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Integration of Skyline Query with the PROMETHEE MCDM Method: A Case Study on Structural Official Selection

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Abstract

The selection of structural officials within higher education institutions is a strategic and complex process that demands objectivity, transparency, and a data-driven approach. However, the increasing number of candidates and the diversity of evaluation criteria, such as years of service, rank, education, age, and performance, pose significant challenges in ensuring fair and efficient decision-making. Addressing this gap, this study proposes a hybrid method by integrating Skyline Query with the Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE), offering a novel contribution to multi-criteria decision-making (MCDM) in public sector human resource selection. Skyline Query is employed as a preselection mechanism to eliminate 161 dominated candidates from an initial dataset of 228, allowing only the 67 most non-dominated candidates to advance to the ranking stage. PROMETHEE is then applied to generate rankings based on leaving and entering flow values. To evaluate the consistency and validity of this combined approach, the resulting rankings are compared with those from the pure PROMETHEE method using Spearman's Rank Correlation. The analysis yields a high correlation coefficient of $\rho = 0.967$, indicating a very strong agreement between the two methods and confirming that the Skyline filtering does not distort ranking quality. The findings demonstrate that the Skyline+PROMETHEE integration significantly enhances the efficiency of the selection process by reducing computational complexity while preserving decision accuracy. Moreover, this approach strengthens the transparency and accountability of structural official selection, particularly in the context of the University of Mataram, and can be generalized to other institutional decision-making scenarios.

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INTRODUCTION

The selection of structural officials is a critical component of public sector organizational management, including in higher education institutions (Meo et al., 2021). At the University of Mataram, one of the strategic positions requiring a rigorous selection process is the Team Leader, which is equivalent to Echelon IV or Head of Subdivision. This role carries significant responsibilities in supporting policy implementtation, managing work programs, and coordinating across departments (Fachri M., 2022). Consequently, the selection process cannot rely solely on intuition or subjective experience but must be conducted through an objective, structured, and methodologically sound approach (Tanti, 2016).

In practice, the selection of structural officials involves numerous candidates with diverse backgrounds and experiences (Rachmad et al., 2009). The process typically considers multiple criteria such as years of service, rank, education level, age, and performance (Axali et al., 2024). These criteria are multidimensional and often conflicting, e.g., younger candidates with higher education qualifications (Kumar, 2025). This complexity calls for a robust and systematic multi-criteria decision-making (MCDM) framework capable of balancing these diverse attributes (Hoseinzade et al., 2021).

One of the widely adopted MCDM methods is PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation), developed by Brans and Mareschal. It is an outranking method that compares alternatives pairwise using preference functions (Vinícius Cardoso de Oliveira et al., n.d.). The method calculates leaving and entering flow values for each alternative, from which the net flow is derived to determine the final ranking (Glavinovic & Vukic, 2023). PROMETHEE is praised for its flexibility in handling both numerical and ordinal data and for producing interpretable results (Tufail et al., 2022). However, the method has a limitation when applied to large datasets, as all alternatives are processed without first filtering out unqualified ones (Trivedi et al., 2023). As a result, the evaluation can become inefficient and may burden the analysis process, especially when many alternatives are far below the average in quality (Gülmez, 2025).

To overcome this limitation, this study incorporates a preselection mechanism using Skyline Query, a database concept introduced by Börzsönyi et al. (Ma & Xu, 2023). Skyline Query is designed to identify non-dominated alternatives by eliminating those that are inferior across all criteria (Sorrentino, n.d.). In this context, an alternative A is said to dominate alternative B if A is better than or equal to B in all criteria and strictly better in at least one criterion (Wan et al., 2024). The result of Skyline Query is a set of non-dominated alternatives, also known as the Pareto-optimal set (Ouadah et al., 2019). By filtering out underqualified candidates at an early stage, the evaluation process can focus on the most promising candidates, thereby improving both computational efficiency and decision accuracy (Yuan et al., 2024).

The integration of Skyline Query as a preselection stage and PROMETHEE as the final ranking method forms a hybrid decision-making approach referred to as Skyline+PROMETHEE. This hybrid aims to reduce analytical complexity, lower computational burden, and improve the validity of final decisions (Gulzar & Alwan, 2022). However, the application of a new hybrid approach requires validation to ensure its consistency with established methods. In this context, it is crucial to examine whether the final rankings produced by Skyline+PROMETHEE are consistent with those generated by pure PROMETHEE.

To address this, the study employs Spearman's Rank Correlation, a non-parametric statistical method used to assess the strength and direction of association between two ranked variables (Yu & Hutson, 2024). Spearman's Rank Correlation Coefficient (ρ), developed by Charles Spearman, is a statistical tool used to measure the strength and direction of the relationship between two ordinal variables (Piscopo et al., 2024). The coefficient value ranges from -1 to +1, where +1 indicates a perfect positive correlation, -1 indicates a perfect negative correlation, and 0 indicates no correlation (Bocianowski et al., n.d.). This method is well-suited for evaluating ranking results, as it does not require the assumption of normal distribution and is not sensitive to data scale (Jiang et al., 2024). Spearman's correlation is commonly used in validating MCDM methods, as it provides insights into how consistent a method is with another in terms of the ranking order of alternatives (Okoye & Hosseini, 2024).

Therefore, this study aims to: (1) develop a structured candidate selection approach for structural positions by integrating Skyline Query and PROMETHEE, (2) objectively filter out the most dominant candidates using Skyline Query, and (3) evaluate the consistency of the hybrid method through Spearman's Rank Correlation. Methodologically, this research contributes by bridging two distinct domains, database querying (Skyline Query) and MCDM (PROMETHEE), into a unified, efficient, and adaptive selection framework. By integrating preselection and ranking into a coherent system, the proposed approach is expected to support more transparent, efficient, and accountable decision-making in structural official selection, both within universities and broader public-sector contexts.

RESEARCH METHODS

This study adopts a quantitative approach, as all stages of analysis are based on numerical data and evaluative scales that can be measured objectively. This approach is selected to enable the evaluation of alternatives based on several relevant criteria, such as years of service, rank, education, age, and performance, in both numerical and ordinal forms.

The research design used is a comparative experiment, with the primary objective of testing and comparing the effectiveness of the PROMETHEE method in two different scenarios: first, PROMETHEE is applied directly to the entire candidate dataset; second, PROMETHEE is applied only to candidates who have been preselected using the Skyline Query.

Skyline queries were originally developed to identify the optimal data points from a large set of alternatives. Each point is assessed based on multiple criteria to filter out non-dominated options in a multi-dimensional space (Gulzar et al., 2017).

Skyline Query is chosen for the preselection stage due to its capability to filter out non-dominated alternatives based on the principle of Pareto dominance (Gulzar & Alwan, 2022). By eliminating less competitive candidates at the outset, the evaluation process can focus on a more relevant and potential subset of data (Mohamud et al., 2024). This step significantly reduces analytical complexity and enhances the efficiency of the final ranking process.

Meanwhile, PROMETHEE is used as the main ranking method because of its advantages in handling multi-criteria problems using flexible preference functions and producing net flow values as the basis for final ranking (Alves et al., 2024). The method also supports transparent interpretation and is grounded in a strong outranking logic (Prima et al., 2024).

As part of the result validation, this study uses Spearman's Rank Correlation to measure the degree of consistency in ranking order (Amman et al., 2023) between the pure PROMETHEE method and the hybrid approach that integrates Skyline Query with PROMETHEE. Spearman's correlation is chosen because it is non-parametric and well-suited for evaluating ranking agreement without requiring specific distributional assumptions for the data (Ejegwa et al., 2024).

Through this approach, the study aims to make a meaningful contribution to the development of a more efficient, objective, and applicable decision-making system for structural official selection, particularly within the context of higher education institutions.

The research methodology consists of several main stages, as illustrated in Figure 1 below.

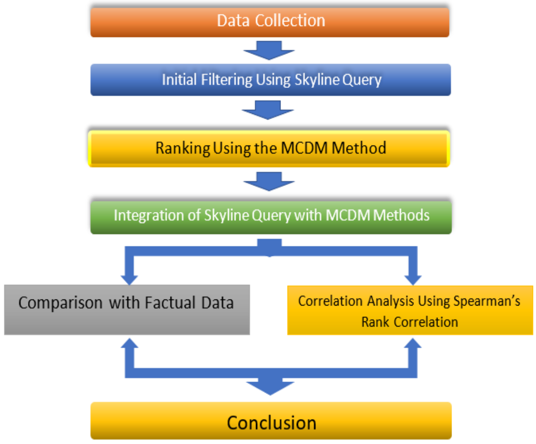

Figure 1. Main stages of the methodology

A. Data Collection

The data used in this study were obtained from two main sources: the GPP Web Application (for years of service, rank/grade, and age) and the Civil Service Subdivision of the University of Mataram (for performance, education, and the list of structural officials equivalent to Echelon IV). All data underwent internal validation to ensure completeness and accuracy.

This study utilized a combination of quantitative and qualitative data to represent key aspects in the selection of structural officials, including administrative, competency, and performance dimensions. Five main variables were used: years of service, rank, age, education, and performance, each reflecting experience, career level, physical and mental readiness, academic capacity, and measurable achievements.

The data were organized in tabular form and processed into a decision matrix, which was then analyzed using Skyline Query for the preselection stage and PROMETHEE for the ranking process. Criteria were evaluated using a scoring system, except for years of service and age, which were analyzed using their original values without categorization.

Table 1. Criteria Scoring for Rank/Grade

Grade	Score
III/a	31
III/b	32
III/c	33
III/d	34
IV/a	41

Table 2. Criteria Scoring for Education

Education	Score
SD/SMP	1
SMA/D-II/D-III	2
S1	3
S2/S3	4

Table 3. Criteria Scoring for Performance

Performance	Score
Low	1
Fair	2
Good	3
Excellent	4

Further evaluation is conducted after all initial data are normalized to ensure they are on a uniform scale, ranging from 0 to 1. This step is essential because each criterion has different units and value ranges, which could affect the calculation results if not standardized.

The normalization method used in this study is Min-Max Normalization, which transforms the original values of each alternative into a comparable scale ranging from 0 to 1. This transformation is essential to ensure that all criteria contribute equally to the decision-making process, regardless of their original units or scales.

1. Benefit and Cost Type Criteria

For benefit-type criteria (i.e., where a higher value is considered better), the normalized value is calculated using Equation (1).

$$\frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

Caption of the formula:

x = the original value of an alternative for a specific criterion

x_{min} = the minimum value among all alternatives for that criterion

x_{max} = the maximum value among all alternatives for that criterion

Conversely, for cost-type criteria (i.e., where a lower value is considered better), the normalization uses Equation (2).

$$\frac{x_{max} - x}{x_{max} - x_{min}} \tag{2}$$

Caption of the formula:

x = the original value of an alternative for a specific criterion

x_{min} = the minimum value among all alternatives for that criterion

x_{max} = the maximum value among all alternatives for that criterion

with the same parameter definitions as in Equation (1).

These normalization formulas are widely adopted in MCDM studies to standardize multi-criteria data prior to further analysis, such as ranking or scoring.

2. Value range of each criterion.

Table IV shows the type, minimum, and maximum values of each criterion based on the initial data.

Table 4. Criteria Value

Criteria	Type	Min	Max
Years of Service	Benefit	0	41
Grade	Benefit	11	45
Age	Cost	17	58
Education	Benefit	1	8
Performance	Benefit	1	4

With data characteristics like these, the analysis conducted in this study has a strong foundation to produce a more transparent, objective, and data-driven structural official selection process. This approach not only enhances the validity of the ranking results but also provides scientific support for strategic decision-making in public sector organizations, particularly in the context of higher education institutions.

B. Initial Filtering Using Skyline Query

The initial stage of the selection process involves the application of Skyline Query, a method based on the concept of dominance in database systems (Zhao et al., 2021). Skyline Query automatically eliminates candidates who are dominated by others, those who perform worse across all considered criteria. The result is a set of non-dominated (Pareto-optimal) candidates, each of whom has a relative advantage in at least one criterion without being completely inferior in others (Damarjati et al., 2024). This stage aims to simplify the solution space and improve the efficiency of the subsequent ranking process.

In general, the Skyline Query does not have an explicit mathematical formula like other numerical methods because it is a dominance-based method in a multidimensional space (Ciaccia & Martinenghi, 2024). However, its fundamental principle can be explained using dominance notation between alternatives as follows.

1. Definition of Dominance in Skyline Query

Given two alternatives A and B, each with values on d criteria, represented as ($a_1, a_2, \ldots, a_d$) and ($b_1, b_2, \ldots, b_d$), then:

$A \prec B$ (A mendominasi B) if and only if:

$$\forall i \in \{1, \ldots d\} : a_i \leq b_i \text{ and } \exists_j \in \{1, \ldots d\} : a_j < b_j \quad (3)$$

Meaning: (1) The value of A is better than or equal to B in all criteria; (2) and strictly better in at least one criterion

Note: If the criterion is a benefit type (the larger, the better), then the operator is reversed.

$$a_i \leq b_i \; and \; a_i < b_i \quad (4)$$

Caption of the formula:

a_i = the value of alternative **A** on criterion ***i***

b_i = the value of alternative **B** on criterion ***i***

Skyline Query Process: (1) Compare each alternative with all other alternatives; (2) Mark alternatives that are dominated by another alternative. Alternatives that are not dominated by any other are included in the Skyline Set (also known as the Pareto-optimal set).

C. Ranking Using the MCDM Method

Candidates who pass the preselection stage are subsequently analyzed using an MCDM method, specifically the PROMETHEE approach. This procedure involves pairwise comparisons among candidates based on each predetermined criterion. The leaving flow and entering flow values are calculated for each alternative, which are then used to determine the net flow as the basis for the final ranking. This method is chosen for its ability to produce logical and mathematically traceable ranking results.

The ranking process using PROMETHEE includes the following stages.

1. Evaluation Matrix

The initial step before constructing the evaluation matrix is to determine the type of each criterion, whether it is a benefit (the higher, the better) or a cost (the lower, the better) criterion. Performance, education, and years of service are considered benefit criteria, while age is classified as a cost criterion. This classification forms the basis for calculating differences between alternatives, preference levels, aggregated preferences, and computing the leaving flow, entering flow, and net flow, leading to the final ranking.

Calculation Formulas:

(1) Benefit Criteria

To ensure that each criterion contributes proportionally in the decision-making process, this study applies normalization techniques to transform raw data into a standardized scale. For benefit-type criteria, where higher values are preferred, the normalization is performed using Equation (5):

$$R_{ij} \frac{[x_{ij} - \min(x_{ij})]}{[\max(x_{ij}) - \min(x_{ij})]} \quad (5)$$

(2) Cost Criteria

Meanwhile, for cost-type criteria—where lower values are more desirable—the normalization follows Equation (6):

$$R_{ij} \frac{[\max(x_{ij}) - x_{ij}]}{[\max(x_{ij}) - \min(x_{ij})]} \quad (6)$$

Caption of the formula:

R_{ij} = normalized value for the ***i-th*** alternative on the ***j-th*** criterion

x_{ij} = original (raw) value of the ***i-th*** alternative on the ***j-th*** criterion

min (x_j) = minimum value among all alternatives for criterion ***j***

max (x_j) = maximum value among all alternatives for criterion ***j***

2. Difference Evaluation

The first step is to calculate the difference in values between alternatives for each criterion. Each alternative is compared pairwise with all other alternatives.

The difference is calculated using the following formula:

$$d(a, b) = f(a) - f(b) \quad (7)$$

where *f(a)* and *f(b)* are the values of alternatives a and b for a given criterion.

3. Preference

The calculated differences are then transformed into preference values using a preference function. The preference value ranges from 0 to 1: a value of 0 indicates no preference (both alternatives are considered equal), while a value of 1 indicates full preference (one alternative is significantly better).

An example of a simple preference function is shown in Equation (8).

$$P(a,b) = \begin{cases} 0 & if\ d(a,b) \leq 0 \\ 1 & if\ d(a,b) \leq 1 \end{cases} \quad (8)$$

Caption of the formula:

P(a, b) = the preference value between alternatives ***a*** and ***b***

d(a, b) = the evaluation difference between ***a*** and ***b***

4. Calculating the Global Preference Index

In the PROMETHEE method, the aggregated preference index represents the overall preference of one alternative over another by combining the individual preference values across all criteria. This is achieved by assigning a weight to each criterion, reflecting its relative importance and summing the weighted preference values accordingly. The formula for calculating the aggregated preference is given in Equation (9).

$$\pi(a,b) = \sum_{j=1}^{n} \omega_j \ . P_j(a,b) \quad (9)$$

Caption of the formula:

π(a,b) = aggregate preference of alternative ***a*** over ***b***

n = total number of criteria

ω_j = weight of the ***j-th*** criterion, where $\sum \omega_j = 1$

$P_j(a, b)$ = preference value of ***a*** over ***b*** based on the ***j-th*** criterion

5. Calculating the Leaving Flow

In the PROMETHEE method, the leaving flow (also known as positive flow) quantifies how strongly an alternative dominates all other alternatives in the decision set. It represents the average preference of a given alternative over the others and is calculated using Equation (10):

$$\emptyset^{+}(a) = \frac{1}{m-1} \sum_{x \in A} \pi(a,x) \quad (10)$$

Caption of the formula:

$\Phi^{+}(a)$ = Leaving Flow of alternative ***a***

m = total number of alternatives in set ***A***

π(a,x) = agregate preference value of alternative ***a*** over alternative ***x***

A = the set of all alternatives

x∈*A* = all alternatives ***x*** in the set, excluding ***a*** itself

6. Calculating the Entering Flow

The entering flow (also referred to as negative flow) measures the extent to which a given alternative is dominated by all other alternatives in the decision set. It is calculated as the average aggregated preference of all other alternatives over the considered alternative, as shown in Equation (11):

$$\emptyset^{-}(a) = \frac{1}{m-1} \sum_{x \in A} \pi(a,x) \quad (11)$$

Caption of the formula:

$\Phi^{-}(a)$ = Entering Flow of alternative ***a***

m = total number of alternatives in set ***A***

π(x, a) = agregate preference value of alternative ***x*** over alternative ***a***

A = the set of all alternatives

x∈*A* = all alternatives ***x*** in the set, excluding ***a*** itself

7. Calculating the Net Flow

Determines the final ranking of alternatives by calculating the difference between the Leaving Flow and the Entering Flow. The net flow serves as the basis for final ranking and is calculated as the difference between the leaving flow and the entering flow, as shown in Equation (12).

$$\emptyset(a) = \emptyset^{+}(a) - \emptyset^{-}(a) \quad (12)$$

Caption of the formula:

$\Phi(a)$ = Net Flow of alternative ***a***

$\Phi^{+}(a)$ = Leaving Flow (how much ***a*** is preferred over others)

$\Phi^{-}(a)$ = Entering Flow (how much ***a*** is less preferred compared to others)

D. Correlation Analysis Using Spearman's Rank Correlation

To test the consistency and stability of the combined approach of Skyline Query and PROMETHEE, a comparative analysis was conducted between the ranking results obtained from the pure PROMETHEE method and those from the combined method. Spearman's Rank Correlation Coefficient (ρ) is used as a non-parametric statistical measure that evaluates the degree of agreement between the ranking orders of the two methods. A high correlation indicates that the preselection approach does not disrupt the stability of the ranking results, but rather simplifies the process without compromising the quality of decision-making.

The general formula for Spearman's rank correlation (without ties) is:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2-1} \quad (13)$$

Caption of the formula:

ρ = Spearman's rank correlation coefficient (ranges from –1 to +1)

d_i = the difference between the ranks of each pair of observations

n = the number of paired observations (data points)

E. Comparison with Factual Data

To ensure the practical validity of the applied method, the ranking results are compared with the actual appointment decisions made by the institution. This analysis aims to assess whether the implemented quantitative approach reflects the real decision-making tendencies of policymakers. This validation also serves as a benchmark to evaluate the method's effectiveness in real-world contexts.

RESULT AND DISCUSSION

A. Data Cleansing

The initial dataset obtained for this study consisted of 1,501 alternatives, each representing a candidate in the selection process. However, not all were included in the analysis. Prior to the evaluation phase, a data cleansing process was carried out to remove invalid or incomplete entries, ensuring that only eligible data were involved in the subsequent selection stages.

The steps taken during the data cleansing process include: (1) Removing data that does not meet the specified criteria; (2) Selecting administrative staff data and removing records related to academic staff or lecturers; (3) Selecting data of structural officials equivalent to Echelon IV, specifically Team Leaders and candidate data that meet the criteria based on information from the Subdivision of Administrative Staff Affairs at the University of Mataram; (4) Excluding data of officials from Echelon III and above. Table 5 presents the results of the data cleansing process.

Table 5. Data Cleansing

Alter-native	Years of Service	Grade	Age	Edu-cation	Perfor-mance
P001	2	31	26	3	3
P002	2	31	27	3	3
P003	5	23	29	3	3
P004	5	23	34	3	3
P005	6	32	34	3	4
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P228	22	31	58	2	3

After the data cleaning process, a new dataset consisting of 228 alternatives was obtained. These 228 alternatives were then subjected to a normalization process, the results of which are shown in Table 6 below.

Table 6. Data Normalization

Alter-native	Years of Service	Grade	Age	Edu-cation	Perfor-mance
P001	0,05	0,59	0,78	0,67	0,67
P002	0,05	0,59	0,76	0,67	0,67
P003	0,12	0,35	0,71	0,67	0,67
P004	0,12	0,35	0,59	0,67	0,67
P005	0,15	0,62	0,59	0,67	1,00
…	…	…	…	…	…
P228	0,54	0,59	0,00	0,33	0,67

B. Initial Filtering with Skyline Query

In the initial stage of analysis, a candidate filtering process was conducted using the Skyline Query method to identify non-dominated alternatives based on five primary criteria: years of service, rank, age, education, and performance. Out of a total of 228 alternatives, the Skyline Query successfully filtered 67 alternatives that met the criteria as non-dominated candidates, meaning that no other alternative was better in all aspects simultaneously. Table 7 presents the results of the initial filtering using the Skyline Query.

Table 7. Initial filtering using the Skyline Query

Alter-native	Years of Service	Grade	Age	Edu-cation	Perfor-mance
P001	0,05	0,59	0,78	0,67	0,67
P002	0,05	0,59	0,76	0,67	0,67
P005	0,15	0,62	0,59	0,67	1
P006	0,24	0,65	0,59	1	0,67
…	…	…	…	…	…
P219	0,73	0,62	0	0,33	1
P220	0,63	0,59	0	0,33	1
P221	0,78	0,68	0	1	0,67
P222	0,63	0,62	0	0,33	1
P225	0,41	0,29	0	0,33	1

C. Ranking with PROMETHEE

In (Wątróbski, 2023) there are several ranking steps using PROMETHEE, including:

1. Evaluation Matrix

Since the data has undergone normalization using the Min-Max method, the evaluation matrix in the PROMETHEE method in this study directly uses the normalized results. Each alternative has an evaluation value for each criterion within the range [0–1], reflecting its relative position compared to other alternatives. This matrix serves as the foundation for calculating the preference level between pairs of alternatives and subsequently determining the values of leaving flow, entering flow, and net flow for final ranking determination.

2. Evaluation Differential

Following the normalization process, the next step is calculating the evaluation differential, or the evaluation difference between alternatives for each criterion. This step aims to measure how much better or worse one alternative is compared to another based on each criterion value.

3. Calculating Preference

After calculating the evaluation differences for each criterion, the next step in the PROMETHEE method is to determine the preference values. Preference indicates the degree to which one alternative is preferred over another based on the evaluation difference on a given criterion.

4. Calculating Aggregate Preference Index

Once preferences for each criterion are calculated, the next step is to aggregate all preferences between alternatives using the criterion weights to obtain the aggregate preference. This aggregate preference value becomes the basis for calculating the Leaving Flow, Entering Flow, and ultimately the Net Flow, which serves as the basis for alternative ranking.

5. Calculating Leaving Flow, Entering Flow, Net Flow, and Ranking from Original Data

Based on the PROMETHEE analysis results of the 228 candidate alternatives, the values of leaving flow (φ^+), entering flow (φ^-), and net flow (φ) were obtained for each alternative. The net flow value is the difference between the leaving flow and the entering flow, which reflects the relative dominance strength of one alternative over another. Table 8 below shows the top 10 alternatives with the highest net flow values.

Table 8. The Highest Net Flow Values

Alternatif	Leaving Flow (φ^+)	Entering Flow (φ^-)	Net Flow (φ)	Rank
P047	0,21	0,01	0,20	1
P012	0,22	0,03	0,19	2
P054	0,20	0,02	0,19	3
P091	0,20	0,01	0,19	4
P083	0,20	0,01	0,18	5
P016	0,21	0,03	0,18	6
P106	0,20	0,02	0,18	7
P111	0,19	0,02	0,18	8
P141	0,20	0,02	0,18	9
P101	0,19	0,02	0,17	10

6. Calculating Leaving Flow, Entering Flow, Net Flow, and Ranking from Skyline Data

The following Table 9 presents the results of the calculation of leaving flow, entering flow, net flow, and the top 10 rankings from the 67 alternatives obtained through the initial filtering using the Skyline Query.

Table 9. Results Of Rankings from Skyline Query Data

Alternatif	Leaving Flow (φ^+)	Entering Flow (φ^-)	Net Flow (φ)	Rank
P047	0,16	0,02	0,14	1
P012	0,17	0,03	0,14	2
P091	0,15	0,02	0,13	3
P054	0,15	0,02	0,13	4
P083	0,15	0,02	0,13	5
P016	0,17	0,04	0,13	6
P106	0,15	0,02	0,13	6
P111	0,14	0,02	0,12	8
P141	0,15	0,02	0,12	8
P127	0,14	0,02	0,12	10

D. Spearman Correlation of Ranking Results

To measure the level of consistency between the rankings generated by the pure PROMETHEE method and the combined Skyline Query+PROMETHEE method, Spearman's Rank Correlation was employed. The following simulation was conducted using 9 common alternatives that appeared in both ranking lists.

Table 10. Calculate the Spearman Correlation Coefficient (ρ)

Alternatif	Rank Promethee	Rank Skyline+ Promethee	$d_i = R_1 - R_2$	d_i^2
P047	1	1	0	0
P012	2	2	0	0
P054	3	4	-1	1
P091	4	3	1	1
P083	5	5	0	0
P016	6	6	0	0
P106	7	6	1	1
P111	8	8	0	0
P141	9	8	1	1

Alternatives P101 and P127 were excluded from the correlation calculation because they did not appear in both datasets.

Based on this data, the difference in ranks (d_i) was calculated for each alternative, then squared to obtain d_i^2, resulting in a total of $\sum d_i^2 = 4$. With the number of alternatives $n = 9$, the Spearman correlation coefficient was computed using the formula:

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2 - 1} = 1 - \frac{6\,x\,4}{9(81 - 1)} = 1 - \frac{24}{720}$$

$$= \mathbf{0,967}$$

This value is very close to 1, indicating a very strong positive relationship between the two methods (Ieva et al., 2025). In other words, the ranking order of alternatives produced by the pure PROMETHEE method tends to be consistent with the ranking of alternatives that were pre-filtered using Skyline Query and then analyzed again using PROMETHEE. The Skyline Query does not cause significant distortion to the final ranking outcome. In fact, this combined approach has proven to simplify the decision-making process by reducing the number of alternatives to be analyzed, without compromising the validity of the results. This reinforces the position of the combined method as an efficient, accurate, and practical approach for multi-criteria selection processes.

E. Comparison of Ranking Results with Factual Data

As external validation, a comparison was made between the ranking results of the pure PROMETHEE method and the Skyline + PROMETHEE method with actual data of appointed structural officials. In the pure PROMETHEE method, several active officials such as P047, P091, and P083 ranked in the top 10, indicating that the method aligns well with real-world outcomes.

Meanwhile, the combined Skyline + PROMETHEE method successfully filtered 67 non-dominated candidates, with some active officials still appearing at the top ranks despite slight shifts. This demonstrates that the combined method simplifies the selection process without compromising result accuracy.

Table 11 presents a comparative analysis between the top-10 PROMETHEE results, Skyline+PROMETHEE results, and actual appointments.

Table 11. Comparative Analysis with Actual Appointments

Alternatif	Rank Promethee	Rank Skyline+ Promethee	Appointed Official?
P047	**1**	**1**	**Yes**
P012	2	2	No
P054	3	4	No
P091	**4**	**3**	**Yes**
P083	**5**	**5**	**Yes**
P016	6	6	No
P106	7	6	No
P111	8	8	No
P141	9	8	No

From this comparison, 3 out of 9 alternatives in the top-10 rankings of both methods were actually appointed officials (P047, P091, and P083). Based on this data, the following performance metrics were calculated:

1. Top-10 Accuracy (PROMETHEE): 33.3% (3 out of 9 top-ranked alternatives are appointed officials)
2. Top-10 Accuracy (Skyline+PROMETHEE): 33.3% (same 3 officials appear in the top-10 after Skyline filtering)
3. Agreement Rate between PROMETHEE and Skyline+PROMETHEE Top-10: 90% (9 out of 10 alternatives appear in both top-10 lists)
4. Precision in Top-10 Suggestions (Actual Officials among Top-10): 33.3%

These results confirm that the Skyline+ PROMETHEE hybrid approach maintains comparable ranking reliability with the pure PROMETHEE method while reducing computational load, from evaluating 228 alternatives to only 67, thereby enhancing efficiency without significantly compromising selection quality.

CONCLUSION

This study presents a hybrid decision-making approach that integrates Skyline Query and PROMETHEE to enhance the selection process of structural officials in higher education institutions using a multi-criteria framework. From an initial dataset of 1,501 alternatives, a data cleansing process yielded 228 valid candidates. These were normalized using the Min-Max method to allow fair comparisons across criteria. The Skyline Query effectively reduced the evaluation scope by identifying 67 non-dominated alternatives, allowing the PROMETHEE method to focus only on the most competitive candidates.

The results demonstrate that the Skyline+PROMETHEE hybrid method significantly improves computational efficiency without compromising the accuracy or fairness of the rankings. This is evidenced by a high Spearman's Rank Correlation coefficient ($\rho = 0.967$) between the rankings generated by the hybrid method and the pure PROMETHEE method. Furthermore, several candidates who ranked highly in both methods were found to be actively serving structural officials, reinforcing the method's practical validity and relevance.

In addition to its technical performance, the hybrid method enhances the transparency and accountability of decision-making by applying systematic, explainable filtering and ranking mechanisms. This makes it especially suitable for institutional environments where selection processes must be justifiable and evidence-based.

However, this study also recognizes certain limitations. The evaluation was conducted within a single institutional context and based on a fixed set of five criteria. Future research is encouraged to apply the hybrid model across different institutions or organizational levels, incorporate additional qualitative metrics (e.g., leadership potential, behavioral assessments), and explore real-time or automated implementation of the method within decision-support systems.

In conclusion, the Skyline+ PROMETHEE approach offers a practical, efficient, and transparent framework for structural official selection and holds potential for broader application in multi-criteria institutional decision-making.

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