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Comparing MCDM Methods for Assessing the Lecturer Performance Index at Dipa Makassar University

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ABSTRACT

Assessing or evaluating the Lecturer's Performance, presented through the Lecturer Performance Index, is a crucial element in the university system that impacts the quality of The University's Three Main Purposes, which include teaching, research, and community service. To ensure objective and accurate evaluations, methods that can accommodate various relevant criteria are needed. One increasingly popular approach is the Multi-Criteria Decision Making (MCDM) method, which allows for evaluating and comparing alternatives based on multiple criteria. This research compares several MCDM methods, namely Weighted Product (WP), Simple Additive Weighting (SAW), and Multi-Objective Optimization by Ratio Analysis (MOORA), used to assess the lecturer's performance at Dipa University Makassar. The WP method can handle criteria with different units, SAW is simpler and easier to apply, while MOORA offers a more comprehensive analysis. This study also identifies challenges in assessing the lecturer's performance, such as the influence of students' subjective evaluations that may lead to bias, as well as the addition of several of the lecturer's performance evaluation criteria such as teaching innovation, student mentoring, international and national journal publications, internal publications, and book publications. Additionally, self-development criteria based on academic fields are considered. The findings of this research are expected to provide insights into effective MCDM methods for the lecturer's performance evaluation and offer recommendations for educational institutions to choose the appropriate and transparent evaluation method. By using MCDM, the objectivity and accuracy of the lecturer's performance evaluations can be improved, biases can be reduced, and contributions can be made toward developing more fair and systematic evaluation standards.

INTRODUCTION

Assessing lecturer performance is a crucial aspect of the university system, as it affects the quality of teaching, research, and community service (the Tridharma). To ensure an objective and accurate evaluation, methods are needed that consider various relevant criteria. One approach gaining popularity is the Multi-Criteria Decision Making (MCDM) method, which allows decision-makers to assess and compare alternatives based on multiple criteria, providing a clearer picture of performance.

In the lecturer's performance evaluation, different MCDM methods can be used, each with its strengths and weaknesses. These methods include Weighted Product (WP), Simple Additive Weighting (SAW), and Multi-Objective Optimization by Ratio Analysis (MOORA), each offering a unique way to analyze evaluation criteria. WP can handle criteria with different units by using weighted multiplication, making it suitable for various types of measurements. The SAW method is simpler and easier to apply, making it more straightforward for decision-making and result interpretation, especially with standardized data. On the other hand, MOORA compares alternatives based on the ratio of criterion values to reference values, providing a more detailed comparison.

The comparison of these methods is essential to determine which is most effective and suitable in the context of the lecturer's performance evaluation. By understanding the strengths and weaknesses of each method, educational institutions can select the most appropriate approach to ensure fair and effective evaluations.

This approach improves lecturer performance and the overall quality of education. The study aims to compare different MCDM methods for evaluating lecturer performance, hoping to provide valuable recommendations for decision-makers at educational institutions in creating a lecturer performance index. The current evaluation system is based on the Tri Dharma of Higher Education, which includes teaching (40%: 20% for attendance and 20% for student evaluations), research (30%), community service (20%), and supporting activities (10%).

One issue with evaluating lecturer performance is that 20% of the assessment relies on students' subjective opinions, which is a significant portion. Questionnaires are often distributed during the final week of classes or exams, but students present at that time may not have attended regularly throughout the semester. Not all students adhere to the

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course requirements or attend regularly, and their evaluations may be influenced by personal emotions or relationships. For instance, students with a positive connection to the lecturer may give higher ratings, while those with negative feelings may rate the lecturer lower, even if the lecturer's performance is unrelated to these personal factors.

The assessments made by students can also be influenced by their preferences for teaching styles. Each student has different preferences regarding how a lecturer teaches. Some students may prefer a more interactive teaching style, while others may favor a traditional, structured approach. As a result, evaluations can be affected by the alignment between the lecturer's teaching style and the student's personal preferences, rather than by the lecturer's actual performance or objectivity.

Grades and final results can also influence students' evaluations of their lecturers. Students with high grades are likely to give positive feedback, while those with low grades tend to offer negative evaluations. This creates a bias, as the ratings reflect students' outcomes rather than the lecturer's teaching quality.

Another factor influencing students' evaluations is their subjective perception of the subject matter. Some students may dislike specific courses or topics, even if the lecturer presents the material effectively. This can lead to biased evaluations, as ratings are based on personal preferences rather than the lecturer's teaching ability. Additionally, a lack of understanding about what constitutes good teaching can affect evaluations. Many students may not fully understand the criteria for effective teaching, such as clarity, student engagement, and constructive feedback. Without this knowledge, their assessments may be influenced by personal impressions or opinions.

Subjective evaluations can introduce bias and unfairness. Moreover, combining quantitative data (e.g., publication count) with qualitative assessments (e.g., teaching quality) is often difficult, leading to an incomplete picture. Factors like the lecturer's workload, institutional support, and external conditions can also impact performance and evaluation results, but these are often hard to control or assess objectively.

Addressing these issues requires a systematic, transparent approach and usage of comprehensive, objective evaluation methods. Developing clear evaluation standards, training evaluators, and applying Multi-Criteria Decision Making (MCDM) can help overcome these challenges.

LITERATURE REVIEW

Objective and accurate lecturer's performance evaluations are essential for providing a fair and comprehensive assessment of a lecturer's contributions to the three pillars of higher education. Various approaches have been developed to improve evaluation quality, including Multi-Criteria Decision Making (MCDM) methods.

MCDM helps address evaluations' complexity and multiple criteria by assessing and comparing alternatives based on relevant factors (Gunawan et al., 2023; Sintaro, 2024; Sudipa, Wardoyo, et al., 2023a). In assessing the lecturer's performance, MCDM enables decision-makers to assess aspects such as teaching, research, community service, and supporting factors, each with its own evaluation criteria. Expected MCDM methods used for performance evaluation include Weighted Product (WP), Simple Additive Weighting (SAW), and Multi-Objective Optimization by Ratio Analysis (MOORA) (M. H. Abdullah, 2024; Alam & Suryani, 2024; Ginting et al., 2021; Mulyani & Hutahaean, 2021; Rozali et al., 2024)..

Weighted Product (WP) is a method that accommodates criteria with different units through weighted multiplication (Shiddieq & Nazib, 2018). It integrates criteria with varying scales, making it well-suited for complex performance evaluations.

Simple Additive Weighting (SAW) is a straightforward and easy-to-apply method (Banamtuan et al., 2024; Nuroji, 2024). SAW involves summing the products of criteria values and their assigned weights (Murtopo & Putri, 2016). which makes it favored for its simplicity and applicability to standardized data.

Multi-Objective Optimization by Ratio Analysis (MOORA) evaluates alternatives by comparing the ratio between criteria values and reference values (M. A. Abdullah & Aldisa, 2023; Surahman, 2024). This method supports more thorough evaluations by providing more precise comparisons between alternatives.

While MCDM methods can enhance objectivity in assessing the lecturer's performance, several challenges persist in practice. One major issue is the subjective nature of student assessments. A lecturer's performance is often evaluated based on student's perceptions, which can be influenced by personal factors, such as emotional connections or preferences for a particular teaching style.

These subjective evaluations are often shaped by personal relationships or individual impressions of the lecturer, introducing potential bias into the assessment (Ismail et al., 2024; Kusumawardani et al., 2023a). Students who feel a personal connection with the lecturer or have a positive relationship with them tend to give higher ratings. While those who harbor negative feelings may provide lower scores. Such evaluations, influenced by personal preferences, can distort the objective assessment of a lecturer’s performance (Andriyani et al., 2024; Kusumawardani et al., 2023b).

Each student has different preferences when it comes to teaching styles. A student's evaluation of the lecturer's performance can be influenced by how well the lecturer's teaching style aligns with their personal preferences (Putri et al., 2023). Not all students prefer interactive teaching over more traditional methods (Anggrawan, 2019). This indicates that student evaluations do not always reflect the lecturer's teaching quality objectively..

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Students' evaluations of lecturers are often influenced by their academic results. Students who earn high grades are often more satisfied with the teaching and give positive feedback. While those with lower grades may offer more negative evaluations, even though the quality of pedagogy is unrelated to their individual performance. This bias, known as the halo effect, can distort the assessment of a lecturer's performance (Anggrawan, 2019; Kumala Hadi, 2020; Unaradjan, 2019).

The lecturer performance evaluations often combine quantitative data (e.g., publication count, research indicators) and qualitative data (e.g., teaching quality, lecturer-student interactions). Integrating these data types is challenging, as they require different analysis and interpretation approaches (Rachmad et al., 2024). Therefore, methods like MCDM, which can integrate diverse data types, are essential for providing a more comprehensive and objective assessment of the lecturer's performance.

To reduce subjective assessments and improve the reliability of the assessment of a lecturer's performance, many studies emphasize the need for clear and structured evaluation standards. These standards should include measurable criteria to minimize or eliminate biases influenced by personal perceptions or irrelevant factors.

Previous research has also shown that a comprehensive and objective evaluation system can help improve the overall quality of higher education (Efendi & Sholeh, 2023; Qurtubi et al., 2023; Supriyadi, 2017; Yulisma et al., 2023). Approaches like MCDM enable the integration of diverse criteria with varying weights, offering a more accurate and comprehensive view of the lecturer's performance. By accounting for multiple dimensions such as teaching, research, community service, and academic support—the evaluation system can generate a more representative and actionable the lecturer's Performance Index for higher education decision-makers.

Incorporating MCDM methods into lecturer evaluations is a crucial phase in reducing subjective bias and ensuring more objective assessments. Methods like WP, SAW, and MOORA each offer unique strengths and limitations, allowing for flexible application based on the evaluation context. However, to achieve genuinely objective results, it is essential to establish clear, standardized evaluation criteria. By effectively combining quantitative and qualitative data, assessing the lecturer's performance systems can become powerful tools for enhancing the quality of higher education and the lecturer's performance.

METHOD

The research process begins with problem analysis and needs assessment, where the research problem is identified, and a problem-solving approach using the MCDM-based DSS method is developed. The second stage is data collection, where input data is gathered according to the evaluation criteria that have been established. The third stage involves comparing methods to evaluate the performance outcomes of the predetermined alternatives. These stages are illustrated in the following Figure 1:

Figure 1. Research Stages

The method comparison used in this study is the MCDM method, which is a technique designed to assist decision-makers in selecting, evaluating, or prioritizing alternatives based on a set of complex and often conflicting criteria (Novianti, 2023; Sudipa, Wardoyo, et al., 2023b). MCDM aims to produce an optimal or satisfactory decision by considering various relevant aspects of a typical situation (Sudipa, Kharisma, et al., 2023). The MCDM methods used in this study include:

Weighted Product (WP)

There are several stages in the SAW method, including (Alam & Suryani, 2024):

Step 1: Normalize the weights to obtain the values $\sum_j^n = 1, W_j = 1$, where j = 1, 2, ..., n represents the number of alternatives, using the following formula:

$$W_j = \frac{W_j}{\sum W_j} \quad (1)$$

Step 2: Calculate the vector S. This step is the same as the normalization process and is computed using the following formula:

$$S_i = \prod_{j=1}^{n} X_{ij}^{Wj} \quad (2)$$

Step 3: Calculate the vector V, or the relative preferences of each alternative, for ranking using the following formula: After the normalization process is complete, the results are sorted from highest to lowest.

$$V_i = \frac{S_i}{\prod_{j=1}^{n} (Xj^*) Wj} \quad (3)$$

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W is the weight of the criteria, Π is the product, S is the value of each alternative, is the preference of the alternative, analogous to vector S, n is the number of criteria, i is the alternative, j is the criterion, and $*$ represents the number of criteria.

Simple Additive Weighting (SAW)

There are several stages in the SAW method, namely (Alam & Suryani, 2024):

Step 1: Set Up the criteria to be used as a reference in decision-making. In SAW, two attributes must be considered: the benefit criterion (where the highest value is considered the best) and the cost criterion (where the lowest value is regarded as the best).

$$r_{ij} = \begin{cases} \dfrac{X_{ij}}{MaxX_{ij}} \; If\ j\ is\ a\ benefit\ attribute \\ \dfrac{MinX_{ij}}{X_{ij}} \; If\ j\ is\ a\ cost\ attribute \end{cases} \quad (4)$$

Max Xij is the highest value of each criterion i, Min Xij is the lowest value of each criterion i, and Xij is the attribute value for each criterion. For Benefit, the highest value is considered the best, and for Cost, the lowest value is considered the best.

Step 2: Create a decision matrix, then normalize it based on the type of attribute (cost/benefit) to produce the normalized matrix r.

Step 3: The final result of the ranking process is obtained by multiplying the normalized matrix (matrix r) by the weight vector to determine the best alternative solution based on the maximum value.

Step 4: After the normalization process is complete, the results are ranked from the highest to the lowest value.

$$V_i = \sum_{j=1}^{n} W_j . r_{ij} \quad (5)$$

Vi is the ranking for each alternative, Wj is the weight value of the ranking (for each criterion), and Rij is the normalized performance rating value.

Multi-Objective Optimization By Ratio Analysis (MOORA)

The steps for solving using the MOORA method are as follows (Alam & Suryani, 2024):

Step 1: Input the criterion values and create the decision matrix.

Step 2: Normalization in the MOORA method is performed to standardize the values of each matrix element so that all elements have a uniform scale. Normalization in MOORA can be calculated using the following equation:

$$X^*ij = \sqrt[xij]{\left[\sum_{i=1}^{m} X^2 ij\right]} \quad (6)$$

Step 3: Optimize the Attributes, where the normalization process is applied to maximize (for benefit attributes) and minimize (for cost attributes). Thus, the optimization problem is focused on:

$$Yi = \sum_{j}^{g} = 1X^*ij - \sum_{j}^{n} = g + 1X^*ij \quad (7)$$

Step 4: Reducing the maximax and min-max values to indicate the significance level of the attributes, with more important attributes given appropriate weights (significance coefficients). The equation used for this calculation is as follows:

$$Yi = \sum_{j}^{g} = WjX^*ij - \sum_{j}^{n} = g + 1WjX^*ij \quad (8)$$

Step 5: Establish the rankings according to the results obtained from the MOORA calculations.

RESULT

In this research, the alternative data used consists of 20 lecturers, including 12 from the Computer Science Study Program, four from the Information Systems program, three from the Information Management program, and one from the Software Engineering program, as shown in Table 1. The criterion data used in Table 1 for the evaluation of lecturer performance was obtained from the lecturer performance reports for the odd and even semesters of the 2023-2024 academic year, directly provided by the lecturers themselves. Additionally, the Lecturer Performance Index (IKD) data was obtained from the Quality Management Unit (UPM), and the field of study data for the lecturers was obtained from the PD DIKTI section of Dipa Makassar University.

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Table 1. Alternative Data and Criteria

ID	Alternative	Class Monitoring (C1)	Teaching Innovation (C2)	Student Mentoring (C3)	International Journals (C4)	National Journals (C5)	Internal Publications (C6)	Book Publications (C7)	Community Service (C8)	Community Service Journal (C9)	Coordinator and Supervision (C10)	Self-Development (C11)	Student Evaluation (C12)
1	**A1**	4,00	4,00	4,00	0,00	4,00	4,00	0,00	4,00	0,00	4,00	3,00	3,62
2	**A2**	3,89	4,00	4,00	0,00	2,00	4,00	0,00	4,00	0,00	4,00	3,00	3,56
3	**A3**	4,00	4,00	4,00	0,00	2,00	2,00	4,00	4,00	0,00	4,00	2,00	3,56
4	**A4**	4,00	4,00	4,00	2,00	4,00	0,00	0,00	4,00	0,00	2,00	4,00	3,26
5	**A5**	4,00	4,00	4,00	0,00	0,00	4,00	4,00	4,00	0,00	4,00	0,00	3,82
6	**A6**	4,00	4,00	4,00	0,00	4,00	0,00	0,00	4,00	0,00	4,00	3,00	3,58
7	**A7**	3,83	4,00	4,00	0,00	0,00	4,00	0,00	4,00	0,00	4,00	0,00	3,11
8	**A8**	3,95	4,00	4,00	0,00	4,00	0,00	4,00	4,00	2,00	4,00	1,00	3,83
9	**A9**	4,00	4,00	4,00	0,00	2,00	2,00	0,00	4,00	0,00	4,00	0,00	3,71
10	**A10**	4,00	4,00	4,00	0,00	2,00	4,00	4,00	4,00	2,00	4,00	2,00	3,28
11	**A11**	3,86	4,00	4,00	0,00	4,00	2,00	4,00	2,00	2,00	4,00	2,00	3,38
12	**A12**	4,00	4,00	4,00	0,00	2,00	4,00	0,00	4,00	0,00	4,00	2,00	3,26
13	**A13**	3,93	4,00	4,00	0,00	2,00	2,00	4,00	4,00	2,00	4,00	2,00	3,29
14	**A14**	4,00	4,00	4,00	2,00	4,00	0,00	4,00	4,00	4,00	4,00	2,00	3,64
15	**A15**	3,94	4,00	4,00	0,00	0,00	4,00	2,00	4,00	2,00	4,00	2,00	3,14
16	**A16**	3,83	4,00	4,00	0,00	0,00	4,00	0,00	4,00	0,00	0,00	3,00	3,61
17	**A17**	4,00	4,00	4,00	0,00	2,00	2,00	2,00	4,00	2,00	0,00	2,00	3,69
18	**A18**	4,00	4,00	4,00	0,00	2,00	2,00	4,00	4,00	0,00	2,00	0,00	3,28
19	**A20**	3,90	4,00	4,00	0,00	4,00	2,00	0,00	4,00	0,00	4,00	0,00	3,66
20	**A21**	4,00	4,00	4,00	0,00	4,00	0,00	0,00	4,00	0,00	4,00	3,00	3,66

Since some criterion values for the alternatives are 0, these values are replaced with a very small number, such as 0.000, 0.0001, or 0.00001, to avoid having a zero value. Another approach could be to exclude alternatives with attribute values of 0 from the calculation if those values are not relevant to the model. However, this is not feasible.

Weighting and normalization of the criterion weights are carried out according to the current percentages for the evaluation of the tri-dharma of higher education. However, the student assessment criterion in the form of a questionnaire is placed in the supporting category with a smaller percentage, and several additional criteria related to the tri-dharma fields that are relevant and important can be seen in Table 2.

Table 2. Criteria and Normalized Weights

Tri Dharma Field	Criterion Code	Criteria	Weight	Normalized weight	Category
Teaching	C1	Class Monitoring	30	0,3	*Benefit*
	C2	Teaching Innovation	5	0,05	*Benefit*
	C3	Student Mentoring	5	0,05	*Benefit*
Research	C4	International Journals	2	0,02	*Benefit*
	C5	National Journals	24	0,24	*Benefit*
	C6	Internal Publications	2	0,02	*Benefit*
	C7	Book Publications	2	0,02	*Benefit*
Community Service	C8	Community Service	15	0,15	*Benefit*
	C9	Community Service Journal	5	0,05	*Benefit*
Supportive	C10	Coordinator and Supervision	4	0,04	*Benefit*
	C11	Self-Development	2	0,02	*Benefit*
	C12	Student Evaluation	4	0,04	*Benefit*
		Total	100	1	

Weighted Product (WP)

Step 1: The normalization of weights can be seen in Table 2.

Step 2: The value of vector S is obtained as follows:

$$S1 = 4^{0,3} \times 4^{0,05} \times 4^{0,05} \times 0,00001^{0,02} \times 4^{0,24} \times 4^{0,02} \times 0,00001^{0,02} \times 4^{0,15} \times 0,00001^{0,05} \times 4^{0,04} \times 3^{0,02} \times 3,62^{0,04}$$

$$S1 = 1,2406$$

S2 and so on up to S20, obtained through the same process using Equation 2, with the results shown in Table 3.

Step 3: The value of vector V is obtained as follows:

$$V1 = \frac{1,2406}{24,9159}$$

$$V1 = 0,0498$$

V2 and so on up to V20, obtained through the same process using Equation 3, with the results shown in Table 3.

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Table 3. Values of Vectors Si and Vi

Value of the i-th alternative	Si	Vi
1	1,2406	0,0498
2	1,0407	0,0418
3	1,3292	0,0533
4	1,1919	0,0478
5	0,0566	0,0023
6	0,9581	0,0385
7	0,0428	0,0017
8	2,2304	0,0895
9	0,8058	0,0323
10	2,4730	0,0993
11	2,5713	0,1032
12	1,0377	0,0416
13	2,4256	0,0974
14	2,9944	0,1202
15	0,1295	0,0052
16	0,0331	0,0013
17	1,4426	0,0579
18	1,0095	0,0405
19	0,9443	0,0379
20	0,9589	0,0385

The values obtained are ranked from the smallest to the largest, resulting in a ranking that can be seen in Table 4.

Table 4. WP Ranking Results

Alternative	Vector	Ranking
A14	0,1202	1
A11	0,1032	2
A10	0,0993	3
A13	0,0974	4
A8	0,0895	5
A17	0,0579	6
A3	0,0533	7
A1	0,0498	8
A4	0,0478	9
A2	0,0418	10
A12	0,0416	11
A18	0,0405	12
A20	0,0385	13
A6	0,0385	14
A19	0,0379	15
A9	0,0323	16
A15	0,0052	17
A5	0,0023	18
A7	0,0017	19

Simple Additive Weighting (SAW)

Step 1: The criteria used in this study can be seen in Table 2.

Step 2: The decision matrix X is shown as follows:

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$$
Xij = \begin{bmatrix}
4,00000 & 4,00000 & 4,00000 & 0,00001 & 4,00000 & 4,00000 & 0,00001 & 4,00000 & 0,00001 & 4,00000 & 3,00000 & 3,61500 \\
3,88667 & 4,00000 & 4,00000 & 0,00001 & 2,00000 & 4,00000 & 0,00001 & 4,00000 & 0,00001 & 4,00000 & 3,00000 & 3,55500 \\
4,00000 & 4,00000 & 4,00000 & 0,00001 & 2,00000 & 2,00000 & 4,00000 & 4,00000 & 0,00001 & 4,00000 & 2,00000 & 3,55500 \\
4,00000 & 4,00000 & 4,00000 & 2,00000 & 4,00000 & 0,00001 & 0,00001 & 4,00000 & 0,00001 & 2,00000 & 4,00000 & 3,25500 \\
4,00000 & 4,00000 & 4,00000. & 0,00001 & 0,00001 & 4,00000. & 4,00000 & 4,00000 & 0,00001. & 4,00000 & 0,00001 & 3,81500 \\
4,00000 & 4,00000 & 4,00000 & 0,00001 & 4,00000 & 0,00001 & 0,00001 & 4,00000 & 0,00001 & 4,00000 & 3,00000 & 3,58000 \\
3,83333 & 4,00000 & 4,00000 & 0,00001 & 0,00001 & 4,00000 & 0,00001 & 4,00000 & 0,00001 & 4,00000 & 0,00001 & 3,11000 \\
3,94667 & 4,00000 & 4,00000 & 0,00001 & 4,00000 & 0,00001 & 4,00000 & 4,00000 & 2,00000 & 4,00000 & 1,00000 & 3,83000 \\
4,00000 & 4,00000 & 4,00000 & 0,00001 & 2,00000 & 2,00000 & 0,00001 & 4,00000 & 0,00001 & 4,00000 & 0,00001 & 3,70500 \\
4,00000 & 4,00000 & 4,00000 & 0,00001 & 2,00000 & 4,00000 & 4,00000 & 4,00000 & 2,00000 & 4,00000 & 2,00000 & 3,27500 \\
3,85833 & 4,00000 & 4,00000 & 0,00001 & 4,00000 & 2,00000 & 4,00000 & 2,00000 & 2,00000 & 4,00000 & 2,00000 & 3,38000 \\
4,00000 & 4,00000 & 4,00000 & 0,00001 & 2,00000 & 4,00000 & 0,00001 & 4,00000 & 0,00001 & 4,00000 & 2,00000 & 3,26000 \\
3,92593 & 4,00000 & 4,00000 & 0,00001 & 2,00000 & 2,00000 & 4,00000 & 4,00000 & 2,00000 & 4,00000 & 2,00000 & 3,28500 \\
4,00000 & 4,00000 & 4,00000. & 2,00000 & 4,00000 & 0,00001. & 4,00000 & 4,00000 & 4,00000. & 4,00000 & 2,00000 & 3,63500 \\
3,94000 & 4,00000 & 4,00000 & 0,00001 & 0,00001 & 4,00000 & 2,00000 & 4,00000 & 2,00000 & 4,00000 & 2,00000 & 3,14000 \\
3,83333 & 4,00000 & 4,00000 & 0,00001 & 0,00001 & 4,00000 & 0,00001 & 4,00000 & 0,00001 & 0,00001 & 3,00000 & 3,60500 \\
4,00000 & 4,00000 & 4,00000. & 0,00001 & 2,00000 & 2,00000 & 2,00000 & 4,00000 & 2,00000 & 0,00001 & 2,00000 & 3,68500 \\
4,00000 & 4,00000 & 4,00000 & 0,00001 & 2,00000 & 2,00000 & 4,00000 & 4,00000 & 0,00001 & 2,00000 & 0,00001 & 3,27500 \\
3,90474 & 4,00000 & 4,00000 & 0,00001 & 4,00000 & 2,00000 & 0,00001 & 4,00000 & 0,00001 & 4,00000 & 0,00001 & 3,66000 \\
4,00000 & 4,00000 & 4,00000 & 0,00001 & 4,00000 & 0,00001 & 0,00001 & 4,00000 & 0,00001 & 4,00000 & 3,00000 & 3,66000
\end{bmatrix}
$$

Step 3: The normalized matrix R is obtained using Equation 4, with the maximum values of C1, C2, C3, C5, C6, C7, C8, C9, C10, and C11=4, the maximum value of C4=2, and the maximum value of C12=3,83.

$$
Xij = \begin{bmatrix}
1,0000000 & 1,0000000 & 1,0000000 & 0,0000050 & 1,0000000 & 1,0000000 & 0,0000025 & 1,0000000 & 0,0000025 & 1,0000000 & 0,7500000 & 0,9438642 \\
0,9716667 & 1,0000000 & 1,0000000 & 0,0000050 & 1,0000000 & 1,0000000 & 0,0000025 & 1,0000000 & 0,0000025 & 1,0000000 & 0,7500000 & 0,9281984 \\
1,0000000 & 1,0000000 & 1,0000000 & 0,0000050 & 1,0000000 & 1,0000000 & 1,0000000 & 1,0000000 & 0,0000025 & 1,0000000 & 0,5000000 & 0,9281984 \\
1,0000000 & 1,0000000 & 1,0000000 & 1,0000000 & 1,0000000 & 0,0000050 & 0,0000025 & 1,0000000 & 0,0000025 & 0,5000000 & 1,0000000 & 0,8498694 \\
1,0000000 & 1,0000000 & 1,0000000. & 0,0000050 & 0,0000050 & 1,0000000. & 1,0000000 & 1,0000000 & 0,0000025. & 1,0000000 & 0,0000025 & 0,9960835 \\
1,0000000 & 1,0000000 & 1,0000000 & 0,0000050 & 1,0000000 & 0,0000050 & 0,0000025 & 1,0000000 & 0,0000025 & 1,0000000 & 0,7500000 & 0,9347258 \\
0,9583333 & 1,0000000 & 1,0000000 & 0,0000050 & 0,0000050 & 1,0000000 & 0,0000025 & 1,0000000 & 0,0000025 & 1,0000000 & 0,0000025 & 0,8120104 \\
0,9866667 & 1,0000000 & 1,0000000 & 0,0000050 & 1,0000000 & 0,0000050 & 1,0000000 & 1,0000000 & 0,5000000 & 1,0000000 & 0,2500000 & 1,0000000 \\
1,0000000 & 1,0000000 & 1,0000000 & 0,0000050 & 1,0000000 & 1,0000000 & 0,0000025 & 1,0000000 & 0,0000025 & 1,0000000 & 0,0000025 & 0,9673629 \\
1,0000000 & 1,0000000 & 1,0000000 & 0,0000050 & 1,0000000 & 1,0000000 & 1,0000000 & 1,0000000 & 0,5000000 & 1,0000000 & 0,5000000 & 0,8550914 \\
0,9645833 & 1,0000000 & 1,0000000 & 0,0000050 & 1,0000000 & 1,0000000 & 1,0000000 & 0,5000000 & 0,5000000 & 1,0000000 & 0,5000000 & 0,8825065 \\
1,0000000 & 1,0000000 & 1,0000000 & 0,0000050 & 1,0000000 & 1,0000000 & 0,0000025 & 1,0000000 & 0,0000025 & 1,0000000 & 0,5000000 & 0,8511749 \\
0,9814833 & 1,0000000 & 1,0000000 & 0,0000050 & 1,0000000 & 1,0000000 & 1,0000000 & 1,0000000 & 0,5000000 & 1,0000000 & 0,5000000 & 0,8577023 \\
1,0000000 & 1,0000000 & 1,0000000. & 1,0000000 & 1,0000000 & 0,0000050. & 1,0000000 & 1,0000000 & 1,0000000. & 1,0000000 & 0,5000000 & 0,9490862 \\
0,9850000 & 1,0000000 & 1,0000000 & 0,0000050 & 0,0000050 & 1,0000000 & 0,5000000 & 1,0000000 & 0,5000000 & 1,0000000 & 0,5000000 & 0,8198433 \\
0,9583333 & 1,0000000 & 1,0000000 & 0,0000050 & 0,0000050 & 1,0000000 & 0,0000025 & 1,0000000 & 0,0000025 & 0,0000025 & 0,7500000 & 0,9412533 \\
1,0000000 & 1,0000000 & 1,0000000. & 0,0000050 & 1,0000000 & 1,0000000 & 0,5000000 & 1,0000000 & 0,5000000 & 0,0000025 & 0,5000000 & 0,9621410 \\
1,0000000 & 1,0000000 & 1,0000000 & 0,0000050 & 1,0000000 & 1,0000000 & 1,0000000 & 1,0000000 & 0,0000025 & 0,5000000 & 0,0000025 & 0,8550914 \\
0,9761850 & 1,0000000 & 1,0000000 & 0,0000050 & 1,0000000 & 1,0000000 & 0,0000025 & 1,0000000 & 0,0000025 & 1,0000000 & 0,0000025 & 0,9556136 \\
1,0000000 & 1,0000000 & 1,0000000 & 0,0000050 & 1,0000000 & 0,0000050 & 0,0000025 & 1,0000000 & 0,0000025 & 1,0000000 & 0,7500000 & 0,9556136
\end{bmatrix}
$$

Step 4: Value of Vi, and Ranking

Step 5: Ranking

$$
\begin{aligned}
V1 = {} & (1,0000000 \times 0,3) + (1,0000000 \times 0,05) + (1,0000000 \times 0,05) + (0,000005 \times 0,02) + (1,0000000 \\
& \times 0,24) + (1,0000000 \times 0,02) + (0,0000025 \times 0,02) + (1,0000000 \times 0,15) + (0,0000025 \\
& \times 0,05) + (1,0000000 \times 0,04) + (0,7500000 \times 0,02) + (0,9438642 \times 0,04)
\end{aligned}
$$

$$V1 = 0,772755169$$

V2 through V20, obtained using the same process as V1 through the equation (5), are sorted from the largest to the smallest values, as shown in Table 5.

Table 5. SAW Ranking Results

Alternative	Vi Value	Ranking
A14	1,017963496	1
A8	0,94100015	2
A11	0,934675361	3
A10	0,844203755	4
A13	0,828753194	5
A3	0,787128287	6
A1	0,772755294	7
A18	0,754204055	8
A4	0,753995453	9
A20	0,753225318	10
A6	0,752389809	11
A19	0,741080818	12
A17	0,72348584	13
A5	0,669844342	14
A12	0,644047722	15
A2	0,643628662	16
A15	0,643294434	17
A9	0,628695292	18
A7	0,499981793	19
A16	0,480151556	20

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Multi-Objective Optimization By Ratio Analysis (MOORA)

Step 1: The decision matrix used is the same as the one used in the SAW method.

Step 2: Normalization Matrix.

$$X_{11} = \frac{4}{\sqrt{\begin{array}{c}4^2 + 3{,}88667^2 + 4^2 + 4^2 + 4^2 + 4^2 + 3{,}83333^2 + 3{,}94667^2 + 4^2 + 4^2 + 3{,}85833^2 + \\ 4^2 + 3{,}92593^2 + 4^2 + 3{,}94^2 + 3{,}83333^2 + 4^2 + 4^2 + 3{,}90474^2 + 4^2\end{array}}}$$

$$X_{11} = 0{,}226042$$

X12 through X1220, obtained using the same process as X1 through equation (6).

Step 3: Multi-objective Optimization Value (yi)

$$y_i = 0{,}226042 + 0{,}223607 + 0{,}223607 + 0{,}000004 + 0{,}316228 + 0{,}320256 + 0{,}000001 + 0{,}227921 + 0{,}000002 + 0{,}246183 + 0{,}309426 + 0{,}230901$$

$$y_i = 2{,}32418$$

y1 through y20, obtained using the same process as y1 through equation (8), are then sorted from the largest to the smallest values, as shown in Table 6.

Table 6. MOORA Ranking Results

Alternative	Vi Value	Ranking
A14	3,58461	1
A10	2,70043	2
A4	2,66808	3
A11	2,58315	4
A13	2,53675	5
A8	2,46758	6
A15	2,35880	7
A1	2,32418	8
A3	2,24196	9
A2	2,15583	10
A17	2,14881	11
A5	2,05430	12
A12	2,04025	13
A20	2,00680	14
A6	2,00169	15
A18	1,89470	16
A19	1,85212	17
A16	1,75171	18
A9	1,70226	19
A7	1,65685	20

The comparison results of MCDM methods in evaluating lecturer performance can be seen in Table 7, with its visualization in Figure 2.

Table 7. MCDM Method Comparison Results

Ranking	WP Method	SAW Method	MOORA Method
1	A14	A14	A14
2	A11	A8	A10
3	A10	A11	A4
4	A13	A10	A11
5	A8	A13	A13
6	A17	A3	A8
7	A3	A1	A15
8	A1	A18	A1
9	A4	A4	A3
10	A2	A20	A2
11	A12	A6	A17
12	A18	A19	A5
13	A20	A17	A12
14	A6	A5	A20
15	A19	A12	A6
16	A9	A2	A18
17	A15	A15	A19
18	A5	A9	A16
19	A7	A7	A9
20	A16	A16	A7

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The rankings from each method for each alternative are summed, the average ranking is then calculated, and the alternatives are sorted based on the lowest average ranking. The results obtained, ranked from 1 to 20, are as follows: A14, A10, A11, A8, A13, A4, A3, A1, A17, A2, A18, A20, A12, A6, A15, A5, A19, A9, A7, A16.

Figure 2. Visualization of Ranking Comparison Results

DISCUSSION

The research findings highlight the importance of developing criteria in the lecturer's performance evaluation. One such criterion is the lecturer's personal development, such as participation in training or scientific conferences related to their field of expertise. This criterion provides a clearer picture of the lecturer's efforts to improve their competencies. By including this criterion, the evaluation of lecturers' performance not only covers academic aspects but also reflects their commitment to self-development in response to the ever-evolving demands of the educational landscape. Additionally, the criterion of teaching innovation is regarded as important because it shows that lecturers do not solely rely on conventional teaching methods but also strive to find new, more effective, and engaging ways to deliver content. The use of cutting-edge technology, interactive approaches, or project-based learning methods can help students better understand the material and increase their engagement in the learning process. This contributes to an overall improvement in the quality of education.

The criterion of student guidance and mentoring is deemed significant as it indicates the lecturer's contribution to students' academic and personal development. Good mentoring supports students' academic achievements and also guides them in developing skills and preparing for the professional world. Therefore, mentoring is a significant indicator in assessing how actively faculty members can play a role in facilitating students' growth and success.

In the field of research, it is significant to map publications in international, national, and internal journals, as well as book publications. This criterion is essential for objectively and comprehensively assessing faculty performance, as it reflects the quality and quantity of their contributions to the Development of knowledge and the university's reputation. While not overlooking the subjective evaluation of students, the researcher has assigned this criterion a 4% weight in the supporting factors category.

The comparison of methods in evaluating lecturer performance shows that the WP and SAW methods produce nearly identical rankings. For example, A14 is ranked first in both methods, A8 is second, and so on. The MOORA method shows some differences, such as A10 being ranked second, while A8 is second in WP and SAW. A14 consistently ranks first across all three methods, indicating that this alternative likely performs very well across all evaluated criteria. Some alternatives rank very differently in the three methods, such as A5, which ranked 16th in WP but 12th in SAW and 18th in MOORA.

CONCLUSION

Based on the comparison of methods in faculty performance evaluation, A14 is the most superior alternative according to all methods. There is strong consistency between WP and SAW in ranking, though MOORA produces a slightly different order, especially for lower ranks. A7, A9, and A17 maintain relatively consistent rankings across all three methods. Using MCDM in faculty performance evaluation improves objectivity and accuracy, reduces bias, and helps develop fairer, more systematic evaluation standards.

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