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A Fuzzy AHP–TOPSIS-Based Group Decision-Making Approach to IT Personnel Selection

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Abstract Global competition and the rapid development of information technologies force organizations to continuously change their ways. Nowadays, organizations need personnel who make a difference through innovative ideas and who keep up with the rapid changes. In this paper, the personnel selection process in a Turkish dairy company's information technology (IT) department is discussed as a group multi-criteria decision-making problem. The main purpose of the paper is to select the best employee candidate for an IT department by integrating fuzzy analytic hierarchy process (fuzzy AHP) with Chang's (Eur J Oper Res 95(3):649–655, 1996) extent analysis and fuzzy The Technique for Order of Preference by Similarity to Ideal Solution (fuzzy TOPSIS). Decision makers' (DMs) verbal evaluations are included in the process using intuitionistic fuzzy numbers. In fuzzy AHP–TOPSIS calculations, during the group decision-making process, hierarchical level weights, reflecting the importance of DMs' verbal evaluations, are utilized. First, with fuzzy AHP, the importance weights of thirty sub-criteria are determined, and then, with fuzzy TOPSIS five IT personnel alternatives are ranked utilizing the weights obtained with fuzzy AHP.

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1 Introduction

The human factor defines the direction of an organization with its dynamic structure. It is important to choose an employee who is in harmony with the work place, the organization, colleagues and the job. Personnel selection is a multi-criteria decision making (MCDM) problem by its nature since there are many potentially competing significant qualitative and quantitative criteria to consider in selecting the best employee to hire for a job.

In this paper, a Turkish dairy company's IT department recruitment process is analyzed and the problem of ranking the employee candidates is solved as a multi-criteria group decision making problem. In order to capture the uncertainty and vagueness of judgments of DMs in the process, an integrated fuzzy MCDM method, fuzzy AHP–TOPSIS is implemented. Fuzzy set theory, pioneered by Zadeh [45], has been applied to many MCDM problems to model the vagueness and imprecision of human cognitive processes [30].

In this study, first fuzzy AHP with Chang's [10] extent analysis is used to determine the importance weights of evaluation criteria and then fuzzy TOPSIS is implemented to rank IT employee alternatives, implementing the criteria weights obtained with fuzzy AHP. In this research, fuzzy AHP is integrated with fuzzy TOPSIS to have both methods' advantages for the personnel selection problem. Fuzzy TOPSIS is easy to use with stable results; however, in fuzzy TOPSIS specific guidelines for assigning criteria weights are not provided; therefore, a systematic method such as fuzzy AHP is needed for DMs for the weighting of criteria. With fuzzy AHP, consistent, reliable criteria weights are obtained and the uncertainty and vagueness of the judgments of DMs is captured by allowing pairwise comparisons between quantitative and qualitative evaluation criteria with linguistic terms, which are then converted to fuzzy numbers. On the other hand, fuzzy AHP, without the integration, gets cumbersome if the numbers of alternatives and/or evaluation criteria are large due to repetitive assessments and a large number of pairwise comparisons. Therefore, in this integration, fuzzy TOPSIS is used afterward to rank the alternatives since fuzzy TOPSIS can be used to rank alternatives in a reasonable time and with little effort without requiring complicated calculations.

Apart from many multi-criteria group decision-making applications, in this paper, it is assumed that in group decision making, DMs may have different hierarchical job levels in the committee. These differences are expressed in terms of linguistic terms which are then incorporated into the group decision-making process with hierarchical level weights (HLW) of DMs. HLW were implemented to reflect the importance levels of DMs verbal evaluations for both evaluation of criteria and ranking of alternatives in fuzzy AHP–TOPSIS.

To the best of the authors' knowledge, HLW in group decision making, fuzzy AHP with Chang's [10] extent analysis and fuzzy TOPSIS have never been integrated to utilize all the methods' advantages in any MCDM study in the literature. To illustrate the applicability of the integration in a real-life system and to demonstrate the effectiveness of the proposed approach for potential practitioners and readers, a case study that focuses on personnel selection for an IT department in Turkey is presented. The results were shared with the company involved, and positive feedback was received since the proposed approach to IT personnel selection is systematic and comprehensive. In the next section, the related literature is given in detail.

2 Literature Review

The analytic hierarchy process (AHP) method was invented by Thomas L. Saaty in 1981 [35]. In AHP, alternatives are evaluated with respect to quantitative and qualitative criteria, in a multi-level, hierarchical structure, and then, a total weighted score is obtained for each alternative to determine the overall ranking. To capture the uncertainty and vagueness in the decision making process, its fuzzy extension, fuzzy AHP has been developed and has been successfully applied to various MCDM problems such as evaluation of weapon systems [32] and naval tactical missile systems [11], locating convenience stores [23], supplier selection [20], evaluation of service quality of healthcare systems [9], prioritization of organizational capital measurement indicators [7], evaluation of IT departments in the manufacturing industry in Taiwan [26], evaluation of intellectual capital for performance contribution in a university [27], analysis of the assessment factors for a renewable energy dissemination program [17], supplier selection in a gear motor company [1], evaluation of academic staff [34] and the selection of tasks for assignment to the disassembly line [4].

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) was developed by Hwang and Yoon [19] based on the idea that the best alternative solution will be on the shortest distance to positive-ideal-solution (PIS) and on the furthest distance to the negative-ideal-solution (NIS). Further developments of TOPSIS were presented by Yoon [44] and Hwang et al. [18]. Simplicity, rationality, comprehensibility, good computational efficiency and ability to measure the relative performance for each alternative in a simple mathematical form are some of the advantages of TOPSIS. Its fuzzy extension, fuzzy TOPSIS, has been applied to various evaluation and ranking problems such as for plant location selection [43], bridge risk assessment [42], evaluating initial training aircrafts in the Air Force Academy in Taiwan [41], evaluating Turkish cement firms on the Istanbul Stock Exchange [15], solving the sealed bid, reverse auction problem of e-sourcing [37], ranking air carriers in Turkey [39] and selection of suppliers in a watch firm [28].

(Fuzzy) AHP integrated with (fuzzy) TOPSIS has been used in several applications in the literature. Generally, in this integration, first the importance weights of criteria are determined with (fuzzy) AHP, and then, the alternatives are ranked with (fuzzy) TOPSIS, using the weights obtained from (fuzzy) AHP. Sun [38] implemented fuzzy AHP and fuzzy TOPSIS to evaluate the performance of notebook computer ODM companies. Amiri [3] used AHP to determine the weights of criteria and fuzzy TOPSIS to rank alternative projects for oil-field development of an Iranian Oil Company. Büyüközkan and Çifçi [8] applied fuzzy AHP and fuzzy TOPSIS to measure the electronic service quality and evaluate hospital web site alternatives. Kutlu and Ekmekçioglu [24] implemented fuzzy AHP and fuzzy TOPSIS for failure mode and effects analysis (FMEA) in an automotive manufacturing facility. Kumar and Singh [22] used fuzzy AHP to determine the weights of criteria and TOPSIS to rank the third party logistics providers. Samvedi et al. [36] quantified risks in a supply chain, integrated fuzzy AHP and fuzzy TOPSIS and evaluated the data from Indian textile and steel industries. Vatansever and Oncel [40] applied fuzzy AHP and fuzzy TOPSIS to rank research assistant candidates for a management department at a University in Turkey. Nazam et al. [33]

used fuzzy AHP and fuzzy TOPSIS for the risk assessment of green supply chain implementation in the textile industry.

Personnel selection is an area where MCDM methods are frequently used. Güngör et al. [16] applied fuzzy AHP, and Dursun and Karsak [14] and Matin et al. [31] implemented fuzzy TOPSIS for personnel selection. Dagdeviren [13] integrated analytic network process (ANP) and TOPSIS for personnel selection in manufacturing systems, where the weights were determined with ANP and final ranking of alternatives was realized with TOPSIS. Lin [29] implemented ANP and fuzzy data envelopment analysis (DEA) for the personnel selection problem of an electric and machinery company in Taiwan. Zhang and Liu [47] used a grey relational analysis (GRA)-based fuzzy MCDM for personnel selection, where the entropy weights of criteria were obtained with intuitionistic fuzzy entropy. Balezentis et al. [5] developed the fuzzy MULTIMOORA for group decision making (MULTIMOORA–FG) and aggregated the subjective evaluations of DM for robust personnel selection process. Alguliyev et al. [2] used a worst-case method to calculate the weights of criteria and fuzzy VIKOR to rank the applicants.

In the literature, the research closest to this study is by Kaya and Kahraman [21], and Boran et al. [6]. Kaya and Kahraman [21] implemented fuzzy AHP with Chang's [10] extent analysis to determine the weights of criteria and fuzzy TOPSIS to rank the energy technology alternatives for energy planning. Boran et al. [6] applied HLW and used intuitionistic fuzzy TOPSIS for personnel selection and presented a numerical example of a sales manager selection process in a manufacturing company. At present, there does not appear to be any research in the literature that focuses on personnel selection for an IT department using HLW in group decision making and implementing the integration of fuzzy AHP with Chang's [10] extent analysis and fuzzy TOPSIS. In the next sections, HLW calculations and the steps of the fuzzy AHP–TOPSIS are presented in more detail, along with a case study carried out in Turkey.

3 The Fuzzy AHP–TOPSIS

3.1 Definitions Related to Fuzzy Numbers

Fuzzy set theory is a mathematical theory of classes with unsharp boundaries [30]. Any crisp theory can be fuzzified by generalizing the concept of a set within that theory to the concept of a fuzzy set [46]. In this paper, due to its simplicity, triangular fuzzy numbers (TFNs) are used in fuzzy AHP and fuzzy TOPSIS. A fuzzy number is a special fuzzy set $F = \{(x, \mu_F(x)), x \in R\}$, where x is a real number, $R: -\infty < x < +\infty$ and $\mu_F(x)$ is a continuous mapping from R to the closed interval [0, 1]. A triangular fuzzy number denoted as $\tilde{M} = (l, m, u)$, where $l \le m \le u$, has the following triangular type membership function:

$$\mu_F(x) = \begin{cases} 0 & x < l \\ x - l/m - l & l \le x \le m \\ u - x/u - m & m \le x \le u \\ 0 & x > u \end{cases}. \tag{1}$$

Basic operations between two positive triangular fuzzy numbers $\tilde{A} = (l_1, m_1, u_1)$ and $\tilde{B} = (l_2, m_2, u_2) l_1 \le m_1 \le u_1, l_2 \le m_2 \le u_2$ are explained as:

$$\tilde{A} + \tilde{B} = (l_1 + l_2, m_1 + m_2, u_1 + u_2), \tag{2}$$

$$\tilde{A} - \tilde{B} = (l_1 - u_2, m_1 - m_2, u_1 - l_2), \tag{3}$$

$$\tilde{A} * \tilde{B} = (l_1 * l_2, m_1 * m_2, u_1 * u_2), \tag{4}$$

$$\frac{\tilde{A}}{\tilde{B}} = \left(\frac{l_1}{u_2}, \frac{m_1}{m_2}, \frac{u_1}{l_2}\right), \tag{5}$$

$$\tilde{A}^{-1} = \left(\frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1}\right). \tag{6}$$

The distance between two positive triangular fuzzy numbers $\tilde{A} = (l_1, m_1, u_1)$ and $\tilde{B} = (l_2, m_2, u_2)$ can be calculated by the vertex method as:

$$d(\tilde{A}, \tilde{B}) = \sqrt{1/3\left((l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2\right)}. \tag{7}$$

If $\tilde{M} = (l, m, u)$ is a positive triangular fuzzy number, $\tilde{M}$ can be defuzzified as [25, 43]:

$$M = (l + 4m + u)/6. \tag{8}$$

3.2 Determination of Hierarchical Level Weights (HLW)

To determine HLW, DMs hierarchical job level in the decision making group needs to be evaluated by the upper management. It is assumed that the importance of DMs' verbal evaluations during the process of evaluation of criteria and ranking alternatives differs based on the

Table 1 Linguistic terms and corresponding intuitionistic fuzzy numbers (IFNs) for rating decision makers' verbal evaluations

Linguistic terms	IFNS $D_k = (\mu_k, \pi_k)$
Very important	(0.80; 0.10)
Important	(0.55; 0.25)
Medium	(0.50; 0.50)
Unimportant	(0.30; 0.50)
Very unimportant	(0.20;0.70)

Table 2 Random index (RI)

Matrix size	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0	0	0.52	0.89	1.11	1.25	1.35	1.4	1.45	1.49	1.52	1.54	1.56	1.58	1.59

hierarchical job level, and therefore, linguistic terms in Table 1 are used for rating DMs' verbal evaluations.

Afterward, assuming there are l DMs, HLW for DM k, denoted as λ_k, is calculated by applying the corresponding intuitionistic fuzzy number (IFNS) $D_k = (\mu_k, \pi_k)$ in Table 1 as [6]:

$$\lambda_k = \frac{\mu_k + \pi_k\left(\frac{\mu_k}{\mu_k+\pi_k}\right)}{\sum_{k=1}^{l} \mu_k + \pi_k\left(\frac{\mu_k}{\mu_k+\pi_k}\right)}, \quad \text{where, } \sum_{k=1}^{l} \lambda_k = 1. \tag{9}$$

Aggregated, total evaluation scores of DMs for each comparison in fuzzy AHP and in fuzzy TOPSIS are calculated utilizing the weighted average of each DM's evaluation using the HLW (λ_k) as:

$$\sum_{i=1}^{k} \lambda_k * P_k, \tag{10}$$

where P_k is the evaluation score of the kth DM.

3.3 Phase 1: Fuzzy AHP

In this paper, first, fuzzy AHP is used to determine the importance weights of criteria and sub-criteria. For fuzzy pairwise comparisons of the criteria and sub-criteria, Chang's [10] extent analysis is used. The stages of the extent analysis are summarized as below.

Let $X = \{x_i\} i = 1, \ldots, n$ be the element set and $G = \{g_j\} j = 1, \ldots, m$ be the objective set, and then, m-extent analysis value is obtained for each element as:

$$M^1_{g_i}, M^2_{g_i}, \ldots, M^m_{g_i}, \quad i = 1, 2, \ldots, n. \tag{11}$$

All elements of $M^j_{g_i,} (j = 1, 2 \ldots, m)$ are TFNs. The value of fuzzy synthetic extent in terms of ith element is shown as:

$$S_i = \sum_{j=1}^{m} M^j g_i \otimes \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M^j g_i\right]^{-1}. \tag{12}$$

In order to obtain $\sum_{j=1}^{m} M^i g_i$, fuzzy numbers are summed as:

$$\sum_{j=1}^{m} M^j_{g_i} = \left(\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j\right). \tag{13}$$

Then, in order to obtain $[\sum_{i=1}^{n} \sum_{j=1}^{m} M^j g_i]^{-1}$, Eqs. (14) and (15) are used.

$$\sum_{i=1}^{n} \sum_{j=1}^{m} M^j_{g_i} = \left(\sum_{i=1}^{n} l_i, \sum_{i=1}^{n} m_i, \sum_{i=1}^{n} u_i\right), \tag{14}$$

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M^j g_i\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i}\right). \tag{15}$$

If M_1 and M_2 are TFNs, the degree of possibility of $M_2 = (l_2, m_2, u_2) \geq M_1 = (l_1, m_1, u_1)$ is defined by Eq. (16) as:

$$(M_2 \geq M_1) = \sup_{y \geq x} \left[\min\left(\mu_{M_1}(x), \mu_{M_2}(y)\right)\right]. \tag{16}$$

This equation is equal to the below expression,

$$V(M_2 \geq M_1) = hgt(M_1 \cap M_2) = \mu_{M_2}(d) = \begin{cases} 1, & \text{if } m_2 \geq m_1, \\ 0, & \text{if } l_1 \geq u_2 \\ \dfrac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}, & \text{otherwise} \end{cases} \tag{17}$$

here d is the ordinate of the highest intersection point between μ_{M_1} and μ_{M_2}. In order to compare M_1 and M_2, $V(M_1 \geq M_2)$ and $V(M_2 \geq M_1)$ values are needed.

The degree of possibility of a convex fuzzy number M to be greater than k convex fuzzy numbers $M_i (i = 1, \ldots, k)$ is defined as:

$$V(M \geq M_1, M_2, \ldots, M_k) = V[(M \geq M_1) \text{ and } (M \geq M_2) \text{ and} \ldots \text{and} (M \geq M_k) = \min V(M \geq M_i), \quad i = 1, \ldots, k. \tag{18}$$

W' vector, $W' = (d'(C_1), d'(C_2), \ldots, d'(C_k))^T$ is computed assuming:

$$d'(C_i) = \min V\left(S_i \geq S_j\right), \quad i = 1, \ldots, k, \; j = 1, \ldots, k, k \neq j. \tag{19}$$

The normalized W vector, which consists of non-fuzzy numbers, is given as:

$$W = (d(C_1), d(C_2), \ldots, d(C_k))^T. \tag{20}$$

In this paper, with the presented stages of extent analysis and fuzzy AHP, importance weights (W vectors) of sub-criteria and criteria are obtained for each pairwise comparison matrix. Afterward, each pairwise comparison matrix is defuzzified with Eq. (8) and the consistency ratio is calculated. Let A be the defuzzified $n \times n$ pairwise comparison matrix, and W be the weight vector obtained from extent analysis. From $AW = \lambda_{\max} W$, the largest eigen

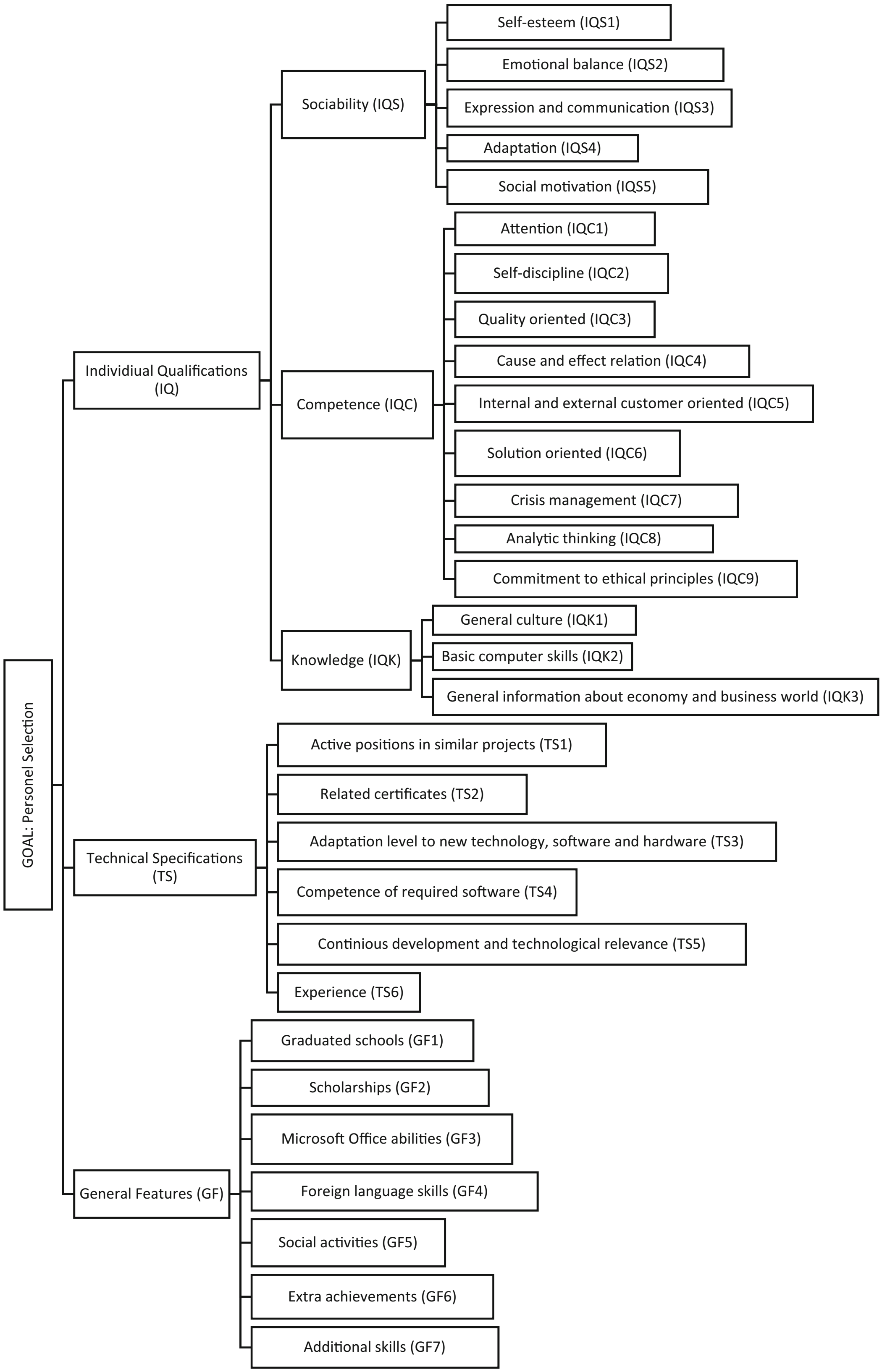

Fig. 1 Criteria and sub-criteria for personnel selection in IT department

value, called the principal eigen value (λ_{max}), is obtained and the consistency index (CI) and consistency ratio (CR) are calculated as:

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n - 1}, \tag{21}$$

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}}. \tag{22}$$

If the CR < 0.10, the comparison is acceptable; otherwise, it is not. Random index (RI), which is the average index for randomly generated weights, is listed in Table 2 based on the matrix size n.

After the determination of consistent, acceptable sub-criteria and criteria weights, in Phase 2, Fuzzy TOPSIS is used to rank the alternatives, using the sub-criteria weights obtained from Fuzzy AHP. Note that the sum of all sub-criteria weights equals 1.

3.4 Phase 2: Fuzzy TOPSIS

Steps of fuzzy TOPSIS [12] are presented below, assuming there are m alternatives to rank and n sub-criteria. A fuzzy decision matrix is given as:

$$\tilde{D} = \begin{bmatrix} \widetilde{x_{11}} & \widetilde{x_{12}} & \cdots & \widetilde{x_{1n}} \\ \widetilde{x_{21}} & \widetilde{x_{22}} & \cdots & \widetilde{x_{2n}} \\ . & . & \cdots & . \\ . & . & \cdots & . \\ . & . & \cdots & . \\ \widetilde{x_{m1}} & \widetilde{x_{m2}} & \cdots & \widetilde{x_{mn}} \end{bmatrix},$$

where $\widetilde{x_{ij}} \forall i,j$ are linguistic variables that are described by positive TFNs $\widetilde{x_{ij}} = (a_{ij}, b_{ij}, c_{ij})$. Weight vector $W = [w_1, w_2, \ldots, w_n]$ for n sub-criteria was obtained from fuzzy AHP previously.

Step 1 For l DMs, calculate the aggregated $\widetilde{x_{ij}} = \frac{1}{l}\left[\widetilde{x_{ij}^1} + \widetilde{x_{ij}^2} + \cdots + \widetilde{x_{ij}^k} + \cdots + \widetilde{x_{ij}^l}\right]$ where $\widetilde{x_{ij}^k}$ is the rating of the kth DM for the ith alternative with respect to the jth criterion.

Step 2 Construct the fuzzy decision matrix $\tilde{D}$ and normalized fuzzy decision matrix $\tilde{S}$. Here, B and C denote the sets of benefit and cost criteria, respectively.

$\tilde{S} = \left[\widetilde{s_{ij}}\right]_{m\times n}$

where $\widetilde{s_{ij}} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right), j \in B$; $\widetilde{s_{ij}} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right)$, $j \in C$; $c_j^* = \max_i c_{ij}, j \in B; a_j^- = \min_i a_{ij}, j \in C$.

Step 3 Construct the weighted normalized fuzzy decision matrix $\tilde{V} = \left[\widetilde{v_{ij}}\right]_{m\times n}$ where $\widetilde{v_{ij}} = \widetilde{s_{ij}} \cdot w_j$ are normalized positive TFNs with ranges in the interval [0, 1].

Step 4 Define the fuzzy positive-ideal solution $A^* = \left(\widetilde{v_1^*}, \widetilde{v_2^*}, \ldots, \widetilde{v_n^*}\right)$ and fuzzy negative-ideal solution $A^- = \left(\widetilde{v_1^-}, \widetilde{v_2^-}, \ldots, \widetilde{v_n^-}\right)$ where $\widetilde{v_j^*} = (1,1,1)$ and $\widetilde{v_j^-} = (0,0,0) j = 1, 2, \ldots, n$.

Step 5 Calculate the distance of each alternative from A^* and A^- with the vertex method $d_i^* = \sum_{j=1}^n d\left(\widetilde{v_{ij}}, \widetilde{v_j^*}\right) \forall i$, $d_i^- = \sum_{j=1}^n d\left(\widetilde{v_{ij}}, \widetilde{v_j^-}\right) \forall i$.

Step 6 Calculate the closeness coefficient of each alternative $\mathrm{CC}_i = \frac{d_i^-}{d_i^- + d_i^*} \forall i$ and rank the alternatives in decreasing order of closeness coefficient (from best to worst) based on CC_i, since as CC_i approaches 1, an alternative A_i is closer to A^* and farther from A^-.

4 Case Study

The case study is of a dairy company in Turkey with more than 4500 employees which has been a manufacturer of milk and dairy products for more than 30 years. The recruitment process in the company for personnel selection in the IT department is analyzed, and three DMs ($l = 3$) (DM_1, DM_2, and DM_3) of the process are identified. Criteria and sub-criteria were determined with the help of interviews with the human resources department and the IT department manager, and company questionnaire and profile reports. These are given in Fig. 1.

Potential employee alternatives are 5 ($m = 5$) IT specialist candidates. An IT specialist can perform a variety of tasks such as data management, system management, computer hardware, software design and database design. After the determination of DMs, criteria and sub-criteria, fuzzy AHP is used to determine the weights of criteria and sub-criteria and then fuzzy TOPSIS is used to rank the potential IT specialist alternatives through the implementation of these weights.

For the process, verbal evaluations of DM_1, DM_2 and DM_3 are rated as "Important," "Important" and "Very Important" based on their job levels. By using the corresponding IFNS in Table 1 and Eq. (9), DMs' HLW are calculated as $\lambda_1 = \lambda_2 = 0.55 + \frac{0.55*0.25}{0.55+0.25} = 0.722$ and $\lambda_3 = 0.8 + \frac{0.8*0.1}{0.8+0.1} = 0.889$. Afterward, normalized HLW are determined as $\lambda_1 = \lambda_2 = 0.3095$ and $\lambda_3 = 0.381$, and these are used in all the fuzzy AHP–TOPSIS calculations as explained in Eq. (10).

In fuzzy AHP, DMs do pairwise comparisons of all criteria and sub-criteria using the linguistic terms and corresponding membership functions of TFNs which are presented in Table 3. Pairwise comparisons of criteria and

Table 3 Fuzzy evaluation scores for the pairwise comparisons in fuzzy AHP

Linguistic terms	Membership function
Absolutely strong (AS)	(2, 5/2, 3)
Very strong (VS)	(3/2, 2, 5/2)
Fairly strong (FS)	(1, 3/2, 2)
Slightly strong (SS)	(1, 1, 3/2)
Equal (E)	(1, 1, 1)
Slightly weak (SW)	(2/3, 1, 1)
Fairly weak (FW)	(1/2, 2/3, 1)
Very weak (VW)	(2/5, 1/2, 2/3)
Absolutely weak (AW)	(1/3, 2/5, 1/2)

Table 4 Pairwise comparisons of main criteria by three decision makers (DM_1, DM_2 and DM_3)

	IQ	TS	GF
IQ	(E, E, E)	(E, SW, E)	(SS, E, FW)
TS	(E, SS, E)	(E, E, E)	(SS, SS, FW)
GF	(SW, E, FS)	(SW, SW, FS)	(E, E, E)

Table 5 Pairwise comparisons of individual qualifications' (IQ) sub-criteria by three decision makers (DM_1, DM_2 and DM_3)

	IQS	IQC	IQK
IQS	(E, E, E)	(SW, SW, E)	(E, E, FW)
IQC	(SS, SS, E)	(E, E, E)	(SS, SS, FW)
IQK	(E, E, FS)	(SW, SW, FS)	(E, E, E)

sub-criteria for 3 DMs are given in Tables 4, 5, 6, 7, 8, 9 and 10.

Using Eq. (10), aggregated, total evaluation scores of DMs for each comparison in fuzzy AHP are calculated, and the obtained aggregated fuzzy evaluation matrices are given in Tables 11, 12, 13, 14, 15, 16 and 17.

Using the matrices presented in Tables 11, 12, 13, 14, 15, 16 and 17, fuzzy synthetic extent values (S_i), weights from Chang's [10] extent analysis ($W_i^{\prime}$), and normalized weights (W_i) are calculated and these are given in Tables 18, 19, 20, 21, 22, 23 and 24.

After the calculations of the weights (W_i) that are given in Tables 18, 19, 20, 21, 22, 23 and 24, the fuzzy matrices presented in Tables 11, 12, 13, 14, 15, 16 and 17 are defuzzified with Eq. (8) and from $AW = \lambda_{\max} W$, $\lambda_{\max}$ is calculated for each matrix. Afterward, with Eq. (21) and Eq. (22), consistency ratios (CR) are calculated and since all the CR values are less than 0.1 as seen in Tables 11, 12, 13, 14, 15, 16 and 17, these comparisons are found to be acceptable. As a result, the sub-criteria weights obtained from fuzzy AHP are presented in Table 25. These weights are then used in fuzzy TOPSIS calculations.

In the fuzzy TOPSIS phase, DMs rate each alternative based on each sub-criterion using the linguistic terms in Table 26.

Evaluations of 5 alternatives with respect to 30 sub-criteria by 3 DMs (DM_1, DM_2 and DM_3) with the linguistic terms presented in Table 26 are given in Table 27.

These linguistic terms are converted to corresponding TFNs which are presented in Table 26. Taking into consideration DM's HLWs, with Eq. (10), the aggregated fuzzy decision matrix ($\tilde{D}$) is determined and presented in Table 28.

All the sub-criteria presented here are assumed to be benefit criteria (B). After the construction of the fuzzy normalized decision matrix ($\tilde{S}$), the fuzzy weighted normalized decision matrix ($\tilde{V}$) is constructed as seen in Table 29.

Assuming,

$$A^{*} = \begin{pmatrix} (1,1,1),(1,1,1),(1,1,1),(1,1,1)(1,1,1),(1,1,1),(1,1,1),(1,1,1),(1,1,1),(1,1,1), \\ (1,1,1),(1,1,1),(1,1,1),(1,1,1)(1,1,1),(1,1,1),(1,1,1),(1,1,1),(1,1,1),(1,1,1), \\ (1,1,1),(1,1,1),(1,1,1),(1,1,1)(1,1,1),(1,1,1),(1,1,1),(1,1,1),(1,1,1),(1,1,1) \end{pmatrix} \text{ and}$$

$$A^{-} = \begin{pmatrix} (0,0,0),(0,0,0),(0,0,0),(0,0,0)(0,0,0),(0,0,0),(0,0,0),(0,0,0),(0,0,0),(0,0,0), \\ (0,0,0),(0,0,0),(0,0,0),(0,0,0)(0,0,0),(0,0,0),(0,0,0),(0,0,0),(0,0,0),(0,0,0), \\ (0,0,0),(0,0,0),(0,0,0),(0,0,0)(0,0,0),(0,0,0),(0,0,0),(0,0,0),(0,0,0),(0,0,0) \end{pmatrix},$$

the distance from fuzzy positive-ideal solution (d_i^{*}), distance from fuzzy negative-ideal solution (d_i^{-}) and closeness coefficients (CC_i) are calculated as shown in Table 30. Based on the CC_i values, alternatives are ranked from best to worst as: alternative 4, alternative 2, alternative 1, alternative 3 and alternative 5.

Table 6 Pairwise comparisons of sociability's (IQS) sub-criteria by three decision makers (DM_1, DM_2 and DM_3)

	IQS1	IQS2	IQS3	IQS4	IQS5
IQS1	(E, E, E)	(E, E, E)	(FW, SW, E)	(FW, SS, SS)	(SW, SS, SS)
IQS2	(E, E, E)	(E, E, E)	(FW, SW, E)	(FW, SS, SS)	(SW, SS, SS)
IQS3	(FS, SS, E)	(FS, SS, E)	(E, E, E)	(E, FS, SS)	(SS, FS, SS)
IQS4	(FS, SW, SW)	(FS, SW, SW)	(E, FW, SW)	(E, E, E)	(SS, E, E)
IQS5	(SS, SW, SW)	(SS, SW, SW)	(SW, FW, SW)	(SW, E, E)	(E, E, E)

Table 7 Pairwise comparisons of competence (IQC) sub-criteria by three decision makers (DM_1, DM_2 and DM_3)

	IQC1	IQC2	IQC3	IQC4	IQC5	IQC6	IQC7	IQC8	IQC9
IQC1	(E, E, E)	(E, E, SS)	(SS, FW, SW)	(SW, FW, FW)	(SS, SW, SW)	(SS, FW, SW)	(SS, SW, SW)	(SW, FW, FW)	(FW, AW, FW)
IQC2	(E, E, SW)	(E, E, E)	(SS, FW, SS)	(SW, FW, FW)	(SS, SW, SW)	(SS, FW, SW)	(SS, SW, SW)	(SW, FW, FW)	(FW, VW, FW)
IQC3	(SW, FS, SS)	(SW, FS, SW)	(E, E, E)	(FW, E, SW)	(E, SS, E)	(E, E, E)	(E, SS, E)	(FW, E, SW)	(VW, SW, SW)
IQC4	(SS, FS, FS)	(SS, FS, FS)	(FS, E, SS)	(E, E, E)	(FS, SS, SS)	(FS, E, SS)	(FS, SS, SS)	(E, E, E)	(SW, SW, E)
IQC5	(SW, SS, SS)	(SW, SS, SS)	(E, SW, E)	(FW, SW, SW)	(E, E, E)	(E, SW, E)	(E, E, E)	(FW, SW, SW)	(VW, FW, SW)
IQC6	(SW, FS, SS)	(SW, FS, SS)	(E, E, E)	(FW, E, SW)	(E, SS, E)	(E, E, E)	(SW, SS, E)	(FW, E, SW)	(VW, SW, SW)
IQC7	(SW, SS, SS)	(SW, SS, SS)	(E, SW, E)	(FW, SW, SW)	(E, E, E)	(SS, SW, E)	(E, E, E)	(FW, SW, SW)	(AW, FW, SW)
IQC8	(SS, FS, FS)	(SS, FS, FS)	(FS, E, SS)	(E, E, E)	(FS, SS, SS)	(FS, E, SS)	(FS, SS, SS)	(E, E, E)	(SW, SW, E)
IQC9	(FS, AS, FS)	(FS, VS, FS)	(VS, SS, SS)	(SS, SS, E)	(VS, FS, SS)	(VS, SS, SS)	(AS, FS, SS)	(SS, SS, E)	(E, E, E)

Table 8 Pairwise comparisons of knowledge (IQK) sub-criteria by three decision makers (DM_1, DM_2 and DM_3)

	IQK1	IQK2	IQK3
IQK1	(E, E, E)	(SW, FW, SW)	(E, E, SW)
IQK2	(SS, FS, SS)	(E, E, E)	(SS, FS, E)
IQK3	(E, E, SS)	(SW, FW, E)	(E, E, E)

Table 11 Aggregated fuzzy evaluation matrix[a] of the main criteria

	IQ	TS	GF
IQ	(1, 1, 1)	(0.90, 1, 1)	(0.81, 0.87, 1.15)
TS	(1, 1, 1.15)	(1, 1, 1)	(0.81, 0.87, 1.31)
GF	(0.90, 1.19, 1.38)	(0.80, 1.19, 1.38)	(1, 1, 1)

[a]Consistency ratio (CR) for the defuzzified version of this matrix is $0.074 < 0.10$

Table 9 Pairwise comparisons of technical specifications(TS) sub-criteria by three decision makers (DM_1, DM_2 and DM_3)

	TS1	TS2	TS3	TS4	TS5	TS6
TS1	(E, E, E)	(E, E, SS)	(FW, E, SS)	(FW,SW, SW)	(SW, SW, E)	(FW, SW, FW)
TS2	(E, E, SW)	(E, E, E)	(FW, E, E)	(FW, SW, FW)	(SW, SW, SW)	(FW, SW, VW)
TS3	(FS, E, SW)	(FS, E, E)	(E, E, E)	(E, SW, FW)	(SS, SW, SW)	(E, SW, AW)
TS4	(FS, SS, SS)	(FS, SS, FS)	(E, SS, FS)	(E, E, E)	(SS, E, SS)	(E, E, SW)
TS5	(SS, SS, E)	(SS, SS, SS)	(SW, SS, SS)	(SW, E, SW)	(E, E, E)	(SW, E, FW)
TS6	(FS, SS, FS)	(FS, SS, VS)	(E, SS, AS)	(E, E, SS)	(SS, E, FS)	(E, E, E)

Table 10 Pairwise comparisons of general feature(GF) sub-criteria by three decision makers (DM_1, DM_2 and DM_3)

	GF1	GF2	GF3	GF4	GF5	GF6	GF7
GF1	(E, E, E)	(E, SS, SS)	(SS, E, FS)	(E, E, SS)	(SS, SS, FS)	(FS, SS, VS)	(FS, FS, AS)
GF2	(E, SW, SW)	(E, E, E)	(SS, SW, SS)	(E, SW, E)	(SS, E, SS)	(FS, E, FS)	(FS, SS, FS)
GF3	(SW, E, FW)	(SW, SS, SW)	(E, E, E)	(SW, E, SW)	(E, SS, E)	(SS, SS, SS)	(SS, FS, SS)
GF4	(E, E, SW)	(E, SS, E)	(SS, E, SS)	(E, E, E)	(SS, SS, SS)	(FS, SS, FS)	(FS, FS, FS)
GF5	(SW, SW, FW)	(SW, E, SW)	(E, SW, E)	(SW, SW, SW)	(E, E, E)	(SS, E, SS)	(SS, SS, SS)
GF6	(FW, SW, VW)	(FW, E, FW)	(SW, SW, SW)	(FW, SW, FW)	(SW, E, SW)	(E, E, E)	(E, SS, E)
GF7	(FW, FW, AW)	(FW, SW, FW)	(SW, FW, SW)	(FW, FW, FW)	(SW, SW, SW)	(E, SW, E)	(E, E, E)

Table 12 Aggregated fuzzy evaluation matrix[a] of the individual qualifications (IQ) sub-criteria

	IQS	IQC	IQK
IQS	(1, 1, 1)	(0.80, 1, 1)	(0.81, 0.87, 1)
IQC	(1, 1, 1.31)	(1.00, 1, 1)	(0.81, 0.87, 1.31)
IQK	(1, 1.19, 1.38)	(0.80, 1.19, 1.38)	(1, 1, 1)

[a]Consistency ratio (CR) for the defuzzified version of this matrix is 0.085 < 0.10

Table 15 Aggregated fuzzy evaluation matrix[a] of knowledge(IQK) sub-criteria

	IQK1	IQK2	IQK3
IQK1	(1, 1, 1)	(0.62, 0.90, 1)	(0.87, 1, 1)
IQK2	(1, 1.15, 1.65)	(1, 1, 1)	(1, 1.15, 1.46)
IQK3	(1, 1, 1.19)	(0.74, 0.90, 1)	(1, 1, 1)

[a]Consistency ratio (CR) for the defuzzified version of this matrix is 0.080 < 0.10

5 Discussion and Conclusions

In this paper, a framework for evaluating and selecting personnel for an IT department is proposed. Personnel evaluation, specifically IT specialist selection, is a complex issue, a MCDM problem that includes many quantitative and qualitative criteria. Due to the imprecise and vague nature of the criteria and evaluations, it is important to express the judgements of DMs with fuzzy numbers, so here an integrated fuzzy MCDM method, namely fuzzy AHP–TOPSIS, is proposed to rank different IT specialists. First, fuzzy AHP is implemented with Chang's [10] extent analysis to determine the weights of sub-criteria, and then, fuzzy TOPSIS is applied to rank the alternatives utilizing the weights obtained from fuzzy AHP.

Table 13 Aggregated fuzzy evaluation matrix[a] of sociability (IQS) sub-criteria

	IQS1	IQS2	IQS3	IQS4	IQS5
IQS1	(1, 1, 1)	(1, 1, 1)	(0.74, 0.90, 1)	(0.85, 0.90, 1.35)	(0.90, 1.00, 1.35)
IQS2	(1, 1, 1)	(1, 1, 1)	(0.74, 0.90, 1)	(0.85, 0.90, 1.35)	(0.90, 1.00, 1.35)
IQS3	(1, 1.15, 1.46)	(1, 1.15, 1.46)	(1, 1, 1)	(1, 1.15, 1.50)	(1.00, 1.15, 1.65)
IQS4	(0.77, 1.15, 1.31)	(0.77, 1.15, 1.31)	(0.72, 0.90, 1)	(1, 1, 1)	(1.00, 1.00, 1.15)
IQS5	(0.77, 1, 1.15)	(0.77, 1, 1.15)	(0.62, 0.90, 1)	(0.90, 1, 1)	(1.00, 1.00, 1.00)

[a]Consistency ratio (CR) for the defuzzified version of this matrix is 0.025 < 0.10

Table 14 Aggregated fuzzy evaluation matrix[a] of competence (IQC) sub-criteria

	IQC1	IQC2	IQC3	IQC4	IQC5	IQC6	IQC7	IQC8	IQC9
IQC1	(1, 1, 1)	(1, 1, 1.19)	(0.72, 0.90, 1.15)	(0.55, 0.77, 1)	(0.77, 1, 1.15)	(0.72, 0.90, 1.15)	(0.77, 1, 1.15)	(0.55, 0.77, 1)	(0.45, 0.59, 0.85)
IQC2	(0.87, 1, 1)	(1, 1, 1)	(0.85, 0.90, 1.35)	(0.55, 0.77, 1)	(0.77, 1, 1.15)	(0.72, 0.90, 1.15)	(0.77, 1, 1.15)	(0.55, 0.77, 1)	(0.47, 0.62, 0.90)
IQC3	(0.90, 1.15, 1.50)	(0.77, 1.15, 1.31)	(1, 1, 1)	(0.72, 0.90, 1)	(1, 1, 1.15)	(1, 1, 1)	(1, 1, 1.15)	(0.72, 0.90, 1)	(0.59, 0.85, 0.90)
IQC4	(1, 1.35, 1.85)	(1, 1.35, 1.85)	(1, 1.15, 1.50)	(1, 1, 1)	(1, 1.15, 1.65)	(1, 1.15, 1.50)	(1, 1.15, 1.65)	(1, 1, 1)	(0.80, 1, 1)
IQC5	(0.90, 1, 1.35)	(0.90, 1, 1.35)	(0.90, 1, 1)	(0.62, 0.90, 1)	(1, 1, 1)	(0.90, 1, 1)	(1, 1, 1)	(0.62, 0.90, 1)	(0.53, 0.74, 0.90)
IQC6	(0.90, 1.15, 1.50)	(0.90, 1.15, 1.50)	(1, 1, 1)	(0.72, 0.90, 1)	(1, 1, 1.15)	(1, 1, 1)	(0.90, 1, 1.15)	(0.72, 0.90, 1)	(0.59, 0.85, 0.90)
IQC7	(0.90, 1, 1.35)	(0.90, 1, 1.35)	(0.90, 1, 1)	(0.62, 0.90, 1)	(1, 1, 1)	(0.90, 1, 1.15)	(1, 1, 1)	(0.62, 0.90, 1)	(0.51, 0.71, 0.85)
IQC8	(1, 1.35, 1.85)	(1, 1.35, 1.85)	(1, 1.15, 1.50)	(1, 1, 1)	(1, 1.15, 1.65)	(1, 1.15, 1.50)	(1, 1.15, 1.65)	(1, 1, 1)	(0.80, 1, 1)
IQC9	(1.31, 1.81, 2.31)	(1.15, 1.65, 2.15)	(1.15, 1.31, 1.81)	(1, 1, 1.31)	(1.15, 1.46, 1.96)	(1.15, 1.31, 1.81)	(1.31, 1.62, 2.12)	(1, 1, 1.31)	(1, 1, 1)

[a]Consistency ratio (CR) for the defuzzified version of this matrix is 0.045 < 0.10

Table 16 Aggregated fuzzy evaluation matrix[a] of technical specifications(TS) sub-criteria

	TS1	TS2	TS3	TS4	TS5	TS6
TS1	(1, 1, 1)	(1, 1, 1.19)	(0.85, 0.90, 1.19)	(0.62, 0.90, 1)	(0.80, 1, 1)	(0.55, 0.77, 1)
TS2	(0.87, 1, 1)	(1, 1, 1)	(0.85, 0.90, 1)	(0.55, 0.77, 1)	(0.67, 1, 1)	(0.51, 0.71, 0.87)
TS3	(0.87, 1.15, 1.31)	(1, 1.15, 1.31)	(1, 1, 1)	(0.71, 0.87, 1)	(0.77, 1, 1.15)	(0.64, 0.77, 0.81)
TS4	(1, 1.15, 1.65)	(1, 1.35, 1.85)	(1, 1.19, 1.54)	(1, 1, 1)	(1, 1, 1.35)	(0.87, 1, 1)
TS5	(1, 1, 1.31)	(1, 1, 1.50)	(0.90, 1, 1.35)	(0.77, 1, 1)	(1, 1, 1)	(0.71, 0.87, 1)
TS6	(1, 1.35, 1.85)	(1.19, 1.54, 2.04)	(1.38, 1.57, 1.92)	(1, 1, 1.19)	(1, 1.19, 1.54)	(1, 1, 1)

[a]Consistency ratio (CR) for the defuzzified version of this matrix is $0.073 < 0.10$

Table 17 Aggregated fuzzy evaluation matrix[a] of general feature (GF) sub-criteria

	GF1	GF2	GF3	GF4	GF5	GF6	GF7
GF1	(1, 1, 1)	(1, 1, 1.35)	(1, 1.19, 1.54)	(1, 1, 1.19)	(1, 1.19, 1.69)	(1.19, 1.54, 2.04)	(1.38, 1.88, 2.38)
GF2	(0.77, 1, 1)	(1, 1, 1)	(0.90, 1, 1.35)	(0.90, 1, 1)	(1, 1, 1.35)	(1, 1.35, 1.69)	(1, 1.35, 1.85)
GF3	(0.71, 0.87, 1)	(0.77, 1, 1.15)	(1, 1, 1)	(0.77, 1, 1)	(1, 1, 1.15)	(1, 1, 1.50)	(1, 1.15, 1.65)
GF4	(0.87, 1, 1)	(1, 1, 1.15)	(1, 1, 1.35)	(1, 1, 1)	(1, 1, 1.50)	(1, 1.35, 1.85)	(1, 1.50, 2.00)
GF5	(0.61, 0.87, 1)	(0.77, 1, 1)	(0.90, 1, 1)	(0.67, 1, 1)	(1, 1, 1)	(1, 1, 1.35)	(1, 1, 1.50)
GF6	(0.51, 0.71, 0.87)	(0.65, 0.77, 1)	(0.67, 1, 1)	(0.55, 0.77, 1)	(0.77, 1, 1)	(1, 1, 1)	(1, 1, 1.15)
GF7	(0.44, 0.57, 0.81)	(0.55, 0.77, 1)	(0.62, 0.90, 1)	(0.50, 0.67, 1)	(0.67, 1, 1)	(0.90, 1, 1)	(1, 1, 1)

[a]Consistency ratio (CR) for the defuzzified version of this matrix is $0.055 < 0.10$

Table 18 Fuzzy synthetic extent values (S_i), weights (W_i'), and normalized weights (W_i) of the main criteria

	S_i	$W_i' = d'(C_i)^T$	$W_i = d(C_i)^T$
IQ	(0.261, 0.315, 0.384)	0.692	0.284
TS	(0.271, 0.315, 0.422)	0.745	0.306
GF	(0.259, 0.370, 0.458)	1	0.410

Table 19 Fuzzy synthetic extent values (S_i), weights (W_i'), and normalized weights (W_i) of the individual qualifications (IQ)

	S_i	$W_i' = d'(C_i)^T$	$W_i = d(C_i)^T$
IQS	(0.251, 0.315, 0.365)	0.634	0.265
IQC	(0.271, 0.315, 0.441)	0.755	0.316
IQK	(0.269, 0.370, 0.458)	1	0.419

It is assumed that, in group decision making, DMs' hierarchical job levels and the importance of their verbal evaluations may be different. Therefore, different from previous fuzzy AHP/TOPSIS applications in the literature, in this paper HLW are implemented in group decision

Table 20 Fuzzy synthetic extent values (S_i), weights (W_i'), and normalized weights (W_i) of the sociability (IQS) sub-criteria

	S_i	$W_i' = d'(C_i)^T$	$W_i = \mathrm{d}(C_i)^{\mathrm{T}}$
IQS1	(0.152, 0.189, 0.255)	0.726	0.181
IQS2	(0.152, 0.189, 0.255)	0.726	0.181
IQS3	(0.169, 0.222, 0.318)	1	0.250
IQS4	(0.144, 0.206, 0.259)	0.847	0.211
IQS5	(0.137, 0.193, 0.238)	0.708	0.177

Table 21 Fuzzy synthetic extent values (S_i), weights (W_i'), and normalized weights (W_i) of the competence (IQC) sub-criteria

	S_i	$W_i' = d'(C_i)^T$	$W_i = d(C_i)^T$
IQC1	(0.065, 0.095, 0.136)	0.403	0.076
IQC2	(0.065, 0.095, 0.137)	0.410	0.077
IQC3	(0.076, 0.107, 0.141)	0.505	0.096
IQC4	(0.087, 0.123, 0.183)	0.785	0.149
IQC5	(0.073, 0.102, 0.135)	0.434	0.082
IQC6	(0.077, 0.107, 0.144)	0.522	0.099
IQC7	(0.073, 0.102, 0.136)	0.442	0.084
IQC8	(0.087, 0.123, 0.183)	0.785	0.149
IQC9	(0.102, 0.146, 0.222)	1	0.189

Table 22 Fuzzy synthetic extent values (S_i), weights (W_i'), and normalized weights (W_i) of the knowledge (IQK) sub-criteria

	S_i	$W_i' = d'(C_i)^T$	$W_i = \mathrm{d}(C_i)^{\mathrm{T}}$
IQK1	(0.242, 0.318, 0.364)	0.619	0.269
IQK2	(0.291, 0.363, 0.500)	1.000	0.435
IQK3	(0.266, 0.318, 0.387)	0.681	0.296

Table 23 Fuzzy synthetic extent values (S_i), weights (W_i'), and normalized weights (W_i) of the technical specifications (TS) sub-criteria

	S_i	$W_i' = d'(C_i)^T$	$W_i = d(C_i)^T$
TS1	(0.110, 0.150, 0.199)	0.468	0.123
TS2	(0.102, 0.145, 0.183)	0.353	0.093
TS3	(0.114, 0.160, 0.205)	0.549	0.145
TS4	(0.134, 0.180, 0.261)	0.813	0.215
TS5	(0.122, 0.158, 0.223)	0.606	0.160
TS6	(0.150, 0.206, 0.297)	1.000	0.264

Table 24 Fuzzy synthetic extent values (S_i), weights (W_i'), and normalized weights (W_i) of the general feature (GF) sub-criteria

	S_i	$W_i' = d'(C_i)^T$	$W_i = d(C_i)^T$
GF1	(0.125, 0.175, 0.260)	1.000	0.212
GF2	(0.109, 0.153, 0.214)	0.802	0.170
GF3	(0.104, 0.139, 0.197)	0.670	0.142
GF4	(0.114, 0.156, 0.229)	0.845	0.180
GF5	(0.098, 0.136, 0.182)	0.598	0.127
GF6	(0.085, 0.124, 0.163)	0.429	0.091
GF7	(0.077, 0.117, 0.158)	0.364	0.077

Table 26 Fuzzy evaluation scores for the alternatives in Fuzzy TOPSIS

Linguistic terms	Membership function
Very poor (VP)	(0, 0, 1)
Poor (P)	(0, 1, 3)
Medium poor (MP)	(1, 3, 5)
Fair (F)	(3, 5, 7)
Medium good (MG)	(5, 7, 9)
Good (G)	(7, 9, 10)
Very good (VG)	(9, 10, 10)

making to reflect the importance levels of DMs' evaluations in fuzzy AHP and fuzzy TOPSIS phases.

The developed methodology seems to be an effective, applicable way for handling this complicated MCDM ranking problem. As seen from the fuzzy AHP–TOPSIS results, based on the 30 sub-criteria considered, the best IT specialist candidate of the 5 alternatives is determined to be alternative 4, and these results were shared with the company involved. For future research, the results of this study may be compared with other fuzzy MCDM methods such as fuzzy PROMETHEE, VIKOR and ELECTRE. Also, correlations between criteria can be investigated with correlated fuzzy AHP, network relationships can be studied with fuzzy analytic network process (ANP), and these methods can then be integrated with fuzzy TOPSIS for MCDM ranking problems.

Table 25 Sub-criteria weights obtained from fuzzy AHP

IQS1	IQS2	IQS3	IQS4	IQS5	IQC1	IQC2	IQC3	IQC4	IQC5
0.014	0.014	0.019	0.016	0.013	0.007	0.007	0.009	0.013	0.007
IQC6	IQC7	IQC8	IQC9	IQK1	IQK2	IQK3	TS1	TS2	TS3
0.009	0.008	0.013	0.017	0.032	0.052	0.035	0.038	0.028	0.044
TS4	TS5	TS6	GF1	GF2	GF3	GF4	GF5	GF6	GF7
0.066	0.049	0.081	0.087	0.070	0.058	0.074	0.052	0.037	0.032

Table 27 Evaluation of alternatives with respect to all criteria by three decision makers (DM_1, DM_2 and DM_3)

Alt	IQS1	IQS2	IQS3	IQS4	IQS5	IQC1
1	(G, MG, G)	(MG, MG, MG)	(G, G, G)	(VG, G, G)	(G, G, MG)	(G, G, MG)
2	(MG, MG, MG)	(F, F, MG)	(MG, MG, F)	(MG, MG, MG)	(G, MG, MG)	(F, MG, F)
3	(VG, G, G)	(G, MG, MG)	(VG, VG, VG)	(G, MG, MG)	(VG, G, G)	(P, P, VP)
4	(G, G, G)	(MG, MG, G)	(F, F, F)	(MP, MP, F)	(MP, F, MP)	(F, F, F)
5	(F, F, F)	(MG, G, MG)	(F, F, F)	(G, G, G)	(G, MG, G)	(F, F, F)

Alt	IQC2	IQC3	IQC4	IQC5	IQC6	IQC7
1	(F, MG, MG)	(MG, G, MG)	(G, MG, MG)	(MG, F, MG)	(MG, MG, F)	(G, F, MG)
2	(MG, MG, F)	(G, G, G)	(G, MG, MG)	(F, MG, F)	(F, F, MG)	(F, F, F)
3	(MG, MG, MG)	(P, MP, P)	(MP, MP, P)	(P, MP, P)	(P, P, P)	(P, P, MP)
4	(MG, G, MG)	(F, F, F)	(MG, G, MG)	(F, F, MG)	(MP, P, MP)	(P, VP, VP)
5	(MG, MG, MG)	(P, MP, P)	(MG, F, F)	(MP, MP, P)	(P, P, P)	(VP, VP, VP)

Alt	IQC8	IQC9	IQK1	IQK2	IQK3	TS1
1	(MG, MG, G)	(G, MG, G)	(F, MG, MG)	(G, G, G)	(F, F, F)	(F, F, F)
2	(G, G, VG)	(G, G, G)	(G, G, G)	(G, G, MG)	(MG, MG, MG)	(F, F, MG)
3	(MP, MP, MP)	(F, F, F)	(G, G, G)	(G, MG, MG)	(G, G, G)	(MP, F, MP)
4	(F, F, F)	(G, G, G)	(G, G, G)	(MG, MG, G)	(F, F, F)	(G, MG, MG)
5	(MP, MP, P)	(G, MG, MG)	(F, F, MG)	(MG, F, MG)	(F, F, F)	(MG, MG, MG)

Alt	TS2	TS3	TS4	TS5	TS6	GF1
1	(F, F, F)	(MG, MG, G)	(F, F, F)	(G, MG, G)	(P, P, F)	(G, G, G)
2	(F, F, F)	(MG, G, MG)	(MG, MG, F)	(G, G, G)	(VP, VP, VP)	(VG, VG, VG)
3	(F, F, F)	(MP, MP, P)	(MP, MP, P)	(MP, P, P)	(G, G, G)	(MG, MG, MG)
4	(G, G, G)	(G, G, G)	(VG, VG, VG)	(G, G, G)	(G, G, G)	(F, F, F)
5	(F, F, MP)	(F, F, F)	(MG, G, MG)	(MG, MG, F)	(MG, MG, F)	(G, G, G)

Alt	GF2	GF3	GF4	GF5	GF6	GF7
1	(MP, F, F)	(G, MG, MG)	(VG, G, VG)	(F, F, F)	(F, F, F)	(MG, F, MG)
2	(G, G, G)	(G, MG, MG)	(VG, VG, VG)	(F, F, F)	(F, F, F)	(F, F, F)
3	(MG, F, F)	(G, G, G)	(G, G, G)	(G, G, G)	(MG, MG, MG)	(MG, MG, G)
4	(F, F, F)	(MG, MG, MG)	(G, MG, MG)	(G, G, MG)	(F, F, F)	(F, F, F)
5	(MG, MG, MG)	(MG, MG, MG)	(F, MG, F)	(MG, F, F)	(F, F, MG)	(F, MG, F)

Table 28 Fuzzy decision matrix ($\tilde{D}$)

Alt	IQS1	IQS2	IQS3	IQS4	IQS5	IQC1
1	(6.38, 8.38, 9.69)	(5, 7, 9)	(7, 9, 10)	(7.62, 9.31, 10)	(6.24, 8.24, 9.62)	(6.24, 8.24, 9.62)
2	(5, 7, 9)	(3.76, 5.76, 7.76)	(4.24, 6.24, 8.24)	(5, 7, 9)	(5.62, 7.62, 9.31)	(3.62, 5.62, 7.62)
3	(7.62, 9.31, 10)	(5.62, 7.62, 9.31)	(9, 10, 10)	(5.62, 7.62, 9.31)	(7.62, 9.31, 10)	(0, 0.62, 2.24)
4	(7, 9, 10)	(5.76, 7.76, 9.38)	(3, 5, 7)	(1.76, 3.76, 5.76)	(1.62, 3.62, 5.62)	(3, 5, 7)
5	(3, 5, 7)	(5.62, 7.62, 9.31)	(3, 5, 7)	(7, 9, 10)	(6.38, 8.38, 9.69)	(3, 5, 7)

Alt	IQC2	IQC3	IQC4	IQC5	IQC6	IQC7
1	(4.38, 6.38, 8.38)	(5.62, 7.62, 9.31)	(5.62, 7.62, 9.31)	(4.38, 6.38, 8.38)	(4.24, 6.24, 8.24)	(5, 7, 8.69)
2	(4.24, 6.24, 8.24)	(7, 9, 10)	(5.62, 7.62, 9.31)	(3.62, 5.62, 7.62)	(3.76, 5.76, 7.76)	(3, 5, 7)
3	(5, 7, 9)	(0.31, 1.62, 3.62)	(0.62, 2.24, 4.24)	(0.31, 1.62, 3.62)	(0, 1, 3)	(0.38, 1.76, 3.76)
4	(5.62, 7.62, 9.31)	(3, 5, 7)	(5.62, 7.62, 9.31)	(3.76, 5.76, 7.76)	(0.69, 2.38, 4.38)	(0, 0.31, 1.62)
5	(5, 7, 9)	(0.31, 1.62, 3.62)	(3.62, 5.62, 7.62)	(0.62, 2.24, 4.24)	(0, 1, 3)	(0, 0, 1)

Alt	IQC8	IQC9	IQK1	IQK2	IQK3	TS1
1	(5.76, 7.76, 9.38)	(6.38, 8.38, 9.69)	(4.38, 6.38, 8.38)	(7, 9, 10)	(3, 5, 7)	(3, 5, 7)
2	(7.76, 9.38, 10)	(7, 9, 10)	(7, 9, 10)	(6.24, 8.24, 9.62)	(5, 7, 9)	(3.76, 5.76, 7.76)
3	(1, 3, 5)	(3, 5, 7)	(7, 9, 10)	(5.62, 7.62, 9.31)	(7, 9, 10)	(1.62, 3.62, 5.62)
4	(3, 5, 7)	(7, 9, 10)	(7, 9, 10)	(5.76, 7.76, 9.38)	(3, 5, 7)	(5.62, 7.62, 9.31)
5	(0.62, 2.24, 4.24)	(5.62, 7.62, 9.31)	(3.76, 5.76, 7.76)	(4.38, 6.38, 8.38)	(3, 5, 7)	(5, 7, 9)

Alt	TS2	TS3	TS4	TS5	TS6	GF1
1	(3, 5, 7)	(5.76, 7.76, 9.38)	(3, 5, 7)	(6.38, 8.38, 9.69)	(1.14, 2.52, 4.52)	(7, 9, 10)
2	(3, 5, 7)	(5.62, 7.62, 9.31)	(4.24, 6.24, 8.24)	(7, 9, 10)	(0, 0, 1)	(9, 10, 10)
3	(3, 5, 7)	(0.62, 2.24, 4.24)	(0.62, 2.24, 4.24)	(0.31, 1.62, 3.62)	(7, 9, 10)	(5, 7, 9)
4	(7, 9, 10)	(7, 9, 10)	(9, 10, 10)	(7, 9, 10)	(7, 9, 10)	(3, 5, 7)
5	(2.24, 4.24, 6.24)	(3, 5, 7)	(5.62, 7.62, 9.31)	(4.24, 6.24, 8.24)	(4.24, 6.24, 8.24)	(7, 9, 10)

Alt	GF2	GF3	GF4	GF5	GF6	GF7
1	(2.38, 4.38, 6.38)	(5.62, 7.62, 9.31)	(8.38, 9.69, 10)	(3, 5, 7)	(3, 5, 7)	(4.38, 6.38, 8.38)
2	(7, 9, 10)	(5.62, 7.62, 9.31)	(9, 10, 10)	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)
3	(3.62, 5.62, 7.62)	(7, 9, 10)	(7, 9, 10)	(7, 9, 10)	(5, 7, 9)	(5.76, 7.76, 9.38)
4	(3, 5, 7)	(5, 7, 9)	(5.62, 7.62, 9.31)	(6.24, 8.24, 9.62)	(3, 5, 7)	(3, 5, 7)
5	(5, 7, 9)	(5, 7, 9)	(3.62, 5.62, 7.62)	(3.62, 5.62, 7.62)	(3.76, 5.76, 7.76)	(3.62, 5.62, 7.62)

Table 29 Fuzzy weighted normalized decision matrix ($\tilde{V}$)

Alt	IQS1	IQS2	IQS3	IQS4	IQS5	IQC1
1	(0.009, 0.011, 0.013)	(0.007, 0.010, 0.013)	(0.013, 0.017, 0.019)	(0.012, 0.015, 0.016)	(0.008, 0.011, 0.013)	(0.004, 0.006, 0.007)
2	(0.007, 0.010, 0.012)	(0.005, 0.008, 0.011)	(0.008, 0.012, 0.015)	(0.008, 0.011, 0.014)	(0.007, 0.010, 0.012)	(0.003, 0.004, 0.005)
3	(0.010, 0.013, 0.014)	(0.008, 0.011, 0.014)	(0.017, 0.019, 0.019)	(0.009, 0.012, 0.015)	(0.010, 0.012, 0.013)	(0.000, 0.000, 0.002)
4	(0.010, 0.012, 0.014)	(0.008, 0.011, 0.014)	(0.006, 0.009, 0.013)	(0.003, 0.006, 0.009)	(0.002, 0.005, 0.007)	(0.002, 0.004, 0.005)
5	(0.004, 0.007, 0.010)	(0.008, 0.011, 0.014)	(0.006, 0.009, 0.013)	(0.011, 0.014, 0.016)	(0.008, 0.011, 0.013)	(0.002, 0.004, 0.005)

Alt	IQC2	IQC3	IQC4	IQC5	IQC6	IQC7
1	(0.003, 0.005, 0.006)	(0.005, 0.007, 0.008)	(0.008, 0.011, 0.013)	(0.004, 0.006, 0.007)	(0.005, 0.007, 0.009)	(0.004, 0.006, 0.008)
2	(0.003, 0.005, 0.006)	(0.006, 0.008, 0.009)	(0.008, 0.011, 0.013)	(0.003, 0.005, 0.007)	(0.004, 0.006, 0.008)	(0.003, 0.004, 0.006)
3	(0.004, 0.005, 0.007)	(0.000, 0.001, 0.003)	(0.001, 0.003, 0.006)	(0.000, 0.001, 0.003)	(0.000, 0.001, 0.003)	(0.000, 0.002, 0.003)
4	(0.004, 0.006, 0.007)	(0.003, 0.004, 0.006)	(0.008, 0.011, 0.013)	(0.003, 0.005, 0.007)	(0.001, 0.003, 0.005)	(0.000, 0.000, 0.001)
5	(0.004, 0.005, 0.007)	(0.000, 0.001, 0.003)	(0.005, 0.008, 0.011)	(0.001, 0.002, 0.004)	(0.000, 0.001, 0.003)	(0.000, 0.000, 0.001)

Alt	IQC8	IQC9	IQK1	IQK2	IQK3	TS1
1	(0.008, 0.010, 0.013)	(0.011, 0.014, 0.016)	(0.014, 0.020, 0.027)	(0.036, 0.047, 0.052)	(0.011, 0.018, 0.025)	(0.012, 0.020, 0.028)
2	(0.010, 0.013, 0.013)	(0.012, 0.015, 0.017)	(0.022, 0.029, 0.032)	(0.032, 0.043, 0.050)	(0.018, 0.025, 0.032)	(0.015, 0.023, 0.031)
3	(0.001, 0.004, 0.007)	(0.005, 0.008, 0.012)	(0.022, 0.029, 0.032)	(0.029, 0.039, 0.048)	(0.025, 0.032, 0.035)	(0.007, 0.015, 0.023)
4	(0.004, 0.007, 0.009)	(0.012, 0.015, 0.017)	(0.022, 0.029, 0.032)	(0.030, 0.040, 0.048)	(0.011, 0.018, 0.025)	(0.023, 0.031, 0.038)
5	(0.001, 0.003, 0.006)	(0.010, 0.013, 0.016)	(0.012, 0.018, 0.025)	(0.023, 0.033, 0.043)	(0.011, 0.018, 0.025)	(0.020, 0.028, 0.036)

Alt	TS2	TS3	TS4	TS5	TS6	GF1
1	(0.009, 0.014, 0.020)	(0.026, 0.034, 0.042)	(0.020, 0.033, 0.046)	(0.031, 0.041, 0.047)	(0.009, 0.020, 0.037)	(0.061, 0.078, 0.087)
2	(0.009, 0.014, 0.020)	(0.025, 0.034, 0.041)	(0.028, 0.041, 0.054)	(0.034, 0.044, 0.049)	(0.000, 0.000, 0.008)	(0.078, 0.087, 0.087)
3	(0.009, 0.014, 0.020)	(0.003, 0.010, 0.019)	(0.004, 0.015, 0.028)	(0.002, 0.008, 0.018)	(0.056, 0.073, 0.081)	(0.044, 0.061, 0.078)
4	(0.020, 0.026, 0.029)	(0.031, 0.040, 0.044)	(0.059, 0.066, 0.066)	(0.034, 0.044, 0.049)	(0.056, 0.073, 0.081)	(0.026, 0.044, 0.061)
5	(0.006, 0.012, 0.018)	(0.013, 0.022, 0.031)	(0.037, 0.050, 0.061)	(0.021, 0.030, 0.040)	(0.034, 0.050, 0.066)	(0.061, 0.078, 0.087)

Alt	GF2	GF3	GF4	GF5	GF6	GF7
1	(0.017, 0.031, 0.045)	(0.033, 0.044, 0.054)	(0.062, 0.071, 0.074)	(0.016, 0.026, 0.037)	(0.012, 0.021, 0.029)	(0.015, 0.022, 0.028)
2	(0.049, 0.063, 0.070)	(0.033, 0.044, 0.054)	(0.066, 0.074, 0.074)	(0.016, 0.026, 0.037)	(0.012, 0.021, 0.029)	(0.010, 0.017, 0.024)
3	(0.025, 0.039, 0.053)	(0.041, 0.053, 0.058)	(0.052, 0.066, 0.074)	(0.037, 0.047, 0.052)	(0.021, 0.029, 0.037)	(0.019, 0.026, 0.032)
4	(0.021, 0.035, 0.049)	(0.029, 0.041, 0.053)	(0.041, 0.056, 0.069)	(0.033, 0.043, 0.050)	(0.012, 0.021, 0.029)	(0.010, 0.017, 0.024)
5	(0.035, 0.049, 0.063)	(0.029, 0.041, 0.053)	(0.027, 0.041, 0.056)	(0.019, 0.029, 0.040)	(0.016, 0.024, 0.032)	(0.012, 0.019, 0.026)

Table 30 Fuzzy AHP–TOPSIS results

Alternative	d_i^-	d_i^*	CC_i	Rankings
1	0.685	29.335	0.0228	3
2	0.710	29.306	0.0237	2
3	0.661	29.361	0.0220	4
4	0.723	29.295	0.0241	1
5	0.652	29.370	0.0217	5

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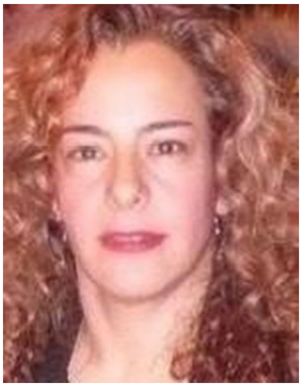

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