

Fig.9. HEP of the target task considering the PSFs distance.

task and the reference task can be calculated as: $d_{I_T} = 0.2429$, $d_{I_E} = 0.1241$, $d_{I_P} = 0.2237$, and $d_{I_{WH}} = 0.1399$.

For example, the distance between "Training" of the reference task and the target task can be calculated as follows:

$$d(I_{tR}, I_{tT}) = \sqrt{\frac{1}{2}\int_0^1 \left[\left(\mu_{I_{tR}}(x) - \mu_{I_{tT}}(x)\right)^2 + \left(\nu_{I_{tR}}(x) - \nu_{I_{tT}}(x)\right)^2 + 0.5\left(\pi_{I_{tR}}(x) - \pi_{I_{tT}}(x)\right)^2 \right]} = 0.2429$$

Through Eq. (17), the combined distance of all PSFs is:

$$D_I = \frac{1}{4} \times [(d_{I_T} \times W_T) \oplus (d_{I_E} \times W_E) \oplus (d_{I_P} \times W_P) \oplus (d_{I_{WH}} \times W_{WH})]$$
$$= (0.1136, 0.1277, 0.1401; 0.1081, 0.1277, 0.1454)$$

And the result of the calculation is still a TIFN.

(2) HEP evaluation for the target task

The HEP of the reference task is already known and the HEP evaluation result is expressed as TIFN. Additionally, the PSF levels of the target task are better than those of the reference task, as indicated by the intuitionistic fuzzy success index. Therefore, the target task is expected to be more reliable. The HEP of the target task can be determined by calculating the PSFs distance between the target and reference tasks using Eq. (18).

$$HEP_T = HEP_R - d_I \otimes HEP_R$$
$$= (0.0390, 0.0698, 0.0998; 0.0125, 0.0698, 0.1248)$$

Fig. 9 gives the evaluation results of the HEP of the target task calculating the PSFs distance.

Step 7: Solution II: Establishing a quantitative relationship between PSFs and HEP.

The second solution, establishing a quantitative relationship between PSFs and HEP, works in the following way.

(1) Determining the PSFs-HEP intuitionistic fuzzy relationship

Given that the PSFs and HEP of the reference task are presented in the form of TIFNs, the relationship between them can be established by treating the PSF evaluation results as independent variables and the HEP as the dependent variable. Intuitive fuzzy reasoning is used as an assessment tool to measure the relationship F of given integrated PSFs level and HEP, which means "if the I_{IFS_R} is, then the human reliability is HEP_R". Thus, it can be determined that there is a quantified relationship between them, and the elements in the relationship F determined by using intuitive fuzzy inference represent the fuzzy possibilities from I_{IFS_R} mapping to HEP_R.

The IFS I_{IFS_R} and HEP_R in the reference task need to be discretized to determine this IF relationship. It may be useful to take $E_{I_{IFS_R}}$ and E_R as discrete subsets of the I_{IFS_R} and the HEP_R of the reference task, respectively, and the two sets are given as follows:

$$E_{IFS_R} = \left\{ \begin{array}{c} 0.4, 0.43, 0.46, 0.49, 0.52, 0.55, 0.58, 061, 0.64, 0.67, 0.7, \\ 0.73, 0.76, 0.79, 0.82, 0.85, 0.88, 0.91, 0.94, 0.97 \end{array} \right\}$$

$$E_R = \left\{ \begin{array}{c} 0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1, \\ 0.11, 0.12, 0.13, 0.14, 0.15, 0.16, 0.17, 0.18, 0.19, 20 \end{array} \right\}$$

Then the set of discrete intuitionistic fuzzy success index and the set of membership and non-membership relations for HEP corresponding to the reference task can be obtained as follows:

$$I_{IFS_R} = \left\{ \begin{array}{c} (0.4, 0, 0.8850), (0.43, 0.1569, 0.6314), (0.46, 0.4955, 0.3779), \\ (0.49, 0.8341, 0.1243), (0.52, 0.8187, 0.1253), (0.55, 0.4633, 0.3710), \\ (0.58, 0.1078, 0.6167), (0.61, 0, 0.8624), (0.64, 0, 1), (0.67, 0, 1), (0.7, 0, 1), \\ (0.73, 0, 1), (0.76, 0, 1), (0.79, 0, 1), (0.82, 0, 1), (0.85, 0, 1), (0.88, 0, 1), \\ (0.91, 0, 1), (0.94, 0, 1), (0.97, 0, 1) \end{array} \right\}$$

$$HEP_R = \left\{ \begin{array}{c} (0.01, 0, 1), (0.02, 0, 0.9091), (0.03, 0, 0.7576), (0.04, 0, 0.6061), \\ (0.05, 0.1667, 0.4545), (0.06, 0.4444, 0.3030), (0.07, 0.7222, 0.1515), \\ (0.08, 1, 0), (0.09, 0.7222, 0.1515), (0.1, 0.4444, 0.3030), \\ (0.11, 0.1667, 0.4545), (0.12, 0, 0.6061), (0.13, 0, 0.7576), \\ (0.14, 0, 0.9091), (0.15, 0, 1), (0.16, 0, 1), (0.17, 0, 1), (0.18, 0, 1), \end{array} \right\}$$

In this way, the IF relationship F between PSFs and HEP is solved, and the membership and non-membership matrices of the PSFs-HEP correlation can be obtained according to Eqs. (19) and (20), as shown in Figs. 10 and 11.

For example, we can obtain $\mu_F(0.05, 0.61)$ and $\nu_F(0.05, 0.61)$ according to Eqs. (19) and (20), respectively:

$$\mu_F(0.05, 0.58) = \mu_{HEP_R}(0.05) \wedge \mu_{IFSR_R}(0.58) = 0.1667 \wedge 0.1078 = 0.1078$$

$$\nu_F(0.05, 0.61) = \nu_{HEP_R}(0.05) \vee \nu_{IFS_R}(0.61) = 0.4545 \vee 0.8624 = 0.8624$$

(2) HEP evaluation for the target task.

The intuitionistic fuzzy success index of the target task is:

$$I_{IFS_T} = (0.4396, 0.5330, 0.6195, 0.4077, 0.5330, 0.6598)$$

$R \setminus I$	0.4	0.43	0.46	0.49	0.52	0.55	0.58	0.61	0.64	0.67	0.7	0.73	0.76	0.79	0.82	0.85	0.88	0.91	0.94	0.97
0.01	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.02	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.03	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.04	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.05	0	0.1569	0.1667	0.1667	0.1667	0.1667	0.1078	0	0	0	0	0	0	0	0	0	0	0	0	0
0.06	0	0.1569	0.4444	0.4444	0.4444	0.4444	0.1078	0	0	0	0	0	0	0	0	0	0	0	0	0
0.07	0	0.1569	0.4955	0.7222	0.7222	0.4633	0.1078	0	0	0	0	0	0	0	0	0	0	0	0	0
0.08	0	0.1569	0.4955	0.8341	0.8187	0.4633	0.1078	0	0	0	0	0	0	0	0	0	0	0	0	0
0.09	0	0.1569	0.4955	0.7222	0.7222	0.4633	0.1078	0	0	0	0	0	0	0	0	0	0	0	0	0
0.1	0	0.1569	0.4444	0.4444	0.4444	0.4444	0.1078	0	0	0	0	0	0	0	0	0	0	0	0	0
0.11	0	0.1569	0.1667	0.1667	0.1667	0.1667	0.1078	0	0	0	0	0	0	0	0	0	0	0	0	0
0.12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Fig.10. The membership matrix of the PSFs-HEP correlation *F*.

The set of membership and non-membership relationship that corresponds to the discrete intuitionistic fuzzy success index of the target task can be obtained using the following procedure:

$$E_{I_{IFS_T}} = \left\{ \begin{array}{c} (0.4, 0, 1), (0.43, 0, 0.8220), (0.46, 0.2184, 0.5826), \\ (0.49, 0.5396, 0.3432), (0.52, 0.8608, 0.1038), (0.55, 0.8035, 0.1341), \\ (0.58, 0.4566, 0.3707), (0.61, 0.1098, 0.6073), (0.64, 0, 0.8438), \\ (0.67, 0, 1), (0.7, 0, 1), (0.73, 0, 1), (0.76, 0, 1), (0.79, 0, 1), (0.82, 0, 1), \\ (0.85, 0, 1), (0.88, 0, 1), (0.91, 0, 1), (0.94, 0, 1), (0.97, 0, 1) \end{array} \right\}$$

Given the relationship matrix of PSFs-HEP correlations F and I_{IFS_T}, the discrete elements on HEP_T can be presented according to Eqs. (21) and (22). For instance, $\mu_{HEP_T}(0.05) = \bigvee_x [\mu_{IFS_T}(x) \wedge \mu_F(x, 0.05)] = 0.1667$, $\nu_{HEP_T}(0.05) = \bigwedge_x [\nu_{IFS_T}(x) \vee \nu_F(x, 0.05)] = 0.4545$.

$$HEP_T = \left\{ \begin{array}{c} (0.01, 0, 1), (0.02, 0, 9091), (0.03, 0, 0.7576), (0.04, 0, 6061), \\ (0.05, 0.1667, 0.4545), (0.06, 0.4444, 0.3030), \\ (0.07, 0.7222, 0.1515), (0.08, 0.8187, 0.1253), \\ (0.09, 0.7222, 0.1515), (0.10, 0.4444, 0.3030), (0.11, 0.1667, 0.4545), \\ (0.12, 0, 0.6061), (0.13, 0, 0.7576), (0.14, 0, 0.9091), (0.15, 0, 1), (0.16, 0, 1), \\ (0.17, 0, 1), (0.18, 0, 1), (0.19, 0, 1), (0.20, 0, 1) \end{array} \right\}$$

Fig. 12 gives the evaluation results of the HEP of the target task considering quantitative relationship between PSFs and HEP.

4.3. Linguistic distance of the target task

The distances between the results of the two solutions and the expert linguistic are calculated for a better understanding of the obtained results. The experts initially give a linguistic evaluation of the HEP, divided into five levels: G= {VL(Very Low), L(Low), RL(Rather low), M (Medium), H(High), RH(rather high), VH(Very High)}. TIFNs of the HEP is demonstrated in Table 14.

The result obtained by solution I is continuous, while the result obtained by solution 2 is discrete. Hence, Eq. (10) and Eq. (11) were used to calculate the distance between each result and the expert linguistic, respectively. It can be observed from Table 15 that the results of both solution I and solution II have the shortest distance to "Low" in the expert linguistic. Therefore, we can get the level of HEP of the target task is "Low".

5. Discussion

This study is dedicated to the advancement and refinement of HRA methods. It introduces a novel HRA research paradigm, in which a reference task based human error model is proposed to evaluate the target task. Meanwhile. the IFS theory is used to deal with the uncertainty of expert knowledge in the quantitation of HRA. The novelty of the developed method and the discussion of the results is as follows.

(1) Effectiveness of the reference task based human error model

In engineering, the scarcity of data makes the mechanism of how task-context relevant PSFs affect HEP unclear, making it difficult to apply many classical HRA methods to new tasks. In addition, obtaining information from experts is often difficult in the absence of benchmarks. To overcome this challenge, this paper proposes a reference task based human error model and presents two solutions for assessing HEP of target task based on reference task: solution I calculates the distance between PSFs of target and reference tasks, while solution II determines the quantitative relationship between PSFs and HEP in the reference task

$R \backslash I$	0.400	0.4300	0.4600	0.4900	0.5200	0.5500	0.5800	0.6100	0.64	0.67	0.7	0.73	0.76	0.79	0.82	0.85	0.88	0.91	0.94	0.97
0.01	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
0.02	0.9091	0.9091	0.9091	0.9091	0.9091	0.9091	0.9091	0.9091	1	1	1	1	1	1	1	1	1	1	1	1
0.03	0.8850	0.7576	0.7576	0.7576	0.7576	0.7576	0.7576	0.8624	1	1	1	1	1	1	1	1	1	1	1	1
0.04	0.8850	0.6314	0.6061	0.6061	0.6061	0.6061	0.6167	0.8624	1	1	1	1	1	1	1	1	1	1	1	1
0.05	0.8850	0.6314	0.4545	0.4545	0.4545	0.4545	0.6167	0.8624	1	1	1	1	1	1	1	1	1	1	1	1
0.06	0.8850	0.6314	0.3779	0.3030	0.3030	0.3710	0.6167	0.8624	1	1	1	1	1	1	1	1	1	1	1	1
0.07	0.8850	0.6314	0.3779	0.1515	0.1515	0.3710	0.6167	0.8624	1	1	1	1	1	1	1	1	1	1	1	1
0.08	0.8850	0.6314	0.3779	0.1243	0.1253	0.3710	0.6167	0.8624	1	1	1	1	1	1	1	1	1	1	1	1
0.09	0.8850	0.6314	0.3779	0.1515	0.1515	0.3710	0.6167	0.8624	1	1	1	1	1	1	1	1	1	1	1	1
0.1	0.8850	0.6314	0.3779	0.3030	0.3030	0.3710	0.6167	0.8624	1	1	1	1	1	1	1	1	1	1	1	1
0.11	0.8850	0.6314	0.4545	0.4545	0.4545	0.4545	0.6167	0.8624	1	1	1	1	1	1	1	1	1	1	1	1
0.12	0.8850	0.6314	0.6061	0.6061	0.6061	0.6061	0.6167	0.8624	1	1	1	1	1	1	1	1	1	1	1	1
0.13	0.8850	0.7576	0.7576	0.7576	0.7576	0.7576	0.7576	0.8624	1	1	1	1	1	1	1	1	1	1	1	1
0.14	0.9091	0.9091	0.9091	0.9091	0.9091	0.9091	0.9091	0.9091	1	1	1	1	1	1	1	1	1	1	1	1
0.15	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
0.16	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
0.17	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
0.18	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
0.19	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
0.20	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Fig.11. The non-membership matrix of the PSFs-HEP correlation F.

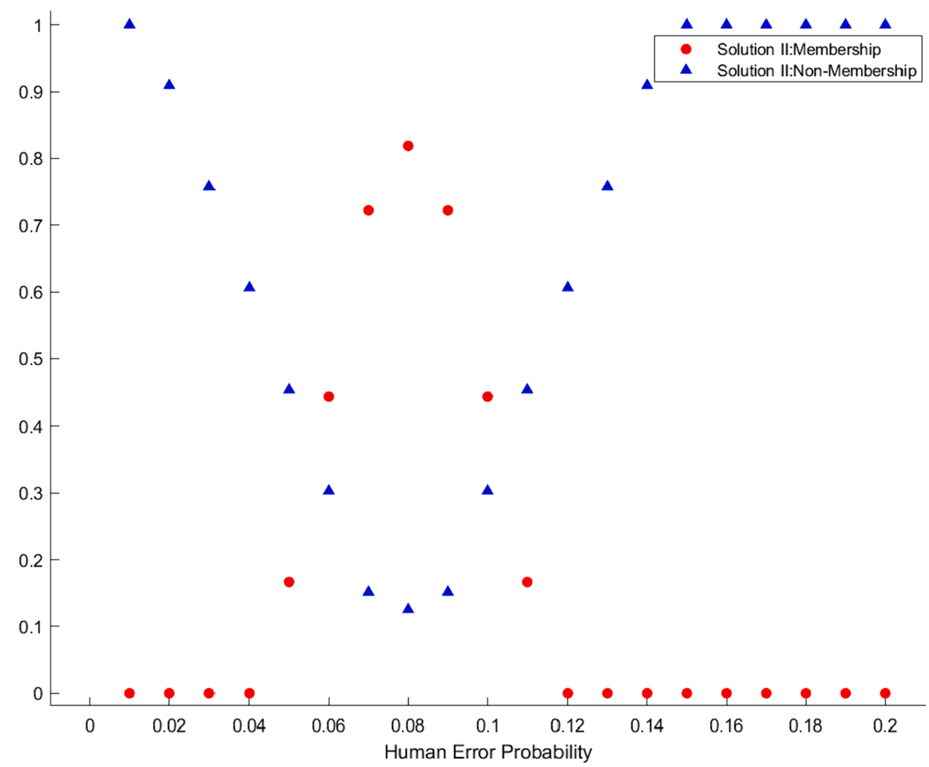

Fig.12. HEP evaluation of target task considering quantitative relationship between PSFs and HEP.

Table 14
TIFN for each level of HEP.

Level	TIFN value
VL	(0.01, 0.02, 0.03; 0, 0.02, 0.04)
L	(0.04, 0.05, 0.06; 0.03, 0.05, 0.07)
RL	(0.07, 0.08, 0.09; 0.06, 0.08, 0.1)
M	(0.1, 0.11, 0.12; 0.09, 0.11, 0.13)
RH	(0.13, 0.14, 0.15; 0.12, 0.14, 0.16)
H	(0.16, 0.18, 0.20;0.15, 0.18, 0.21)
VH	(0.20, 0.23, 0.26; 0.19, 0.23, 0.27)

and then maps it to the target task. The reference task is a highly similar task to the target task, and in the case study, a simulated human-in-the-loop experiment is developed for the space refueling task (target task) process, using it as the reference task to collect task-relevant information such as PSFs and HEP. This research paradigm offers a new perspective

Table 15
Distance between each result and Linguistic.

Method	VL	RL	L	M	H	RH	VH
Solution I	0.204	0.172	0.158	0.195	0.232	0.243	0.259
Solution II	0.409	0.353	0.284	0.353	0.410	0.443	0.467

for HRA studies in scenarios where data for target tasks are scarce.

(2) HEP quantification using the proposed TIFN-HRA

Expert knowledge plays a crucial role in the quantification of HRA. To better reflect the uncertainty in expert cognition, we propose an IFS-based method for evaluating the PSFs. Since IFS theory adeptly captures the ambiguity of expert knowledge, which is common in the assessment

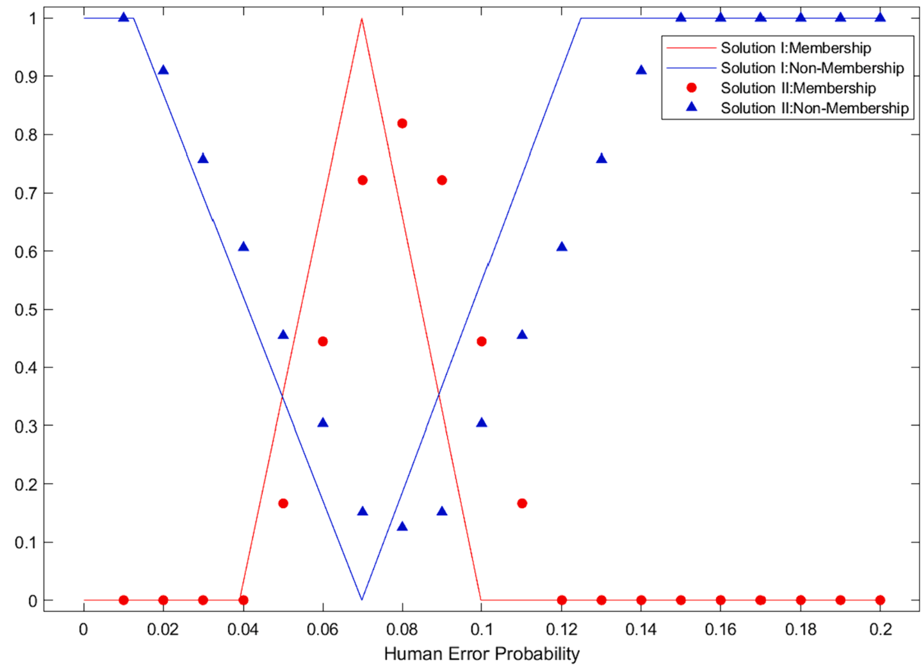

Fig.13. Comparison of the HEP of two solutions for target task.

of PSFs. The proposed method named TIFN-HRA quantifies the two solutions in the proposed human error model based on IFS using the aggregation algorithm of TIFN. In addition, solution II is an improvement on the literature (Tyagi & Akram, 2013), taking into account experts' credibility, and solution I is the original result of this study. The computational procedure of the proposed solution I is more concise compared to solution II.

(3) Analysis and comparison of the two solutions in TIFN-HRA

The results of the HEP analysis for the target task can be obtained through the two solutions, as shown in Fig. 13.

Firstly, for the solution of calculating PSF distance, it is known that the HEP with the highest confidence is around 0.0689, which is lower than that of the reference task. The result indicates that HEP is influenced by context, and the current context is determined by the level of PSFs. Qualitatively, when the level of PSFs is higher, the result of HEP will be lower, and the proposed method just accords with this relationship.

Secondly, solution II calculated the quantitative relationship of PSFs-HEP. According to the analysis, the highest membership is found when the HEP is 0.08, which was 0.8187. However, the method is still limited by the granularity of the given discrete set (the selected interval and the number of elements), which needs to be studied more thoroughly to obtain more accurate results. Additionally, the results obtained by both solutions show the shortest distance from the "Low" level in the expert linguistic. However, the calculation process of solution I is simpler and gives continuous result, which can give an explicit result to the decision maker.

6. Conclusion

In the case of unavailable or scare data, decision makers usually use the linguistics of experts for the quantification of HRA. To deal with the problem of knowledge/data limitations that create uncertainty in HEP assessment, a reference task based HRA approach is proposed in this paper. IFS theory is applied to capture hesitation degree in expert linguistics, which is more in line with human perception. Then, an aggregation algorithm for PSFs based on TIFN is proposed, and two solutions for quantifying HEP are proposed: considering PSFs distance and calculating PSFs-HEP relationship. A case study of a spaceflight refueling mission is conducted, and the feasibility and effectiveness of the two methods are demonstrated. The distances between the results of the two solutions and the expert linguistic are calculated and both results have the shortest distance to "Low". However, comparatively, solution I is simpler, and the result is clearer, which is more favorable to the decision maker. This research is expected to provide original contributions of HRA. In future, it will be exciting to perform HRA by integrating Bayesian networks and fault tree analysis within intuitionistic fuzzy environment.

The proposed method in this paper expands the field of HRA but still has its limitations. On the one hand, the premise of the reference task-based model proposed in this paper is the need to identify a reference task for the target task, which may require the development of human factor experiment for the target task. On the other hand, in many cases, HEP is dependent on human behavior and proneness, which may involve research in human neuroscience and psychology that are beyond the scope of this study. Therefore, our model can be viewed as a tool for providing preliminary assessment results, supplying a basis for subsequent in-depth research and initial decision-making by stakeholders.

CRediT authorship contribution statement

Xing Pan: Formal analysis, Data curation, Conceptualization. **Song Ding:** Writing – original draft, Methodology. **Xianheng Zhao:** Visualization, Methodology, Formal analysis. **Wenjin Zhang:** Writing – review & editing, Visualization, Supervision, Funding acquisition. **Dujun Zuo:** Methodology, Investigation. **Liuwang Sun:** Formal analysis, Data curation.

Data availability

The data that has been used is confidential.

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Appendix A

We created a symbol table which includes the frequently used noun abbreviations and symbols in this document, as shown below:
Notation list.

Notation	Interpretation
HRA	Human reliability analysis
FS	Fuzzy set
IFS	Intuitionistic fuzzy set
IFN	Intuitionistic fuzzy number
HEP	Human error probability
PSFs	Performance shaping factors
TIFN	Triangular intuitionistic fuzzy number
m	The number of experts
n	The number of PSFs
$\mu_A(x)$	Membership of IF set A on X
$\nu_A(x)$	Non-membership of IF set A on X
$\pi_A(x)$	Intuitionistic index
c_i	Credibility of i^{th} expert
F	Quantitative relationship between PSFs and HEP
$d_{I_t}(I_{t_R}, I_{t_T}), t = 1, 2, \cdots, n$	Distance of each PSF between the target task and the reference task
D_I	PSFs distance between reference task and target task
$I_t, t = 1, 2, \cdots, m$	Integrated level of each PSF
I_{IFS_R}	Integrated level of PSFs of the reference task
I_{IFS_T}	Integrated level of PSFs of the target task
HEP_R	HEP of reference task
HEP_T	HEP of target task
$W_t, t = 1, 2, \cdots, m$	Integrated weight of each PSF
$E_{I_{IFS R}}$	Discrete elements on I_{IFS_R}
E_R	Discrete elements on E_R
$E_{I_{IFS T}}$	Discrete elements on I_{IFS_T}
E_T	Discrete elements on E_T

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