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Multi-criteria IT personnel selection on intuitionistic fuzzy information measures and ARAS methodology

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Abstract

Global challenge and the speedy growth of information technologies compel organizations to constantly change their ways. At the present time, associations need IT personnel who create a difference by creative thoughts and who preserve with the rapid amendments. Since the evaluation of IT personnel selection (ITPS) consists of different alternatives and criteria, therefore, IT personnel selection could be regarded as a multi-criteria decision making (MCDM) problem. The doctrine of intuitionistic fuzzy sets (IFSs) is an effective tool to elucidate the uncertain information in an MCDM problem. The main objective of the paper is to choose the best IT personnel candidate by integrating intuitionistic fuzzy Additive Ratio Assessment (IF-ARAS) method with divergence measure, improved score function and IF-aggregation operators. In the developed methodology, the weights of criteria and decision experts (DEs) are computed based on proposed IF-divergence measure method intuitionistic fuzzy preference evaluation method, respectively. Next, the decision experts judgments are aggregated of the proposed method to evade the loss of data. Finally, the proposed IF-ARAS method is implemented to solve the IT-personnel selection (ITPS) problem to indicate the applicability of the presented approach. In addition, a comparative analysis is provided to discuss the obtained results for validating the developed methodology. The analysis illustrates that the IF-ARAS method is effective and well consistent with the existing ones.

Keywords: Intuitionistic fuzzy sets, divergence measure, personnel selection, multi-criteria decision making, ARAS.

1 Introduction

Human resource management (HRM) is a way of managing people even if staffing and personnel selection, performance assessment, incentive system, training and development. Evaluation process in personnel selection can be largely classified into subjective and objective processes. Subjective process incorporates personality appraisal, stress and managing mode inventories, interviews, and supervisor ratings, while objective one comprises work samples, biographical data viz. gender and age, situational judgment tests, and skill tests [14]. Here, various customary methods implemented in IT personnel selections (ITPSs) in different organizations, associations, teams, and businesses. The human aspect characterizes the direction of an association with its dynamic configuration. It is vital to select a candidate who is in harmony with the work place, the association and the job. IT personnel selection is an MCDM problem by its nature since there are various potentially significant qualitative and quantitative criteria to presume for choosing the ideal candidate to hire for a job. Personnel selection (PS) is a way for selecting persons who meet the criterion requirements for a certain job to the fullest possible scope. Consequently, when finished accurately, the PS problem includes three key ideas: i) To evaluate the selection criteria and their relative significance, ii) To give a suitable numerical scale for determining employees over the criteria, and iii) To obtain comparative preference order via a dependable approach. Nonetheless, personnel selection is considered as a complex, multidimensional MCDM problem. Additional, it can be

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described as an uncertain, subjective issue, as it depends on features such as organizational goals, existing tools, and individual judgments of decision experts (DEs). With reference to the significance and complication of the process of ITPSs, as well as the multi-criteria characteristics of the problem, MCDM methods have been implemented to choose the best employee. In the literature, personnel selection is a region where MCDM approaches are often implemented. Alguliyev et al. [2] developed a worst-case approach to evaluate the criteria weights and fuzzy VIKOR to rank the alternatives. Ebrahimnejad et al [11] proposed a new MCGDM method based on group decision assessment under interval-valued hesitant fuzzy (IVHF)-environment to rank the IT outsourcing services selection. Samanlioglu et al [31] discussed the PS approach in a Turkish information technology (IT) department using fuzzy AHP-TOPSIS method. In some real cases, existence of the imprecise parameters leads to complex situations in decision making process. Considering the uncertainty and vagueness in the procedure of the evaluation approach is more interested. To address the issue, fuzzy set theory, initiated by Zadeh [39], is an appropriate tool to handle the vagueness and imprecision of human cognitive processes in many MCDM problems. Hence, DEs could assign their preferences and judgments for a potential candidate under the selected criteria under a fuzzy environment. In this case, some authors have considered the fuzzy sets theory and its developments in the procedure of their proposed evaluation and selection approaches in IT area [2, 31]. The analysis of the literature specifies that considering the fuzzy sets (FSs) theory in process of the proposed method is more interesting to handling uncertainties. The linguistic expressions of alternative evaluation and criteria weights are generally characterized by FSs for handling the fuzziness of real life problems. Fuzzy set employs a crisp number from 0 to 1 for the membership value. Nonetheless, finding the exact membership function for FSs is not easy in some circumstances. In these conditions, utilizing FSs for linguistic assessment is not efficient. To handle these circumstances, we can utilize intuitionistic fuzzy sets (IFSs) [4], as an extension of FSs. IFSs allocates to each element in the form of triplet a membership, non-membership and a hesitancy degree. As a result, IFS is more powerful way for handling imprecision and uncertainty than FSs. Since its demonstration, IFS has attracted more and more concentration from authors for giving the applications to MCDM in which there are two hot issues: (i) Evaluation of criteria weights; (ii) Aggregation of information related alternatives under the criteria. For the first issue, Li [17] proposed various linear programming models to obtain optimal criteria weights by maximizing the inclusive values of alternatives. Next, Xia and Xu [36] introduced two models to evaluate the optimal criteria weights for MCDM, and also proposed two sets of entropy and cross entropy measures for IFNs. Mishra et al [24] developed a multi objective optimization model based on satisfaction degree of each alternative to determine the optimal criteria weights. Mishra and Rani [23] proposed MCDM method to assist the interactive or interdependent features among criteria in a set based on Shapley function using entropy measure linear programming model. For the second issue, numerous researches have been developed regarding the aggregation approaches in the last decades. For illustration, on IF-environment, Xu [37] developed various weighted geometric and averaging operators. Apart from them, various different kinds of the methods for evaluating MCDM problems have been introduced by the different authors [23, 25, 30, 36, 40]. The aim of current study is to extend ARAS in IFSs to illustrate the applicability of the IF-ARAS method in IT personnel selection (ITPS) problems. When decision experts (DEs) make a decision to determine and choose an appropriate alternative, this generally introduces a complex problem concerning multiple criteria. For this purpose, Additive Ratio Assessment (ARAS) methodology can be an appropriate approach. ARAS relies on the concept that the phenomenon of complex domains with conflicting criteria can be illustrated by utilizing easy relative comparisons as pioneered by Zavadskas and Turskis [41]. Afterwards, various extensions of ARAS methodology have been fruitfully implemented in various disciplines such as transportation, economics, management, sustainable development and construction. Turskis and Zavadskas [33] developed Fuzzy AHP and Fuzzy ARAS method for logistic centers location problem. Ecer [12] applied Fuzzy AHP and ARAS method for evaluating Mobile banking services by two methods. Dahooie et al. [8] developed SWARA and Grey ARAS method to solve IT personnel selection problem. Bykzkan and Ger [7] developed Combined AHP and ARAS methods for IVIFSs to solve digital supply chain selection problem. In this study, we develop integrated ARAS approach, which could be implemented in decision making problems on IFSs. In distinction, IFNs offer an opportunity for a much more adequate model to evaluate real life problems. Each IFNs element is described by an ordered triplet, and each triplet is characterized by a membership and a non-membership and hesitancy degree, thus flexibility of IFSs is more than FSs for articulating linguistic assessments. Utilizing the proposed methodology, it can lead to the higher accuracy of assessment of alternatives in the decision-making process. For integrating ARAS method with IFSs, the improved score function and arithmetic operations of IFSs are utilized, and some modifications are performed in the weighted normalization model. This combination is proposed for the first time in literature in this presented study. In addition, to obtain criteria weights, divergence and entropy measures are proposed and compared with existing measures for IFSs to show the effectiveness. We employ the ITPSs problem to illustrate the process and to represent the performance of the proposed method in the real-world decision-making problems. We also make a comparison between the proposed approach and some existing methods to demonstrate the validity of the obtained results. The major outcomes of manuscript are summarized as follows:

• To develop a new decision making method named as ARAS under an IF-environment.
• To determine criteria weights, new divergence and entropy measures are developed and compared with existing to show the usefulness.
• The modifications of the ARAS method, operators of IFSs and the improved score function procedure are used to develop the integrated approach.
• The proposed approach is applied to an IT personnel selection problem.

2 Preliminaries

Basic ideas about FSs, IFSs, entropy and divergence measures are mentioned in this subsection. In 1965, Zadeh [39] pioneered the idea of fuzzy sets (FSs) which are characterized by a membership function and grown flourishing applications in different disciplines.

Definition 2.1. [39] *Let $U = \{u_1, u_2, \cdots, u_n\}$ be a finite discourse set, then a fuzzy set $\widetilde{X}$ on U is given by, $\widetilde{X} = \{\langle u_i, \mu_{\widetilde{X}}(u_i)\rangle \;:\; u_i \in U\}$ where $\mu_{\widetilde{X}}(u_i)(0 \le \mu_{\widetilde{X}}(u_i) \le 1)$ is the degree of membership of u_i to $\widetilde{X}$ in U. Next, De Luca and Termini* [10] *initiated the concept of entropy for $\widetilde{X}$ as follows:*

$$H_{DL}(\widetilde{X}) = -\frac{1}{n}\sum_{i=1}^{n}[\mu_{\widetilde{X}}(u_i)ln\mu_{\widetilde{X}}(u_i) + (1-\mu_{\widetilde{X}}(u_i)ln(1-\mu_{\widetilde{X}}(u_i)]. \tag{1}$$

In 1989, Pal and Pal [28] *pioneered exponential entropy for FS which is given by,*

$$H_{PP}(\widetilde{X}) = \frac{1}{n(\sqrt{e}\;-1)}\sum_{i=1}^{n}[\mu_{\widetilde{X}}(u_i)e^{1-\mu_{\widetilde{X}}(u_i)} + (1-\mu_{\widetilde{X}}(u_i))e^{\mu_{\widetilde{X}}(u_i)} - 1]. \tag{2}$$

Subsequently, Bhandari and Pal [5] *proposed divergence measure to compute the degree of discrimination for FSs as follows:*

$$J_{BP}(\widetilde{X}, \widetilde{Y}) = \sum_{i=1}^{n}[\mu_{\widetilde{X}}(u_i)ln\frac{\mu_{\widetilde{X}}(u_i)}{\mu_{\widetilde{Y}}(u_i)} + (1-\mu_{\widetilde{X}}(u_i))ln\frac{(1-\mu_{\widetilde{X}}(u_i))}{1-\mu_{\widetilde{Y}}(u_i)}]. \tag{3}$$

Fan and Xie [13], *Jain and Chhabra* [16] *established divergence measures based on exponential function for FSs as follows:*

$$J_{FX}(\widetilde{X}, \widetilde{Y}) = \sum_{i=1}^{n}[\{1-(1-\mu_{\widetilde{X}}(u_i))e^{\mu_{\widetilde{X}}(u_i)-\mu_{\widetilde{Y}}(u_i)} + (1-\mu_{\widetilde{X}}(u_i))e^{\mu_{\widetilde{Y}}(u_i)-\mu_{\widetilde{X}}(u_i)}\}] \tag{4}$$

$$J_{JC}(\widetilde{X}\|\widetilde{Y}) = \sum_{i=1}^{n}[(\mu_{\widetilde{X}}(u_i)-\mu_{\widetilde{Y}}(u_i))exp(\frac{\mu_{\widetilde{X}}(u_i)}{\mu_{\widetilde{Y}}(u_i)}) + (\mu_{\widetilde{Y}}(u_i)-\mu_{\widetilde{X}}(u_i))exp(\frac{1-\mu_{\widetilde{X}}(u_i)}{1-\mu_{\widetilde{Y}}(u_i)})] \tag{5}$$

And its symmetric divergence measure is

$$J_{JC}(\widetilde{X}\|\widetilde{Y}) = \sum_{i=1}^{n}[(\mu_{\widetilde{X}}(u_i)-\mu_{\widetilde{Y}}(u_i))\{exp(\frac{\mu_{\widetilde{X}}(u_i)}{\mu_{\widetilde{Y}}(u_i)}) - exp(\frac{1-\mu_{\widetilde{X}}(u_i)}{1-\mu_{\widetilde{Y}}(u_i)})\}] \tag{6}$$

In fuzzy theory, the membership degree of an element is represented by a number from the interval $[0,1]$, while non membership is essentially its complement. But, in consequence, this assumption does not meet with human intuition. Accordingly, Atanassov [4] *pioneered the idea of intuitionistic fuzzy sets (IFSs) by portraying a membership and a nonmembership functions as a sum of values is less than or equal to one.*

Definition 2.2. [4] *An IFS X on $U = \{u_1, u_2, \cdots, u_n\}$ is given by,*

$$X = \{\langle u_i, \mu_X(u_i), \nu_X(u_i)\rangle \;:\; u_i \in U\}, \tag{7}$$

where $\mu_X : U \to [0,1]$ and $\nu_X : U \to [0,1]$ show the membership degree and non-membership degree of u_i to X in U, with the condition,

$$0 \le \mu_X(u_i) \le 1,\; 0 \le \nu_X(u_i) \le 1 \;\text{ and }\; 0 \le \mu_X(u_i) + \nu_X(u_i) \le 1,\; \forall\, u_i \in U. \tag{8}$$

The intuitionistic index of an element $u_i \in U$ to X is defined by, $\pi_X(u_i) = \mu_X(u_i) - \nu_X(u_i)$ and $0 \le \pi_X(u_i),\ \forall\, u_i \in U$.

For simplicity, Xu [38] characterized the intuitionistic fuzzy number (IFN) $\mathcal{E} = (\mu_{\mathcal{E}}, \nu_{\mathcal{E}})$ which holds $\mu_{\mathcal{E}}, \nu_{\mathcal{E}} \in [0, 1]$ and $0 \leq \mu_{\mathcal{E}} + \nu_{\mathcal{E}} \leq 1$.

Definition 2.3. [38] *Consider $\mathcal{E}_j = (\mu_j, \nu_j),\ j = 1(1)n$, be IFN. Therefore,*

$$S(\mathcal{E}_j) = (\mu_j - \nu_j), \quad \hbar(\mathcal{E}_j) = (\mu_j + \nu_j), \tag{9}$$

are the score and accuracy functions of the IFN $\mathcal{E}_j$, respectively. Here, $S(\mathcal{E}_j) \in [-1, 1]$ and $h(\mathcal{E}_j) \in [0, 1]$ are called score degree and accuracy degree.

Since $S(\mathcal{E}_j) \in [-1, 1]$, when numerous score values have been aggregated through linear weighted summation and it may be appeared that the positive score values are neutralize by the negative score values. Hence, Xu et al. (2015) developed an improved score function for IFNs as follows:

Definition 2.4. [38] *Let $\mathcal{E}_j = (\mu_j, \nu_j)$ be an IFN. Then*

$$S^*(\mathcal{E}_j) = \frac{1}{2}(S(\mathcal{E}_j) + 1), \quad \hbar^\circ(\mathcal{E}_j) = \frac{1}{2}(\mu_j + \nu_j), \tag{10}$$

are normalized score and uncertainty functions, respectively. Evidently, $S^*(\mathcal{E}_j) \in [0, 1]$ and $h^\circ(\mathcal{E}_j) \in [0, 1]$. Let $\mathcal{E}_1 = (\mu_1, \nu_1)$ and $\mathcal{E}_2 = (\mu_2, \nu_2)$ be IFNs. Then, a system can be achieved effortlessly to compare any two IFNs based on the normalized score $S^*(\mathcal{E}_j)$ and uncertainty functions $h^\circ(\mathcal{E}_j)$ as follows:
(i) If $S^*(\mathcal{E}_1) > S^*(\mathcal{E}_2)$, then $\mathcal{E}_1 > \mathcal{E}_2$.
(ii) If $S^*(\mathcal{E}_1) = S^*(\mathcal{E}_2)$, then,
(a) if $\hbar^\circ(\mathcal{E}_1) > \hbar^\circ(\mathcal{E}_2)$, then $\mathcal{E}_1 < \mathcal{E}_2$;
(b) if $\hbar^\circ(\mathcal{E}_1) = \hbar^\circ(\mathcal{E}_2)$, then $\mathcal{E}_1 = \mathcal{E}_2$.

Definition 2.5. [37] *Let $\mathcal{E}_j = (\mu_j, \nu_j),\ j = 1(1)n$ be IFNs, then IFWAO is given by,*

$$IFWA_W(\mathcal{E}_1, \mathcal{E}_2, \cdots, \mathcal{E}_n) = [1 - \prod_{j=1}^{n}(1 - \mu_j)^{w_j}, \prod_{j=1}^{n} \nu_j^{w_j}], \tag{11}$$

where $w_j = (w_1, w_2, \cdots, w_n)^T$ is a weight vector of $\mathcal{E}_j,\ j = 1(1)n$, with $\sum_{j=1}^{n} w_j,\ w_j \in [0, 1]$.

In IFSs, divergence measure is prominent tool to compute the degree of discrimination. First, Vlachos & Sergiadis [34] pioneered the notion of divergence for IFSs. Later on, Montes et al [27] discussed new axiomatic definition of divergence measure as follows:

Definition 2.6. [27] *Let $X, Y \in IFSs$, then $J : IFS(U) \times IFS(U) \to R$ is said to be divergence measure, if it holds the postulates:*
$(D1)$ $J(X, Y) = J(Y, X)$;
$(D2)$ $J(X, Y) = 0$ if and only if $X = Y$;
$(D3)$ $J(X \cap Z, Y \cap Z) \leq J(X, Y)$ for every $Z \in IFSs(U)$;
$(D4)$ $J(X \cup Z, Y \cup Z) \leq J(X, Y)$, for every $Z \in IFSs(U)$.

Definition 2.7. [32] *A mapping $e : IFS(U) \to [0, 1]$ is said to be entropy for IFSs, if it fulfills the following postulates:*
$(P1)$ $e(X) = 0$ if and only if X is a crisp set;
$(P2)$ $e(X) = 1$ if and only if $\mu_X(u_i) = \nu_X(u_i)$, for all $u_i \in U$;
$(P3)$ $e(X) \leq e(Y)$ if X is less fuzzy than Y, i.e. $\mu_X(u_i) \leq \mu_Y(u_i)$ and $\nu_X(u_i) \geq \nu_Y(u_i)$, for $\mu_Y(u_i) \leq \nu_Y(u_i)$ or $\mu_X(u_i) \geq \mu_Y(u_i)$ and $\nu_X(u_i) \leq \nu_Y(u_i)$, for $\mu_Y(u_i) \geq \nu_Y(u_i)$, for any $u_i \in U$.
$(P4)$ $e(X) = e(X^c)$.

3 New divergence measures for IFSs

In this section, we will discuss new divergence and entropy measures for IFSs to facilitate the developed weight determining method.

For measuring the uncertainty of IFS, Szmidt and Kacprzyk [32] first and foremost estimated a set of axiomatic condition. Soon after, numerous IF-entropy measures have been proposed by various authors and examined their allied concerns in various disciplines [3, 18, 20, 24, 22, 26, 23, **?**, 34, 35]. Next, to compute the degree of discrimination for FSs, Bhandari and Pal [5] initially pioneered the divergence measure. Afterward, many divergence measures have been developed and implemented various areas [13, 16, 19]. On the similar way, the notion of divergence measure is utilized to IFSs. Firstly, Vlachos and Sergiadis [34] initiated the divergence measure, established the relation between divergence and entropy measures and implemented in the image segmentation and medical diagnosis. After that, different researchers have paid concentration on divergence measure for IFSs, IVIFSs and HFSs [3, 18, 22, 26, 27, 29, 34, 36, 42]. However, the IF-divergence measures possibly invalid which will be considered in the following section. To evade such an issue, we develop new divergence measures for IFSs. Here, corresponding to Jain and Chhabra [16], we propose the following divergence measure for IFSs

$$J_I(X\|Y) = \frac{1}{n(exp(2)-1)}\sum_{i=1}^{n}[(\mu_X(u_i)-\mu_Y(u_i))exp\{\frac{\mu_X(u_i)}{\frac{1}{2}(\mu_X(u_i)+\mu_Y(u_i))}\}+(\nu_X(u_i)-\nu_Y(u_i))exp\{\frac{\nu_X(u_i)}{\frac{1}{2}(\nu_X(u_i)+\nu_Y(u_i))}\}]. \quad (12)$$

The symmetric form of divergence measure is defined by,

$$J_1(X,Y) = J_1(X\|Y)+J_1(Y\|X) = \frac{1}{2n(exp(2)-1)}\sum_{i=1}^{n}[(\mu_X(u_i)-\mu_Y(u_i))\{exp(\frac{\mu_X(u_i)}{\frac{1}{2}(\mu_X(u_i)+\mu_Y(u_i))}) - exp(\frac{\mu_Y(u_i)}{\frac{1}{2}(\mu_X(u_i)+\mu_Y(u_i))})\}+(\nu_X(u_i)-\nu_Y(u_i))\{exp(\frac{\nu_X(u_i)}{\frac{1}{2}(\nu_X(u_i)+\nu_Y(u_i))})-exp(\frac{\nu_Y(u_i)}{\frac{1}{2}(\nu_X(u_i)+\nu_Y(u_i))})\}]. \quad (13)$$

Theorem 3.1. *The function given by Eq. (13) is an IF-divergence measure, and holds the given postulate.*

The Proof of Theorem 3.1 is provided in Appendix A.1.

Here, the divergence measure $J_1(X\|Y)$ expresses discrimination uncertain information, while entropy exposes uncertain information and $J_1(X\|X^c)$ expresses uncertain information of X i.e., $J_1(X\|X^c)$ estimates amount of uncertainty of IFS X. Additionally, Vlachos and Sergiadis [34] established the relation between entropy and divergence measure for IFSs.

Proposition 3.2. *The relation between $J_1(X\|X^c)$ and $e(X)$ for IFS is defined by,*

$$e(X) = 1 - J_1(X\|X^c). \quad (14)$$

where,

$$e(X) = \frac{-1}{n(exp(2)-1)}\sum_{i=1}^{n}[(\mu_X(u_i)-\nu_X(u_i))\{exp(\frac{2\mu_X(u_i)}{\mu_X(u_i)+\nu_X(u_i)})-exp(\frac{2\nu_X(u_i)}{(\mu_X(u_i)+\nu_X(u_i))})\}-exp(2)+1]. \quad (15)$$

Proof. The proof is omitted. ☐

Theorem 3.3. *The function $e(X)$ defined by Eq. (15), is an IF-entropy measure.*

Proof. The proof is similar to the Theorem 4 in Ansari et al [3]. ☐

Based on Mishra and Rani [23], we propose the IF-divergence measure as,

$$J_2(X,Y) = \frac{1}{n(1-e^{\frac{-1}{2}})}\sum_{i=1}^{n}[\{\frac{1}{2}(exp\{-(\frac{\nu_X(u_i)+1-\mu_X(u_i)}{2})\}+exp\{-(\frac{\nu_Y(u_i)+1-\mu_Y(u_i)}{2})\}) - exp\{-\frac{(\nu_X(u_i)+\nu_Y(u_i)+2-\mu_Y(u_i)-\mu_Y(u_i))}{4}\}\}I_{[\mu_X(u_i)\geq\nu_X(u_i)]}+\{\frac{1}{2}(exp\{-(\frac{\mu_X(u_i)+1-\nu_X(u_i)}{2})\} +exp\{-\frac{\mu_Y(u_i)+1-\nu_Y(u_i)}{2})\})-exp\{-\frac{(\mu_X(u_i)+\mu_Y(u_i)+2-\nu_X(u_i)-\nu_Y(u_i))}{4}\}\}I_{[\mu_X(u_i)<\nu_X(u_i)]}]. \quad (16)$$

Theorem 3.4. *The function given by Eq. (16) is an IF-divergence measure, and also holds the axioms (J1)-(J10) in Theorem 3.1.*

4 IF-ARAS method for MCDM

Decision making process comprises a logical and scientific way for choosing a feasible course of action among multiple options. Whilst we consider only one criterion for each alternative, the problem is concentrated as single criterion decision-making (SCDM) and SCDM turns out to be less complicated because the decision can be constructed implicitly by choosing the optimal one under the best single criterion. Nevertheless, numerous real-life decision-making problems are evaluated under multiple criteria. Such problems turn into MCDM processes, where various MCDM approaches utilize the importance (i.e. weights) vectors of criteria. The main purpose of the study is to use IF-ARAS method to select the best IT personnel. Here, the weights of ITPSs assessment criteria are evaluated with the IF-divergence measure approach. After the evaluation of the criteria and expert weights, IF-ARAS approach is implemented first time on IFSs to select the IT personnel selections. IF-ARAS approach implements the logical comparison in the ratio of the sum for normalized and weighted criterion values to obtain the optimality degree of the alternative. An MCDM approach is incorporated into the assessments to decrease bias and partiality. The workflow of the IF-ARAS approach is given in Figure 1. Brief descriptions of these methods are given below:

Step 1. Originate the alternative and criteria.

In the MCDM procedure, our objective is to choose the most desirable alternative among set of m alternatives $X = \{X_1, X_2, \cdots, X_m\}$ under the criteria set $P = \{P_1, P_2, \cdots, P_n\}$. Consider a committee of l experts $E = \{E_1, E_2, \cdots, E_l\}$ has been formed to obtain the desirable alternative(s).

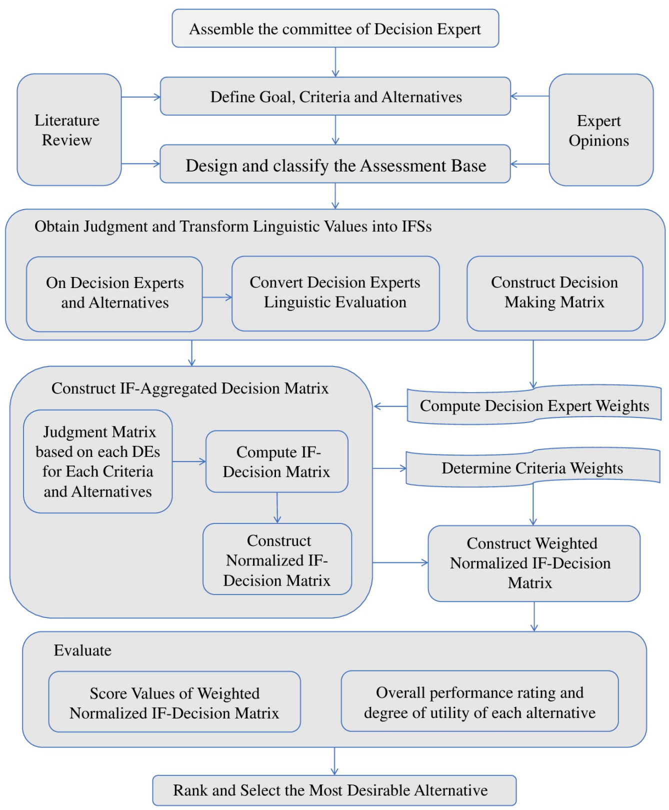
Step 2. Evaluation of decision experts weight.

There are l decision experts with weight values $\lambda = (\lambda_1, \lambda_2, \cdots, \lambda_l)^T$. These weights are considered as linguistic values and expressed in IFNs. Let $G_k = (\mu_k, \nu_k, \pi_k)$ be an IFN for evaluation of the k^{th} expert. Therefore, the importance of the k^{th} expert is given by,

$$\lambda_k = \frac{\mu_k + \pi_k(\frac{\mu_k}{\mu_k+\nu_k})}{\sum_{k=1}^{l}(\mu_k + \pi_k(\frac{\mu_k}{\mu_k+\nu_k})}), \quad k = 1(1)l. \tag{17}$$

Step 3. Construct IF-aggregated decision matrix.

In the MCDM procedure, all the individual decision evaluations require to be combined into a group evaluation to create IF aggregated decision matrix $\mathbb{R} = (\mathcal{E}_{ij})_{m\times n}$. To facilitate that, IFWAO Eq. (11) (Xu, 2007) is implemented.



(a) Figure1.Diagrammatic Representation of the IF-ARAS Method for Personnel Selection

Step 4. Calculate weight vector of criteria.

In MCDM method, criteria are not always considered to be equal weight. Let $w = (w_1, w_2, \cdots, w_n)^T$ such that $\sum_{j=1}^{n} w_j = 1$, $w_j \in [0, 1]$ be a weight vector of criterion set. Successively to reach w, we utilize the divergence measure approach to calculate the weight w_j for each criterion as follows:

$$w_j = \frac{\frac{1}{m-1}(\sum_{i=1}^{m}\sum_{k=1,k\neq i}^{m} J(\mathcal{E}_{ij}, \mathcal{E}_{kj}))}{(\sum_{j=1}^{n}(\sum_{i=1}^{m}\sum_{k=1,k\neq i}^{m} J(\mathcal{E}_{ij}, \mathcal{E}_{kj})))}, \quad j = 1(1)n. \tag{18}$$

Step 5. Determine optimal performance rating.

$$\mathbb{R}_0 = \begin{cases} \max \mathcal{E}_{ij} & j \in X_b \\ \min \mathcal{E}_{ij} & j \in X_n \end{cases} \tag{19}$$

where X_b and X_n are the benefit and non-benefit criterion sets, respectively.

Step 6. Generate normalized IF-decision matrix.

In decision making process, the IF-aggregated decision matrix $\mathbb{R} = (\mathcal{E}_{ij})_{m\times n}$ is converted into normalized IF-aggregated decision matrix $\mathbb{N} = (\mathcal{C}_{ij})_{m\times n}$ such that,

$$\mathcal{C}_{ij} = \begin{cases} \mathcal{E}_{ij} = \langle \mu_{ij}, \nu_{ij} \rangle & j \in X_b \\ (\mathcal{E}_{ij})^c = \langle \nu_{ij}, \mu_{ij} \rangle & j \in X_n \end{cases} \quad i = 1(1)m, \tag{20}$$

where X_b and X_n denote the beneficial & non-beneficial criterion sets, respectively.

Step 7. Create weighted normalized IF-decision matrix.

When the weight vector $w = (w_1, w_2, \cdots, w_n)^T$ of the criterion $P_j : \ j = 1(1)n$ is determined, then weighted normalized IF-decision matrix $\mathbb{N}_w = (\overline{\mathcal{C}}_{ij})_{m\times n}$ is assembled as follows:

$$\overline{\mathcal{C}_{ij}} = \bigoplus_{j=1}^{n} w_j \mathcal{C}_{ij} = \langle 1 - \prod_{j=1}^{n} (1-\mu_{ij})^{w_j}, \prod_{j=1}^{n} (\nu_{ij})^{w_j} \rangle, \tag{21}$$

where $\overline{\mathcal{C}_{ij}} = \langle \overline{\mu}_{ij}, \overline{\nu}_{ij} \rangle$ is the weighted IFN.

Step 8. Evaluation of Score values .

By Eq. (10), the score values of weighted normalized IF-decision matrix $\mathbb{N}_w = (\overline{\mathcal{C}}_{ij})_{m\times n}$ are computed as follows:

$$\mathbb{S}^*(\overline{\mathcal{C}}_{ij}) = [\frac{1}{2}((\frac{\overline{\mu}_{ij} - \overline{\nu}_{ij}}{2}) + 1)]; \ i = 1(1)m, \ j = 1(1)n. \tag{22}$$

Step 9. Calculate the overall performance rating and degree of utility.

The overall performance values can be computed by using the expression:

$$\mathbb{M}_i = \sum_{j=1}^{n} \mathbb{S}^*(\overline{\mathcal{C}}_{ij}), \ i = 1(1)m. \tag{23}$$

The best alternative has the greatest value of the utility degree, while the worst alternative shows the lowest value of M_i. By considering the evaluation procedure, the optimality function M_i has direct and proportional relation with $\mathcal{E}_{ij}$ and weights w_j of the explored criteria and their comparative persuade on the desirable outcomes. As a result, the maximum the value of the function M_i illustrates the more efficient alternative. The preferences of alternatives can be evaluated based on M_i. Therefore, it is appropriate to determine and rank the alternatives when IF-ARAS method is implemented. To obtain desirable alternatives, it is not only essential to compute the best ranked alternative but also significant to find out relative impact of obtained alternatives, in relation to the most favorable alternative. In order to the variant utility degree is evaluated by comparing the examined variant with optimal one $\mathbb{R}_0$. The expression for evaluating degree of utility $\mathbb{Q}_i$ of alternative $X_i : \ i = 1(1)m$ is defined by,

$$\mathbb{Q}_i = \frac{M_i}{\mathbb{R}_0}; \ i = 1(1)m. \tag{24}$$

It is clear that $\mathbb{Q}_i \in [0, 1]$ and can be ordered in an increasing sequence, which is the required order of preference. The relative efficiency of a feasible alternative is computed according to the utility function.

Step 10. Choose the most desirable one.

The determined alternatives are ranked by ascending $\mathbb{Q}_i$ i.e., the maximum value $\mathbb{Q}_i$ of alternative is the optimal one. Therefore, the most acceptable alternative can be determined using the following formula:

$$\mathbb{M}^* = \{\mathbb{M}_i \mid \max_i \mathbb{Q}; \ i = 1(1)m\}, \tag{25}$$

where $\mathbb{M}_i$ is most desirable alternative, $i = 1(1)m$.

Step 11. End.

5 Case study: IT outsourcing personnel selection problem

The utilization of MCDM approaches can diminish the occurrence of human errors and personal biases. However, the underestimation of the significance of suitable efficient approaches for the criterion selection method may outcome in an incorrect concluding alternative and poorer the validity considered for MCDM approaches. Nonetheless, the literature review specifies that earlier studies are generally focused on the quantitative decision-making methods, and not adequate concentration has been paid to the ways in which criteria are chosen. In human resource management literature, methods for ITPSs criteria can be categorized into two key types: i) job analysis, ii) competency-based method. Corresponding to the strengths and flaws of these methods discussed in the following section, present study utilizes a competency-based method for ITPSs by implementing a hybrid intuitionistic fuzzy additive ratio assessment (IF-ARAS) method based on divergence measure methodology. In this section, a real case study is prepared to indicate the applicability and suitability of the developed approach. In this case, a group with three decision makers (E_1, E_2, E_3) is founded to evaluate five IT specialist candidate alternatives $(X_1, X_2, \cdots, X_5)$ under three main criteria and various sub-criteria as Individual Qualifications (IQ) [Expression and communication (IQS1), Emotional balance (IQS2), Quality oriented (IQC1), Internal and external customer oriented (IQC2), Crisis management (IQC3), Basic computer skills (IQK1), General information about economy and business world (IQK2)], Technical Specifications (TS) [Adaptation level to new technology, software and hardware (TS1), Competence of required software (TS2), Continuous development and technological relevance (TS3), Experience (TS4)] and General Features (GF) [Microsoft Office abilities (GF1), Foreign language skills (GF2), Social activities (GF3), Extra achievements (GF4)]. In this respect, the criteria are defined based on current practice of the company regarding to the risk competency criteria. However, the selected main criteria for the assessment of IT outsourcing projects are defined. The major outcome is evaluated as recognizing the best IT personnel selection option with a set of five distinctive IT personnel alternative using three main criteria, fifteen sub-criteria. Linguistic values are described in the form of non-numeric, i. e., words or sentences. Linguistic terms are more appropriate for handling the complex real-life selection problems. As a result, various authors developed diverse linguistic scales. Now, the linguistic values for preference rating of DEs and performance values of alternatives and criteria are presented in Tables 1 and 2.

Table 1: Linguistic terms for importance rating DEs

Linguistic terms	IFNs
Extremely qualified (EQ)	(1.0,0.0)
Very very qualified (VVQ)	(0.9,0.1)
Very qualified (VQ)	(0.7,0.2)
Qualified (Q)	(0.6,0.3)
Less qualified (LS)	(0.4,0.5)
Very less qualified (VLQ)	(0.3,0.6)
Extremely less qualified (EL)	(0.1,0.8)

Linguistic terms	IFNs
Extremely high (EH)	(1.0,0.0)
Very high (VH)	(0.9,0.1)
High (H)	(0.7,0.2)
Slightly high (SH)	(0.6,0.3)
Average (A)	(0.5,0.4)
Slightly low (SL)	(0.4,0.5)
Low (L)	(0.3,0.6)
Very low (VL)	(0.2,0.7)
Extremely low (EL)	(0.1,0.8)

(c) Table 2: Performance evaluation in form linguistic terms for rating alternatives

The weights of experts are calculated from Table 1 and Eq. (17) and presented in Table 3. Table 4 illustrates the linguistic values by DEs for the criteria of considered IT personnel selection. Based on experts judgments and using Eq. (11) and Table 4, the IF-aggregated decision matrix is created and depicted in Table 5.

Decision expert	E_1	E_2	E_3
Linguistic terms	VVQ	Q	VQ
IFNs	(0.9, 0.1)	(0.6, 0.3)	(0.7, 0.2)
Weights	0.3346	0.3071	0.3583

(d) Table 3: Decision expert weight evaluation

Using Eq. (18) and Table 5, the criterion weights are computed by using Eq. (16) in terms of proposed divergence measure. By using MATLAB software, the criterias weights are calculated as follows:

$$w = (0.0298, 0.0048, 0.0632, 0.0186, 0.1133, 0.0069, 0.0213, 0.0427, 0.0905, 0.0592, 0.1081, 0.01812, 0.0662, 0.02610, 0.0006)^T$$

	IQS1	IQS2	IQC1	IQC2	IQC3
X_1	(H,H,H)	(SH,SH,SH)	(SH,H,SH)	(SH,A,SH)	(H,A,SH)
X_2	(SH,SH,A)	(A,A,SH)	(H,H,H)	(A,SH,A)	(A,A,A)
X_3	(VH,VH,VH)	(H,SH,SH)	(L,SL,L)	(L,SL,L)	(L,L,SL)
X_4	(A,A,A)	(SH,SH,H)	(A,A,A)	(A,A,SH)	(L,VL,VL)
X_5	(A,A,A)	(SH,H,SH)	(L,SL,L)	(SL,SL,L)	(VL,VL,VL)
	IQK1	**IQK2**	**TS1**	**TS2**	**TS3**
X_1	(H,H,H)	(A,A,A)	(SH,SH,H)	(A,A,A)	(H,SH.H)
X_2	(H,H,SH)	(SH,SH,SH)	(SH,H,SH)	(SH,SH,A)	(H,H,H)
X_3	(H,SH,SH)	(H,H,H)	(SL,SL,L)	(SL,SL,L)	(SL,L,L)
X_4	(SH,SH,H)	(A,A,A)	(H,H,H)	(VH,VH,VH)	(H,H,H)
X_5	(SH,A,SH)	(A,A,A)	(A,A,A)	(SH,H,SH)	(SH,SH,H)
	TS4	**GF1**	**GF2**	**GF3**	**GF4**
X_1	(L,L,A)	(H,SH,SH)	(VH,H,VH)	(A,A,A)	(A,A,A)
X_2	(VL,VL,VL)	(H,SH,SH)	(VH,VH,VH)	(A,A,A)	(A,A,A)
X_3	(H,H,H)	(H,H,H)	(H,H,H)	(H,H,H)	(SH,SH,SH)
X_4	(H,H,H)	(SH,SH,SH)	(H,SH,SH)	(H,H,SH)	(A,A,A)
X_5	(SH,SH,A)	(SH,SH,SH)	(A,SH,A)	(SH,H,H)	(A,A,SH)

(e) Table 4: Evaluation of alternatives w. r. t. criteria by three decision experts

The first step in using the proposed extension of the IF-ARAS method is the determination of the optimal performance ratings of ITPSs and this is done by using the formula Eq. (19). The obtained optimal performance ratings of ITPSs are depicted in Table 6. Since all considered criteria are benefit type, thus no need to normalize the given IF-aggregated decision matrix. Next, the WIF-aggregated decision matrix for ITPSs is constructed according to Tables 5-6 and Eq. (21) and depicted in Table 7.

Using Table 7 and Eq. (22), the score values $S^*(\overline{\mathcal{C}}_{ij})$ of IFNs are given in Table 8. Based on Eq. (23), overall performance rating of each ITPS is computed and demonstrated in Table 10. Using Eq. (24), degree of utility or relative quality($\mathbb{Q}_i$) is computed as follows:

$$\mathbb{Q}_1 = 0.9438,\ \mathbb{Q}_2 = 0.9550,\ \mathbb{Q}_3 = 0.9514,\ \mathbb{Q}_4 = 0.9623,\ \mathbb{Q}_5 = 0.9377.$$

Then, the ranking order for the SPSs is determined as $\mathbb{Q}_4 > \mathbb{Q}_2 > \mathbb{Q}_3 > \mathbb{Q}_1 > \mathbb{Q}_5$. Hence, the desirable IT personnel selection alternative is $\mathbb{Q}_4$ i. e., X_4 is the best IT personnel selection alternative. Here, we utilize the rank correlation (r_P) to compare the outcomes of the IF-ARAS method with the existing ones. The comparison outcomes between the IF-ARAS method and the existing ones are demonstrated in Table 9. Some MCDM methods have been developed in recent years within the context of uncertain environments. Each of these methods has characteristics and steps which differentiate it from the others. We have tried to select methods for the comparison which have good efficiency in the literature and could be applicable in the considered multi-criteria decision-making problem. After a literature survey, the methods of Alguliyev et al [2], Dahooie et al [8] and Samanlioglu et al [31] are selected for the comparative analysis and the illustrative example is solved using them. As can be observed in Table 9, the correlation coefficients are greater than 0.6 except correlation between IF-ARAS method and Alguliyev et al [2] method, which is 0.5; as a result, the relationships between ranking outcomes are strong and/or very strong. Based on this analysis, we can observe that the outcome of the IF-ARAS method is consistent with the existing ones. The major advantages of the IF-ARAS technique are given as follows:

(*a*) It is based on broader standard of Additive Ratio Assessment (ARAS) with information measures to solve IT personnel selection problems in comparison to TFN-VIKOR (Compromise programming), Fuzzy AHP-TOPSIS, Grey SWARA-ARAS methods. Because IF-ARAS method considers improved score values (deviations) from optimal alternative while the other methods only consider a single criterion of the minimum distance from PIS (ideal point) and NIS (anti-ideal point).

(*b*) To concentrate on uncertainty in MCDM problems, all the inputs, viz. the evaluations of alternatives on criteria by several decision experts, DEs weights by the experts, and criterion weights by DEs are considered in uncertain classification by the IFNs.

(*c*) The implementation of the fuzzy and aggregation operator of IF-ARAS method facilitates to obtain the utility based solution (score model) for the IT personnel selection problem in single phase only when compared with the two-phase methods [8, 31].

(*d*) The proposed method can be effortlessly employed utilizing the commercially existing software MATLAB and other associated mathematical programming tool.

6 Conclusions

Personnel selection is a major assignment in the HRM discipline, and it plays significant role in the success of any organization, apart from the type of industry and business activities. Nevertheless, it becomes especially significant when choosing the right

	IQS1	IQS2	IQC1	IQC2	IQC3
X_1	(0.7000,0.2000)	(0.6000,0.3000)	(0.6338,0.2649)	(0.5712,0.3277)	(0.5885,0.3064)
X_2	(0.5667,0.3326)	(0.5384,0.3608)	(0.7000,0.2000)	(0.5331,0.3662)	(0.7000,0.2000)
X_3	(0.9000,0.1000)	(0.6367,0.2619)	(0.3659,0.5338)	(0.4105,0.4850)	(0.3376,0.5621)
X_4	(0.5000,0.4000)	(0.6392,0.2594)	(0.5000,0.4000)	(0.5384,0.3608)	(0.2350,0.6648)
X_5	(0.5000,0.4000)	(0.6338,0.2649)	(0.3324,0.5673)	(0.3659,0.5338)	(0.2000,0.7000)
	IQK1	**IQK2**	**TS1**	**TS2**	**TS3**
X_1	(0.7000,0.2000)	(0.5000,0.4000)	(0.6392,0.2594)	(0.5000,0.4000)	(0.6723,0.2265)
X_2	(0.6674,0.2313)	(0.6000,0.3000)	(0.6338,0.2649)	(0.5667,0.3326)	(0.7000,0.2000)
X_3	(0.6367,0.2619)	(0.7000,0.2000)	(0.3659,0.5338)	(0.3659,0.5338)	(0.3352,0.5645)
X_4	(0.6392,0.2594)	(0.5000,0.4000)	(0.7000,0.2000)	(0.9000,0.1000)	(0.7000,0.2000)
X_5	(0.5712,0.3277)	(0.5000,0.4000)	(0.5000,0.4000)	(0.6338,0.2649)	(0.6392,0.2594)
	TS4	**GF1**	**GF2**	**GF3**	**GF4**
X_1	(0.3376,0.5621)	(0.6367,0.2617)	(0.7000,0.2000)	(0.5000,0.4000)	(0.5000,0.4000)
X_2	(0.2000,0.7000)	(0.6723,0.2265)	(0.9000,0.1000)	(0.5000,0.4000)	(0.5000,0.4000)
X_3	(0.7000,0.2000)	(0.7000,0.2000)	(0.7000,0.2000)	(0.7000,0.2000)	(0.6000,0.3000)
X_4	(0.7000,0.2000)	(0.6000,0.3000)	(0.6367,0.2619)	(0.6674,0.2313)	(0.5000,0.4000)
X_5	(0.5375,0.3603)	(0.6000,0.3000)	(0.4702,0.4274)	(0.6697,0.2291)	(0.4811,0.4164)

(f) Table 5: Aggregated decision matrix for IT personnel selection problem

	IQS1	IQS2	IQC1	IQC2	IQC3
$\mathbb{R}_0$	(0.9000,0.1000)	(0.6392,0.2594)	(0.7000,0.2000)	(0.5712,0.3277)	(0.7000,0.2000)
	IQK1	**IQK2**	**TS1**	**TS2**	**TS3**
$\mathbb{R}_0$	(0.7000,0.2000)	(0.7000,0.2000)	(0.7000,0.2000)	(0.9000,0.1000)	(0.7000,0.2000)
	TS4	**GF1**	**GF2**	**GF3**	**GF4**
$\mathbb{R}_0$	(0.7000,0.2000)	(0.7000,0.2000)	(0.9000,0.1000)	(0.7000,0.2000)	(0.6000,0.3000)

(g) Table 6: Optimal intuitionistic fuzzy performance values for IT personnel selection

person for professional jobs viz. IT personnel selection. As a result, it is essential to evaluate eligible ITPs in a more systematic way, derived from high standards of competency. In the present paper, a concise survey of the literature has been presented, and numerous competencies have been recognized from the existing competency structures. Evidently, for the existence of multiple facets of competency, the ITPS involves a multi-criteria problem, which should be evaluated by using MCDM approaches. In this manuscript, a novel framework known as IF-ARAS for estimating ITPSs is introduced. The proposed method is based on the improved score function, some amendments in the conventional ARAS method and an approach for calculating of criteria weights. To calculate the criteria weights, we develop new IF-entropy and IF-divergence measures and also compare with the existing IF-information measures. An IT personnel selection problem is implemented to illustrate the applicability and effectiveness of the proposed method. To authenticate the results, a comparison between the developed method and existing ones is discussed. The main outcome of the developed method is the evaluation of optimal alternative according to the relative comparison of assessment of the alternatives with each other distinct existing works in which the assessment of the alternatives is evaluated through some theoretical benchmarks in real-world decision making. The improved score function is implemented for ranking the alternatives based on relative assessments where the first parameter (membership degree) is mentioned as the more the better, the second parameter (non-membership degree) is pointed as the less the better, and the last one (hesitancy degree) is referred to as the less the better. There are several directions for future research as a follow-up of this study. The proposed approach makes use of IFSs. A promising research topic can be the use of classical fuzzy logic and comparison of its results with a sensitivity analysis. Integrating other MCDM methods with interval-valued intuitionistic fuzzy sets, hesitant fuzzy sets (HFSs), interval-valued hesitant fuzzy sets and Pythagorean fuzzy sets can help explore their effectiveness and also provide new scientific perspectives. In the future, researchers can focus on the comparison of the results with different MCDM techniques. Also, we can extend proposed method to various MCDM problems, such as digital supplier selection, sustainable development (Acar et al., [1]) and project selection, alongside others and developed some new information measures.

Conflict of interest The authors declare that they have no conflict of interest.

Appendix A

A.1. Proof of the Theorem 3.1

(J1). $J_1(X,Y) = J_1(Y,X)$;

(J2). $0 \leq J_1(X,Y) \leq 1,\ J_1(X,X^c) = 1$ if and only if $X \in P(U)$ and $J_1(X,Y) = 0$ if and only if $X = Y$;

(J3). $J_1(X^c,Y) = J_1(X,Y^c)$;

(J4). $J_1(X,Y) = J_1(X^c,Y^c)$;

	IQS1	IQS2	IQC1	IQC2	IQC3
$\mathbb{R}_0$	(0.0663,0.9337)	(0.0049,0.9935)	(0.0733,0.9033)	(0.0156,0.9795)	(0.1275,0.8333)
X_1	(0.0352,0.9532)	(0.0044,0.9942)	(0.0615,0.9195)	(0.0156,0.9795)	(0.0957,0.8746)
X_2	(0.0246,0.9677)	(0.0037,0.9951)	(0.0733,0.9033)	(0.0141,0.9815)	(0.1275,0.8333)
X_3	(0.0663,0.9337)	(0.0048,0.9936)	(0.0234,0.9611)	(0.0098,0.9866)	(0.0456,0.9368)
X_4	(0.0204,0.9731)	(0.0049,0.9935)	(0.0429,0.9437)	(0.0143,0.9812)	(0.0299,0.9548)
X_5	(0.0204,0.9731)	(0.0048,0.9936)	(0.0252,0.9648)	(0.0084,0.9884)	(0.0250,0.9604)
	IQK1	**IQK2**	**TS1**	**TS2**	**TS3**
$\mathbb{R}_0$	(0.0083,0.9890)	(0.0253,0.9663)	(0.0501,0.9336)	(0.1881,0.8119)	(0.0688,0.9091)
X_1	(0.0083,0.9890)	(0.0147,0.9807)	(0.0426,0.9440)	(0.0608,0.9204)	(0.0639,0.9158)
X_2	(0.0076,0.9899)	(0.0193,0.9747)	(0.0420,0.9449)	(0.0729,0.9052)	(0.0688,0.9091)
X_3	(0.0070,0.9908)	(0.0253,0.9663)	(0.0193,0.9736)	(0.0404,0.9448)	(0.0239,0.9667)
X_4	(0.0070,0.9908)	(0.0147,0.9807)	(0.0501,0.9336)	(0.1881,0.8119)	(0.0688,0.9091)
X_5	(0.0058,0.9923)	(0.0147,0.9807)	(0.0292,0.9616)	(0.0881,0.8850)	(0.0586,0.9232)
	TS4	**GF1**	**GF2**	**GF3**	**GF4**
$\mathbb{R}_0$	(0.1220,0.8403)	(0.1220,0.8403)	(0.1414,0.8586)	(0.2697,0.6570)	(0.0050,0.9934)
X_1	(0.0435,0.9396)	(0.1067,0.8651)	(0.0766,0.8980)	(0.1655,0.7873)	(0.0038,0.9950)
X_2	(0.0238,0.9622)	(0.1135,0.8517)	(0.1414,0.8586)	(0.1655,0.7873)	(0.0038,0.9950)
X_3	(0.1220,0.8403)	(0.1220,0.8403)	(0.0766,0.8980)	(0.2697,0.6570)	(0.0050,0.9934)
X_4	(0.1220,0.8403)	(0.0943,0.8780)	(0.0648,0.9151)	(0.2497,0.6824)	(0.0038,0.9950)
X_5	(0.0800,0.8955)	(0.0943,0.8780)	(0.0412,0.9453)	(0.2511,0.6807)	(0.0036,0.9952)

(h) Table 7: Weighted aggregated decision matrix for IT personnel selection problem

(J5). $J_1(X,Y) \leq J_1(X,Z)$ and $J_1(Y,X) \leq J_1(X,Z)$ for $X \subseteq Y \subseteq Z$;
(J6). $J_1(X \cup Y, X \cap Y) = J_1(X,Y)$;
(J7). $J_1(X \cup Y, Z) \leq J_1(X,Z) + J_1(Y,Z)$, for any $Z \in IFS(U)$;
(J8). $J_1(X \cap Y, Z) \leq J_1(X,Z) + J_1(Y,Z)$, for any $Z \in IFS(U)$;
(J9). $J_1(X \cap Z, Y \cap Z) \leq J_1(X,Y)$, for any $Z \in IFS(U)$;
(J10). $J_1(X \cup Z, Y \cup Z) \leq J_1(X,Y)$, for any $Z \in IFS(U)$; Since the proof is straightforward, so we omited the proof.

A.2. Comparative example

Next, Burillo and Bustince (1996) developed an IF-entropy $e_{bb}(X)$ Szmidt and Kacprzyk (2001) expressed an entropy $e_{sk}(X)$. Hung and Yang (2006) introduced two IF-entropies $e^2_{hy}(X)$ and $e_s(X)$. Vlachos and Sergiadis (2007) pioneered an entropy measure $e_{vs}(X)$. Zhang and Jiang (2008) proposed an entropy measure $e_{zj}(X)$. Wei et al. (2012) defined intuitionstic fuzzy entropy $e_w(X)$. Mishra et al (2017a) introduced entropy measure $e_m(X)$ which can be listed below:

$$e_{bb}(X) = \frac{1}{n}\sum_{i=1}^{n}(1-\mu_X(u_i)-\nu_X(u_i)) \tag{26}$$

$$e_{sk}(X) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{(1-\nu_X(u_i))\wedge(1-\mu_X(u_i))}{(1-\nu_X(u_i))\vee(1-\mu_X(u_i))}\right) \tag{27}$$

$$e_{zj}(X) = \frac{1}{n}\sum_{i=1}^{n}\frac{\mu_X(u_i)\wedge\nu_X(u_i)}{\mu_X(u_i)\vee\nu_X(u_i)} \tag{28}$$

$$e^2_{hc}(X) = \frac{1}{n}\sum_{i=1}^{n}(1-\mu^2_X(u_i)-\nu^2_X(u_i)-\pi^2_X(u_i)) \tag{29}$$

$$e_s(X) = -\frac{1}{n}\sum_{i=1}^{n}(\mu_X(u_i)ln\mu_X(u_i)+\nu_X(u_i)ln\nu_X(u_i)+\pi_X(u_i)ln\pi_X(u_i)) \tag{30}$$

$$e_{vs}(X) = -\frac{1}{nln2}\sum_{i=1}^{n}(\mu_X(u_i)ln\mu_X(u_i)+\nu_X(u_i)ln\nu_X(u_i)+(\mu_X(u_i)+\nu_X(u_i))ln(\mu_X(u_i)+\nu_X(u_i))-\pi_X(u_i)ln2) \tag{31}$$

	$\mathbb{R}_0$	X_1	X_2	X_3	X_4	X_5
IQS1	0.2832	0.2702	0.2642	0.2832	0.2618	0.2618
IQS2	0.2529	0.2526	0.2521	0.2528	0.2529	0.2528
IQC1	0.2925	0.2855	0.2925	0.2656	0.2695	0.2651
IQC2	0.2590	0.2590	0.2581	0.2558	0.2583	0.2550
IQC3	0.3236	0.3053	0.3236	0.2772	0.2688	0.2662
IQK1	0.2548	0.2548	0.2544	0.2541	0.2541	0.2534
IQK2	0.2647	0.2585	0.2611	0.2647	0.2585	02585
TS1	0.2791	0.2747	0.2743	0.2614	0.2791	0.2669
TS2	0.3441	0.2851	0.2919	0.2739	0.3441	0.3008
TS3	0.2899	0.2870	0.2899	0.2643	0.2899	0.2838
TS4	0.3204	0.2760	0.2654	0.3204	0.3204	0.2961
GF1	0.3204	0.3104	0.3155	0.3204	0.3041	0.3041
GF2	0.3207	0.2946	0.3207	0.2946	0.2874	0.2740
GF3	0.4032	0.3446	0.3446	0.4032	0.3918	0.3926
GF4	0.2526	0.2522	0.2522	0.2526	0.2522	0.2521
Overall performance rating $\mathbb{M}_i$	4.4611	4.2105	4.2605	4.2442	4.2929	4.1832

(i) Table 8: Computational Table for IT personnel selection problem

Methods	Criterion weight	DEs Weight	Benchmark	Ranking order	Optimal choice	Correlation Coefficient
Alguliyev et al (2015) method	Worst case method	Not applicable	TFNs based Modified VIKOR method	$\mathbb{Q}_3 \succ \mathbb{Q}_4 \succ \mathbb{Q}_1 \succ \mathbb{Q}_2 \succ \mathbb{Q}_5$	$\mathbb{Q}_3$	0.50
Dahooie et al (2017) method	SWARA method	Not applicable	Grey ARAS method	$\mathbb{Q}_2 \succ \mathbb{Q}_4 \succ \mathbb{Q}_3 \succ \mathbb{Q}_1 \succ \mathbb{Q}_5$	$\mathbb{Q}_2$	0.90
Samanlioglu et al (2018) method	Fuzzy AHP method	Completely known & numeric	Fuzzy TOPSIS method	$\mathbb{Q}_4 \succ \mathbb{Q}_2 \succ \mathbb{Q}_1 \succ \mathbb{Q}_3 \succ \mathbb{Q}_5$	$\mathbb{Q}_4$	0.90
Proposed method	Entropy and divergence measures based method	Completely known & numeric	Intuitionistic Fuzzy ARAS method	$\mathbb{Q}_4 \succ \mathbb{Q}_2 \succ \mathbb{Q}_3 \succ \mathbb{Q}_1 \succ \mathbb{Q}_5$	$\mathbb{Q}_4$	-

(j) Table 9: Performance comparison of fuzzy approaches for IT personnel selection

$$e_w(X) = \frac{1}{n}\sum_{i=1}^{n}[\{\sqrt{2}cos(\frac{\mu_X(u_i)-\nu_X(u_i)}{4})\pi - 1\} \times \frac{1}{\sqrt{2}-1}] \tag{32}$$

$$e_m(X) = \frac{1}{n\sqrt{e}(\sqrt{e}-1)}\sum_{i=1}^{n}[e - (\frac{\mu_X(u_i)+1-\nu_X(u_i)}{2})e^{\frac{\mu_X(u_i)+1-\nu_X(u_i)}{2}} - (\frac{\nu_X(u_i)+1-\mu_X(u_i)}{2})e^{\frac{\nu_X(u_i)+1-\mu_X(u_i)}{2}}] \tag{33}$$

Example 6.1. [3, 42] *Let $X \in IFS(U)$. For any positive real number n, De et al. (2000) introduced $IFS(U)$ X^n as follow:*

$$X^n = \{\langle u_i, [\mu_X(u_i)]^n, 1-[1-\nu_X(u_i)]^n\rangle \ : \ u_i \in U\}. \tag{34}$$

We assume $X \in IFS(U)$ given by,

$$X = \{(6, 0.1, 0.8), (7, 0.3, 0.5), (8, 0.5, 0.4), (9, 0.9, 0), (10, 1.0, 0)\}. \tag{35}$$

By considering the categorization of linguistic terms, De et al. (2000) observed X as LARGE on U. By utilizing Eq. (34), we obtain:

$X^{\frac{1}{2}}$ treated as More or less LARGE.
X^2 treated as Very LARGE.
X^3 treated as Quite very LARGE.
X^4 be treated as Very very LARGE.

Here, we utilize these IFSs to compare the entropies and results are depicted in Table A1. It is noteworthy that from mathematical logical concern, the IF-entropies of given IFSs have following pattern:

$$e(X^{\frac{1}{2}}) \geq e(X) \geq e(X^2) \geq e(X^3) \geq e(X^4). \tag{36}$$

X	$X^{1/2}$	X	X^2	X^3	X^4
$e_{bb}(X)$	0.4090	0.5000	0.4900	0.4670	0.4670
$e_{sk}(X)$	0.3450	0.3740	0.1970	0.1310	0.1090
$e_{hy}^2(X)$	0.3420	0.3440	0.2610	0.1990	0.1610
$e_s(X)$	0.4330	0.4310	0.3270	0.2530	0.2080
$e_{vs}(X)$	0.5518	0.5217	03491	0.2354	0.1417
$e_{zj}(X)$	0.2851	0.3050	0.1042	0.0383	0.0161
$e_w(X)$	0.4545	0.4377	0.3029	0.2159	0.1709
$e_m(X)$	0.5522	0.5333	0.3758	0.2719	0.2149
$e(X)$	0.5416	0.5072	0.3255	0.2113	0.1523

(k) Table A1: Comparison of IF-entropy with various existing ones

According to Table A1, the performances of $e_s(X)$, $e_{vs}(X)$, $e_w(X)$, $e_m(X)$,$e_a(X)$ and $e(X)$ are good, but the performances of $e_{bb}(X)$, $e_{sk}(X)$,$e_{hy}^2(X)$ and $e_{zj}(X)$ are poor, these entropy measures do not satisfy the requirement condition Eq. (39). From the Example 3.1, we can conclude that the performances of e(X) given in Eq. (15), is better than the some existing entropy measures.

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Multi-criteria IT personnel selection on intuitionistic fuzzy information measures and ARAS methodology

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انتخاب پرسنل IT چند معیاره روی اندازه‌های اطلاعات فازی شهودی و روش‌شناسی ARAS

چکیده. رقابت جهانی و رشد سریع تکنولوژی اطلاعات، همواره سازمان‌ها را ناگزیر به تغییر روش هایشان می‌کنند. در حال حاضر، شرکت‌ها نیازمند پرسنل IT می‌باشند که با اندیشه‌های خلاق باعث ایجاد تفاوت، و حفظ اصلاحات سریع می‌شوند. چون سنجش انتخاب پرسنل IT (ITPS) شامل گزینه ها و معیارهای متفاوت می‌باشد، از این رو، انتخاب پرسنل باید به عنوان یک مسئله تصمیم‌گیری چند-معیاره (MCDM) درنظر گرفته شود. دکترین مجموعه‌های فازی شهودی (IFSs) یک ابزار مؤثر در روشن‌سازی اطلاعات نامعلوم در یک مسئله MCDM می‌باشد. هدف اصلی این مقاله، انتخاب بهترین کاندید پرسنل IT به کمک روش ارزیابی ضریب جمعی (IF-ARAS) باندازه واگرا، بهبود بخشیدن تابع امتیاز و عملگرهای IF- انباشتگی است. در روش‌شناسی توسعه یافته، وزن‌های معیار و متخصصین، تصمیم (DEs) به ترتیب براساس روش اندازه IF- واگرای پیشنهادی و روش ارزیابی ترجیحی فازی شهودی محاسبه شده‌اند. سپس داوری‌های متخصصین تصمیم از روش پیشنهادی جمع شده‌اند تا از دست رفتن داده‌ها اجتناب شود. بالاخره، روش IF-ARAS پیشنهاد شده جهت حل مسئله انتخاب پرسنل IT اجرا شده تا کاربردی بودن روش ارائه شده را خاطر نشان کند. علاوه برآن، یک تحلیل مقایسه‌ای فراهم گردیده تا نتایج بدست آمده برای اعتبار بخشیدن به روش‌شناسی توسعه یافته را بررسی کند. تجزیه و تحلیل روشن می‌سازد که روش IF-ARAS کار او با روش‌های موجود سازگار است.