Personnel Selection with the Intuitionistic Fuzzy PROMETHEE Method

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Abstract: *Decision-making problems encountered in individual or institutional life often involve uncertainties. Although these uncertainties are frequently overlooked in small-scale decision-making processes, their negative effects increase as the problem's size and complexity grow, necessitating their consideration. In this context, intuitionistic fuzzy sets have begun to be used as an effective tool for solving decision-making processes where uncertainties are systematically evaluated. From a corporate perspective, selecting personnel who will work long-term or hold critical positions is a crucial decision that involves various uncertainties. This study examines the advantages of using the intuitionistic fuzzy PROMETHEE method for personnel selection in businesses and presents an application example. Additionally, the effects of uncertainties on the decision-making process are evaluated by applying the classical PROMETHEE and TOPSIS methods to the same set of alternatives. This study should be seen as an exemplary study. Therefore, it can be used in any country, in any field, and with varying selection criteria. This will serve as a resource for future studies.*

Keywords: **Personnel selection, Intuitionistic Fuzzy, MCDM, PROMETHEE method.**

1 Introduction

Globalization has intensified interactions among businesses, causing competition to emerge across multiple dimensions. As a result, a company's competitive environment has become increasingly uncertain, characterized by reduced visibility, heightened volatility, and a rapidly evolving landscape. This dynamic promotes the emergence of novel interactions and relationships among market participants, further complicating strategic decision-making. In such a context, traditional decision-making approaches often prove inadequate, emphasizing the need for advanced methods capable of handling uncertainty and complexity. Consequently, the integration of fuzzy set theory with multi-criteria decision-making techniques has gained considerable attention in the literature, offering robust tools to support strategic decisions under uncertain and dynamic conditions. The fragmentation of value chains and complex supply chains make the overall competitive landscape more complex and the positioning of individual companies more uncertain. One of the most significant resources for businesses is their employees. Therefore, for businesses to survive in a competitive environment, they must work with highly skilled personnel who have high performance in capability, knowledge, and skills. Companies that select the most suitable personnel for a job will be able to adapt more quickly to changes in the competitive environment. Under the influence of globalization, interaction between businesses is increasing, while also shifting the scale of competition between them to new dimensions. The competitive landscape in which a company operates has become more uncertain, with lower visibility and higher levels of uncertainty: a new dynamic characterized by a higher rate of change and potential new interactions and relationships between players. The fragmentation of value chains and complex supply chains make the picture of both relative strength in the overall competition and future direction more complex and the position of individual companies more uncertain [1]. One of the most important resources for businesses is their employees. Therefore, to survive in a competitive environment, businesses must employ highly qualified personnel with high performance in terms of talent, knowledge, skills, and other abilities. Businesses that have selected the most suitable personnel for the job will be able to adapt more quickly to changes in the competitive environment.

Personnel selection can be defined as identifying the most suitable candidate for a suitable position in a business.

Selecting the most suitable candidate for the job reduces workplace accidents, reduces personnel training expenses, increases productivity within the business, and enhances commitment between the business and the business [2].

When a business hires employees, criteria are determined based on past work experience and research. However, today's job requirements and processes are rapidly changing. Therefore, traditional personnel selection approaches based on static job characteristics are no longer sufficient [3]. Developing effective personnel selection approaches is crucial for finding the right people for the right jobs. The relevance of the selected criteria to future changing conditions and their effectiveness in the future are uncertain.

Schmidt has shown that the GMA (General Mental Ability) test has high validity and that adding GMA and other criteria with high validity to the evaluation increases the validity of personnel selection [4]. Therefore, multi-criteria decision making (MCDM) methods are widely used to help decision makers select the best employee for the specified job by considering the candidates' various qualifications, skills and performance criteria [5].

PROMETHEE (The Preference Ranking Organization Method for Enrichment Evaluation), one of the multi-criteria decision-making methods, can be used as a decision-making method in both selection and ranking problems. Çitil [6] used it to determine the most appropriate transportation service provider, Vetschera and De Almeida used it for portfolio selection, Abedi et al. used it for copper exploration [7], and Çitil and Tuğrul used it to rank school and student achievement [8], [9], [11]. In this study, we will use the PROMETHEE method, which is an extension of the PROMETHEE method with heuristic sets. The PROMETHEE method evaluates alternatives by making pairwise comparisons according to the criteria selected by the decision maker. In the PROMETHEE method, the decision maker determines a criterion function and the parameters of this function for each criterion during these comparisons. With the PROMETHEE method, it is possible to perform both partial and full rankings by evaluating the advantages of alternatives over each other in a single step [10].

In this study, the intuitionistic fuzzy PROMETHEE method was chosen because it allows for the consideration of the criteria determined for personnel selection and the uncertainties inherent in these criteria. In a decision-making problem, the criteria determined may not always fully represent the relevant problem. In this context, in criterion weights expressed in fuzzy sets, the membership value indicates the degree to which the criterion represents the problem, while the non-membership value indicates the degree to which it does not. Furthermore, the uncertainty value defined in addition to the weights determined by the intuitionistic fuzzy sets also reflects the uncertainty situations that the criterion may encounter in the future. This approach will increase the validity of the personnel selection process, enable more effective decisions under uncertainty, and enable each criterion to be analyzed with appropriate evaluation functions.

2 Preliminaries

Intuitionistic fuzzy sets were defined by Atanassov [12].

Definition 1. Let X be a non-empty set. The set A satisfying the conditions

$$\mu_A,\, \nu_A, \pi_A: X \to [0,1]$$

and

$$\mu_A(x) + \nu_A(x) + \pi_A(x) = 1 \qquad (1)$$

for $x \in X$

$$A = \{< x, \mu_A(x), \nu_A(x) > | x \in X\} \qquad (2)$$

is called an intuitionistic fuzzy set on X and is abbreviated as $A \in IFS(X)$ [12]. Here, $\mu_A(x)$ and $\nu_A(x)$ respectively represent the degree to which x is a member and a non-member of the intuitionistic fuzzy set A, for each $x \in X$. The intuitionistic fuzzy value is defined by Xu [13] as $\tilde{\alpha} = (\mu_{\tilde{\alpha}}, \nu_{\tilde{\alpha}}, \pi_{\tilde{\alpha}})$. Here $\mu_{\tilde{\alpha}}(x), \nu_{\tilde{\alpha}}(x), \pi_{\tilde{\alpha}}(x) \in [0,1]$ and $\mu_{\tilde{\alpha}}(x) + \nu_{\tilde{\alpha}}(x) + \pi_{\tilde{\alpha}}(x) = 1$.

Definition 2. The following operations are defined on intuitionistic fuzzy values [14]. Let $\tilde{a} =< \mu_{\tilde{a}}, \nu_{\tilde{a}} >$, $\tilde{b} =< \mu_{\tilde{b}}, \nu_{\tilde{b}} >$ two intuitionistic fuzzy values;

$$\tilde{a} \otimes \tilde{b} =< \mu_{\tilde{a}}\mu_{\tilde{b}}, \nu_{\tilde{a}} + \nu_{\tilde{b}} - \nu_{\tilde{a}}\nu_{\tilde{b}} > \quad (3)$$

$$\tilde{a} \oplus \tilde{b} =< \mu_{\tilde{a}} + \mu_{\tilde{b}} - \mu_{\tilde{a}}\mu_{\tilde{b}}, \nu_{\tilde{a}}\nu_{\tilde{b}} > \quad (4)$$

$$\oplus_{j=1}^{m} \tilde{a}_j = \langle 1 - \Pi_{j=1}^{m}(1 - \mu_j), \Pi_{j=1}^{m} \nu_j \rangle \quad (5)$$

$$\otimes_{j=1}^{m} \tilde{a}_j = \langle \Pi_{j=1}^{m} \mu_j, \Pi_{j=1}^{m}(1 - \nu_j) \rangle \quad (6)$$

$$\tilde{a}^{\lambda} =< \mu_{\tilde{a}}{}^{\lambda}(1 - \nu_{\tilde{a}}{}^{\lambda}) > \quad , \lambda > 0 \quad (7)$$

$$\lambda \tilde{a} =< 1 - (1 - \mu_{\tilde{a}})^{\lambda}, \nu_{\tilde{a}}{}^{\lambda} > \quad , \lambda > 0 \quad (8)$$

Definition 3. Let $\tilde{\alpha} = (\mu_{\tilde{\alpha}}, \nu_{\tilde{\alpha}}, \pi_{\tilde{\alpha}})$ be an intuitionistic fuzzy value defined as follows. The distance of $\tilde{\alpha}$ from the perfect alternative is measured by the function (9). To rank the intuitionistic fuzzy values, then images of all intuitionistic fuzzy values are found under the following function. The found values are ranked. The intuitionistic fuzzy value with the smallest value has the highest preference value [15].

$$\rho(\tilde{a}) = 0.5(1 + \pi_{\tilde{a}})(1 - \mu_{\tilde{a}}) \quad (9)$$

Definition 4. Let the set of alternatives be $X = \{x_1, x_2, x_3, \dots, x_n\}$. The intuitionistic preference relation B is defined as $B = (b_{ij})_{n \times n} \subset X \times X$. Here,

$$(b_{ij})_{n \times n} =< (x_i, x_j), \mu(x_i, x_j), \nu(x_i, x_j) > \text{ for all } i,j=1,2,3,\dots,n.$$

For convenience, $(b_{ij})_{n \times n}$ is often written as $< \mu_{ij}, \nu_{ij} >$. In this context, the value μ_{ij} represents the degree to which x_i is preferred over x_j , ν_{ij} represents the degree to which x_i is not preferred over x_j , and

$$\pi(x_i, x_j) = \pi_{ij} = 1 - \mu(x_i, x_j) - \nu(x_i, x_j)$$

represents the degree of uncertainty or hesitation. The values μ_{ij} and ν_{ij} satisfy the following conditions [13]:

$$\forall i,j=1,2,3,\dots,n \quad 0 \leq \mu_{ij} + \nu_{ij} \leq 1, \ \mu_{ij} = \nu_{ji}, \ \mu_{ii} = \nu_{ii} = 0.5. \quad (10)$$

Definition 5. Let $\tilde{a}_j = \langle t_{\tilde{a}_j}, 1 - f_{\tilde{a}_j} \rangle$ (,j=1,2,3,…,n) be a collection of intuitionistic fuzzy values, and let $\sum_{j=1}^{n} w_j$ be a weight vector w= $(w_1, w_2, \dots, w_n)^T$. The Intuitionistic Fuzzy Weighted Average Operator (IFWA) is defined as follows:

$$IFWA_w = (\tilde{a}_1, \tilde{a}_2, \dots, \tilde{a}_n) = w_1\tilde{a}_1 \oplus w_2\tilde{a}_2 \oplus \dots \oplus w_n\tilde{a}_n. \quad (11)$$

3 Intuitionistic Fuzzy PROMETHEE Method

The family of PROMETHEE preference ranking methods, which includes PROMETHEE I for partial ranking of alternatives and PROMETHEE II for full ranking of alternatives, was developed by Brans [10]. As decision-making scenarios became increasingly complex, several extensions of the PROMETHEE method were developed. These include PROMETHEE III, designed to address diverse problems and solution sets; PROMETHEE IV, which enables full or partial ranking of alternatives when the feasible solution set is continuous; PROMETHEE V, developed for problems involving segmentation constraints; PROMETHEE VI, aimed at modeling human reasoning processes; PROMETHEE GDSS, intended for group decision-making; and GAIA, which provides graphical representation and visual analysis. The traditional PROMETHEE method could not help in decision-making under uncertainty and fuzziness, which necessitated the extension of the PROMETHEE method. Therefore, Goumas and Lygerou first extended the PROMETHEE method with fuzzy numbers [16], and Huchang and Zeshui extended it with intuitionistic fuzzy sets [17].

Preference ranking methods are used to determine whether candidate alternatives are preferable, incomparable, or indifferent to each other based on the criteria. Preference ranking methods are useful for improving the decision-maker's preference based on the values of specific criteria. At the same time, these methods are strong in ranking alternatives with very different criteria, such as color and price of a car. Therefore, PROMETHEE methods are widely applied in many areas such as health, economy, education, and agriculture [18].

The steps of the intuitionistic fuzzy PROMETHEE method are as follows:
Step 1: Define the set of alternatives $X = \{x_1, x_2, \dots, x_n\}$ for the decision-making problem and the set of criteria $C = \{c_1, c_2, \dots, c_m\}$ along with the fuzzy weight vector $\widetilde{W} = (\widetilde{w}_1, \widetilde{w}_2, \widetilde{w}_3, \dots, \widetilde{w}_n)^T$ for the solution of the problem.

Step 2: The decision maker evaluates the alternatives x_i $(i = 1,2,\dots,n)$ for each criterion c_k $(k = 1,2,\dots,m)$ by providing numerical values a_{ik}.

Step 3: For each criterion c_k $(k = 1,2,\dots,m)$, a matrix $U^{(k)}$ is formed according to the chosen criterion function. Let $f_k(x)$ be the chosen criterion function, then:

$$U^{(k)} = \left(u_{ij}^{k}\right)_{n\times n} = f_k\left(u_{ij}^{k}\right) = f\left(a_{ik} - a_{jk}\right) \tag{12}$$

Step 4: Using the elements of the matrix $U^{(k)}$ and equation (10), form the intuitionistic preference matrix $B^{(k)}$ for each criterion c_k.

$$B^{(k)} = \left(b_{ij}^{k}\right)_{n\times n} = \begin{bmatrix} - & b_{12}^{k} & \dots & b_{1n}^{k} \\ b_{21}^{k} & - & \dots & b_{2n}^{k} \\ \vdots & \vdots & - & \vdots \\ b_{n1}^{k} & b_{n2}^{k} & \dots & - \end{bmatrix} \tag{13}$$

Substituting $b_{ij}^{(k)} = \langle \mu_{ij}^{(k)}, \nu_{ij}^{(k)} \rangle$ into equation (13), we get:

$$B^{(k)} = \begin{bmatrix} - & \left(\mu_{12}^{(k)}, \nu_{12}^{(k)}\right) & \dots & \left(\mu_{1n}^{(k)}, \nu_{1n}^{(k)}\right) \\ \left(\mu_{21}^{(k)}, \nu_{21}^{(k)}\right) & - & \dots & \left(\mu_{2n}^{(k)}, \nu_{2n}^{(k)}\right) \\ \vdots & \vdots & - & \vdots \\ \left(\mu_{n1}^{(k)}, \nu_{n1}^{(k)}\right) & \left(\mu_{n1}^{(k)}, \nu_{n1}^{(k)}\right) & \dots & - \end{bmatrix} \tag{14}$$

Step 5: After obtaining all the $B^{(k)}$ preference matrices, the intuitionistic decision matrix $R = \left(r_{ij}\right)_{n\times n}$ is derived using the IFWA operator as follows:

$$r\left(x_i, x_j\right) = r_{ij} = \bigoplus_{k=1}^{m} \left(\widetilde{w}_j \otimes b_{ij}^{(k)}\right) \tag{15}$$

The r_{ij} obtained in the equation above represents the degree of preference of alternative x_i over alternative xj according to all the criteria. In the equation, $\widetilde{w}_k =< \mu_{\widetilde{w}_k}, \nu_{\widetilde{w}_k} >$ and rearranging the terms using equation 2, we get:

$$r_{ij} = \left(1 - \prod_{k=1}^{m}\left(1 - \mu_{ij}^{(k)} \mu_{\widetilde{w}_k}\right), \prod_{k=1}^{m}\left(\nu_{ij}^{(k)} + \nu_{\widetilde{w}_k} - \nu_{ij}^{(k)} \nu_{\widetilde{w}_k}\right)\right) \tag{16}$$

Step 6: The positive and negative flows of the intuitionistic decision matrix are obtained using equations (17) and (18) [15].

$$\tilde{\varphi}^{+}(x_i) = \frac{1}{n-1} \bigoplus_{j=1, i\neq j}^{n} r\left(x_i, x_j\right) = \frac{1}{n-1} \bigoplus_{j=1, i\neq j}^{n} r_{ij} \tag{17}$$

$$\tilde{\varphi}^{-}(x_i) = \frac{1}{n-1} \bigoplus_{j=1, i \neq j}^{n} r(x_j, x_i) = \frac{1}{n-1} \bigoplus_{j=1, i \neq j}^{n} r_{ji} \tag{18}$$

Using these flows, the net flow is calculated, and the preference ranking of alternatives is determined. Liao and Xu used equation (9) to calculate the deviation between $\tilde{\varphi}^{+}(x_i)$ and $\tilde{\varphi}^{-}(x_i)$ to obtain the net flow [17]. The deviation between $\tilde{\varphi}^{+}(x_i)$ and $\tilde{\varphi}^{-}(x_i)$ is calculated as follows:

$$\rho\left(\tilde{\varphi}(x_i)\right) = \tilde{\varphi}^{+}(x_i) - \tilde{\varphi}^{-}(x_i) \tag{19}$$

The alternative with the smallest deviation has the highest preference value.

In PROMETHEE methods, preference functions are used instead of the normalized values of the criteria to compare alternatives. Brans and Vincke have defined six different preference functions that can typically be used in the PROMETHEE methods [10]. The ability to select a preference function and its parameters independently for each criterion distinguishes the PROMETHEE method from other MCDA methods. The definitions and graphs of these functions are given in Table (1).

Table 1. Definitions of Criterion Preference Functions

Criterion	Criterion Definition	Criterion Variables
Type I	$p(x) = \begin{cases} 0 & , x \leq 0 \\ 1 & , 0 < x \end{cases}$	-
Type II	$p(x) = \begin{cases} 0 & , l \leq 0 \\ 1 & , 0 < l \end{cases}$	l
Type III	$p(x) = \begin{cases} 0 & , x < 0 \\ x/m & , 0 \leq x \leq m \\ 1 & m < x \end{cases}$	m
Type IV	$p(x) = \begin{cases} 0 & , x \leq q \\ 1/2 & , q < x \leq q + p \\ 1 & , q + p < x \end{cases}$	q, p
Type V	$p(x) = \begin{cases} 0 & , x \leq 0 \\ (x - s)/r & , s < x \leq s + r \\ 1 & , s + r < x \end{cases}$	s, r
Type VI	$p(x) = \begin{cases} 0 & , x \leq 0 \\ 1 - e^{-x^2/2\sigma^2} & , 0 < x \end{cases}$	σ

Ordinary (Type I) Preference Function: This criterion is used when the magnitude of the difference between two alternatives does not matter [19]. For example, if the candidate with the most languages spoken is preferred, this preference function can be used. U-shape (Type II) Preference Function: This is a special case of the level function. It is used when a difference between two alternatives should only be considered after exceeding a certain threshold [19]. For example, if a candidate with more than 3 years of experience is preferred, this preference function is used.

V-shape (Type III) Preference Function: Similar to Type II, this function increases linearly as the difference between two alternatives increases [19]. For instance, in a job selection process, if the income difference between two jobs exceeds 100 TL, then a preference can be made based on the income difference *d*, with the function $\frac{d}{100}$.

Level (Type IV) Preference Function: Suitable for qualitative criteria. This function is used when small or large deviations need to be differentiated, and the criterion has more than one level [19]. For example, the difference in the number of programming languages between two candidates could be represented as 0 if the difference is 0,0.5 if the difference is 1, and 1 if the difference is more than 1.

Linear (Type V) Preference Function: This function is defined with two parameters. If the difference in scores between two alternatives is smaller than the first parameter, the alternatives are considered equal; if the difference is between the first and second parameters, the preference value increases linearly, and if the difference exceeds the second parameter, the alternative with the higher score is chosen. These parameters are defined by the decision maker or evaluators. This is one of the most commonly used preference functions [19].

Gaussian (Type VI) Preference Function: This function is used when the data exhibit a normal distribution. The preference increases gradually from zero as the differences between the criterion values grow. Here, σ is the standard deviation of the data group.

Other preference functions have also been defined. Podvezko and Podviezko defined a multi-step preference function for criteria with discrete values, and the C-shaped preference function for situations where small differences between criteria are more important than large ones [19].

4 An Application of the Heuristic Fuzzy PROMETHEE Method in Personnel Selection

The criteria used for personnel selection vary across different job sectors. Therefore, there is no universal criterion or parameter applicable to all personnel selection problems. For instance, in a job where experience gained over time is crucial, age may be an important and desirable criterion, whereas, for selecting an athlete for a sports club, age may become an undesirable or irrelevant factor beyond a certain threshold. Due to these reasons, we will conduct an application using six of the most well-known criterion functions. As an example scenario, let us consider a personnel selection process for the Internet banking department of a bank. Furthermore, let us assume that our scenario involves 15 candidates and 3 decision-makers. Let $A = \{A_1, A_2, A_3, \dots, A_{15}\}$ be the set of alternatives and $C = \{C_1, C_2, C_3, C_4, C_5, C_6\}$ be the set of criteria. The descriptions of these criteria are provided in Table 2.

Table 2. Criteria and their descriptions

Criterion Number	Criterion Description
C_1	Previous experience in this field
C_2	Years of experience in software development
C_3	Foreign language exam score
C_4	Knowledge and experience with certifications such as ISO27001, ISO9001
C_5	Integrity Test
C_6	Score obtained in a nationwide examination

The scores obtained by the candidates based on their performance in examinations, resumes, and tests related to the given criteria are shown in Table 3.

Criterion functions have been chosen based on expert opinions and industry standards. Parameters have been determined through historical data and expert evaluations. The identified criterion function types and parameters are as follows:

C1 : Type I criterion function. No parameter definition is required (values are 0 or 1).
C2 : Type II criterion function. Max=20, Min=0, l=6.
C3 : Type III criterion function. Max=100, Min=50, m=20.
C4 : Type IV criterion function. Value set {0,1,2,3,4,5}, q=2, p=1.
C5 : Type V criterion function. Max=100, Min=0, s=30, r=60.
C6 : Type VI criterion function. Max=100, Min=10, standard deviation=12,150.

In the heuristic fuzzy PROMETHEE method, there can be a single decision-maker or multiple decision-makers. When multiple decision-makers are involved, the importance of criteria may vary among them. In the heuristic fuzzy PROMETHEE method, criterion weights are represented by heuristic fuzzy values, whereas, in the TOPSIS method, they are represented by normal values.

Table 3. Candidates and Their Scoreson Criteria

	C_1	C_2	C_3	C_4	C_5	C_6
A_1	1	0	25	0	80	75
A_2	0	15	40	2	70	80
A_3	1	3	50	3	40	78
A_4	0	1	27	4	50	89
A_5	0	2	10	5	50	81
A_6	0	1	12	1	40	92
A_7	0	7	8	2	20	67
A_8	1	9	16	3	90	70
A_9	0	13	32	2	100	87
A_{10}	0	8	19	3	100	76
A_{11}	1	9	5	0	20	76
A_{12}	1	2	34	1	80	47
A_{13}	0	2	28	3	50	50
A_{14}	1	2	37	2	60	75
A_{15}	1	12	45	4	70	70

Table 4. Intuitionistic Fuzzy and Normal Values of Linguistic Variables

Linguistic Expression	Intuitionistic Fuzzy Numeric Value
Very Important	(0.90, 0.10)
Important	(0.75, 0.20)
Medium	(0.50, 0.45)
Unimportant	(0.35, 0.60)
Very Unimportant	(0.10, 0.90)

Since we will evaluate the problem using both the heuristic fuzzy PROMETHEE and TOPSIS methods, different approaches will be employed to determine the criterion weights. In the heuristic fuzzy PROMETHEE method, a group of three decision-makers will assess the criteria using linguistic variables. Subsequently, using these assessments and the importance values of the decision-makers, the criterion weights will be calculated as heuristic fuzzy values utilizing the IFWA operator. The importance values of the decision-makers are provided in Table 5, and their assessments of the criteria are presented in Table 6.

Table 5. Decision Makers and Their Weights

DM_1	DM_2	DM_3
Important	Medium	Very Important
0.3562	0.2375	0.4061

Table 6. Evaluation of the Importance of Criteria by the Decision Makers

	C_1	C_2	C_3	C_4	C_5	C_6
DM_1	VI	U	M	U	I	M
DM_2	VI	U	U	VI	VI	M
DM_3	I	M	U	M	M	I

For the TOPSIS method, the criteria weights will be calculated using the Entropy method.

The Entropy method is used to derive the criteria weights by utilizing the values present in the decision matrix.

One of the strengths of Entropy is that it provides more objective results based on the scores of alternatives without requiring the evaluations of decision makers.

If the alternatives are selected based on the intuitionistic fuzzy values in Table 3 and the criteria weights are based on the intuitionistic fuzzy values in Table 7, and the Intuitionistic Fuzzy PROMETHEE method is applied, then positive and negative flows as shown in Table 8 can be obtained. To rank these flow values, the formula (19) is applied, and the net flow as shown in Table 8 is obtained. These net flow scores are then ranked from the smallest to the largest, yielding the ranking of the alternatives. This ranking is presented in Table 9. The TOPSIS method is also applied as in the literature, and the obtained ranking is provided in Table 9.

Table 7. Criteria Weights

Weights	μ_{wj}	ν_{wi}	w_j
w_1	0.8549	0.1325	0.4695
w_2	0.4157	0.5338	0.2310
w_3	0.4080	0.5415	0.0909
w_4	0.6254	0.3488	0.1445
w_5	0.5843	0.3974	0.0551
w_6	0.6227	0.3237	0.0087
Method	IF–PROMETHEE	IF–PROMETHEE	TOPSIS

Table 8. Positive, Negative and Net Flows

	Positive Flows	Negative Flows	Net Flows
A_1	0.89540816327	0.89540821291	−0.00000004965
A_2	0.89540852861	0.89540816327	0.00000036535
A_3	0.89583009466	0.89583009466	−0.00042193139
A_4	0.89542150707	0.89540816327	0.00001334380
A_5	0.89541145675	0.89540816327	0.00000329349
A_6	0.92153018122	0.89540816327	0.02612201795
A_7	0.91823962585	0.89540816327	0.02283146258
A_8	0.89540816327	0.89645801232	−0.00104984905
A_9	0.89540819734	0.89540816327	0.00000003408
A_{10}	0.89540913806	0.89540816327	0.00000097480
A_{11}	0.89540816327	0.89540816338	−0.00000000012
A_{12}	0.89540816327	0.89541491534	−0.00000675208
A_{13}	0.89582074477	0.89540816327	0.00041258150
A_{14}	0.89540816327	0.89564588948	−0.00023772621
A_{15}	0.89540816327	0.93839712054	−0.04298895728

Table 9. Evaluations Made and Resulting Rankings

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.
TOPSIS	A_{15}	A_8	A_{11}	A_3	A_{14}	A_{12}	A_1	A_2	A_9	A_{10}	A_5	A_7	A_4	A_{13}	A_6
PROMETHEE	A_{15}	A_8	A_3	A_{14}	A_{11}	A_{12}	A_1	A_2	A_9	A_{10}	A_4	A_5	A_{13}	A_7	A_6
IF PROMETHEE	A_{15}	A_8	A_3	A_{14}	A_{12}	A_1	A_{11}	A_9	A_2	A_{10}	A_5	A_4	A_{13}	A_7	A_6

The main objective of comparing the Intuitionistic Fuzzy PROMETHEE method with TOPSIS and Entropy, using weights determined by intuitionistic fuzzy sets, is that in both TOPSIS and Entropy, the decision maker does not influence except in determining the criteria.

When criteria weighting is done using Entropy, the scores obtained by the alternatives from the criteria are used, and the decision maker has no intervention in the criteria weights. Similarly, in the TOPSIS method, the decision matrix used is composed of the scores the alternatives receive from the criteria, just like in the PROMETHEE method.

In the TOPSIS method, each column in the decision matrix is treated as a vector, and by converting it into a unit vector, a normalized matrix is created. In the PROMETHEE method, however, the normalization process of the decision matrix is performed using the criteria functions and parameters determined for each criterion.

The data obtained by the decision maker to evaluate the alternatives can be either discrete or continuous. Odvese and Tertsea [20] stated that making this distinction between discrete and continuous data ensures that the data is processed, analyzed, and interpreted correctly. This contributes to making better decisions and improving the reliability of research results.

By using the PROMETHEE method and selecting the correct criteria functions, the decision-making process will become more effective and accurate.

5 Conclusion

In our study, the Intuitionistic Fuzzy PROMETHEE, PROMETHEE, and TOPSIS methods were applied to the same set of alternatives, with the alternatives receiving the same scores. In the Intuitionistic Fuzzy PROMETHEE method, the intuitionistic fuzzy criteria weights, based on the evaluation of a three-person decision-making group, were used, while in the PROMETHEE and TOPSIS methods, the criteria weights were obtained using the Entropy method.

By using the Entropy and TOPSIS methods together, the decision-makers had no impact on the evaluation process because the scores of the alternatives, the criteria evaluations, and the criteria weights were all determined statistically. The criteria weights obtained by the Entropy method are based on the distribution of the scores. Therefore, a criterion that is considered important by the decision-makers may have a low or excessively high weight.

In the evaluation using the TOPSIS method, all criteria were evaluated in the same way, and the different characteristics of the criteria were ignored. With the use of the PROMETHEE method, decision-makers became more effective in the decision-making process, and the criteria were evaluated with criteria functions. Thus, the alternatives were better distinguished by using more information during the evaluation.

In the Intuitionistic Fuzzy PROMETHEE method, a group was involved in the criteria weighting process, followed by the decision-making process. In the rankings obtained, the alternatives were evaluated with a specific criteria function and its parameters for each criterion. This approach allowed for the selection of appropriate functions and parameters according to the characteristics of the criteria.

With the use of intuitionistic fuzzy sets, the alternatives could be evaluated with more information.

When Table 9 is examined, it can be seen that when the evaluation of alternatives and the determination of criteria weights were performed with more information, except for A_5, the rankings of the alternatives either declined or improved. This demonstrates that the use of more information in the evaluation process is important.

One of the advantages of the Intuitionistic Fuzzy PROMETHEE method is that it can evaluate according to the characteristic properties of the data used. For example, consider the presence of a front camera and the price of a phone as criteria. The values that alternatives can take for the front camera range from 0 to 1 , while the price can take any value between 0 and 1000 . In this case, the criteria need to be evaluated in different ways and with different parameters. By using intuitionistic fuzzy sets, the uncertainty of the future impact of the criteria chosen for the decision-making process will also be taken into account.

This study created an example for recruiting staff to any institution in Türkiye. However, this study and example can be used to select staff for any institution and position in any country, in any field, with modifications to the criteria, and will serve as a resource for future studies.

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