

Article

Personnel Selection in a Coffee Shop Company Based on a Multi-Criteria Decision-Aiding and Artificial Intelligence Approach

Diego Alonso Gastélum-Chavira ¹, Denisse Ballardo-Cárdenas ^{2,*}  and Ernesto León-Castro ³

¹ Department of Economic and Management Sciences, Universidad Autonoma de Occidente, Culiacán 80120, SI, Mexico; diego.chavira@uadeo.mx

² Department of Engineering and Systems, Universidad Autonoma de Occidente, Culiacán 80120, SI, Mexico

³ Faculty of Economics and Administrative Sciences, Universidad Catolica de la Santisima Concepcion, Concepcion 4081393, Chile; eleon@ucsc.cl

* Correspondence: denisse.ballardo@uadeo.mx; Tel.: +52-667-759-1300 (ext. 2309)

Abstract: Human capital management is a strategic element for companies in a globalized world. Therefore, they must use strategies and methods to recruit and select personnel assertively to focus their training, strengthening, and business growth efforts. Personnel selection can be seen as a decision problem and can be addressed in a multi-criteria decision-making context. This work aims to present the selection process of a barista in a Mexican coffee shop. The baristas could be the face of the company to customers, and they could significantly impact their overall experience. The personnel selection process included eleven candidates and three criteria. This process was performed using the ELECTRE-III to model the preferences of a decision-maker and RP2-NSGA-II+H, a multi-objective evolutionary algorithm that exploits fuzzy outranking relations to derive multi-criteria rankings. The ordering obtained with the algorithm did not have any inconsistency concerning the integral preference model, and it allowed for the selection of a candidate to occupy the barista position. The results show the relevance of combining preference modeling with multi-criteria analysis methods for decision-making and artificial intelligence techniques.



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1. Introduction

Nowadays, companies must face various challenges in the world of work. The demand for people who perform adequately and use their knowledge, skills, and attitudes in changing environments is increasingly relevant. This relevance lies in the fact that companies can obtain competitive advantages that allow them to maintain and grow in the market. Therefore, human capital management is a strategic element for these companies in a globalized world. Understanding the strategic importance of personnel selection, competency management, human capital development, the significant effects on development, organizational performance, and the retention of competent human capital place a company in a stronger position. Organizations must use strategies and methods to recruit and select personnel assertively to focus their training, strengthening, and business growth efforts.

Personnel selection can be seen as a decision problem, which must be posed appropriately. It is because, as Keeney (1996) [1] points out, the resolution begins when the decision problem is established. Within organizations, various decisions are made based on intuition and experience. Regarding using intuition versus formulas in decision-making, Kahneman (2011) [2] states that final decisions should be entrusted to formulas, especially in environments of low validity, to maximize the success of predictions in problems with uncertainty and unpredictability.

Specifically, the personnel selection problem can be addressed as a Multi-Criteria Decision Analysis (MCDA) problem. MCDA is an area of operations research that allows for addressing problems where criteria are present, some of which conflict. According to Roy (1990) [3], the purpose of Decision Aid is to help overcome ambiguity, uncertainty, and an abundance of bifurcations.

In MCDA, decision problems can be structured to select one or several solution alternatives from a set of alternatives; this type of problem is known as choice. Likewise, a ranking of these alternatives can be obtained in descending order based on the preferences of the decision-maker(s); this problem is known as the ranking problem. Moreover, obtaining a classification of alternatives is possible where the classes are defined a priori and have an order of preference; this problem is known as ordinal classification or sorting. The personnel selection problem can be approached as any MCDA problem: choice, ordering, or ordinal classification.

In general, problems in MCDA can be addressed by various approaches: multi-objective mathematical programming, multi-attribute utility theory, outranking relations, and preference disaggregation (Zopounidis, 2009) [4]. One of them is the functional approach, which is based on the idea that the utility of an alternative can be represented by a function that assigns a numerical value for each combination of alternative and criterion. These utility functions can be additive, multiplicative, or another function that reflects the relations between the alternatives and the criteria. MAUT and MAVT, methods of this approach, define functions to determine the degree of satisfaction with the alternatives concerning the criteria (see Zopounidis and Doumpos (2009) [5] for more information). On the other hand, the fuzzy set approach manages the uncertainty and imprecision associated with criteria and preferences. According to Slowinski (2009) [6], in flexible multi-objective linear programming using fuzzy coefficients, preference semantics and uncertainty are found together, and in that circumstance, a fuzzy set representation can be used for operations research and decision analysis. Fuzzy AHP, Fuzzy TOPSIS, and Fuzzy UTADIS are methods from this approach. Mathematical Programming (MP) is another approach used to address MCDA problems. This approach models the MCDA problem as a mathematical optimization problem, aiming to find the best combination of alternatives that maximizes or minimizes an objective function, subject to certain restrictions. For Slowinski (2009) [6], the first Multi-Criteria Decision Support Systems (MCDSSs) were mainly oriented for multi-objective mathematical programming problems. He presented a list of eight MCDSSs that included the multi-objective programming approach. Linear programming, integer programming, non-linear programming, and dynamic programming are methods from the mathematical programming approach. Likewise, the relational approach directly compares alternatives and evaluates their preference relations. Instead of assigning numerical values to alternatives or using utility functions to represent the decision-maker's preferences, this approach is based on the relative comparison of alternatives based on the considered criteria. In the relational approach, MCDA problems can be addressed, among others, from the perspective of outranking relations, with its multiple methods, highlighting two of the most prominent families: ELECTRE (B Roy, 1968) [7] and PROMETHEE (Brans, Vincke, and Mareschal, 1986) [8]. An outranking relation represents the decision-maker's preference integration model. Based on the decision-maker's preferences, Roy and Bouyssou (1986) [9] state that the value-focused approach is descriptive, which proposes a value or utility function to model the decision-maker's global preference, a functional system. Moreover, the authors affirm that outranking methods are constructive forms of building decision-maker preferences using outranking relations, which are considered relational systems.

On the other hand, some MCDA problems can be formulated as optimization problems. However, the complexity of this type of problem leads to high-dimensional solutions where the performance of exhaustive search algorithms is frequently low, especially the time needed to explore the solution space. Therefore, the use of heuristic algorithms for optimization problems is recommended. A heuristic technique consists of rules that seek good solutions with a reasonable computational cost. A heuristic is approximate because it

provides a good solution with relatively little effort without ensuring optimality. According to Reinefeld (2009) [10], a heuristic is a technique to find a solution in a graph or a decision tree with one or more solutions. A Metaheuristic is a process that guides and modifies the operations of heuristics to produce solutions efficiently. For Marinakis (2009) [11], heuristics and metaheuristics are important solution approaches to try to solve complex problems, mainly combinatorial problems; they are simple and have short running times. Taboo Search, Simulated Annealing, Evolutionary Methods, and Swarm Intelligence are examples of metaheuristics.

This work aims to present the selection process of a barista in a Mexican company dedicated to developing products and providing services related to prepared drinks based on coffee. A barista plays a fundamental role in the quality of the company's products, focusing on preparing coffee-based drinks. It is especially true if the barista has solid skills in preparing coffee drinks, as it can positively influence customer satisfaction and the company's reputation. Additionally, in some cases, baristas could be the face of the company to customers. Interaction with customers can significantly impact their overall experience. Hiring trained, skilled, and courteous baristas can improve the customer experience, build brand loyalty, and influence the company's positive reputation, which can attract more customers. It could increase the productivity and efficiency of the company by having a smoother and more profitable operation. Something important in hiring baristas is that they properly fit the company's culture and are committed to its values, as this can promote a collaborative and harmonious work environment.

Investing time and resources in identifying and hiring the most suitable candidates for the position is important. Therefore, in this work, the preferences of a company decision-maker were modeled on a set of competency-based criteria to evaluate a set of job applicants. This modeling was carried out using the outranking method ELECTRE-III. The fuzzy outranking relation obtained with said method is exploited using a multi-objective evolutionary algorithm to generate a ranking of job applicants in descending order of preferences. The article is organized as follows: Section 2 briefly presents works on personnel selection using MCDA, Fuzzy Logic, and multi-objective evolutionary algorithms. Section 3 shows the methodology for selecting personnel for the barista position. The results and discussion are presented in Section 4, while conclusions and future work are shown in Section 5.

2. Related Works

Various studies on personnel selection using MCDA, Fuzzy Logic, and multi-objective evolutionary algorithms have been presented in the literature. To name a few, Kabak, Burmaoğlu, and Kazançoğlu (2012) [12] used Fuzzy ANP, Fuzzy TOPSIS, and Fuzzy ELECTRE for a sniper selection. Here, ten criteria were considered to evaluate six candidates. Using the KM algorithm, Sang, Liu, and Qin (2015) [13] proposed an analytical solution to fuzzy TOPSIS. They took data from Chen (2000) [14] related to a software enterprise that wanted to hire a system analyst engineer from three candidates. Chang (2015) [15] combined Fuzzy Delphi, ANP, and TOPSIS to select optimal public relations personnel. This work included twelve criteria, four candidates, and three decision-makers.

Jasemi (2018) [16] presented a fuzzy ELECTRE approach where linguistic variables determined the weights and ranks. Their work provided a numerical example of a pipe manufacturing plant in Iran that needed to employ an industrial engineer. Five candidates, eight criteria, and four decision-makers were involved. Samanlıoğlu, Taskaya, Gulen, and Cokcan (2018) [17] used Fuzzy AHP and Fuzzy TOPSIS methods to select an employee in an IT department. This work included three criteria, twenty-five sub-criteria, five candidates, and three decision-makers.

Luo and Xing (2019) [18] proposed an approach for personnel selection, which included the Best–Worst, MABAC, and PROMETHEE methods and Linguistic Neutrosophic Numbers. They used data from Liang, Zhao, and Hong (2019) [19]. Kilic, Demirci, and Denle (2020) [20] joined Intuitionistic Fuzzy DEMATEL and Intuitionistic Fuzzy ELECTRE

to select an engineer for an air filter company. The work included five criteria, five candidates, and three decision-makers.

Chen and Hung (2020) [21] proposed a method that uses linguistic variables, TOPSIS, and entropy methods to eliminate unsuitable candidates. Moreover, they used PROMETHEE to aggregate data and derive a candidate's ranking. The case provided in this work is related to selecting a marketing manager, including twenty candidates, eight criteria, and three decision-makers. Chuang, Hu, Liou, and Tzeng (2020) [22] combined RST, DEMATEL based on ANP, and PROMETHEE-AS to create a data-driven multiple-attribute decision-making model. They explored a database with 390 employee evaluations and three aspects divided into twelve attributes to aid human resource managers in personnel selection and improvement.

Li, He, and Wang (2022) [23] proposed a data-driven decision-making approach that combines Data Analytics Algorithms and MCDM methods. They proposed a linear group best–worst method to obtain the weights of each criterion and used Intuitionistic Fuzzy Numbers to capture the decision-maker's preferences. The case included in their work included five candidates, eight criteria, and three decision-makers. Danişan, Özcan, and Eren (2022) [24] used Weighted Scoring, AHP, TOPSIS, and PROMETHEE methods for personnel selection in the textile sector. The work included thirty candidates and sixteen criteria. Leyva-Lopez, Solano-Noriega, Gastelum-Chavira, and Gaxiola-Valenzuela (2022) [25] presented a personnel selection process using a hybrid MCDA approach, which uses the ELECTRE-III method to model the preferences of decision-makers and a metaheuristic based-on multi-objective evolutionary algorithms to derive a ranking. The case included twenty-six candidates, nine criteria, and one decision-maker.

Nalbant (2024) [26] joined Interval type 2-based fuzzy DEMATEL and ANP for a personnel selection process that included twenty-two criteria and twenty-two candidates. Pinto-DelaCadena, Liern, and Vinueza-Cabezas (2024) [27] compared the Canos-Liern, TOPSIS, OWA, and Expert Evaluation Replication methods in four cases using fifty candidates and ten criteria. Finally, Mandal et al. (2024) [28] presented a hybrid MCDM framework to select a PhD supervisor using an Interval-Valued Intuitionistic fuzzy Analytic Hierarchy Process and TOPSIS. The case included five candidates, eight criteria, and three decision-makers. Table 1 summarizes the previous works related to personnel selection using MCDA methods.

From Table 1, it is noted that the related works here presented perform combinations of multi-criteria methods. It could represent practical and theoretically grounded challenges for analysts and decision-makers when addressing personnel selection. For instance, Kabak, Burmaoğlu, and Kazançoğlu (2012) [12] used Fuzzy ANP, Fuzzy TOPSIS, and Fuzzy ELECTRE for a sniper selection. Although the combination of these three methods can provide a complete framework that considers both the hierarchical relationships between the criteria and the detailed evaluation of the candidates, criteria evaluation and weight assignment in Fuzzy ANP, as well as fuzzy evaluation in Fuzzy TOPSIS and Fuzzy ELECTRE, largely depend on the subjective judgments of decision-makers. It can introduce bias and variability in the results, and integrating them is an important challenge. Likewise, the combination of Fuzzy Delphi, ANP, and TOPSIS presented in Chang (2015) [15] could be an effective strategy for personnel selection. However, it is important to consider the possible challenges and practical problems that may arise during its implementation. For example, the sensitivity in the choice of parameters and data normalization in TOPSIS or the definition of membership functions in Fuzzy Delphi. The same applies to the practical problems that may arise when combining Weighted Scoring, AHP, TOPSIS, and PROMETHEE methods in Danişan, Özcan, and Eren (2022) [24], including those related to the definition of compensatory and non-compensatory weights for functional and relational methods.

Table 1. References on personnel selection using MCDA methods.

Title	Reference	Methods
A fuzzy hybrid MCDM approach for professional selection	Kabak, Burmaoğlu, and Kazançoğlu (2012) [12]	Fuzzy ANP, Fuzzy TOPSIS, Fuzzy ELECTRE
The Use of a Hybrid MCDM Model for Public Relations Personnel Selection	Chang (2015) [15]	Fuzzy Delphi, ANP and TOPSIS
An analytical solution to fuzzy TOPSIS and its application in personnel selection for knowledge-intensive enterprise	Sang, Liu, and Qin (2015) [13]	Fuzzy TOPSIS using the KM algorithm
A new fuzzy ELECTRE-based multiple criteria method for personnel selection	Jasemi (2018) [16]	Fuzzy ELECTRE
A Fuzzy AHP–TOPSIS-Based Group Decision-Making Approach to IT Personnel Selection	Samanlioglu, Taskaya, Gulen, and Cokcan (2018) [17]	Fuzzy AHP, Fuzzy TOPSIS
A Hybrid Decision-Making Framework for Personnel Selection Using BWM, MABAC, and PROMETHEE	Luo and Xing (2019) [18]	Best–Worst, MABAC, and PROMETHEE methods, and Linguistic Neutrosophic Numbers
An integrated decision analysis methodology based on IF-DEMATEL and IF-ELECTRE for personnel selection	Kilic, Demirci, and Denle (2020) [20]	Intuitionistic Fuzzy DEMATEL and Intuitionistic Fuzzy ELECTRE
A two-phase model for personnel selection based on multi-type fuzzy information	Chen and Hung (2020) [21]	Linguistic variables, TOPSIS, PROMETHEE, and entropy methods
A data-driven madm model for personnel selection and improvement	Chuang, Hu, Liou, and Tzeng (2020) [22]	RST, DEMATEL-based on ANP, PROMETHEE-AS
A data-driven decision-making framework for personnel selection based on LGBWM and IFNs	Li, He, and Wang (2022) [23]	Linear group best–worst and IFN
Personnel Selection with Multi-Criteria Decision-Making Methods in the Ready-to-Wear Sector	Danişan, Özcan, and Eren (2022) [24]	Weighted Scoring, AHP, TOPSIS, PROMETHEE
A Personnel Selection Model for a Software Development Company based on the ELECTRE III	Leyva-Lopez et al. (2022) [25]	ELECTRE-III and a Multi-objective Evolutionary Algorithm
Method and a Variant of NSGA-II Application of Interval Valued Intuitionistic Fuzzy Uncertain MCDM Methodology for Ph.D Supervisor Selection Problem	Mandal et al. (2024) [28]	Interval-Valued Intuitionistic fuzzy Analytic Hierarchy Process and TOPSIS
A methodology for personnel selection in business development: An interval type 2-based fuzzy DEMATEL-ANP approach	Nalbant (2024) [26]	Interval type 2-based fuzzy DEMATEL and ANP
A Comparative Analysis of Multi-Criteria Decision Methods for Personnel Selection: A Practical Approach	Pinto-DelaCadena, Liern, and Vinueza-Cabezas (2024) [27]	Canos-Liern, TOPSIS, OWA, and Expert Evaluation Replication

Source: Own.

On the other hand, the combination of ELECTRE-III and a multi-objective evolutionary algorithm, as presented in Leyva-Lopez et al. (2022) [25], could imply practical problems in understanding the jargon of evolutionary computation by a decision-maker. However, typically, this part is transparent for such decision-makers. Moreover, the configuration of the parameters to run the algorithm could require experience to get good results.

Literature on personnel selection in an MCDA context using metaheuristics like evolutionary algorithms is scarce. Thus, this work contributes in at least two ways: (i) Using a multi-objective evolutionary algorithm to exploit the fuzzy outranking relation instead of the distillation method (see Giannoulis and Ishizaka (2010) [29]), classically used with ELECTRE-III. It contributes to the literature by suggesting that using artificial intelligence techniques can improve results compared to techniques that do not have mechanisms to minimize inconsistencies between the rankings and the fuzzy outranking relation, like the distillation method. Finding a solution without inconsistencies concerning the decision-maker's comprehensive model of preferences allows any company to have greater clarity regarding the decision to select, in this case, its personnel, and (ii) the decision support process to personnel selection in a company through a multi-criteria-multi-objective approach. This includes determining the weights and obtaining the preference and indifference thresholds to model the vagueness in the decision-maker's determination of the values of said thresholds. It also includes interpreting the rankings obtained and selecting the best alternatives, in this case, the best candidate.

3. Methodology for Selecting Personnel for the Barista Position

This section presents how the problem of personnel selection for the barista position in the coffee-related services company was approached. The work was performed in a Mexican company with several coffee shops and employees.

3.1. Data Source

The company provided the study data, and the authors of this work did not participate in their generation. This company carried out a personnel recruitment process that considered the characteristics of the barista position and integrated the evaluations, as shown in Appendix A.

3.2. Problem Statement

The approach to the problem of personnel selection for the barista position in the company from a relational approach was defined as follows:

Let

- A: a set of applicants to occupy the position of barista in the company;
- G: a set of criteria for evaluating A defined by a decision-maker;
- W: a set of criteria weights obtained from the decision-maker;
- T: sets of preference values issued by the decision-maker about G;
- S: a fuzzy outranking relation that allows for comparing the elements of A created with a method that integrates the data from A, C, W, and T.

The problem is to obtain a ranking O of A in decreasing order of preference from the exploitation of S; this ordering should be as consistent as possible with the information contained in S, where applicants who are in the highest positions in the ranking are considered preferential to occupy the position of barista.

3.3. Method

Two phases are distinguished when approaching decision problems from the perspective of outranking relations: modeling and exploitation. Both phases can be performed with a decision-maker or a group of decision-makers. When a group of decision-makers is included in the modeling phase, it can be sequential or parallel and synchronous or asynchronous. The objective in a group decision-making process is to obtain consensus in the process and results. It is possible to address multi-criteria group decision ranking problems using a computational system like that presented in Leyva et al. (2017) [30]. Regardless of whether the decision process includes one or more decision-makers, in the modeling phase, the decision-maker's preferences are modeled on criteria that evaluate alternatives.

From the modeling phase, an outranking relation is obtained that can be fuzzy or crisp. When the relation is fuzzy, the values in the pairwise comparison between alternatives

are between 0 and 1. Meanwhile, when the relation is crisp, the values in the pairwise comparison of alternatives are 0 or 1. In both cases, fuzzy or crisp, it is possible to know what one alternative is like compared to another. In the exploitation phase, this outranking relation is taken as input, and an attempt is made to obtain a recommendation in the form of a choice, ranking, or sorting, which is as consistent as possible with the information contained in the outranking relation.

In this work, the phase of modeling of ELECTRE-III was used to address the personnel selection problem. The ELECTRE-III method is based on eliminating alternatives that are not superior to the others in any of the criteria and choosing the best alternative from those that remain. It is based on the pairwise comparison of the alternatives concerning each criterion considered.

ELECTRE-III is robust to uncertainty in data and expert judgments as it relies on a relative comparison between alternatives rather than requiring precise data. It allows for modeling the decision-maker's vagueness concerning the values of alternatives on each criterion. It is possible through indifference, preference, and veto thresholds. In this work, the veto threshold was not used, but it allows for vetting an alternative a_1 even if it is better than alternative a_2 in all criteria except for the criterion or criteria where a veto value was defined.

In ELECTRE-III, the sensitivity to the criteria weights and the decision-maker's preferences are addressed with thresholds of agreement and disagreement. Criterion weights are considered votes for or against whether alternative a_1 is at least as good as an alternative a_2 . These weights are considered non-compensatory.

The ELECTRE-III method ranks alternatives based on their relative superiority, meaning that some alternatives may not be superior or inferior to others. However, in this work, only the phase of modeling of ELECTRE-III was used. In the exploitation phase, alternatives were ranked with RP^2 -NSGA-II+H (Leyva, Solano, Figueira, Liu, and Gastelum, 2021) [31], a Multi-Objective Evolutionary Algorithm (MOEA). RP^2 -NSGA-II+H was designed to tackle instances of the multi-criteria ranking problem by exploiting a fuzzy outranking relation. The ELECTRE-III/MOEA approach has been used in the personnel selection problem (Leyva et al. (2022) [25]. In addition to RP^2 -NSGA-II+H, others works were the ELECTRE-III/MOEA approach, which can be found in Leyva and Aguilera (2005) [32], SADAGE (Leyva López, Dautt Sánchez, and Aguilera Contreras, 2008) [33], SADGAGE (Leyva et al., 2017) [30], and RP^2 -MOGA+H (Leyva, Solano, and Gastelum, 2021) [34]. Applications of the ELECTRE-III/MOEA approach in other domains include: comparing economic sectors (Leyva et al., 2013) [35], sociodemographic analysis (Leyva-López, Gastélum-Chavira, and Lopez Portillo-Tostado, 2015) [36], parafinancial credit ranking model (Gastelum-Chavira, Leyva-Lopez, Solano-Noriega, Ahumada-Valenzuela, and Alvarez-Carrillo, 2017) [37], and storage location assignment problem (Fontana, López, Cavalcante, and Noriega, 2020) [38].

Other multi-criteria methods like VIKOR, TOSIS, AHP, and BWM were not considered for this personnel selection problem. VIKOR seeks a compromise solution between alternatives and aims to find the alternative closest to the ideal and the most acceptable. It considers the distances between each alternative and the ideal and the worst alternatives to calculate a utility index. According to Çalı (2019) [39], VIKOR proposes compromise ranking and compromise solutions based on an ideal point and enables the decision-maker to reflect their preferences. TOPSIS is based on the idea that the best alternative is the closest Euclidean distance to the ideal solution and the greatest Euclidean distance to the negative ideal solution. It calculates a relative proximity score for each alternative based on distances (benchmarks). The alternatives are compared directly to these benchmarks (see Hwang and Yoon (1981) [40] for more information). AHP decomposes a decision-making problem into a hierarchy of criteria and alternatives. It makes pairwise comparisons to determine their relative weights and preferences. Then, a normalization and summary process is carried out to obtain a ranking of alternatives. In AHP, according to Pardalos (1995) [41], to determine a numerical scale on a finite set of potential alternatives, AHP arbitrarily associates a single fixed number to each of his categories of ratios. BWM is

based on the idea of identifying the best and the worst elements concerning each criterion. In BWM, the best and worst elements are determined for each criterion and then used to calculate their relative weights. The weights are assigned to each alternative based on their relative importance (Rezaei, 2015) [42].

Compared to ELECTRE-III and PROMETHEE II, RP²-NSGA-II+H is robust enough to deal with irrelevant alternatives. Moreover, again compared to ELECTRE-III and PROMETHEE II, RP²-NSGA-II+H can identify and try to minimize non-rational violations of explicit preferences, e.g., given two alternatives, a1 and a2, in a fuzzy outranking relation where, in a global sense, a1 is preferred a2, a non-rational violation is presented if a1 is not preferred a2 in the ranking.

Due to the properties of RP²-NSGA-II+H and the sturdiness of ELECTRE-III for uncertainty in data and expert judgments, the ELECTRE-III/MOEA approach was chosen to perform this personnel selection problem. Figure 1 shows the general process for selecting personnel in the company.

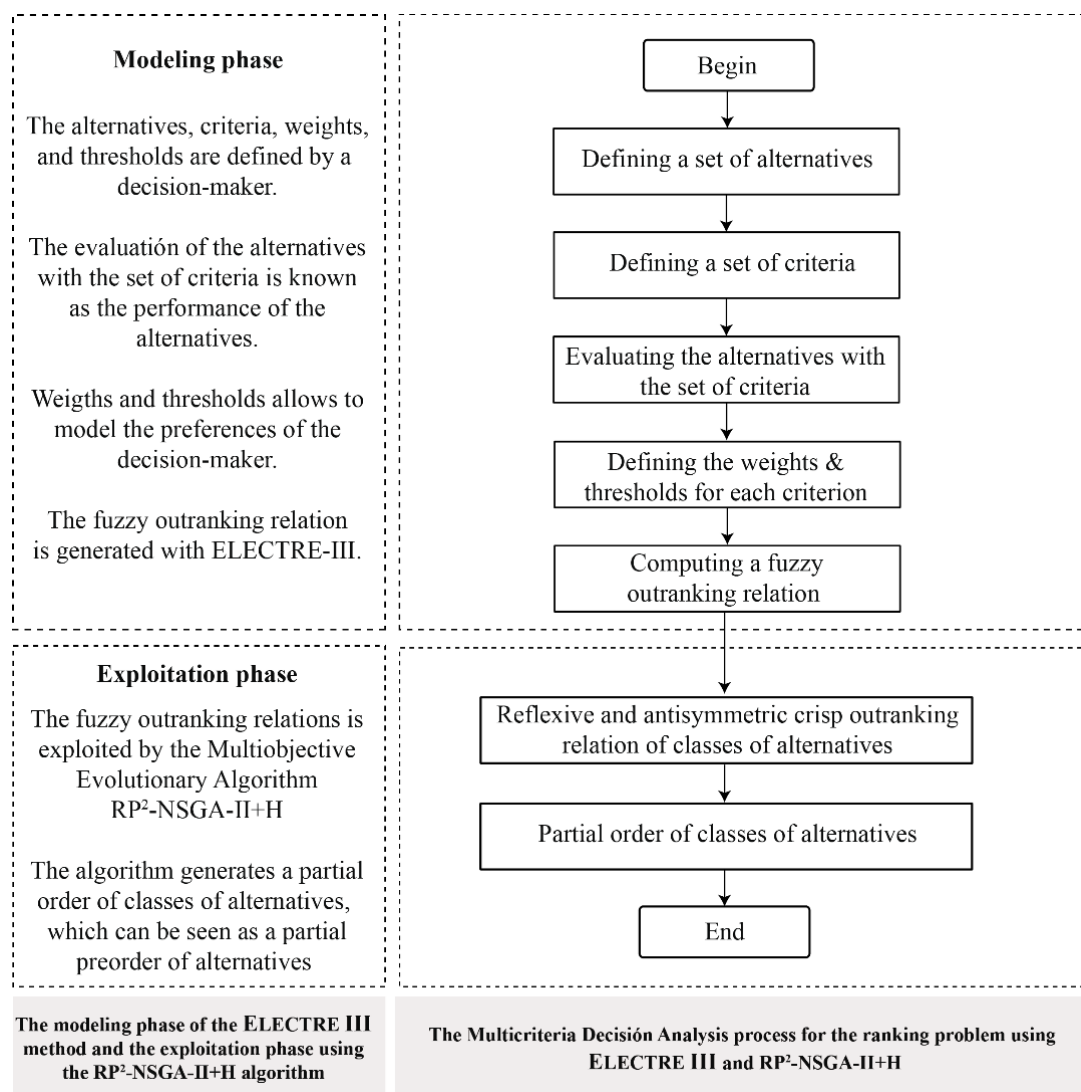


Figure 1. The general process for selecting personnel in the company. Source: Own.

3.3.1. Defining the Set of Alternatives

As mentioned in the problem statement, the set of alternatives corresponds to the set of applicants to occupy the barista position in the coffee shop company. In this case, it was made up of 11 candidates.

3.3.2. Defining the Criteria

Following the functions that the ideal candidate for the barista position must perform, the specific competencies were analyzed: knowledge, skills, and attitudes, each with sub-competencies. For this work, each competence corresponds to an evaluation criterion. The orientation of all criteria is to maximize. Table 2 presents the criteria for selecting personnel for the coffee shop company.

Table 2. Criteria considered for personnel selection.

Label	Competency (Criterion)	Sub-Competencies (Sub-Criterion)
C1	Knowledge	It includes 5 sub-competencies: numerical analysis, customer service, teamwork, verbal communication, and written communication.
C2	Skills	It includes 12 sub-competencies: responsibility, control, mental health, physical health, initiative, impact, listening, energy, stress tolerance, kindness, adaptability, and complaint management.
C3	Attitudes	It includes 6 sub-competencies: commitment, motivation for the work to be done, commercial spirit, sociability, self-motivation, and flexibility.

Source: Own with data from the company.

3.3.3. Evaluating the Alternatives with the Set of Criteria

The evaluation of the alternatives was carried out by the company and provided for the development of this study. The values of criteria and sub-criteria are presented in Appendix A. These values are on a scale of 0–100. Table 3 presents the values of the candidates for the barista position for each criterion.

Table 3. Values of the candidates for the barista position.

Alternative	Criterion		
	Knowledge	Skills	Attitudes
a1	80	36	9
a2	35	40	71
a3	45	28	80
a4	10	48	46
a5	75	72	31
a6	20	35	66
a7	25	38	49
a8	90	37	31
a9	15	77	17
a10	85	40	77
a11	55	80	91

Source: Own with data from the company.

3.3.4. Defining the Weights and Thresholds for Each Criterion

The set of weights or relative importance of the criteria obtained from the decision-maker was determined through Personal Construction Theory (Kelly, 1955) [43], which can be found in Rogers, Bruen, and Maystre (2000) [44]. Here, the decision-maker was asked to compare the criteria with each other to determine their weight. For instance, given a set of criteria $C = \{c_1, c_2, \dots, c_n\}$, the decision-maker is asked if criteria c_1 is more important than c_2 ; if it is true, a counter for c_1 counts one, zero otherwise. Then, the decision-maker is asked for c_1 concerning the rest of the criteria counting one if c_1 is more important. This process is repeated for all criteria. Table 4 shows the weights of each criterion obtained with Personal Construction Theory to evaluate candidates for the barista position.

Table 4. Weights of the criteria to evaluate candidates for the barista position.

	C1	C2	C3	Quantity	Quantity + 1	Weight
C1	-	>	>	2	3	0.50
C2	<	-	>	1	2	0.33
C3	<	<	-	0	1	0.17
	Sum			3	4	1.00

Source: Own.

On the other hand, the values of the indifference and preference thresholds issued by the decision-maker on the set of criteria were obtained through an elicitation process using successive approximations. In this case, no veto thresholds were defined. Using successive approximations implies presenting scenarios to the decision-maker for each threshold on each criterion. For instance, for the indifference threshold on the knowledge criterion, the decision-maker is asked to express his/her preference between two values, e.g., 60 and 90. Due to the criterion being oriented to maximize, the decision-maker's preference is probably 90. Next, the decision-maker is asked to express his/her preference between two new values, e.g., 80 and 90; in this scenario, the decision-maker's preference is probably 90. Next, the decision-maker is asked again to express his/her preference between two new values, e.g., 85 and 90; in this scenario, the decision-maker probably expresses that they are indifferent. Sometimes, decision-makers' preferences are non-linear or have maximum or minimum limits; thus, it is probably necessary to transform raw data using, for instance, fuzzy values and expressing such preferences as trapezoidal functions, as presented in Gastelum et al. (2017) [37]. Table 5 presents the thresholds of the evaluation criteria.

Table 5. Thresholds of the evaluation criteria.

Label	Criterion	Thresholds	
		Indifference	Preference
C1	Knowledge	5	6
C2	Skills	3	4
C3	Attitudes	5	6

Source: Own.

3.3.5. Computing the Fuzzy Outranking Relation

The fuzzy outranking relation was created using the ELECTRE III method (Bernard. Roy and Bouyssou, 1993) [45] using the alternatives, criteria, weights, and thresholds data from Tables 2–5. The ELECTRE III method generates a concordance relation and, if veto thresholds have been defined, a discordance relation. Then, ELECTRE III generates the fuzzy outranking relation that is considered the integral model of preferences. This fuzzy outranking relation is used to know how an alternative is compared to another based on the relation “being at least as good as”. To generate a fuzzy outranking relationship using the ELECTRE III method, see Figueira, Mousseau, and Roy (2005) [46]. In this work, the OutrankingTools R package version 1.0 available in CRAN (2023) [47] was used to generate the fuzzy outranking relation.

A fuzzy outranking relation is a fuzzy binary relation S^σ in A , where $S^\sigma: A \times A \rightarrow [0, 1]$ and A is the set of alternatives; so that $S^\sigma(a, b)$ represents the credibility that a and b remain in the relation S^σ . A fuzzy outranking relation has the reflective property $S^\sigma(a, a) = 1; \forall a \in A$, and it is usually asymmetric $S^\sigma(a, b) \Rightarrow \neg S^\sigma(b, a); \forall a, b \in A$. To illustrate the above, consider a set of alternatives $A = \{a, b, c, d\}$ and a fuzzy outranking relation S^σ on A (see Figure 2), such that $aS^\sigma b$ means “ a is at least as good as b ”.

	a	b	c	d
a	1.0	0.2	0.7	0.2
b	0.7	1.0	1.0	0.0
c	0.3	1.0	1.0	0.0
d	1.0	0.9	0.5	1.0

Figure 2. Example of a fuzzy outranking relation. Source: own.

In the comparison between two alternatives, $a, b \in A$ from Figure 2, the following question can be answered: What is the degree of credibility that a is at least as good as b ? In this case, the answer is $S^\sigma(a, b) = 0.2$. In the same sense, when faced with the question: What is the degree of credibility that b is at least as good as a ? The answer is $S^\sigma(b, a) = 0.7$. It should be noted that the closer the response value is to 1.0, the more credible it is that any alternative is at least as good as the other alternative in question.

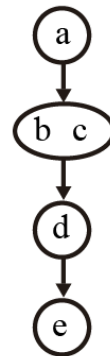
The comparison between pairs of alternatives in the fuzzy outranking relation allows for the generation of an ordering of said alternatives in the exploitation stage. In the multi-criteria ranking problem, three types of orders can be presented: (i) total order, (ii) total preorder, and (iii) partial preorder, which are presented in Figure 3.

Different types of rankings of alternatives

Total order



Partial order



Partial preorder

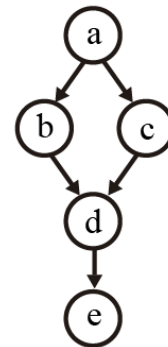


Figure 3. Different types of rankings of alternatives. Source: own.

3.3.6. Exploiting Fuzzy Outranking Relation

When exploiting a fuzzy outranking relation S^σ , it is usually transformed into a crisp outranking relation S^λ . A crisp relation can be defined with a function that assigns the value 1 to the ordered pairs in the relation and 0 to those not in the relation. To define whether an ordered pair $(a, b) \in A \times A; a, b \in A$; is in the relationship, a cut-off level $\lambda \rightarrow [0, 1]$ is defined, also known as the credibility level. A cut-off level can be seen as a minimum or demanding level regarding credibility. Once a cut-off level is defined, the level of credibility of any pair of alternatives can be known, that is, $S^\lambda(a, b) = \{1, \text{ if } (a, b) \geq \lambda; 0, \text{ otherwise}\}$. Figure 4 presents the transformation of a fuzzy outranking relation to different crisp outranking relations based on various cut-off levels λ .

Transforming a Fuzzy outranking relation to a set of Crisp outranking relations

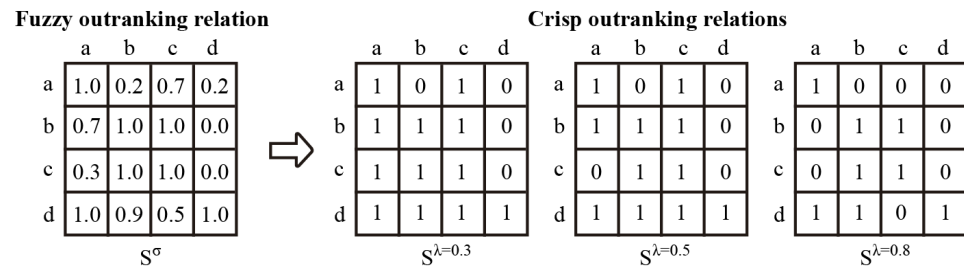


Figure 4. Different crisp outranking relations generated from a fuzzy outranking relation. Source: Own.

When comparing a pair of alternatives $a, b \in S^\lambda$, four possible results can be obtained: (i) a is indifferent to b (aIb), (ii) a is preferred to b (aPb), (iii) a is not preferred to b ($a \neg Pb$), or iv) a is incomparable to b (aRb). The indifference relation between a and b occurs when $S^\lambda(a, b) = 1$ and $S^\lambda(b, a) = 1$. The preference relation between a and b occurs when $S^\lambda(a, b) = 1$ and $S^\lambda(b, a) = 0$. The non-preference relation between a and b occurs $S^\lambda(a, b) = 0$ and $S^\lambda(b, a) = 1$. The incomparability relation between a and b occurs when $S^\lambda(a, b) = 0$ and $S^\lambda(b, a) = 0$. As shown in Figure 4, the incomparability between alternatives increases as the cut-off level increases (near or equal to 1); when the cut-off level decreases, the indifference between alternatives increases (near or equal to 0).

From the point of view of outranking relations between pairs of alternatives, i.e., indifference, preference, and incomparability, only the preference relation is present in total order. In a total preorder, the relations of indifference and preference are present. In the partial preorder, the relations of incomparability and preference are present, as well as the relation of indifference. Figure 5 exemplifies these preference relations in multi-criteria rankings as the cut-off level λ increases.

Preference relations in multicriteria rankings

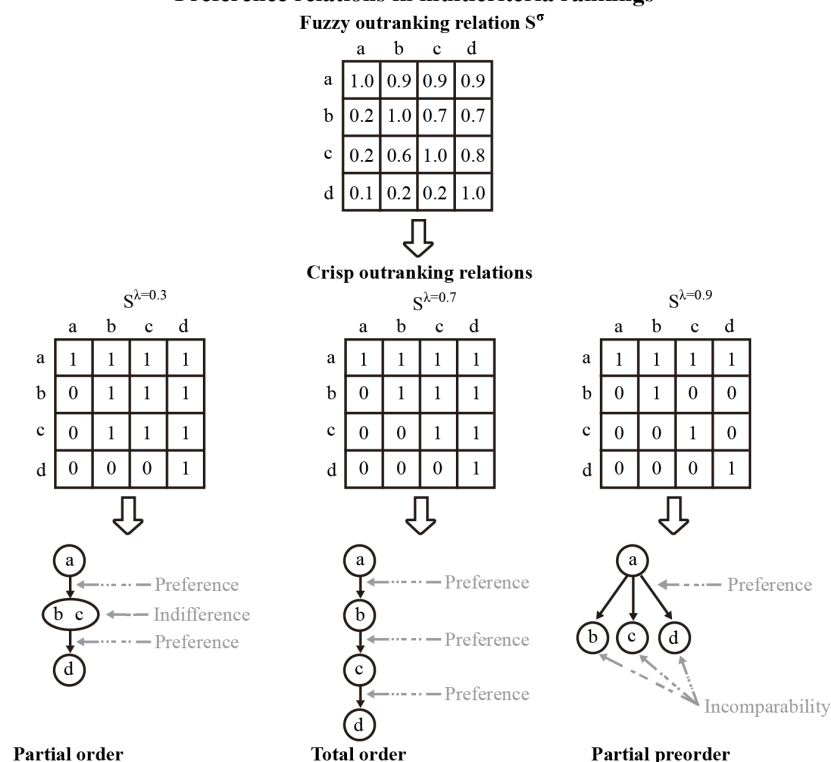


Figure 5. Preference relations in multi-criteria rankings. Source: Own.

As mentioned, to exploit the fuzzy outranking relation S^σ for the personnel selection problem, the multi-objective evolutionary algorithm RP^2 -NSGA-II+H was used. Evolutionary algorithms are Artificial Intelligence (AI) techniques inspired by biological evolution and natural selection principles. These algorithms are used as optimization and search tools in complex, multidimensional solutions. Evolutionary algorithms can solve problems where traditional strategies may be insufficient or impractical.

The use of RP^2 -NSGA-II+H to exploit S^σ instead of the ELECTRE-III distillation method was because the multi-objective evolutionary algorithm presented fewer inconsistencies between the generated ordering and the corresponding crisp outranking relation. It was known after analyzing the ranking of alternatives, which was automatically generated by the R OutrankingTools package version 1.0 after creating the fuzzy outranking relation with ELECTRE-III.

Regarding inconsistencies, given a pair of alternatives in a crisp outranking relation $a, b \in S^\lambda$ and an ordering O generated from exploiting said relation, an inconsistency occurs when the preference relation between a and b are different in S^λ and O . For example, while in the relation aPb , in the ordering occurs $a \neg Pb$, aIb or aRb .

Based on the preferential relations contained in the fuzzy outranking relation to be exploited, RP^2 -NSGA-II+H can generate a partial order of classes of alternatives (equivalent to partial preorders of alternatives), a partial preorder, or a total order. It is relevant because when using methods that can only generate total orders, e.g., the presented method in Leyva-Lopez and Aguilera-Contreras (2005) [32], there is a risk of obtaining rankings with multiple inconsistencies between the crisp outranking relation and said rankings. It occurs because these types of methods require the presence of preference relations to generate the ordering, which leads to inconsistencies.

On the other hand, when methods for exploitation are used, but they require a cut-off level defined by a decision-maker or thresholds, e.g., ELECTRE III, there is a risk that an ordering is obtained that is not an adequate solution due to inconsistencies concerning the fuzzy outranking relation, or that there may be another ordering with fewer inconsistencies, but not being able to generate it due to the defined cut-off level.

In this work, RP^2 -NSGA-II+H was chosen for personnel selection because it has been used by Leyva-Lopez et al. (2022) [25] for this type of problem with good performance. RP^2 -NSGA-II+H tries to optimize three objectives simultaneously. The first objective ($Obj_{heterogeneity}$) is to minimize the number of alternatives that are not indifferent to each other within the same class. The second objective ($Obj_{incoherence}$) is to minimize the inconsistency between pairs of alternatives a, b ; $a \in C_1$ and $b \in C_2$; C_1 and C_2 being two different classes of a ranking ordering, where C_1 is preferred to C_2 ($C_1 \succ C_2$) but bPa or aIb , or aRb . The third objective (Obj_{Cut}) is to maximize the cut-off level of each ranking during the multiple generations of the algorithm. RP^2 -NSGA-II+H receives a minimum cut-off level λ_0 , e.g., $\lambda_0 = 0.5$, and the algorithm tries to maximize it, bringing it closer to the value of 1.0. However, RP^2 -NSGA-II+H includes a mechanism that does not allow the cut-off level to get too close to 1.0 because this increases the incomparability between the alternatives, which could decrease the quality of the orderings it generates. Due to the algorithm facing a multi-objective problem, it generates a set of solutions that form a Pareto optimal front because, generally, there is no single optimal solution. The model to be optimized is presented below:

$$\text{Min}(Obj_{heterogeneity}), \text{Min}(Obj_{incoherence}), \text{Max}(Obj_{Cut}) \quad (1)$$

s.t.

$$S_{P_k(A)} \in \theta \quad (2)$$

$$f \leq 0.2 \times (|A| \times |A - 1|/2) \quad (3)$$

$$\lambda \in [0, 1]; \lambda \geq \lambda_{min} \quad (4)$$

where A is the set of alternatives, θ corresponds to the reflexive and anti-symmetric crisp outranking relations of classes of alternatives in A , to which $S_{P_k(A)}$ belongs. f is a function that counts the number of incompatibilities between pairs of alternatives in $S_{P_k(A)}$, based on the crisp outranking relation S_A^λ . λ is the cutting level obtained by RP²-NSGA-II+H for a given solution, and λ_{min} is the minimum cutting level provided by the decision-maker.

Then, the fuzzy outranking relation generated by the R OutrankingTools package was provided for RP²-NSGA-II+H to obtain the ranking of candidates for the barista position. This algorithm was executed with the following parameters: population size = 80, number of generations = 1000, lambda minimum value = 0.60, probability of crossover = 0.90, and probability of mutation = 0.05.

3.3.7. Selecting the Candidate for the Barista Position

As the ordering obtained with RP²-NSGA-II+H did not specifically allow the candidate for the barista position to be selected, other selection methods were used. First, the Net Flow Rule was used. This approach is commonly used in the PROMETHEE II multi-criteria method (Brans et al., 1986) [8] to evaluate and classify alternatives based on their input and output relations. The net flow is calculated by subtracting the output flow from the input flow for each alternative in a preference ranking. For calculating the input flow for each alternative, the partial preferences of all the alternatives that have a directed relation toward the alternative in question are counted. On the other hand, to calculate the output flow for each alternative, the partial preferences of all the alternatives towards which the alternative in question has a directed relation are counted. The Net Flow Rule is based on the principle that alternatives with a higher (positive) net flow are preferred over those with a lower (negative) net flow in the context of the ranking, in this case, obtained with RP²-NSGA-II+H.

However, the ranking obtained with the Net Flow Rule did not reflect the best candidate to be selected. Then, the decision-maker requested to analyze the ordering based on the candidate, which would provide greater certainty concerning the rest of the candidates, considering the preference relations between several alternatives. To support the selection of candidates, the PROMETHEE I and II methods were used. They used preference functions to model the preferences of the decision-maker. They used a preference approach where alternatives are compared in pairs based on each criterion. The PROMETHEE I generates a partial preorder using positive and negative flows, meanwhile PROMETHEE II generates a total order using net flows, which are obtained by the difference between positive and negative flows.

4. Results and Discussion

After running OutrankingTools in R Studio with the performances of Table 3, the criteria weights of Table 4, and the indifference and preference thresholds of Table 5, the fuzzy outranking relation in Figure 6 was obtained.

As mentioned, OutrankingTools generates a ranking based on the distillation method. A crisp outranking relation S_A^λ must be generated from a series of thresholds and decision rules to generate such a ranking.

In the distillation method, first, the highest degree of credibility between pairs of alternatives is identified in the fuzzy outranking relation S_A^σ . In this case, said value corresponds to $\lambda_{Max} = 1.0$. Then, a discrimination threshold $\lambda_{Threshold}$ is calculated and obtained using the values α y β , as follows: $\lambda_{Threshold} = \alpha + \beta \times \lambda_{Max}$. OutrankingTools uses the values $\alpha = 0.3$ and $\beta = -0.15$, as suggested in Bernard. Roy and Bouyssou, 1993 [45]. Therefore, $\lambda_{Threshold} = 0.3 + (-0.15) \times 1.0 = 0.15$. The difference between the values of λ_{Max} and $\lambda_{Threshold}$ allows us to calculate a cut-off level $\lambda_{Cut-off} = \lambda_{Max} - \lambda_{Threshold}$; it is $\lambda_{Cut-off} = 1.0 - 0.15 = 0.85$. Subsequently, the immediately lower degree of credibility λ_{Below} regarding $\lambda_{Cut-off}$ is identified, with this being $\lambda_{Below} = 0.83$.

Fuzzy outranking relation

	a1	a2	a3	a4	a5	a6	a7	a8	a9	a10	a11
a1	1.00	0.50	0.83	0.50	0.50	0.83	0.83	0.33	0.50	0.50	0.50
a2	0.50	1.00	0.33	0.67	0.17	1.00	1.00	0.50	0.67	0.33	0.00
a3	0.17	0.67	1.00	0.67	0.17	0.67	0.67	0.17	0.67	0.17	0.00
a4	0.50	0.33	0.33	1.00	0.17	0.33	0.50	0.50	0.67	0.33	0.00
a5	1.00	0.83	0.83	0.83	1.00	0.83	0.83	0.50	0.67	0.33	0.50
a6	0.50	0.17	0.33	0.67	0.17	1.00	1.00	0.50	0.67	0.00	0.00
a7	0.50	0.33	0.33	0.67	0.17	0.83	1.00	0.50	0.67	0.33	0.00
a8	1.00	0.83	0.83	0.50	0.67	0.83	0.83	1.00	0.67	0.83	0.50
a9	0.50	0.33	0.33	0.83	0.33	0.83	0.33	0.33	1.00	0.33	0.33
a10	1.00	1.00	1.00	0.67	0.67	1.00	1.00	1.00	0.67	1.00	0.50
a11	0.50	1.00	1.00	1.00	0.50	1.00	1.00	0.50	1.00	0.50	1.00

Figure 6. Fuzzy outranking relation generated with OutrankingTools. Source: Own.

In constructing the crisp outranking relation $\text{crisp } S_A^\lambda$, each pair of alternatives, $(a, b) \in S_A^\sigma$, is compared, assigning the value of 1 if $\sigma(a, b) > \lambda_{\text{Below}}$ and $(\sigma(a, b) - \sigma(b, a)) > \lambda_{\text{Threshold}}$, or the value of 0 otherwise.

Once S_A^λ is constructed, two total preorders are generated, one descending O_{Desc} and another ascending O_{Asc} . Next, an integration process is carried out between O_{Desc} and O_{Asc} to generate the final ordering. The reader can see a developed example of the distillation method in Giannoulis and Ishizaka (2010) [29]. Figure 7 shows the ranking of candidates for the barista position generated by OutrankingTools (see Appendix B).

Ranking generated by ELECTRE-III method

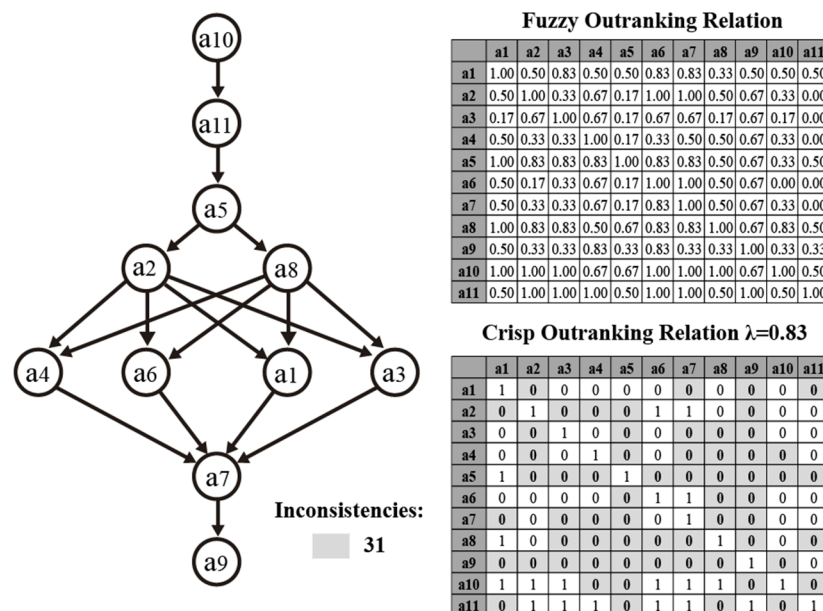


Figure 7. Candidate ranking generated by OutrankingTools. Source: Own.

As can be seen in Figure 7, the ranking generated with the distillation method has 31 inconsistencies concerning the crisp outranking relation for a cut-off level $\lambda = 0.83$ ($S_A^{\lambda=0.83}$). It is based on the S_A^λ created by assigning the value of 1 if $\sigma(a, b) > 0.83$ and $(\sigma(a, b) - \sigma(b, a)) > 0.15$, or the value of 0 otherwise.

The result obtained with ELECTRE-III was considered unsuitable for selecting personnel for the barista position. Then, the exploitation of S_A^σ of Figure 6 was performed

using RP²-NSGA-II+H. The result obtained with this algorithm was an ordering without inconsistencies for a cut-off level $\lambda = 0.83$. The objective functions had the following values: $\text{Obj}_{\text{heterogeneity}} = 0$, $\text{Obj}_{\text{incoherence}} = 1$, and $\text{Obj}_{\text{Cut}} = 0.83$. Figure 8 presents the ordering generated by RP²-NSGA-II+H.

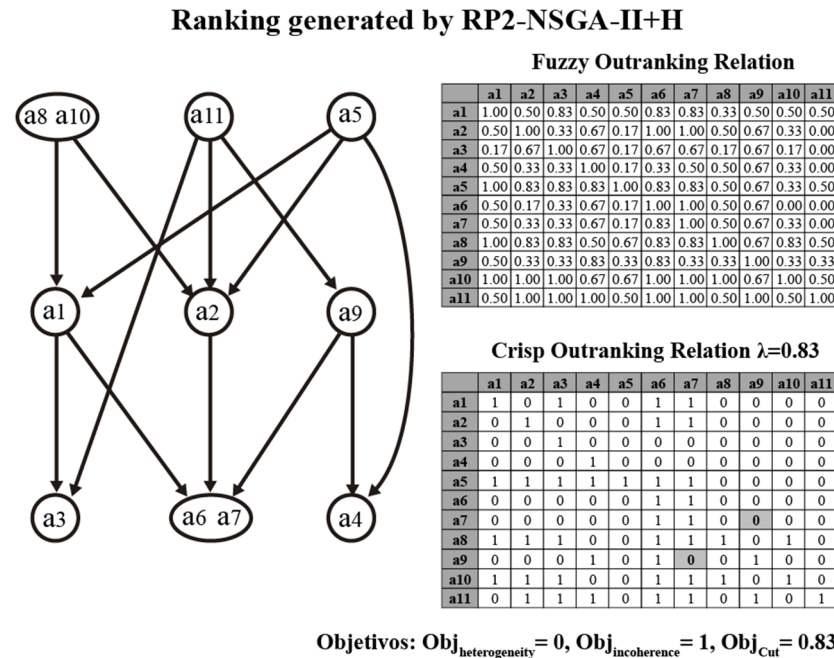


Figure 8. Ranking obtained with RP²-NSGA-II+H. Source: Own.

The exploitation of the fuzzy outranking relation through RP²-NSGA-II+H ended at this point. Now, the decision-maker had to choose the candidate he/she considered most suitable to fill the barista position. However, this ranking shows that a8, a10, a11, and a5 were the best candidates for the vacant position. It is noted that a8 and a10 are indifferent to each other.

Likewise, it can be observed that the relation between these four candidates is incomparable, i.e., $a8Ra11$, $a8Ra5$, $a10Ra11$, $a10Ra5$, and $a11Ra5$. The incomparability relation indicates no clear difference between them in terms of their performance on the evaluated criteria. It means that although these three candidates may be the most preferred overall, a clear relationship of superiority cannot be established between them based on the cut-off level of $\lambda = 0.83$.

On the other hand, if the relation between the four candidates had been one of indifference, i.e., $a8Ia11$, $a8Ia5$, $a10Ia11$, $a10Ia5$, or $a11Ia5$, nor could a clear superiority be distinguished between these candidates in terms of their performance on the evaluated criteria. However, it implies that the four candidates are equally preferable according to the criteria considered in the analysis, like with $a8Ia10$.

Similarly, if two candidates, a and b, were indifferent to each other (aIb) and incomparable to the other candidate, c (aRc and bRc), it would lead to greater complexity for the decision-maker. The choice between the two indifferent alternatives, a and b, can be complex due to the lack of clear differentiation in performance in the evaluated criteria. Furthermore, the incomparable candidate c adds a layer of complexity since its performance cannot be directly compared to the other two candidates. This case is presented in the ranking obtained by RP²-NSGA-II+H.

Then, the decision-maker was supported in selecting the candidate based on the ranking obtained with RP²-NSGA-II+H. First, we tried to obtain the best candidate using the Net Flow Rule. The ordering obtained with the Net Flow Rule was $(a_5, a_{11}) \succ (a_8, a_{10}) \succ a_9 \succ a_1 \succ a_2 \succ a_4 \succ a_3 \succ (a_6, a_7)$. Candidates a5 and a11 have the highest net flow,

indicating an output considerably larger than their input. It suggests that they are highly preferred over the other candidates in the set. However, the ordering obtained with the Net Flow Rule does not allow us to discern which candidate should be selected.

For this reason, to select one of four candidates, the decision-maker considered choosing the one that allowed for greater certainty compared to the other candidates, considering the preference relations between several alternatives. When analyzing the relations of the four candidates, it was observed that a_8 is indifferent to a_{10} . Both candidates have a relation of incomparability with a_{11} and a_5 , while a_{11} is incomparable to a_5 . Moreover, it was observed that the relations of a_8 and a_{10} concerning a_9 and a_4 are incomparable, while a_{11} is preferred to a_9 and a_4 , but incomparable to a_1 . Candidate a_5 is incomparable to a_9 but preferred to a_4 while a_9 is preferred to a_4 . The four candidates are preferred to a_2 ; thus, the ranking was cut by removing a_2 , a_6 , and a_7 to be analyzed in disaggregated form, obtaining the rankings shown in Figure 9.

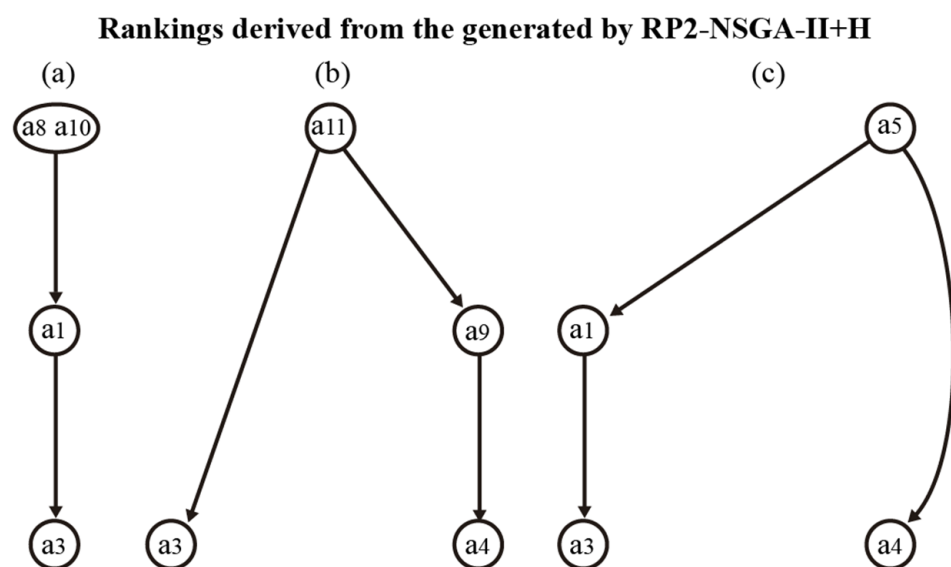


Figure 9. Rankings derived by cutting the obtained by RP²-NSGA-II+H. (a) a_8 and a_{10} are indifferent each other and preferred to a_1 and a_3 . (b) a_{11} is preferred to a_3 , a_9 , and a_4 ; a_3 is incomparable to a_9 and a_4 . (c) a_5 is preferred to a_1 , a_3 , and a_4 ; a_4 is incomparable to a_1 and a_3 . Source: Own.

From Figure 9, the following three rankings were presented:

- a. $(a_8 \succ, a_{10}) \succ a_1 \succ a_3$;
- b. $a_{11} \succ a_3$ and $a_{11} \succ a_9 \succ a_4$; and
- c. $a_5 \succ a_1 \succ a_3$ and $a_5 \succ a_4$.

As it can be observed, the ranking in Figure 9c provided more information than in Figure 9a concerning the non-top candidates. The same occurred between the rankings in Figure 9a,c. Borrowing the term from the optimization area, the rankings in Figure 9b,c could be considered non-nominated solutions. From the above, candidates a_{11} or a_5 should be selected.

However, the PROMETHEE I and II methods were used to support the selection of candidates a_{11} or a_5 (see Appendix C). For that purpose, the PROMETHEE package in R Studio with the performances of Table 3 was used the criteria weights of Table 4. In this case, a linear preference function for the criteria were selected. The outputs of the PROMETHEE package version 1.1 are two rankings: a partial preorder with PROMETHEE I and total order with PROMETHEE II. The total order was $a_{11} \succ a_{10} \succ a_5 \succ a_8 \succ a_1 \succ a_2 \succ a_3 \succ a_9 \succ a_4 \succ a_7 \succ a_6$. This order suggested that candidate a_{11} should be selected. On the other hand, the partial preorder suggested the candidate a_{10} or a_{11} . This ranking is shown in Figure 10.

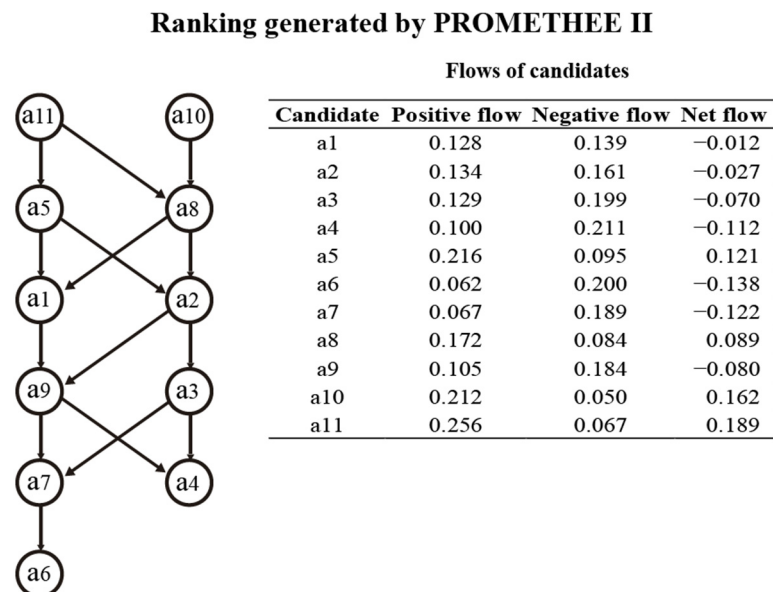


Figure 10. Ranking obtained with PROMETHEE II. Source: Own.

The obtained results of PROMETHEE I and II support that the candidate a11 should be selected. Moreover, considering the rankings of RP2-NSGA-II+H, net flow, the cut rankings, and PROMETHEE I and II, the candidate a11 was always on top. Only in the ranking of the distillation method of ELECTRE-III (Figure 7) was the candidate a11 in second place.

5. Conclusions and Future Work

This work presented the personnel selection process in a Mexican coffee shop company. During the process, the skills of 11 candidates to fill a barista vacancy were analyzed. The ELECTRE-III method was used to model the decision-maker's preferences. The fuzzy outranking relation obtained by ELECTRE-III was first exploited using the distillation method to generate a ranking that would allow for the selection of the best candidate to occupy the barista position. The ranking obtained had 31 inconsistencies concerning a crisp outranking relationship for a cut-off level of 0.83. It implied that 62 pairs of alternatives out of the 121 possible (51.24%) in said relation had inconsistencies without considering the reflective property. Then, the same fuzzy outranking relation was exploited with RP2-NSGA-II+H, a multi-objective evolutionary algorithm, to obtain an ordering of candidates. The result generated with said algorithm had one inconsistency regarding the crisp outranking ratio for a cut-off level of 0.83. The partial preorder of candidates obtained with RP2-NSGA-II+H had four candidates with incomparable and indifference relations at the top of the ranking.

With this ranking obtained, the RP2-NSGA-II+H process ended, but the decision-maker could not select the appropriate candidate for their needs. Then, the decision-maker was supported to select the candidate to occupy the barista position using other techniques. It does not imply that RP2-NSGA-II+H was unsuitable for the personnel selection process; on the contrary, the algorithm found a solution in a multi-objective context that allowed candidate a11 to be selected.

The results show the relevance of combining preference modeling with multi-criteria analysis methods for decision-making and artificial intelligence techniques. It is because multi-criteria analysis methods, such as ELECTRE-III, allow the uncertainty and imprecision of the decision-maker to be appropriately modeled, and multi-objective evolutionary algorithms, such as RP2-NSGA-II+H, try to find solutions with fewer or no inconsistencies regarding comprehensive preference models. When addressing decision problems, compatible or complementary tools, methods, and techniques must be used to support the decision-maker in their work.

The combination of MCDA and artificial intelligence, such as the one presented in this work, could allow those responsible for human resources and other areas of organizations to make decisions more assertively than when using a single area of knowledge, especially if only intuition, experience, or both are used. These decisions could not only correspond to the selection of personnel but also identify and organize their employees based on their profiles, selecting training programs, support in granting incentives based on employee performance, and selecting suppliers, among others.

The results obtained in this process reflect the conclusion that Simon (1987) [48] pointed out that by joining the strengths of management sciences, operations research, and artificial intelligence, it is possible to address all types of decision-making tasks and problem-solving the mind faces.

The number of inconsistencies in the ordering obtained with the distillation method puts on the table the need to analyze said method against a greater number of instances to know its limitations. However, this result does not allow us to conclude that it is inappropriate for personnel selection or other situations. Likewise, the ordering obtained with RP2-NSGA-II+H does not imply that it is better than the distillation method. For this, an in-depth study is required, which remains as future work, along with the combination of ELECTRE-III and RP²-NSGA-II+H for other personnel selection situations or applications.

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Data Availability Statement: The data presented in this study is available on request from the corresponding authors, and the dataset was jointly completed by the team, so the data is not publicly available. However, they can be taken from the Appendices A–C.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Evaluation of Candidates Based on Sub-Criteria

The company evaluated each candidate using the sub-competencies (sub-criteria) belonging to the three criteria: knowledge, skills, and attitudes. The sub-criteria were ordered for each criterion from most important to least important. The most important sub-criterion of a specific criterion was assigned a maximum possible weight; for the knowledge criterion, the maximum weight was 5; for skills, it was 12; and for attitudes, it was 6. The least important sub-criterion of each criterion was weighted 1. Table A1 presents the sub-criteria ordered by weight in their respective criteria.

Table A1. Weights of each sub-criterion ordered by the score in their respective criteria.

Label	Criterion	Sub-Criterion	Weight
SC1_1	Knowledge	Customer service	5
SC1_2		Verbal communication	4
SC1_3		Numerical analysis	3
SC1_4		Teamwork	2
SC1_5		Written communication	1
SC2_1	Skills	Responsibility	12
SC2_2		Control	11
SC2_3		Mental health	10
SC2_4		Physical health	9
SC2_5		Initiative	8
SC2_6		Impact	7
SC2_7		Listening	6
SC2_8		Energy	5
SC2_9		Stress tolerance	4
SC2_10		Kindness	3
SC2_11		Adaptability	2
SC2_12		Complaint management	1

Table A1. *Cont.*

Label	Criterion	Sub-Criterion	Weight
SC3_1	Attitudes	Commitment	6
SC3_2		Motivation for the work to be done	5
SC3_3		Commercial spirit	4
SC3_4		Sociability	3
SC3_5		Self-motivation	2
SC3_6		Flexibility	1

Source: Own.

The weights of the sub-criteria, shown in Table A1, were used to obtain the values of each candidate for the barista position by sub-criterion. For it, a profile was formed for each candidate based on the sub-criteria. For each criterion, said profile was created by identifying the dominant sub-criterion (sub-competency) that the candidate possesses. Once the dominant sub-criterion was identified, the maximum possible value was assigned depending on the criterion. For the knowledge criterion, the maximum value was 5; for skills, it was 12; and for attitudes, it was 6. The least dominant sub-criterion of each criterion was the value 1. Table 3 presents the sub-criteria ordered by weight in their respective criteria. Subsequently, these values were added to each criterion. Tables A2–A4 show the values provided by the company for the 11 candidates.

Table A2. Values of sub-criteria of the knowledge criterion.

Alternative	Sub-Criteria of the Knowledge Criterion				
	SC1_1	SC1_2	SC1_3	SC1_4	SC1_5
a1	4	5	1	3	2
a2	1	4	3	5	2
a3	4	2	3	1	5
a4	2	1	3	5	4
a5	3	5	2	4	1
a6	2	1	4	5	3
a7	1	3	5	2	4
a8	5	3	4	1	2
a9	1	4	2	3	5
a10	3	5	4	2	1
a11	4	1	5	2	3

Source: Own with information from the company.

Table A3. Values of sub-criteria of the skills criterion.

Alternative	Sub-Criteria of the Skills Criterion											
	SC2_1	SC2_2	SC2_3	SC2_4	SC2_5	SC2_6	SC2_7	SC2_8	SC2_9	SC2_10	SC2_11	SC2_12
a1	10	2	6	8	3	4	7	1	9	12	5	11
a2	3	10	1	7	12	2	8	6	4	9	11	5
a3	5	1	3	8	4	9	10	7	12	2	11	6
a4	4	8	9	6	1	3	12	7	11	10	5	2
a5	7	10	9	5	12	8	2	1	11	6	3	4
a6	2	10	5	3	9	1	12	6	8	7	4	11
a7	3	2	6	4	10	11	9	12	7	1	5	8
a8	1	4	8	10	12	7	3	5	2	6	11	9
a9	12	10	4	11	5	2	9	7	3	8	6	1
a10	7	5	2	6	9	11	3	4	10	8	1	12
a11	6	12	10	8	9	11	5	2	1	4	3	7

Source: Own with information from the company.

Table A4. Values of sub-criteria of the attitudes criterion.

Alternative	Sub-Criteria of the Attitudes Criterion					
	SC3_1	SC3_2	SC3_3	SC3_4	SC3_5	SC3_6
a1	1	2	5	3	4	6
a2	3	6	4	2	5	1
a3	6	4	2	5	1	3
a4	3	2	5	6	1	4
a5	2	3	6	1	4	5
a6	4	6	1	3	5	2
a7	5	1	3	4	6	2
a8	4	1	5	2	3	6
a9	2	1	4	6	3	5
a10	6	3	5	2	1	4
a11	5	4	6	3	2	1

Source: Own with information from the company.

Each value of each sub-criterion was added to a value that contributed to its corresponding criterion through a weighted sum. For this reason, each value of the sub-criterion was multiplied by the corresponding weight from Table A1, and subsequently, these products were added. That is, $\text{weightedSum}(a_m) = SC1(x_1) \times w_1 + SC2(x_2) \times w_2 + \dots + SC_n(x_n) \times w_n$. For instance, for alternative a1 in Table A2 and the weights in Table A1, the weighted sum for the Knowledge criterion was calculated as follows: $\text{weightedSum}(a1) = 4 \times 5 + 5 \times 4 + 1 \times 3 + 3 \times 2 + 2 \times 1 = 20 + 20 + 3 + 6 + 2 = 51$.

The weighted sums were then standardized for each criterion as follows:

- Obtain the highest and lowest possible weighted sum of the criterion in question; for criterion C1 $\text{minSum} = 35$ and $\text{maxSum} = 55$; for C2 $\text{minSum} = 364$ and $\text{maxSum} = 650$; and for C3 $\text{minSum} = 56$ and $\text{maxSum} = 91$;
- Subtract the lowest possible weighted sum from the weighted sum and divide the result by the difference between the highest and lowest possible weighted sum of the criterion in question and
- Multiply the result by 100. It is $(\text{weightedSum} - \text{minSum}) / (\text{maxSum} - \text{minSum}) \times 100$. For example, for alternative a1 of Table A2, the value of the knowledge criterion is $(51 - 35) / (55 - 35) \times 100 = 16/20 \times 100 = 80$.

Appendix B. Code in R to Obtain the Ranking of Candidates Using ELECTTE-III

```
install.packages("OutrankingTools")

library(OutrankingTools)

PerformanceTable = cbind(c(80,35,45,10,75,20,25,90,15,85,55),
c(36,40,28,48,72,35,38,37,77,40,80),
c(9,71,80,46,31,66,49,31,17,77,91))

Alternatives = c("a1","a2","a3","a4","a5","a6","a7","a8","a9","a10","a11")

Criteria = c("c1","c2","c3")

MinMaxCriteria = c("max","max","max")

Weights = c(0.50,0.33,0.17)

IndifferenceThresholds = c(5,3,5)

PreferenceThresholds = c(6,4,6)

VetoThresholds = c(NA,NA,NA)

ELECTRE = Electre3_SimpleThresholds (PerformanceTable, Alternatives, Criteria, MinMaxCriteria, Weights,
IndifferenceThresholds, PreferenceThresholds, VetoThresholds).
```

Appendix C. Code in R to Obtain the Ranking of Candidates Using PROMETHEE I and II

```
install.packages(P'ROMETHEE')
library(P'ROMETHEE')

performanceTable <- as.data.frame(cbind(c(80,35,45,10,75,20,25,90,15,85,55),
c(36,40,28,48,72,35,38,37,77,40,80),
c(9,71,80,46,31,66,49,31,17,77,91)))

PreferenceFunctions = as.data.frame(rbind(c("Linear","Linear","Linear"),
c("Linear","Linear","Linear"),
c("Linear","Linear","Linear"),
c("Linear","Linear","Linear"),
c("Linear","Linear","Linear"),
c("Linear","Linear","Linear"),
c("Linear","Linear","Linear"),
c("Linear","Linear","Linear"),
c("Linear","Linear","Linear"),
c("Linear","Linear","Linear")))

PreferenceThresholds = as.data.frame(cbind(c(6,6,6,6,6,6,6,6,6,6,6),
c(4,4,4,4,4,4,4,4,4,4,4),
c(6,6,6,6,6,6,6,6,6,6,6)))

IndifferenceThresholds = as.data.frame(cbind(c(5,5,5,5,5,5,5,5,5,5,5),
c(3,3,3,3,3,3,3,3,3,3,3),
c(5,5,5,5,5,5,5,5,5,5,5)))

Weights = as.data.frame(cbind(c(0.50,0.50,0.50,0.50,0.50,0.50,0.50,0.50,0.50,0.50,0.50),
c(0.33,0.33,0.33,0.33,0.33,0.33,0.33,0.33,0.33,0.33,0.33),
c(0.17,0.17,0.17,0.17,0.17,0.17,0.17,0.17,0.17,0.17,0.17)))
MinMax =
as.data.frame(cbind(c("max","max","max","max","max","max","max","max","max","max","max"),
c("max","max","max","max","max","max","max","max","max","max","max"),
c("max","max","max","max","max","max","max","max","max","max","max")))

Gauss<-as.data.frame(cbind(c(0,0,0,0,0,0,0,0,0,0,0),
c(0,0,0,0,0,0,0,0,0,0,0),
c(0,0,0,0,0,0,0,0,0,0,0)))

Rankings = PROMETHEE (performanceTable, PreferenceFunctions, PreferenceThresholds,
IndifferenceThresholds, Weights, MinMax, Gauss)

Rankings
```

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