Development of an Intelligent Decision Support Model for Multi-Criteria Evaluation of Bank Employees Using the Fuzzy TOPSIS Method

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Abstract. Although decision-making in human resources within the banking sector increasingly requires a data-driven and transparent approach, subjectivity remains a major problem in current evaluation practices. This article proposes an intelligent decision support model for the quarterly appraisal of employees in bank human resource management, based on fuzzy multi-criteria decision-making and the TOPSIS method (Technique for Order Preference by Similarity to Ideal Solution). To address this problem, a system of criteria has been developed, including accuracy, productivity, teamwork and collaboration, innovativeness, attendance, number of completed projects, level of code optimization, degree of software correctness, creative project solutions, and adoption of new technologies. These criteria combine both quantitative indicators and qualitative measures expressed linguistically by HR specialists and managers. To model the uncertainty inherent in linguistic assessments, trapezoidal fuzzy numbers and membership functions are employed to construct a fuzzy decision matrix. By incorporating criteria weights and experts' competence coefficients, the fuzzy TOPSIS procedure evaluates each employee's performance according to the distances from the fuzzy ideal and anti-ideal solutions; the closeness coefficient is then computed and the alternatives are ranked accordingly. A representative application in the banking sector indicates that the proposed model standardizes the appraisal process, enhances transparency, and reduces the influence of subjective bias in decisions such as compensation and promotion. The findings also suggest that a fuzzy TOPSIS–based approach can be effectively integrated into banks' human resource information systems as an intelligent decision support module.

Keywords. Fuzzy logic, TOPSIS, multi-criteria decision making, human resource management, banking sector, decision support systems.

Introduction.

In the modern banking sector, human resource management is no longer merely a support function; rather, it represents one of the strategic directions that shape a bank's competitive advantage, customer satisfaction, and financial stability through the selection and development of personnel possessing competencies such as compliance with regulatory requirements, confidentiality and ethical conduct, accuracy in documentation and reporting, sensitivity to operational and reputational risks, and the continuous execution of control mechanisms. As a result of digital transformation, the rapid diffusion of digital banking products, and changes in service delivery models, the requirements imposed on bank employees have become more complex, multidimensional, and dynamic. Under these conditions, the quality of HR decisions—such as recruitment, promotion, succession pool formation, and the identification of training priorities—directly influences the bank's overall performance outcomes [1-3].

The relevance of this study stems from the fact that employee performance appraisal in banks is often grounded in managerial opinion, partial observation, and non-standardized criteria. However, the banking environment demands that decisions be justifiable, explainable, and measurable—both from the perspective of regulatory compliance and internal audit—and supported by quantifiable indicators. Moreover, since the relative importance of evaluation criteria varies by department and role, expressing qualitative criteria about the same employee in linguistic terms increases uncertainty in assessment and may lead to subjective judgment. For this reason, fuzzy logic–based multi-criteria approaches, particularly the Fuzzy TOPSIS method, are of substantial scientific and practical significance: they enable the systematic organization of quarterly performance appraisal in banks through a unified procedure, integrate heterogeneous indicators (quantitative and qualitative) within a single model, and thereby facilitate more transparent, comparable, and well-justified decisions regarding rewards and development plans [4,5].

In traditional practice, a significant share of HR decisions is made on the basis of subjective expert judgments, experience-based evaluations, and criteria that may be formal in some cases and informal in others. In such settings, comparisons of candidates or employees across multiple criteria are frequently conducted in an unsystematic manner, the relative importance of criteria is not explicitly articulated, and it becomes difficult to structure outcomes in a reusable, transparent, and explainable form. Consequently, two major issues arise: on the one hand, in complex decision-making situations where numerous indicators must be considered, an "intuition-driven" approach is insufficient; on the other hand, limited transparency and objectivity in the decision-making process can adversely affect both employee motivation and organizational culture [6-9].

Fuzzy logic and fuzzy set theory provide a more appropriate modeling framework for evaluation contexts in which the boundaries between "completely true" and "completely false" are not well-defined and values belong to categories only to a certain degree. Fuzzy multi-criteria decision-making approaches preserve the structural advantages of classical MCDM methods while enabling criterion values and weights to be represented using fuzzy numbers, thereby allowing the uncertainty inherent in the banking human resources environment to be explicitly taken into account [10-13].

An analysis of the existing literature indicates that, although fuzzy multi-criteria decision-making (MCDM) approaches have been studied in the contexts of human resource management, recruitment, project selection, and related domains, the development of fuzzy TOPSIS–based models for comprehensive employee evaluation in the banking sector—and their empirical validation using real-world data—has not yet been examined in a sufficiently systematic and extensive manner. This gap necessitates the formulation of a more structured approach to the intelligent support of HR decision-making in banks [14-17].

Accordingly, the objective of this article is to develop an intelligent decision support model for employee appraisal in the banking sector, grounded in fuzzy MCDM principles and the TOPSIS method, and to demonstrate its capabilities through an illustrative banking application. To achieve this objective, an appropriate set of evaluation criteria for bank HR decisions is first established. Next, a scheme is proposed for modeling both numerical and linguistic assessments under these criteria using fuzzy numbers. Finally, employee rankings are computed via the fuzzy TOPSIS algorithm, and the resulting outputs are analyzed from a practical perspective [18].

2. Literature Review

The literature on human resource management in the banking sector indicates that, within financial institutions, human capital is widely recognized as one of the key strategic determinants of a bank's competitiveness, service quality, and sustainable development [18–20]. Against the backdrop of product and technology advantages being relatively quickly imitated by market participants, the recruitment, retention, and development of personnel with strong professional competencies are viewed as a more "difficult-to-replicate" resource that underpins a bank's long-term advantage [18–20]. Consequently, HR decisions in banks—such as recruitment, appraisal, reward allocation, and the formation of succession pools—constitute high-responsibility, multi-criteria processes that require the involvement of multiple stakeholders, including HR units, line managers, risk/compliance functions, and internal audit [21–23].

In recent years, HR analytics, decision support systems (Decision Support Systems—DSS), and the integration of artificial intelligence applications into HR decision-making have emerged as a prominent research direction [24,25]. In this stream of work, the primary emphasis typically lies on prediction and optimization based on the analysis of structured data (e.g., KPIs, attendance records, performance scores) and unstructured data (e.g., managerial opinions, 360-degree feedback, and text-based notes). In particular, issues such as employee turnover prediction, early detection of performance decline, and the modeling of satisfaction and motivation indicators have been extensively investigated [24,25]. Nevertheless, another problem that is critical for banking HR practice—namely, the comparative evaluation of employees simultaneously across multiple, potentially conflicting criteria (e.g., productivity–accuracy–teamwork–innovativeness–attendance) and the transformation of such evaluations into decisions through an explainable ranking mechanism—has been addressed in the literature in a relatively less systematic manner. As a result, many DSS approaches remain limited to a "prediction module," while multi-criteria decision-making mechanisms are not fully integrated into the operational layer of HR decision execution [21–23].

Fuzzy logic–based models are considered more appropriate in situations where "completely true–completely false" type boundaries are inadequate—that is, in contexts dominated by uncertainty, imprecision, and linguistic information. Fuzzy set theory and the theory of linguistic variables make it possible to model the degree to which an element "partially belongs" to a given concept. In the human resources context, this provides a practical mechanism for converting expert assessments such as "low," "medium," "high," and "very high" into a mathematical representation and incorporating them into a decision-making model [1,2].

In the development of decision support systems for intelligent human resource management, the literature proposes fuzzy multi-criteria approaches in which HR management tasks are formulated as multi-criteria decision-making (MCDM) problems under fuzzy environments, and corresponding models are constructed using fuzzy optimization and MCDM methods [16,17]. These studies indicate that intelligent systems grounded in fuzzy logic and multi-criteria optimization not only enhance the transparency of HR decisions, but also enable the modeling of expert judgment and uncertain information.

MCDM methods constitute formal approaches that allow for the systematic evaluation and ranking of alternatives (candidates/employees) in the presence of multiple—and sometimes conflicting—criteria. Methods such as AHP and ANP are primarily applied to determine criteria weights. AHP derives weights by conducting pairwise comparisons of criteria within a hierarchical structure and formalizes the decision maker's priorities. ANP, in turn, models interdependencies and feedback among criteria (e.g., the influence of "teamwork" on "productivity," or "innovativeness" on "quality"), thereby providing a more realistic weighting procedure [3,4]. Methods such as TOPSIS and VIKOR, by contrast, are used to rank alternatives once weights are known. TOPSIS is based on the logic of "closeness to the ideal solution and distance from the anti-ideal solution," producing a closeness coefficient within the 0–1 interval, whereas VIKOR employs a compromise solution perspective to obtain a consensus-oriented ranking in group decision-making settings [5–7]. Outranking methods such as ELECTRE and PROMETHEE can, in certain cases, mitigate limitations associated with the “full compensation” logic and facilitate the construction of stronger preference relations among alternatives [8,9].

However, a key limitation of MCDM applications in the HR context is that, in many studies, both criterion values and weights are treated as crisp (precise) numerical inputs, requiring experts to provide “exact scores” [10,11]. In the banking environment, by contrast, a number of criteria are behavior- and competency-oriented (e.g., teamwork, innovative approach, process discipline), and measuring such criteria with full precision is difficult in practice. Furthermore, in part of the existing work, the systematic inclusion of bank-specific requirements—such as a risk/compliance culture, adherence to control mechanisms, accuracy of reporting, and sensitivity to reputational risk—remains limited within the criteria system, and the resulting evaluation model does not fully align with the bank’s actual governance logic [18–20]. Although some studies propose a method, they do not sufficiently clarify the implementation mechanism (e.g., how data are collected, how linguistic judgments are quantified, and how results are operationalized as an HRIS/DSS module), which weakens the model’s practical transferability [21–23].

For these reasons, the literature has increasingly developed fuzzy hybrid MCDM approaches. Fuzzy AHP accounts for expert uncertainty by estimating criteria weights through linguistic pairwise comparisons. Fuzzy TOPSIS and fuzzy VIKOR, in turn, generate rankings by modeling linguistic evaluations of alternatives using trapezoidal (or triangular) fuzzy numbers [12–15]. The advantage of these approaches is that qualitative observations and judgments of the “low–medium–high” type are transformed into a mathematical decision matrix; the evaluation process is standardized; and results are presented through explainable indicators such as distances and closeness coefficients. A recurring drawback, however, is the insufficient justification of a domain-specific criteria system (here, banking HR) and the limited description of a realistic application scenario [10,11].

Prior studies have already established modified TOPSIS-based multi-criteria optimization models for HR management, fuzzy MCDM approaches that support collective decision-making, and the conceptual principles of intelligent decision support systems. Nevertheless, the modeling of recruitment and career progression decisions in the banking sector—specifically at the branch or department level—using a fuzzy TOPSIS model grounded in criteria aligned with a bank’s internal HR strategy remains relatively underexplored as a distinct research object. From this perspective, the present study aims to address the identified research gap by building on existing scientific and methodological results in intelligent HR management, systematizing bank-specific HR criteria, evaluating bank employees' performance, and validating the approach using real banking data.

The purpose of this study is precisely to address this issue by enabling employee appraisal in the banking sector, based on an appropriate criteria system, through a unified mechanism that jointly accounts for uncertain (linguistic) and quantitative indicators. The proposed solution is structured as a sequence of stages: (i) systematization of criteria (performance and behavior/competency) derived from the bank's HR strategy and role requirements; (ii) determination of criteria weights; (iii) collection of expert judgments on a linguistic scale and fuzzification using trapezoidal fuzzy numbers; (iv) aggregation of expert opinions using competence coefficients and construction of the fuzzy decision matrix; (v) normalization and weighting; (vi) identification of FPIS/FNIS (ideal/anti-ideal) solutions, computation of distances, and ranking based on the closeness coefficient; and (vii) sensitivity checking and explainable linkage of results to decisions such as reward allocation. In this way, the proposed approach seeks to move banking HR decisions beyond subjective observation toward a formal, transparent, and audit-explainable DSS mechanism [5,6,16,17].

3. Methodology

The objective of this study is to construct a fuzzy multi-criteria decision-making model that supports human resource decision-making in the banking sector and to demonstrate the application of this model through a concrete banking case. The methodology consists of sequential stages that enable (i) the evaluation of bank employees or candidates across multiple criteria, (ii) the modeling of experts' linguistic judgments using fuzzy numbers, and (iii) the computation of a ranking indicator for each alternative.

3.1. Problem Formulation

In this study, the aim is to conduct a multi-criteria evaluation of bank employees' quarterly performance and to derive an objective ranking based on the results obtained. The evaluated alternatives are bank employees $A = \{A_1, A_2, \dots, A_m\}$, while the criteria $C = \{C_1, C_2, \dots, C_n\}$ represent quantitative and qualitative performance indicators (e.g., accuracy, productivity, teamwork and collaboration, innovativeness, attendance, number of completed projects, etc.). The assessment is performed by a panel of experts $D = \{D_1, D_2, \dots, D_k\}$ (HR specialists and relevant managers). Since measurement is uncertain for a subset of criteria, the corresponding values are provided on a linguistic scale (e.g., "low–medium–high"). The problem is therefore formulated as calculating the overall preference degree for each employee and ranking employees accordingly, while explicitly accounting for these linguistic evaluations and the weights of the criteria [10,11,16,17].

The criteria to be used were first compiled as a broad list based on the literature review and the bank's human resources strategy, and were subsequently systematized through expert discussions with HR specialists and managers. As a result, a consolidated criteria set was formed that integrates indicators related to professional competence and performance as well as behavior- and competency-oriented measures [18–20].

Within the bank's IT division, the work of front-end developers is of strategic importance for ensuring user experience across digital banking channels and maintaining the stable operation of systems. The evaluation of this activity should not be limited to workload or output volume; it must also reflect the quality of outcomes and behavioral indicators in a team environment. As shown in Table 1, employees' quarterly appraisal is conducted on the basis of multi-criteria measures including productivity (e.g., number of completed projects, tasks delivered on time, level of code optimization), accuracy (e.g., number of coding errors, test pass rate, degree of software correctness), teamwork and collaboration (e.g., participation in discussions, joint problem solving, mentoring), innovativeness (e.g., adoption of new technologies, use of effective tools, creative solutions), and attendance (e.g., frequency of lateness). Such an approach provides the necessary methodological foundation to ensure timely and high-quality releases in the bank's digital products, reduce risks and defects, and support more transparent and well-justified decisions regarding rewards, promotion, and development planning.

Table 1.

Grouping of Criteria and Sub-Criteria.

Main Criteria		Sub-Criteria	
C_1	**Productivity**	C_{11}	Number of completed projects
		C_{12}	Timely delivery of assigned tasks
		C_{13}	Level of code optimization
C_2	**Accuracy**	C_{21}	Number of code defects (bugs)
		C_{22}	Test pass rate (%)
		C_{23}	Degree of software correctness
C_3	**Teamwork and Collaboration**	C_{31}	Participation in team discussions
		C_{32}	Contribution to joint problem solving
		C_{33}	Mentoring activity
C_4	**Innovativeness**	C_{41}	Adoption/implementation of new technologies
		C_{42}	Use of tools that improve performance indicators

		C_{43}	Creative project solutions
C_5	**Attendance**	C_{51}	Frequency of lateness

Some of these criteria are treated as “benefit-type” (e.g., C_1, C_4, meaning that preference increases as the value increases), whereas others are treated as “cost-type” (e.g., C_5, meaning that preference decreases as the value increases). This classification is subsequently used in constructing the ideal and anti-ideal solution points.

To form the model inputs, an expert group was established consisting of staff from the bank’s human resources department, heads of the relevant organizational units, and managers involved in the decision-making process. The experts were asked to assess, on the one hand, the relative importance of the criteria and, on the other hand, the level of each candidate/employee with respect to these criteria.

The qualitative criteria were evaluated using a linguistic scale. This linguistic scale typically includes levels such as “very low,” “low,” “medium,” “high,” and “very high.” When comparing multiple candidates under the same criterion, experts perform a relative evaluation using this scale; these evaluations are then converted into a mathematical representation during the fuzzy modeling stage [1,2].

From a mathematical perspective, the linguistic variable can be formulated as follows:

$$L=\{T_1, T_2, \dots, T_n\}$$

Here, L denotes the linguistic variable, and T_i represents the set of linguistic terms selected for that variable. For example:

Skill = {very low, low, medium, high, very high}.

Each T_i is subsequently formalized as a fuzzy set and described by the corresponding membership function.

In evaluating the criteria, the linguistic variables are modeled using trapezoidal membership functions. The trapezoidal membership function is expressed as follows [12,13]:

$$\mu(x;a,b,c,d) = \begin{cases} 0, x \le a; \\ \frac{x-a}{b-a}, a < x \le b; \\ 1, b < x \le c; \\ \frac{d-x}{d-c}, c < x < d; \\ 0, x \ge d\} \end{cases}$$

Fuzzification is one of the most critical stages of fuzzy logic methodology and involves transforming experts' numerical assessments into fuzzy membership functions corresponding to linguistic variables. Whereas in classical multi-criteria decision-making methodologies the decision matrix consists solely of crisp numerical values, in the fuzzy approach this matrix is composed of fuzzy numbers (most commonly trapezoidal or triangular fuzzy numbers). This feature makes it possible to account for the uncertainty and subjectivity that exist in real-world settings [1,2,12,13].

From a mathematical standpoint, the fuzzy decision matrix can be expressed as follows:

$$\tilde{R} = \begin{bmatrix} \tilde{r}_{11} & \cdots & \tilde{r}_{1n} \\ \tilde{r}_{21} & & \tilde{r}_{2n} \\ \vdots & \ddots & \vdots \\ \tilde{r}_{m1} & \cdots & \tilde{r}_{mn} \end{bmatrix}$$

Here, $\tilde{r}_{ij}$ denotes the fuzzy evaluation of the i-th alternative with respect to the j-th criterion; m is the number of alternatives, and nnn is the number of criteria.

In the fuzzy multi-criteria decision-making process, once the decision matrix has been constructed, the next step is the aggregation and normalization stage. First, the weight coefficients provided by the experts for each criterion, w_j, are determined. These weights reflect the relative importance of the criteria in the decision-making process. Mathematically, the normalized form of the weights is expressed as follows:

$$\sum_{j=1}^{n} w_j = 1,\ w_j \ge 0$$

Here, w_j denotes the weight of the j-th criterion.

Next, the fuzzy decision matrix $\tilde{R}$~ is normalized according to the type of each criterion. For instance, for a benefit-type criterion, normalization can be performed as follows [12,13,14]:

$$\tilde{r}_{ij}^* = \frac{\tilde{r}_{ij}}{max_i \, \tilde{r}_{ij}}$$

and for cost-type criteria:

$$\tilde{r}_{ij}^* = \frac{min_i \, \tilde{r}_{ij}}{\tilde{r}_{ij}}$$

As a result, all criteria are mapped onto the [0,1] interval and become comparable. In the subsequent stage, aggregation is performed. In this process, the normalized values are multiplied by the corresponding criterion weights:

$$\tilde{v}_{ij} = w_j \cdot \tilde{r}_{ij}^*$$

and the final weighted (adjusted) fuzzy decision matrix is formed as follows:

$$\tilde{V} = \begin{bmatrix} \tilde{v}_{11} & \cdots & \tilde{v}_{1n} \\ \tilde{v}_{21} & & \tilde{v}_{2n} \\ \vdots & \ddots & \vdots \\ \tilde{v}_{m1} & \cdots & \tilde{v}_{mn} \end{bmatrix}$$

In this study, the adopted approach is the centroid (center-of-gravity) method for trapezoidal fuzzy numbers, as this method is both straightforward and computationally efficient [13,14].

Accordingly, the final defuzzified scores for each alternative can be expressed as follows:

$$D_i = f(\tilde{r}_{i1}, \tilde{r}_{i2}, \dots, \tilde{r}_{in})$$

Here, D_i denotes the final defuzzified score of the i-th alternative.

In the first step, the expert weights α_k are normalized; that is, the sum of all experts' weights is set equal to 1, and none of the weights is negative:

$$\sum_{k=1}^{m} \alpha_k = 1, \; \alpha_k \geq 0$$

Here, m denotes the total number of experts, and k is the expert index (i.e., the q_k expert).

If the experts' reliability is evaluated using separate scores (q_k), their weights are computed based on the relative proportions of these scores:

$$\alpha_k = \frac{q_k}{\sum_{l=1}^{m} q_l}$$

Here, l is the summation index (i.e., an auxiliary symbol used to enumerate experts as the "l-th expert").

In some cases, a filtering rule is applied to exclude experts with very low reliability. Under this rule, the weight of any expert whose reliability score falls below the threshold τ is set to zero, and the remaining weights are then re-normalized:

$$\alpha_k = 0 \text{ if } q_k < \tau, \quad \text{then } \sum_{k=1}^{m} \alpha_k = 1$$

After the evaluations of all experts are weighted, they are aggregated [5,12,19]. Mathematically, this is expressed as a weighted fuzzy average:

$$\tilde{x}_{ij} = \bigoplus_{k=1}^{m} \alpha_k \otimes \tilde{x}_{ij}^{(k)}$$

Here, $\otimes$ denotes fuzzy multiplication and $\oplus$ denotes fuzzy addition. That is, the experts' assessments are multiplied by the weights α_k and then combined using the $\oplus$ operator to obtain $\tilde{x}_{ij}$.

If the evaluations are expressed as trapezoidal fuzzy numbers—i.e., each expert provides an assessment with four parameters, $\tilde{x}_{ij}^{(k)}=(a_{ij}^{(k)}, b_{ij}^{(k)}, c_{ij}^{(k)}, d_{ij}^{(k)})$ —then the aggregated assessment is obtained by computing the weighted average for each parameter separately:

$$\tilde{x}_{ij} = \left(\sum_{k=1}^{m} \alpha_k a_{ij}^{(k)},\ \sum_{k=1}^{m} \alpha_k b_{ij}^{(k)},\ \sum_{k=1}^{m} \alpha_k c_{ij}^{(k)},\ \sum_{k=1}^{m} \alpha_k d_{ij}^{(k)} \right)$$

The resulting $\tilde{x}_{ij}$ values are then multiplied by the corresponding criteria weights and subsequently incorporated into the next stage, following the standard steps of the TOPSIS method:

$$\tilde{v}_{ij} = w_j \cdot \tilde{r}_{ij}^{*}$$

Thus, incorporating expert weights enhances the objectivity of the results, balances subjective differences, and makes the decision-making process more robust.

A matrix is constructed consisting of fuzzy evaluations for the alternatives (a_i) and criteria (C_j). This matrix is composed of trapezoidal fuzzy numbers obtained from the fuzzy-logic stage:

$$\tilde{R} = \left[\tilde{r}_{ij}\right]_{m\times n}$$

Next, the weights for each criterion (w_j) are applied, resulting in a weighted fuzzy matrix:

$$\tilde{V} = \left[\tilde{v}_{ij}\right]_{m\times n}, \qquad \tilde{v}_{ij} = w_j \cdot \tilde{r}_{ij}^{*}$$

The core principle of the TOPSIS method is that the best alternative should be the closest to the ideal solution and the farthest from the worst (anti-ideal) solution [5]. In the fuzzy setting, these solutions are defined as follows [5, 12]:

$$A^{+} = \{\tilde{v}_1^{+}, \tilde{v}_2^{+}, \dots, \tilde{v}_n^{+}\},\ \tilde{v}_j^{+} = max_i\, \tilde{v}_{ij}$$
$$A^{-} = \{\tilde{v}_1^{-}, \tilde{v}_2^{-}, \dots, \tilde{v}_n^{-}\},\ \tilde{v}_j^{-} = min_i\, \tilde{v}_{ij}$$

Here, A^{+} denotes the fuzzy ideal solution, and A^{-} denotes the fuzzy anti-ideal solution.

For each alternative, distances to both the ideal and the anti-ideal solutions are computed. Various distance metrics (e.g., Euclidean, vertex-based, etc.) can be used for this purpose [12,14]. In the simplest case:

$$d_i^{+} = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}_j^{+}\right), \quad d_i^{-} = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}_j^{-}\right)$$

Here, d(·) denotes the distance function between two fuzzy numbers.

To obtain the final ranking of alternatives, the closeness coefficient is computed [5,12,14]:

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-}$$

If CC_i is closer to 1, the corresponding alternative is considered closer to the ideal solution.

4. Result.

To demonstrate the practical applicability of the proposed fuzzy TOPSIS–based multi-criteria decision-making model, the study draws on an illustrative case from the human resources practice of one local commercial bank [10,11,16,17]. The appraisal is conducted on a quarterly basis, and the analysis considers six front-end specialists working in the IT unit of the bank's mortgage department. The employees (alternatives) are denoted by aia_iai (a_1, a_2, ..., a_n). The evaluations are expressed in linguistic terms, as presented in Table 2; since the sub-criteria are identical across the alternatives, the main criteria ($C_1, C_2, \ .. \ , C_5$) are used for the evaluation of each alternative [5,12,14].

If there are mmm alternatives (employees) and nnn criteria, the initial evaluation matrix is defined as follows

$$R = [r_{ij}]_{m \times n}.$$

Here, r_{ij} denotes the score assigned by the experts to the i-th alternative with respect to the j-th criterion (either on a 1–10 scale or in linguistic terms) [5].

Table 2.

Linguistic Evaluation of Alternatives by Experts Across the Main Criteria.

Expert	Alternative	Experts' Linguistic Evaluation of Alternatives Across the Main Criteria				
		C_1	C_2	C_3	C_4	C_5
E_1	a_1	high	high	medium	high	low
	a_2	low	medium	very low	low	high
	a_3	very high	medium	very low	very high	high
	a_4	very low	very high	medium	high	high
	a_5	high	high	high	high	high
	a_6	low	low	very low	high	medium

$\boldsymbol{E_2}$	a_1	medium	high	medium	medium	low
	a_2	medium	medium	very high	high	high
	a_3	medium	high	low	high	high
	a_4	very low	medium	medium	medium	medium
	a_5	high	high	medium	high	high
	a_6	low	medium	low	medium	medium
$\boldsymbol{E_3}$	a_1	high	high	medium	high	low
	a_2	low	medium	very low	high	high
	a_3	very high	medium	very low	high	high
	a_4	very low	very high	medium	high	high
	a_5	high	high	high	high	high
	a_6	low	low	very low	high	medium
$\boldsymbol{E_4}$	a_1	medium	low	high	high	low
	a_2	low	medium	very low	high	high
	a_3	very high	medium	very low	very high	high
	a_4	medium	high	medium	medium	high
	a_5	very high	medium	high	medium	high
	a_6	medium	medium	very low	high	medium
$\boldsymbol{E_5}$	a_1	high	high	high	high	medium
	a_2	medium	medium	low	high	medium
	a_3	high	medium	low	high	high
	a_4	medium	very high	medium	medium	high
	a_5	medium	high	high	medium	high
	a_6	low	low	very low	high	medium

This type of assessment serves as an initial basis for transforming experts' subjective judgments into mathematical representations. Subsequently, these evaluations must be converted—during the fuzzification stage—into membership functions using trapezoidal fuzzy numbers (Figure 1).

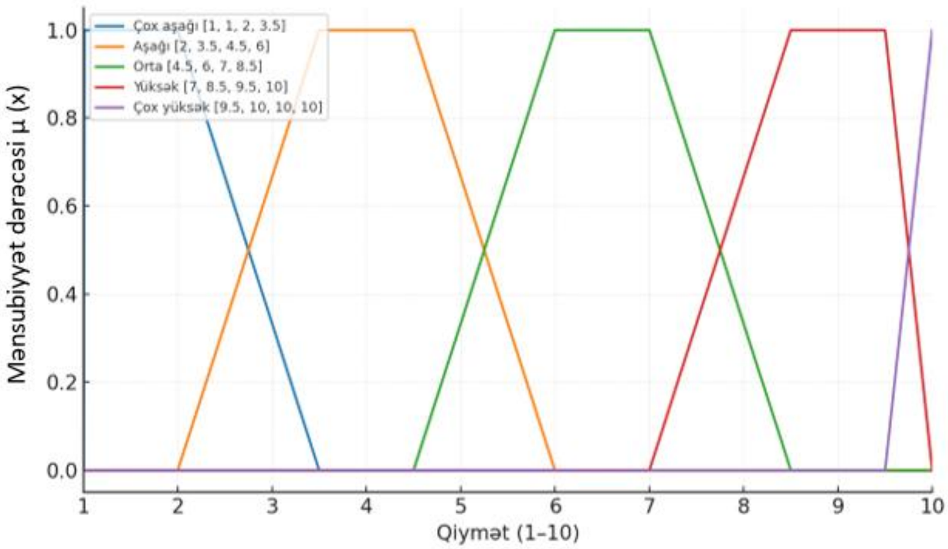

Figure 1. Transformation of the linguistic terms "Very Low, Low, Medium, High, Very High" on the 1–10 scale into membership functions of trapezoidal fuzzy numbers. The corresponding parameter sets are: [1,1,2,3.5], [2,3.5,4.5,6], [4.5,6,7,8.5], [7,8.5,9.5,10], [9.5,10,10,10].

Each expert E_k evaluates each alternative A_i under each criterion C_j using a linguistic term; this term is then converted into a trapezoidal fuzzy number:

$$\tilde{r}_{ij}^{k} = \left(a_{ij}^{(k)},\, b_{ij}^{(k)},\, c_{ij}^{(k)},\, d_{ij}^{(k)}\right)$$

This scale is sufficiently broad to capture uncertainty and can be aligned with the corresponding linguistic variables (Table 3).

Table 3.

Trapezoidal Fuzzy Numbers Corresponding to Linguistic Terms.

Expert	Alternatives	Fuzzified Scores for the Criteria				
		C_1	C_2	C_3	C_4	C_5
E_1	a_1	[7, 8.5, 9.5, 10]	[7, 8.5, 9.5, 10]	[4.5, 6, 7, 8.5]	[7, 8.5, 9.5, 10]	[2, 3.5, 4.5, 6]
	a_2	[2, 3.5, 4.5, 6]	[4.5, 6, 7, 8.5]	[1, 1, 2, 3.5]	[7, 8.5, 9.5, 10]	[7, 8.5, 9.5, 10]
	a_3	[9.5, 10, 10, 10]	[4.5, 6, 7, 8.5]	[1, 1, 2, 3.5]	[9.5, 10, 10, 10]	[7, 8.5, 9.5, 10]

	a_4	[1, 1, 2, 3.5]	[9.5, 10, 10, 10]	[4.5, 6, 7, 8.5]	[7, 8.5, 9.5, 10]	[7, 8.5, 9.5, 10]
	a_5	[7, 8.5, 9.5, 10]	[7, 8.5, 9.5, 10]	[7, 8.5, 9.5, 10]	[7, 8.5, 9.5, 10]	[7, 8.5, 9.5, 10]
	a_6	[2, 3.5, 4.5, 6]	[2, 3.5, 4.5, 6]	[1, 1, 2, 3.5]	[7, 8.5, 9.5, 10]	[4.5, 6, 7, 8.5]
E_2	a_1	[4.5, 6, 7, 8.5]	[7, 8.5, 9.5, 10]	[4.5, 6, 7, 8.5]	[4.5, 6, 7, 8.5]	[2, 3.5, 4.5, 6]
	a_2	[4.5, 6, 7, 8.5]	[4.5, 6, 7, 8.5]	[4.5, 6, 7, 8.5]	[7, 8.5, 9.5, 10]	[7, 8.5, 9.5, 10]
	a_3	[4.5, 6, 7, 8.5]	[7, 8.5, 9.5, 10]	[2, 3.5, 4.5, 6]	[7, 8.5, 9.5, 10]	[7, 8.5, 9.5, 10]
	a_4	[1, 1, 2, 3.5]	[4.5, 6, 7, 8.5]	[4.5, 6, 7, 8.5]	[4.5, 6, 7, 8.5]	[4.5, 6, 7, 8.5]
	a_5	[7, 8.5, 9.5, 10]	[7, 8.5, 9.5, 10]	[4.5, 6, 7, 8.5]	[7, 8.5, 9.5, 10]	[7, 8.5, 9.5, 10]
	a_6	[2, 3.5, 4.5, 6]	[4.5, 6, 7, 8.5]	[2, 3.5, 4.5, 6]	[4.5, 6, 7, 8.5]	[4.5, 6, 7, 8.5]
E_3	a_1	[7,8.5,9.5,10]	[7,8.5,9.5,10]	[4.5,6,7,8.5]	[7,8.5,9.5,10]	[2,3.5,4.5,6]
	a_2	[2,3.5,4.5,6]	[4.5,6,7,8.5]	[1,1,2,3.5]	[7,8.5,9.5,10]	[7,8.5,9.5,10]
	a_3	[9.5,10,10,10]	[4.5,6,7,8.5]	[1,1,2,3.5]	[7,8.5,9.5,10]	[7,8.5,9.5,10]
	a_4	[1,1,2,3.5]	[9.5,10,10,10]	[4.5,6,7,8.5]	[7,8.5,9.5,10]	[7,8.5,9.5,10]
	a_5	[7,8.5,9.5,10]	[7,8.5,9.5,10]	[7,8.5,9.5,10]	[7,8.5,9.5,10]	[7,8.5,9.5,10]
	a_6	[2,3.5,4.5,6]	[2,3.5,4.5,6]	[1,1,2,3.5]	[7,8.5,9.5,10]	[4.5,6,7,8.5]
E_4	a_1	[4.5, 6, 7, 8.5]	[2, 3.5, 4.5, 6]	[7, 8.5, 9.5, 10]	[7, 8.5, 9.5, 10]	[2, 3.5, 4.5, 6]

	a_2	[2, 3.5, 4.5, 6]	[4.5, 6, 7, 8.5]	[1, 1, 2, 3.5]	[7, 8.5, 9.5, 10]	[7, 8.5, 9.5, 10]
	a_3	[9.5, 10, 10, 10]	[4.5, 6, 7, 8.5]	[1, 1, 2, 3.5]	[9.5, 10, 10, 10]	[7, 8.5, 9.5, 10]
	a_4	[4.5, 6, 7, 8.5]	[7, 8.5, 9.5, 10]	[4.5, 6, 7, 8.5]	[4.5, 6, 7, 8.5]	[7, 8.5, 9.5, 10]
	a_5	[9.5, 10, 10, 10]	[4.5, 6, 7, 8.5]	[7, 8.5, 9.5, 10]	[4.5, 6, 7, 8.5]	[7, 8.5, 9.5, 10]
	a_6	[4.5, 6, 7, 8.5]	[4.5, 6, 7, 8.5]	[1, 1, 2, 3.5]	[7, 8.5, 9.5, 10]	[4.5, 6, 7, 8.5]
E_5	a_1	[7, 8.5, 9.5, 10]	[7, 8.5, 9.5, 10]	[7, 8.5, 9.5, 10]	[7, 8.5, 9.5, 10]	[4.5, 6, 7, 8.5]
	a_2	[4.5, 6, 7, 8.5]	[4.5, 6, 7, 8.5]	[2, 3.5, 4.5, 6]	[7, 8.5, 9.5, 10]	[4.5, 6, 7, 8.5]
	a_3	[7, 8.5, 9.5, 10]	[4.5, 6, 7, 8.5]	[2, 3.5, 4.5, 6]	[7, 8.5, 9.5, 10]	[7, 8.5, 9.5, 10]
	a_4	[4.5, 6, 7, 8.5]	[9.5, 10, 10, 10]	[4.5, 6, 7, 8.5]	[4.5, 6, 7, 8.5]	[7, 8.5, 9.5, 10]
	a_5	[4.5, 6, 7, 8.5]	[7, 8.5, 9.5, 10]	[7, 8.5, 9.5, 10]	[4.5, 6, 7, 8.5]	[7, 8.5, 9.5, 10]
	a_6	[2, 3.5, 4.5, 6]	[2, 3.5, 4.5, 6]	[1, 1, 2, 3.5]	[7, 8.5, 9.5, 10]	[4.5, 6, 7, 8.5]

Normalized expert competence coefficients (as defined by the decision maker) are: E_1=0.18, E_2=0.18, E_3=0.35, E_4=0.10, E_5=0.19. This selection mathematically reflects the organization's managerial policy.

$$\alpha = (0.18,\ 0.18,\ 0.35,\ 0.10,\ 0.19)$$

There are two principal mechanisms for determining weights: (i) a direct policy-based approach (fixed values set by management decision), and (ii) a score/competence-based approach—for example, assigning each expert a competence score q_k and then normalizing these scores. The second approach enhances transparency and can be updated over time.

$$\alpha_k = q_k \sum_{t=1}^{5} q_t\,, \quad k = 1, \dots, 5$$

The resulting weight vector α\alphaα is then used in the next step to aggregate the experts' evaluations: for each (employee A_i, criterion C_j), the five experts' trapezoidal fuzzy assessments are combined using these weights to obtain the final fuzzy value $\tilde{r}_{ij}$.

$$\tilde{r}_{ij} = \sum_{k=1}^{5} \alpha_k \tilde{r}_{ij}^{(k)} = \left(\sum_{k=1}^{5} \alpha_k a_{ij}^{(k)}, \sum_{k=1}^{5} \alpha_k b_{ij}^{(k)}, \sum_{k=1}^{5} \alpha_k c_{ij}^{(k)}, \sum_{k=1}^{5} \alpha_k d_{ij}^{(k)} \right)$$

Normalized weights, as specified by management for this study:

E_1=0.18, E_2=0.18, E_3=0.35, E_4=0.10, E_5=0.19.

This selection mathematically reflects the organization's managerial policy.

$$\alpha = (0.18,\ 0.18,\ 0.35,\ 0.10,\ 0.19)$$

Using the expert weights provided by the bank's management, the aggregated fuzzy decision matrix for a_1 - a_6 × C_1– C_5 was computed using the Python programming language, and the final results are presented in Table 4.

Table 4.

the aggregated fuzzy decision matrix for $a_1 - a_6$

Alternatives	Aggregated Results by Criteria				
	C_1	C_2	C_3	C_4	C_5
a_1	[6.3, 7.8, 8.8, 9.58]	[6.5, 8, 9, 9.6]	[5.225, 6.725, 7.725, 8.935]	[6.55, 8.05, 9.05, 9.73]	[2.745, 3.975, 4.975, 6.475]
a_2	[2.925, 4.425, 5.425, 6.925]	[4.5, 6, 7, 8.5]	[1.82, 2.375, 3.375, 4.875]	[7, 8.5, 9.5, 10]	[6.525, 8.025, 9.025, 9.715]
a_3	[8.125, 8.995, 9.365, 9.73]	[4.95, 6.45, 7.45, 8.77]	[1.37, 1.925, 2.925, 4.425]	[7.7, 8.92, 9.64, 10]	[7, 8.5, 9.5, 10]
a_4	[2.015, 2.45, 3.45, 4.95]	[8.35, 9.13, 9.41, 9.73]	[4.5, 6, 7, 8.5]	[5.825, 7.325, 8.325, 9.295]	[6.55, 8.05, 9.05, 9.73]
a_5	[6.775, 8.175, 9.075, 9.71]	[6.75, 8.25, 9.25, 9.85]	[6.55, 8.05, 9.05, 9.73]	[6.275, 7.775, 8.775, 9.565]	[7, 8.5, 9.5, 10]

a_6	[2.25, 3.75, 4.75, 6.25]	[2.7, 4.2, 5.2, 6.7]	[1.18, 1.45, 2.45, 3.95]	[6.55, 8.05, 9.05, 9.73]	[4.5, 6, 7, 8.5]

Because the aggregated fuzzy numbers $\tilde{r}_{ij} = (a_{ij}, b_{ij}, c_{ij}, d_{ij})$ are measured on different scales across criteria, they are mapped onto the [0,1][0,1][0,1] interval using reference vectors. The objective is to use, for benefit-type criteria, the component-wise maxima as the reference, and for cost-type criteria, the component-wise minima, followed by a component-wise linear transformation. This procedure satisfies the requirements of (i) boundedness, (ii) monotonicity, (iii) shape preservation, and (iv) consistency with the FPIS/FNIS stage of TOPSIS. Accordingly, component-wise maxima for benefit criteria and component-wise minima for cost criteria are defined as follows. (Here, "component-wise maximum" means that, instead of selecting a single maximum value, separate maxima are taken for each of the four trapezoidal components):

$$M_j = \left(\max_i a_{ij}\,,\ \max_i b_{ij}\,,\ \max_i c_{ij}\,,\ \max_i d_{ij}\right),$$
$$m_j = \min_i a_{ij}\,,\ \min_i b_{ij}\,,\ \min_i c_{ij}\,,\ \min_i d_{ij}$$

Normalization for benefit-type criteria (j∈B)

$$\frac{\tilde{r}^*_{ij}=\tilde{r}_{ij}}{M_j=\left(\frac{a_{ij}}{M_j^{(a)}},\frac{b_{ij}}{M_j^{(b)}},\frac{c_{ij}}{M_j^{(c)}},\frac{d_{ij}}{M_j^{(d)}}\right)}, \qquad 0 \le \tilde{r}^*_{ij} \le 1.$$

Normalization for cost-type criteria (j∈C)

$$\frac{\tilde{r}^*_{ij}=m_j}{\tilde{r}_{ij}=\left(\frac{m_j^{(a)}}{a_{ij}},\frac{m_j^{(b)}}{b_{ij}},\frac{m_j^{(c)}}{c_{ij}},\frac{m_j^{(d)}}{d_{ij}}\right)}, \qquad 0 \le \tilde{r}^*_{ij} \le 1.$$

Properties

1. Mapping to [0,1]: for benefit criteria, $\frac{a_{ij}}{M_j^{(a)}}$; for cost criteria, $\frac{m_j^{(a)}}{a_{ij}}$. The same mapping is applied analogously to the bbb, ccc, and ddd components.
2. Order preservation: if a≤ b ≤ c ≤d and $M_j^{(a)} \le M_j^{(b)} \le M_j^{(c)} \le M_j^{(d)}$, then the component ordering is also preserved in the normalized values.
3. Ranking invariance under linear scaling: since the reference values are taken from component-wise extrema, the linear rescaling of the scale does not distort the ranking.
4. Practical robustness: on the 1–10 scale, $a_{ij}, b_{ij}, c_{ij}, d_{ij} > 0$, so division-by-zero does not arise; in the general case, a safeguard with ε>0 can be applied.

Based on the fuzzified values, the reference vectors are obtained as follows:

M_1=(8.125, 8.995, 9.365, 9.730)
M_2=(8.350, 9.130, 9.410, 9.850)
M_3=(6.550, 8.050, 9.050, 9.730)
M_4=(7.700, 8.920, 9.640, 10.000)
m_5=(2.475, 3.975, 4.975, 6.475)

Qeyd: fayda meyarları (C_1–C_4) üçün $\tilde{r}_{ij}^* = \tilde{r}_{ij} \oslash$ M; xərc meyarı (C_5) üçün $\tilde{r}_{ij}^*$= $m_5 \oslash \tilde{r}_{ij}$.

Daha sonra alternativlərin meyarlar üzrə aqreqasiya və normalizasiya nəticəsində əldə olunan qiymətləri əldə olunur.

Məqsəd əldə etdiyimiz normalizə olunmuş fuzzy qərar matrisi $\tilde{R}^* = \left[\tilde{r}_{ij}^*\right]_{m\times n}$ üzərinə meyarların nisbi əhəmiyyətini əks etdirən çəki vektoru tətbiq etməkdir və nəticədə çəki tətbiq edilmiş–normalizə olunmuş fuzzy matris $\tilde{V}^* = \left[\tilde{v}_{ij}^*\right]_{m\times n}$ qurulur. Bankın əsas meyarının innovasiya olduğunu nəzərə alaraq C_4 (İnnovativlik) meyarına daha yüksək çəki verilir. Meyarların çəkilərin üzrə qiymətləndirilməsi cədvəl 5-də gğstərilmişdir.

Note: For benefit-type criteria (C_1–C_4), $\tilde{r}_{ij}^* = \tilde{r}_{ij} \oslash$M; for the cost-type criterion (C_5), $\tilde{r}_{ij}^*$= $m_5 \oslash \tilde{r}_{ij}$.

Next, the criterion-wise scores obtained through aggregation and normalization for the alternatives are derived. The objective is to apply the weight vector—reflecting the relative importance of the criteria—to the normalized fuzzy decision matrix $\tilde{R}^* = \left[\tilde{r}_{ij}^*\right]_{m\times n}$, thereby constructing the weighted–normalized fuzzy matrix $\tilde{V}^* = \left[\tilde{v}_{ij}^*\right]_{m\times n}$. Considering that innovation is a primary strategic priority for the bank, a higher weight is assigned to criterion C_4 (Innovativeness). The evaluation of the criteria weights is presented in Table 5.

table 5.

Criteria weight values.

Criterion	Weight, w_j
C_1	0.20
C_2	0.15
C_3	0.15
C_4	0.35
C_5	0.15

The weight constraints, the specification of the weight vector, and the weighting operation can be expressed as follows:

$$\mathrm{w} = (0.20{,}0.15{,}0.15{,}0.35{,}0.15),\ \sum_{j=1}^{5} w_j = 1,\ w_j \geq 0$$

$$\tilde{v}_{ij} = w_j \cdot \tilde{r}_{ij}^{*} = \left(w_j a_{ij}^{*},\ w_j b_{ij}^{*},\ w_j c_{ij}^{*},\ w_j d_{ij}^{*}\right)$$

The final result matrix is expressed as follows, and the corresponding values are provided in Table 6:

$$\tilde{V} = \left[\tilde{v}_{ij}\right]_{m\times n},\ \ \tilde{v}_{ij} \in \left[0, w_j\right]^4$$

Assigning a larger weight to C_4 proportionally increases the impact of high normalized values under this criterion on the final ranking; C_5 (a cost criterion), by contrast, is kept at a moderate weight to ensure that the penalization effect remains balanced.

Table 6.

$\tilde{V}$: fuzzy values after applying the weights.

Alternatives	$\tilde{v}_{ij}$				
	C_1	C_2	C_3	C_4	C_5
a_1	[0.155, 0.173, 0.188, 0.197]	[0.117, 0.131, 0.143, 0.146]	[0.120, 0.125, 0.128, 0.138]	[0.298, 0.316, 0.329, 0.341]	[0.150, 0.150, 0.150, 0.150]
a_2	[0.072, 0.098, 0.116, 0.142]	[0.081, 0.099, 0.112, 0.129]	[0.042, 0.044, 0.056, 0.075]	[0.318, 0.333, 0.345, 0.350]	[0.057, 0.074, 0.083, 0.10]
a_3	[0.200, 0.200, 0.200, 0.200]	[0.089, 0.106, 0.119, 0.134]	[0.031, 0.036, 0.048, 0.068]	[0.350, 0.350, 0.350, 0.350]	[0.053, 0.070, 0.079, 0.097]
a_4	[0.050, 0.054, 0.074, 0.102]	[0.150, 0.150, 0.150, 0.148]	[0.103, 0.112, 0.116, 0.131]	[0.265, 0.287, 0.302, 0.325]	[0.057, 0.074, 0.082, 0.100]
a_5	[0.167, 0.182, 0.194, 0.200]	[0.121, 0.136, 0.147, 0.150]	[0.150, 0.150, 0.150, 0.150]	[0.285, 0.305, 0.319, 0.335]	[0.053, 0.070, 0.079, 0.097]
a_6	[0.055, 0.083, 0.101, 0.128]	[0.048, 0.069, 0.083, 0.102]	[0.027, 0.027, 0.041, 0.061]	[0.298, 0.316, 0.329, 0.341]	[0.082, 0.099, 0.107, 0.114]

Based on the weighted–normalized fuzzy matrix $\tilde{V} = \left[\tilde{v}_{ij}\right]$, the fuzzy ideal and anti-ideal solutions—positive (FPIS) and negative (FNIS)—are determined. Next, the distance of each alternative to these two reference points is computed, and finally the closeness coefficient ($\mathrm{C}C_i$) is calculated to obtain the ranking. For benefit-type criteria, the ideal (FPIS) corresponds to the largest components and the anti-ideal (FNIS) to the smallest components; for cost-type criteria, the opposite holds

Benefit-type criterion C_j:

$$\tilde{A}_j^+ = \left(\max_i v_{ij}^{(a)}, \max_i v_{ij}^{(b)}, \max_i v_{ij}^{(c)}, \max_i v_{ij}^{(d)}\right),$$
$$\tilde{A}_j^- = \left(\min_i v_{ij}^{(a)}, \min_i v_{ij}^{(b)}, \min_i v_{ij}^{(c)}, \min_i v_{ij}^{(d)}\right)$$

Cost-type criterion $\boldsymbol{C_j}$:

$$\tilde{A}_j^+ = \left(\min_i v_{ij}^{(a)}, \min_i v_{ij}^{(b)}, \min_i v_{ij}^{(c)}, \min_i v_{ij}^{(d)}\right),$$
$$\tilde{A}_j^- = \left(\max_i v_{ij}^{(a)}, \max_i v_{ij}^{(b)}, \max_i v_{ij}^{(c)}, \max_i v_{ij}^{(d)}\right)$$

The Euclidean distance between trapezoidal fuzzy numbers can be obtained using the following expressions:

$$D(\tilde{x}, \tilde{y}) = \sqrt{\frac{1}{4}\left[\left(a_x - a_y\right)^2 + \left(b_x - b_y\right)^2 + \left(c_x - c_y\right)^2 + \left(d_x - d_y\right)^2\right]}$$

The TOPSIS distances are then computed using the following formulas:

$$D_i^+ = \sqrt{\sum_j D\left(\tilde{v}_{ij}, \tilde{A}_j^+\right)^2}, \quad D_i^- = \sqrt{\sum_j D\left(\tilde{v}_{ij}, \tilde{A}_j^-\right)^2}$$

The computed trapezoidal components of the ideal $\tilde{A}^+$ and anti-ideal $\tilde{A}^-$ solutions are presented in Tables 7 and 8, respectively.

Table 7.

Computed Trapezoidal Component Values for the Ideal Solution $\tilde{A}^+$

Criterion	0	1	2	3
C_1	0.2	0.2	0.2	0.2
C_2	0.15	0.15	0.15	0.15
C_3	0.15	0.15	0.15	0.15
C_4	0.35	0.35	0.35	0.35
C_5	0.053	0.07	0.079	0.097

Table 8.

Computed trapezoidal component values for the anti-ideal solution $\tilde{A}^{-}$

Criterion	0	1	2	3
C_1	0.05	0.054	0.074	0.102
C_2	0.048	0.069	0.083	0.102
C_3	0.027	0.027	0.041	0.061
C_4	0.265	0.287	0.302	0.325
C_5	0.15	0.15	0.15	0.15

Distances between trapezoidal fuzzy numbers are measured using the vertex method, which allows all four components of the trapezoid (a,b,c,d) to be taken into account in a symmetric and stable manner. Within the TOPSIS framework, the distances are computed using the Euclidean metric, after which the closeness coefficient is defined as follows:

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-}, \quad 0 \le CC_i \le 1$$

In this study, the matrix $\tilde{V}$ was constructed using weights that prioritize criterion C_4 (Innovativeness), and all computations were performed on this $\tilde{V}$.

Table 9 presents, for each alternative, the distances to the fuzzy ideal solution and the fuzzy anti-ideal solution, the computed values of the closeness coefficient, and the resulting ranking

Table 9.

Computed ideal and anti-ideal distances, closeness coefficients, and ranking of alternatives.

Alternativlər	D_i^+	D_i^-	CC_i	Sıra
a_1	0.04983	0.19048	0.79265	1
a_2	0.09303	0.15493	0.62483	2
a_3	0.11309	0.16781	0.59740	3
a_4	0.14886	0.13100	0.46808	4
a_5	0.14595	0.09886	0.40381	5
a_6	0.18073	0.06236	0.25654	6

At this stage, the score of each candidate ($a_1 \ldots a_6$) is computed based on how close the candidate's profile is to the "best possible profile" (the ideal solution) and how far it is from the "worst profile" (the anti-ideal solution). For this purpose, the closeness coefficient is defined on the [0,1] interval: the larger the value, the better the candidate. The resulting ranking is: $a_1 > a_2 > a_3 > a_4 > a_5 > a_6$

1. a_1 ranks first, as it performs strongly on innovativeness (C_4) and the other main criteria, while the cost criterion (C_5) is at a moderate level. Overall, it is the profile closest to the ideal solution.
2. a_2 ranks second and appears highly balanced: C_4 is strong, C_1–C_3 are moderate-to-good, and the value under C_5 is low. It therefore seems to be a stable and reliable choice.
3. a_3 ranks third. Although C_1 and C_4 are very strong, it falls behind due to high values under the cost criterion (C_5).
4. a_4 ranks fourth. It performs well in communication/coordination (C_2), but its overall outcome remains moderate because innovativeness (C_4) stays at a mid-level.
5. a_5 ranks fifth. While C_4 is good, C_1 and C_3 are weak and C_5 is relatively high; therefore, it is farther from the ideal solution.
6. a_6 ranks sixth. Despite a good score on C_4, weaknesses across the other criteria place it at the lowest position.

Discussion

The results of the study indicate that the proposed fuzzy TOPSIS–based multi-criteria decision-making model is a practically applicable, structured, and explainable decision support tool for the banking human resources environment. The fact that the ranking outcomes obtained in the illustrative application scenario coincide with the experts' actual selections demonstrates the model's adequacy and its ability to successfully emulate the practical appraisal process. In particular, the alternative with the highest closeness coefficient being identical to the candidate who was in fact appointed to the position confirms that the model is not merely a theoretical construct, but also accurately reflects real decision-making logic.

In this study, the vertex method was adopted as the baseline approach; it compares the trapezoidal components (a,b,c,d) in a four-dimensional space using an Euclidean-type metric, thereby preserving the full fuzzy information without reducing it to a single scalar. As an alternative, in the widely used centroid approach, each trapezoid is first scalarized (COA—center of area), after which the classical TOPSIS distances are computed over these scalar vectors. This comparison is conducted in order to assess the sensitivity (robustness) of the results to the choice of method.

For example, for the weighted trapezoid corresponding to A_1–C_1, $\tilde{v}_{11}$=(a,b,c,d)=(0.155, 0.173, 0.188, 0.197). The centroid (COA) scalar is computed as: z_{11}=(a+2b+2c+d)/6 = (0.155+2·0.173+2·0.188+0.197)/ 6 = 1.074/6 ≈ 0.179.

Thus, under the centroid approach, the representative scalar value for A_1–C_1 is approximately 0.179. The same procedure is applied to obtain z_{ij} for all remaining entries; then the ideal/anti-ideal solutions and distances are computed based on these scalars.

All computations were implemented in the Python programming language according to the algorithm derived from the formulas presented above, and the comparative results are reported in Table 10

Table 10.

Comparative scores of alternatives computed using the vertex and centroid methods.

Alternative	D_i^+ - vertex	D_i^+ - centroid	D_i^- - vertex	D_i^- - centroid	CC_i - vertex	CC_i - centroid	Sıra - vertex	Sıra - centroid
a_1	0.04986	0.04238	0.19045	0.19170	0.79251	0.81895	1	1
a_2	0.09309	0.08754	0.15509	0.15733	0.62492	0.64251	2	2
a_3	0.11294	0.11185	0.16785	0.16595	0.59778	0.59737	3	3
a_4	0.14898	0.14742	0.13097	0.12907	0.46784	0.46681	4	4
a_5	0.14592	0.14219	0.09898	0.09790	0.40417	0.40776	5	5
a_6	0.18057	0.17709	0.06219	0.06034	0.25619	0.25415	6	6

Under the Spearman rank correlation analysis, both methods yield the same ordering:

$a_1 > a_2 > a_3 > a_4 > a_5 > a_6$.

Accordingly, since the rank differences are $d_i = 0$, the correlation coefficient is ρ=1.0 (perfect agreement). This indicates that the results are robust and that the choice of distance method does not alter the final decision.

The comparison of the distance methods (vertex vs. centroid) therefore produces an identical ranking with a Spearman rank correlation of ρ=1.0. Moreover, when the weight of C_4 was varied within the 0.30–0.40 range, the ranking remained unchanged: the maximum rank shift was 0, and only minor fluctuations in the closeness coefficients were observed. These findings confirm that the fuzzy TOPSIS outputs are robust with respect to both methodological choice and parameter variation.

In the context of multi-criteria decision-making, these results highlight several important points. First, clearly structuring the criteria and formally classifying each criterion as either benefit-type or cost-type helps to surface rules that are often implicitly present in decision-making but rarely documented explicitly. This gives HR specialists and managers an opportunity to "step outside" the decision logic, creates a more reflective view of the appraisal process, and provides an additional platform for discussion aimed at improving evaluation practices. Second, determining and modeling criteria weights using a fuzzy approach demonstrates that experts' intuitive judgments of the "how important is it?" type can be translated into a formal algorithm, thereby increasing the consistency of HR decisions.

The choice of the fuzzy TOPSIS algorithm is another relevant issue for discussion. Compared with other MCDM methods such as AHP, ANP, VIKOR, and related techniques, TOPSIS is primarily advantageous because it is grounded in the concept of ideal and anti-ideal solutions, while producing an outcome in the form of a closeness coefficient within the [0,1] interval. For banking HR practice, this yields an easily interpretable and intuitively meaningful indicator—namely, "closeness to the ideal candidate profile." Even when closeness coefficients lie within a relatively narrow range (e.g., when all candidates satisfy minimum requirements), the approach still introduces an additional "calibration" capability for HR decision-making: managers can identify not only the top-ranked candidate but also the "second-best" option as a reserve alternative [3,4,7].

One factor that further strengthens the model's practical relevance is the sensitivity analysis. The fact that variations in criteria weights within a reasonable interval do not radically affect the ranking of alternatives—i.e., the best alternative remains stable—demonstrates the robustness of the model. In this sense, the proposed approach does not merely reproduce the subjective viewpoint of a specific expert group; rather, it remains sufficiently resilient to future updates in the criteria system and their weights. This increases the model's adaptability under evolving HR strategic priorities in banks (e.g., placing greater emphasis on customer orientation and relatively less on purely technical skills).

At the same time, the limitations of the study should be recognized. The illustrative application was conducted within a single bank and for a specific job group, which does not allow the results to be automatically generalized to the entire banking sector. Second, because both the criteria weights and the linguistic evaluations are based on expert judgment, the model's initial configuration is constrained by the experience and perspectives of the selected experts. Third, at this stage, the model has not been subjected to a formal comparative evaluation against other MCDM methods (e.g., fuzzy VIKOR, PROMETHEE), which remains a direction for future work [7,9].

Nevertheless, these limitations do not negate the usefulness of the proposed model; rather, they indicate additional research directions for its further development. The key conclusion is that a fuzzy TOPSIS–based multi-criteria decision support model can structure HR decision-making in banking, translate expert opinion into a formal algorithm, and—by reducing the influence of subjective bias to a certain extent—enable more transparent and better-justified decisions.

Conclusion

1. The article proposes a model to support HR decision-making in the banking sector, based on fuzzy multi-criteria decision-making principles and the TOPSIS method, while also accounting for linguistic criteria (trapezoidal fuzzy numbers combined with the ideal/anti-ideal solution concept).
2. A structured criteria framework is developed for the banking context; expert judgments are fuzzified, weights are applied, and a ranking is obtained via fuzzy TOPSIS using the closeness coefficient. The illustrative application demonstrates consistency between the resulting ranking and actual HR decisions.
3. The proposed approach transforms decision-making from a "black box" into a traceable, explainable, and repeatable mechanism; the results can be integrated into an HRIS/DSS module and automated in the form of rankings and recommendations.
4. Future research should consider broader application of the model across different banks and job groups, comparative evaluation of fuzzy TOPSIS against methods such as fuzzy VIKOR/PROMETHEE/ELECTRE, the incorporation of more advanced aggregation mechanisms for expert judgments in group decision-making settings, integration with machine learning and predictive analytics, and separate examination of ethical and fairness aspects (bias and discrimination risk).

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