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Development Of Smart Lecturer Assessment SPK Using Saw Based On Student Evaluation Data

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ABSTRACT

Lecturer performance assessment is a crucial effort in ensuring the quality of higher education. However, the processing of student evaluation data is often still performed manually, a time-consuming approach that is prone to subjectivity and lacks effectiveness in generating objective decisions. This study aims to develop an intelligent Decision Support System (DSS) to identify the top-performing lecturer based on student evaluation data using the Simple Additive Weighting (SAW) method. The SAW method was selected for its ability to conduct multi-criteria assessment through weighting, value normalization, and preference value calculation, thereby producing an objective ranking of alternatives. The study employs seven assessment criteria: mastery of subject matter, ability to convey material, discipline, interaction and communication, teaching methods, assessment objectivity, and the ability to motivate students. Data regarding 15 lecturer alternatives were processed through stages involving criteria selection, weighting, decision matrix construction, normalization, and preference value calculation. The results demonstrate that the SAW method successfully generates a ranking of alternatives in a systematic, transparent, and measurable manner. Alternative V10 achieved the highest preference score of 0.90 and was consequently recommended as the best lecturer. The findings confirm that applying the SAW method enhances objectivity and efficiency in the lecturer assessment process and supports more accurate decision-making within the higher education environment.

INTRODUCTION

Advancements in information technology have driven digital transformation across various sectors, including higher education. Higher education institutions are required to enhance the quality of academic services by implementing systems that support objective, data-driven decision-making processes (Setiawan et al., 2021). The quality of a higher education institution is significantly influenced by the quality of its lecturers, who are the primary facilitators of the learning process. Lecturers play a crucial role in knowledge transfer, student guidance, and the production of high-quality academic outcomes (Lisdiyanto, 2023; Valerian et al., 2025). Lecturer performance evaluation is a key activity undertaken by higher education institutions to ensure educational quality. The results of these evaluations can serve as a basis for granting awards, determining promotions, and improving the quality of instruction (Gemawaty & Yuliani, 2023; Kurniawati, 2021). Student evaluation data typically encompasses various aspects, such as subject matter mastery, communication skills, teaching methods, discipline, and the lecturer's ability to motivate students (Setiawan et al., 2021). A common issue that arises. The processing of student evaluation data is still carried out manually, which is time-consuming and potentially introduces subjectivity into decision-making (Setaidhi et al., 2021).

LITERATURE REVIEW

Decision Support System (DSS) is an information system designed to assist individuals and organizations in making effective decisions. The decision-making process within a DSS generally involves multiple criteria—which may comprise various sub-criteria depending on the specific problem requirements—and transforms data into relevant information. This enables the system to provide recommendations or decision alternatives for resolving semi-structured problems in a more objective and systematic manner (Teguh Santoso et al., 2023). DSSs are designed with flexible and adaptive characteristics, allowing them to support decision-making for semi-structured and unstructured problems by integrating human judgment with information technology capabilities (Faizal & Irfan, 2025; Sulaiman, 2025; Randa Ersada & Husnul Khair, 2025). A DSS provides analytical capabilities that assist decision-makers in generating decisions that are more objective, accurate, and accountable (Aventi et al., n.d.). It enables decision-makers to evaluate various alternatives based on specific criteria using quantifiable algorithms (Aditia et al., 2025). These scenarios highlight the importance of a systematic approach to evaluating alternatives based on multiple criteria. One effective

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approach is Multi-Criteria Decision Making (MCDM), as it offers a structured analytical framework for the decision-making process (Rahman, 2025). A DSS serves as a system for organizing and integrating various resources. Combining human intellect with computer capabilities to enhance quality. The characteristics of a Decision Support System (DSS) include (Normah et al., 2022):

1. Supports effective organizational decision-making.
2. Keeps the user as the main decision-maker, with the system as a support tool.
3. Solves structured and semi-structured problems.
4. Provides interactive access to relevant information.
5. Integrates subsystems into a unified system.
6. Uses data and models to generate decision recommendations.

The Simple Additive Weighting (SAW) method is a Decision Support System technique that employs the concept of weighted sum values to determine the best alternative (Khozainuz Zuhri et al., 2024. The Simple Additive Weighting (SAW) method is (Rizki et al., 2025) (Safrizal & Panji Wijaya Komara, 2022) (Mahrizon, 2022) (Valerian et al., 2025):

1. Determine the criteria to be used in decision-making, denoted as Cj.
2. Determine the alternatives to be selected as the decision, denoted as Aj.
3. Determine the preference weight or level of importance (W) for each criterion:
   W = [W1, W2, W3, ..., Wj] (1)
4. Determine the suitability rating table for each alternative against each criterion.
5. Construct the decision matrix (X) based on the suitability rating table for each alternative against each criterion.
6. Determine the value of X for each alternative (Ai) against each criterion (Cj), where:
   i = 1, 2, ..., m and j = 1, 2, ..., n (2)
   Normalize the decision matrix X by calculating the normalized performance rating value (rij) for alternative (Ai) against criterion (Cj).
7. The resulting normalized performance rating values (rij) form the normalized matrix (R).
   $$R = \begin{vmatrix} r11 & r12 & \dots & r1j \\ \dots & \dots & \dots & \dots \\ ri1 & ri2 & \dots & rij \end{vmatrix} \quad (3)$$
8. Calculate the final preference value. The final preference result (Vi) is obtained by summing the products of the elements of the normalized matrix (R) rows and the corresponding preference weights (W) associated with the matrix columns.

METHOD

This study applies the Simple Additive Weighting (SAW) method to identify the best lecturer based on student evaluation data. The process includes collecting evaluation data, defining seven assessment criteria, assigning weights, constructing and normalizing the decision matrix, and calculating preference scores. Lecturers are then ranked based on their scores, with the highest score indicating the best lecturer. SAW provides an objective, systematic, transparent, and practical approach for supporting lecturer assessment decisions.

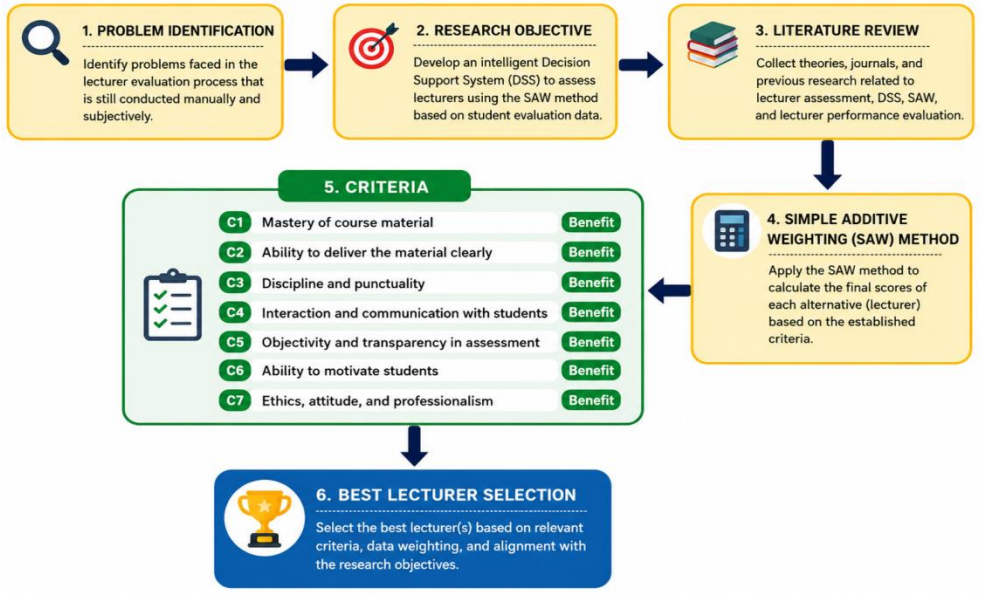


Figure 1. Research Methodology

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RESULT

Input and Output

Input and Output Needs Analysis The data used in this study were obtained from student evaluations of lecturers collected at the end of each semester at the university. This data serves as the basis for the assessment and selection of the best lecturers. The study program and faculty established several assessment criteria used as input variables, namely mastery of course material, learning methods and strategies, lecturer discipline, communication skills, interaction with students, and objectivity in the assessment process. All of these criteria were processed using the Simple Additive Weighting (SAW) method to generate preference scores for each lecturer. The output variable from the best lecturer ranking system, based on the highest to lowest preference scores, can be used as a basis for decision-making in determining the best lecturers objectively, transparently, and measurable.

Determination of Criteria

After identifying the input variables to be used in the Simple Additive Weighting (SAW) method, each variable is defined as an assessment criterion—designated as C1, C2, C3, C4, C5, C6, C7, and so forth, depending on the total number of criteria employed in the study. These criteria are derived from student evaluations of lecturer performance and serve as the basis for the "best lecturer" assessment process. Each criterion is assigned a specific weight of importance in accordance with study program or faculty policies, ensuring that the SAW calculation process yields a ranking of the best lecturers that is objective, systematic, and accurate. Explanation of each criterion:

1) C1 Mastery of subject matter: The lecturer's ability to understand and explain material within their field of expertise.
2) C2 Ability to deliver material: Clarity of delivery, logical structure, and the ease with which students grasp the material.
3) C3 Discipline: Attendance and punctuality in starting and ending classes.
4) C4 Interaction and communication: The lecturer's ability to answer questions, engage in discussion, and establish effective communication.
5) C5 Teaching methods and media: The use of effective strategies, technology, and instructional media.
6) C6 Objectivity in assessment: Fairness and transparency in assigning grades.
7) C7 Student motivation: The lecturer's ability to encourage participation, creativity, and enthusiasm for learning.

The criteria used in this study have been established and detailed in Table 1, serving as the basis for the calculation process using the Simple Additive Weighting (SAW) method.

Table 1. Kriteria

Research Criteria	ᵓ
Mastery of Course Material	Benefit
Ability to Deliver Course Material	Benefit
Discipline and Punctuality	Benefit
Interaction and Communication with Students	Benefit
Interaction and Communication with Students	Benefit
Objectivity and Transparency in Assessment	Benefit
Ability to Motivate Students	Benefit

Once the assessment criteria have been established, the next step is to assign preference weights or levels of importance to each criterion based on the obtained score ranges.

a) Criteria with scores of $71 > Ci \leq 80$ are assigned a weight of 0.10 and categorized as "Sufficient."
b) Criteria with scores of $81 \leq Ci \leq 90$ are assigned a weight of 0.15 and categorized as "Good." Meanwhile,
c) Criteria with scores of $Ci \geq 91$ are assigned the highest weight of 0.20 and categorized as "Very Good." The level of importance for each criterion is shown in Table 2.

After the assessment criteria are determined, the next step is to assign weights to each criterion based on its level of importance within the decision-making process. These weights reflect the contribution of each criterion to the selection of the best lecturer using the Simple Additive Weighting (SAW) method. The higher the assigned weight, the greater the criterion's influence on the final calculation result. The level of importance for each criterion is presented in Table 2.

Table 2. Importance level variables for each criterion

Average value	Weight	Description
Target market		
C1>70	0,10	Not Good
C1=> **80**	0,15	Good
C1=> **90**	0,20	Very Good

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Once the assessment criteria have been established, the next step is to determine the weight of each criterion based on its level of importance. In the Simple Additive Weighting (SAW) method, weights serve as multipliers in the calculation of preference values, thereby influencing the final ranking results. The weights for each criterion in this study are as follows:

1. Criterion C1 has a weight of 20% (0.20).
2. Criterion C2 has a weight of 20% (0.20).
3. Criterion C3 has a weight of 15% (0.15).
4. Criterion C4 has a weight of 15% (0.15).
5. Criterion C5 has a weight of 10% (0.10).
6. Criterion C6 has a weight of 10% (0.10).
7. Criterion C7 has a weight of 10% (0.10).

Data Processing

The collected student evaluation data is subsequently processed using the Simple Additive Weighting (SAW) method. The data processing involves assigning values to each criterion for every lecturer (acting as an alternative). The values for each criterion used in the SAW calculation process are presented in Table 2.

Table 3. Research Data

CI	C2	C3	C4	C5	C6	C7
95	84	100	75	89	97	93
90	98	98	78	80	89	88
92	91	78	90	96	84	79
80	82	90	88	95	86	89
78	93	85	86	97	85	79
89	88	86	80	89	80	95
99	79	88	90	85	79	98
85	89	90	88	83	95	80
68	80	94	94	82	93	87
90	86	95	92	84	95	86
87	84	98	90	81	92	94
77	90	80	79	79	92	92
86	98	70	89	77	70	90
87	80	70	90	79	74	84
85	79	79	99	75	77	85

The table below shows the process of converting data into weights for each criterion. Table 3. Data Process

Table 4. Proces Research Data

CI	C2	C3	C4	C5	C6	C7
0,20	0,15	0,20	0,10	0,15	0,20	0,20
0,20	0,20	0,20	0,10	0,15	0,15	0,15
0,20	0,20	0,10	0,20	0,20	0,15	0,10
0,15	0,15	0,20	0,15	0,20	0,15	0,15
0,10	0,20	0,15	0,15	0,20	0,15	0,10
0,15	0,15	0,15	0,15	0,15	0,15	0,20
0,20	0,10	0,15	0,20	0,15	0,10	0,20
0,15	0,15	0,20	0,15	0,15	0,20	0,15
0,00	0,15	0,20	0,20	0,15	0,20	0,15
0,20	0,15	0,20	0,20	0,15	0,20	0,15
0,15	0,15	0,20	0,20	0,15	0,20	0,20
0,10	0,20	0,15	0,10	0,10	0,20	0,20
0,15	0,20	0,10	0,15	0,10	0,10	0,20
0,15	0,15	0,10	0,20	0,10	0,10	0,15
0,15	0,10	0,10	0,20	0,10	0,10	0,15

Once the value for each alternative is obtained, the next step is to construct a decision matrix based on the values of the respective alternatives across each criterion.

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Normalization Process

The decision matrix is subsequently normalized using Equation (1). This process aims to standardize the value scales of the alternatives so that they can be used to calculate preference values via the SR method.

Process for determining Criterion (C1)

$$R_{11} = \frac{(0,20)}{MAX(0,20;0,20;0,20;0,15;0,10;0,15;\ 0,20;0,15;0,15;0,20;0,15;0,10;0,15;0,15;0,15)} = 1$$
$$R_{12} = \frac{(0,20)}{MAX(0,20;0,20;0,20;0,15;0,10;0,15;\ 0,20;0,15;0,15;0,20;0,15;0,10;0,15;0,15;0,15)} = 1$$
$$R_{13} = \frac{(0,20)}{MAX(0,20;0,20;0,20;0,15;0,10;0,15;\ 0,20;0,15;0,15;0,20;0,15;0,10;0,15;0,15;0,15)} = 1$$
$$R_{14} = \frac{(0,15)}{MAX(0,20;0,20;0,20;0,15;0,10;0,15;\ 0,20;0,15;0,15;0,20;0,15;0,10;0,15;0,15;0,15)} = 0,75$$
$$R_{15} = \frac{(0,10)}{MAX(0,20;0,20;0,20;0,15;0,10;0,15;\ 0,20;0,15;0,15;0,20;0,15;0,10;0,15;0,15;0,15)} = 0,50$$
$$R_{16} = \frac{(0,15)}{MAX(0,20;0,20;0,20;0,15;0,10;0,15;\ 0,20;0,15;0,15;0,20;0,15;0,10;0,15;0,15;0,15)} = 0,75$$
$$R_{17} = \frac{(0,20)}{MAX(0,20;0,20;0,20;0,15;0,10;0,15;\ 0,20;0,15;0,15;0,20;0,15;0,10;0,15;0,15;0,15)} =$$

Process for determining Criterion (C2)

$$R_{21} = \frac{(0,15)}{MAX(0,15;0,20;0,20;0,15;0,20;0,15;\ 0,10;0,15;0,15;0,15;0,15;0,20;0,20;0,15;0,10)} = 0,75$$
$$R_{22} = \frac{(0,20)}{MAX(0,15;0,20;0,20;0,15;0,20;0,15;\ 0,10;0,15;0,15;0,15;0,15;0,20;0,20;0,15;0,10)} = 1$$
$$R_{23} = \frac{(0,20)}{MAX(0,15;0,20;0,20;0,15;0,20;0,15;\ 0,10;0,15;0,15;0,15;0,15;0,20;0,20;0,15;0,10)} = 1$$
$$R_{24} = \frac{(0,15)}{MAX(0,15;0,20;0,20;0,15;0,20;0,15;\ 0,10;0,15;0,15;0,15;0,15;0,20;0,20;0,15;0,10)} = 0,7$$
$$R_{25} = \frac{(0,20)}{MAX(0,15;0,20;0,20;0,15;0,20;0,15;\ 0,10;0,15;0,15;0,15;0,15;0,20;0,20;0,15;0,10)} =$$
$$R_{26} = \frac{(0,15)}{MAX(0,15;0,20;0,20;0,15;0,20;0,15;\ 0,10;0,15;0,15;0,15;0,15;0,20;0,20;0,15;0,10)} = 0,75$$
$$R_{27} = \frac{(0,10)}{MAX(0,15;0,20;0,20;0,15;0,20;0,15;\ 0,10;0,15;0,15;0,15;0,15;0,20;0,20;0,15;0,10)} = 0,50$$

Process for determining Criterion (C3)

$$R_{31} = \frac{(0,20)}{MAX(0,20;0,20;0,10;0,20;0,15;0,15;\ 0,15;0,20;0,20;0,20;0,20;0,15;0,10;0,10;0,10)} = 1$$
$$R_{32} = \frac{(0,20)}{MAX(0,20;0,20;0,10;0,20;0,15;0,15;\ 0,15;0,20;0,20;0,20;0,20;0,15;0,10;0,10;0,10)} = 1$$
$$R_{33} = \frac{(015)}{MAX(0,20;0,20;0,10;0,20;0,15;0,15;\ 0,15;0,20;0,20;0,20;0,20;0,15;0,10;0,10;0,10)} 0,75$$
$$R_{34} = \frac{(0,20)}{MAX(0,20;0,20;0,10;0,20;0,15;0,15;\ 0,15;0,20;0,20;0,20;0,20;0,15;0,10;0,10;0,10)} = 1$$
$$R_{35} = \frac{(0,15)}{MAX(0,20;0,20;0,10;0,20;0,15;0,15;\ 0,15;0,20;0,20;0,20;0,20;0,15;0,10;0,10;0,10)} = 0,50$$
$$R_{36} = \frac{(0,15)}{MAX(0,20;0,20;0,10;0,20;0,15;0,15;\ 0,15;0,20;0,20;0,20;0,20;0,15;0,10;0,10;0,10)} = 0,50$$
$$R_{37} = \frac{(0,15)}{MAX(0,20;0,20;0,10;0,20;0,15;0,15;\ 0,15;0,20;0,20;0,20;0,20;0,15;0,10;0,10;0,10)} = 0,50$$

Process for determining Criterion (C4)

$$R_{41} = \frac{(0,10)}{MAX(0,10;0,10;0,20;0,15;0,15;0,15;\ 0,20;0,15;0,20;0,20;0,20;0,10;0,15;0,20;0,20)} = 0,75$$
$$R_{42} = \frac{(0,10)}{MAX(0,10;0,10;0,20;0,15;0,15;0,15;\ 0,20;0,15;0,20;0,20;0,20;0,10;0,15;0,20;0,20)} = 0,75$$
$$R_{43} \frac{(0,20)}{MAX(0,10;0,10;0,20;0,15;0,15;0,15;\ 0,20;0,15;0,20;0,20;0,20;0,10;0,15,0,20;0,20)} = 1$$
$$R_{44} = \frac{(0,15)}{MAX(0,10;0,10;0,20;0,15;0,15;0,15;\ 0,20;0,15;0,20;0,20;0,20;0,10;0,15;0,20;0,20)} = 0,50$$
$$R_{35} = \frac{(0,15)}{MAX(0,10;0,10;0,20;0,15;0,15;0,15;\ 0,20;0,15;0,20;0,20;0,20;0,10;0,15;0,20;0,20)} = 0,50$$
$$R_{46} = \frac{(0,15)}{MAX(0,10;0,10;0,20;0,15;0,15;0,15;\ 0,20;0,15;0,20;0,20;0,20;0,10;0,15;0,20;0,20)} = 0,50$$
$$R_{47} = \frac{(0,20)}{MAX(0,10;0,10;0,20;0,15;0,15;0,15;\ 0,20;0,15;0,20;0,20;0,20;0,10;0,15;0,20;0,20)} = 1$$

Process for determining Criterion (C5)

$$R_{51} = \frac{(0,15)}{MAX(0,15;0,15;0,20;0,20;0,20;0,20;0,15;\ 0,15;0,15;0,15;0,15;0,15;0,15;0,10;0,10;0,10;0,10;0,10)} = 0,50$$
$$R_{52} = \frac{(0,15)}{MAX(0,15;0,15;0,20;0,20;0,20;0,20;0,15;\ 0,15;0,15;0,15;0,15;0,15;0,15;0,10;0,10;0,10;0,10;0,10)} = 0,50$$
$$R_{53} = \frac{(0,20)}{MAX(0,15;0,15;0,20;0,20;0,20;0,20;0,15;\ 0,15;0,15;0,15;0,15;0,15;0,15;0,10;0,10;0,10;0,10;0,10)} = 1$$
$$R_{54} = \frac{(0,20)}{MAX(0,15;0,15;0,20;0,20;0,20;0,20;0,15;\ 0,15;0,15;0,15;0,15;0,15;0,15;0,10;0,10;0,10;0,10;0,10)} = 1$$
$$R_{55} = \frac{(0,20)}{MAX(0,15;0,15;0,20;0,20;0,20;0,20;0,15;\ 0,15;0,15;0,15;0,15;0,15;0,15;0,10;0,10;0,10;0,10;0,10)} = 1$$
$$R_{56} = \frac{(0,15)}{MAX(0,15;0,15;0,20;0,20;0,20;0,20;0,15;\ 0,15;0,15;0,15;0,15;0,15;0,15;0,10;0,10;0,10;0,10;0,10)} = 0,50$$
$$R_{57} = \frac{(0,15)}{MAX(0,15;0,15;0,20;0,20;0,20;0,20;0,15;\ 0,15;0,15;0,15;0,15;0,15;0,15;0,10;0,10;0,10;0,10;0,10)} = 0,50$$

Process for determining Criterion (C4)

$$R_{61} = \frac{(0,20)}{MAX(0,20;0,15;0,15;0,15;0,15;0,15;\ 0,10;0,20;0,20;0,20;0,20;0,20;0,20;0,10,0,10;0,10)} = 1$$
$$R_{62} = \frac{(0,15)}{MAX(0,20;0,15;0,15;0,15;0,15;0,15;\ 0,10;0,20;0,20;0,20;0,20;0,20;0,20;0,10,0,10;0,10)} = 0,50$$
$$R_{63} = \frac{(0,15)}{MAX(0,20;0,15;0,15;0,15;0,15;0,15;\ 0,10;0,20;0,20;0,20;0,20;0,20;0,20;0,10,0,10;0,10)} = 0,50$$
$$R_{64} = \frac{(0,15)}{MAX(0,20;0,15;0,15;0,15;0,15;0,15;\ 0,10;0,20;0,20;0,20;0,20;0,20;0,20;0,10,0,10;0,10)} = 0,50$$
$$R_{65} = \frac{(0,15)}{MAX(0,20;0,15;0,15;0,15;0,15;0,15;\ 0,10;0,20;0,20;0,20;0,20;0,20;0,20;0,10,0,10;0,10)} = 0,50$$
$$R_{66} = \frac{(0,15)}{MAX(0,20;0,15;0,15;0,15;0,15;0,15;\ 0,10;0,20;0,20;0,20;0,20;0,20;0,20;0,10,0,10;0,10)} = 0,50$$
$$R_{67} = \frac{(0,10)}{MAX(0,20;0,15;0,15;0,15;0,15;0,15;\ 0,10;0,20;0,20;0,20;0,20;0,20;0,20;0,10,0,10;0,10)} = 0,75$$

Process for determining Criterion (C5)

$$R_{71} = \frac{(0,20)}{MAX(0,20;0,15;0,10;0,15;0,10;0,20;\ 0,20;0,15;0,15;0,15;0,20;0,20;0,20;0,15;0,15)} = 1$$
$$R_{72} \frac{(0,15)}{MAX(0,15;0,15;0,20;0,20;0,20;0,15;\ 0,15;0,15;0,15;0,15;0,15;0,10;0,10;0,10;0,10)} = 0,50$$
$$R_{73} = \frac{(0,10)}{MAX(0,15;0,15;0,20;0,20;0,20;0,15;\ 0,15;0,15;0,15;0,15;0,15;0,10;0,10;0,10;0,10)} = 0,50$$
$$R_{74} = \frac{(0,15)}{MAX(0,15;0,15;0,20;0,20;0,20;0,15;\ 0,15;0,15;0,15;0,15;0,15;0,10;0,10;0,10;0,10)} = 0,50$$
$$R_{75} = \frac{(0,10)}{MAX(0,15;0,15;0,20;0,20;0,20;0,15;\ 0,15;0,15;0,15;0,15;0,15;0,10;0,10;0,10;0,10)} = 0,75$$
$$R_{76} = \frac{(0,20)}{MAX(0,15;0,15;0,20;0,20;0,20;0,15;\ 0,15;0,15;0,15;0,15;0,15;0,10;0,10;0,10;0,10)} = 1$$
$$R_{77} = \frac{(0,20)}{AX(0,15;0,15;0,20;0,20;0,20;0,15;\ 0,15;0,15;0,15;0,15;0,15;0,10;0,10;0,10;0,10)} 1$$

The normalization of values for each alternative across all criteria yields the normalization matrix presented in Table 4 below:

Table 5. Normalization Results

CI	C2	C3	C4	C5	C6	C7
1,00	0,75	1,00	0,50	0,75	1,00	1,00
1,00	1,00	1,00	0,50	0,75	0,75	0,75
1,00	1,00	0,50	1,00	1,00	0,75	0,50
0,75	0,75	1,00	0,75	1,00	0,75	0,75
0,50	1,00	0,75	0,75	1,00	0,75	0,50
0,75	0,75	0,75	0,75	0,75	0,75	1,00
1,00	0,50	0,75	1,00	0,75	0,50	1,00
0,75	0,75	1,00	0,75	0,75	1,00	0,75
0,00	0,75	1,00	1,00	0,75	1,00	0,75
1,00	0,75	1,00	1,00	0,75	1,00	0,75
0,75	0,75	1,00	1,00	0,75	1,00	1,00

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0,50	1,00	0,75	0,50	0,50	1,00	1,00
0,75	1,00	0,50	0,75	0,50	1,00	1,00
0,75	0,75	0,50	1,00	0,50	1,00	0,75
0,75	0,50	0,50	1,00	0,50	1,00	0,75

Final Results

The final stage of the Simple Additive Weighting (SAW) method involves calculating the preference value for each alternative by multiplying the normalized matrix (R) by the weight of each criterion and then summing the products using Equation (2). The resulting preference values serve as the basis for ranking the lecturers. The alternative with the highest preference value is designated as the best lecturer based on the student evaluation results.

W = [0.20; 0.20; 0.15; 0.15; 0.10; 0.10; 0.10]

Ranking results based on student evaluations

V1 = (1,00 × 0,2) + (0,75 × 0,2) + (1,00 × 0,15) + (0,50 × 0,15) + (0,75 × 0,1) + (1,00 × 0,1) + (1,00 × 0,1)
= 0,2 + 0,15 + 0,15 + 0,075 + 0,075 + 0,1 + 0,
= 0,85

V2 = (1,00 × 0,2) + (1,00 × 0,2) + (1,00 × 0,15) + (0,50 × 0,15) + (0,75 × 0,1) + (0,75 × 0,1) + (0,75 × 0,1)
= 0,2 + 0,2 + 0,15 + 0,075 + 0,075 + 0,075 + 0,075
=0,85

V3 = (1,00 × 0,2) + (1,00 × 0,2) + (0,50 × 0,15) + (1,00 × 0,15) + (1,00 × 0,1) + (0,75 × 0,1) + (0,50 × 0,1)
= 0,2 + 0,2 + 0,075 + 0,15 + 0,1 + 0,075 + 0,05
= 0,85

V4 = (0,75 × 0,2) + (0,75 × 0,2) + (1,00 × 0,15) + (0,75 × 0,15) + (1,00 × 0,1) + (0,75 × 0,1) + (0,75 × 0,1)
= 0,15 + 0,15 + 0,15 + 0,1125 + 0,1 + 0,075 + 0,075
=0,8125

V5 = (0,50 × 0,2) + (1,00 × 0,2) + (0,75 × 0,15) + (0,75 × 0,15) + (1,00 × 0,1) + (0,75 × 0,1) + (0,50 × 0,1)
= 0,1 + 0,2 + 0,1125 + 0,1125 + 0,1 + 0,075 + 0,05
= 0,75

V6 = (0,75 × 0,2) + (0,75 × 0,2) + (0,75 × 0,15) + (0,75 × 0,15) + (0,75 × 0,1) + (0,75 × 0,1) + (1,00 × 0,1)
= 0,15 + 0,15 + 0,1125 + 0,1125 + 0,075 + 0,075 + 0,1
= 0,775

V7 = (1,00 × 0,2) + (0,50 × 0,2) + (0,75 × 0,15) + (1,00 × 0,15) + (0,75 × 0,1) + (0,50 × 0,1) + (1,00 × 0,1)
= 0,2 + 0,1 + 0,1125 + 0,15 + 0,075 + 0,05 + 0,1
= 0,7875

V8 = (0,75 × 0,2) + (0,75 × 0,2) + (1,00 × 0,15) + (0,75 × 0,15) + (0,75 × 0,1) + (1,00 × 0,1) + (0,75 × 0,1)
= 0,15 + 0,15 + 0,15 + 0,1125 + 0,075 + 0,1 + 0,075
= 0,8125

V9 = (0,50 × 0,2) + (0,75 × 0,2) + (1,00 × 0,15) + (1,00 × 0,15) + (0,75 × 0,1) + (1,00 × 0,1) + (0,75 × 0,1)
= 0,1 + 0,15 + 0,15 + 0,15 + 0,075 + 0,1 + 0,075
= 0,8

V10 = (1,00 × 0,2) + (0,75 × 0,2) + (1,00 × 0,15) + (1,00 × 0,15) + (0,75 × 0,1) + (1,00 × 0,1) + (0,75 × 0,1)
= 0,2 + 0,15 + 0,15 + 0,15 + 0,075 + 0,1 + 0,075
= 0,9

V11 = (0,75 × 0,2) + (0,75 × 0,2) + (1,00 × 0,15) + (1,00 × 0,15) + (0,75 × 0,1) + (1,00 × 0,1) + (1,00 × 0,1)
= 0,15 + 0,15 + 0,15 + 0,15 + 0,075 + 0,1 + 0,1
=0,875

V12 = (0,50 × 0,2) + (1,00 × 0,2) + (0,75 × 0,15) + (0,50 × 0,15) + (0,50 × 0,1) + (1,00 × 0,1) + (1,00 × 0,1)
= 0,1 + 0,2 + 0,1125 + 0,075 + 0,05 + 0,1 + 0,1
= 0,7375

V13 = (0,75 × 0,2) + (1,00 × 0,2) + (0,50 × 0,15) + (0,75 × 0,15) + (0,50 × 0,1) + (1,00 × 0,1) + (1,00 × 0,1)
= 0,15 + 0,2 + 0,075 + 0,1125 + 0,05 + 0,1 + 0,1
=0,7875

V14 = (0,75 × 0,2) + (0,75 × 0,2) + (0,50 × 0,15) + (1,00 × 0,15) + (0,50 × 0,1) + (1,00 × 0,1) + (0,75 × 0,1)
= 0,15 + 0,15 + 0,075 + 0,15 + 0,05 + 0,1 + 0,075
= 0,75

V15 = (0,75 × 0,2) + (0,50 × 0,2) + (0,50 × 0,15) + (1,00 × 0,15) + (0,50 × 0,1) + (1,00 × 0,1) + (0,75 × 0,1)
= 0,15 + 0,1 + 0,075 + 0,15 + 0,05 + 0,1 + 0,075
= 0,7

Ranking Results

Based on calculations using the Simple Additive Weighting (SAW) method, preference values were obtained for each alternative; these values subsequently served as the basis for the ranking process. The preference values were calculated by multiplying the normalized matrix by the weight of each criterion and summing the results to yield a final

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value for each alternative. The higher the preference value obtained, the higher the priority level of the corresponding alternative.

Table 6. Ranking Results

Rank Alternative	Preference	Value Rating
1	V10	0,9
2	V11	0,875
3	V1	0,85
4	V2	0,85
5	V3	0,85
6	V4	0,8125
7	V8	0,8125
8	V9	0,8
9	V7	0,7875
10	V13	0,7875
11	V6	0,775
12	V5	0,75
13	V14	0,75
14	V12	0,7375
15	V15	0,7

The ranking results in Table 6 show that alternative V10 achieved the highest preference score of 0.90, thereby securing first place and being recommended as the best lecturer based on student evaluations. This indicates that V10 demonstrated the best level of achievement across all assessment criteria compared to the other alternatives. Alternative V11 ranked second with a preference score of 0.875, while V1, V2, and V3 all obtained an identical preference score of 0.85; consequently, these three alternatives exhibited relatively equal performance levels and occupied the subsequent positions. Next, V4 and V8 achieved a preference score of 0.8125, followed by V9 with 0.80, and V7 and V13, which each scored 0.7875. Meanwhile, the alternative with the lowest preference score was V15 at 0.70, placing it 15th in the ranking. This score indicates that V15 demonstrated a lower level of achievement compared to the other alternatives based on the weights and criteria applied in this study.

DISCUSSION

This study successfully developed an intelligent Decision Support System (DSS) for evaluating the best lecturer using the Simple Additive Weighting (SAW) method, based on student evaluation data. The SAW method is capable of processing assessment data across seven criteria—namely subject matter mastery, delivery skills, discipline, interaction and communication, teaching methods, assessment objectivity, and the ability to motivate students—through processes of weighting, normalization, and preference value calculation. The research results demonstrate that the SAW method yields an assessment process that is more objective, systematic, transparent, and measurable compared to manual data processing. Based on the calculated preference values, alternative V10 achieved the highest score of 0.90 and is thus recommended as the best lecturer according to the student evaluations. Consequently, the application of the SAW method proves effective in assisting study programs and higher education institutions to identify the best lecturer more effectively, efficiently, and accurately, while also supporting improvements in the quality of evaluation processes and decision-making within the academic environment.

CONCLUSION

This study developed a Decision Support System (DSS) for evaluating and ranking lecturer performance based on student evaluation data using the Simple Additive Weighting (SAW) method. The proposed approach integrates seven lecturer performance criteria, namely mastery of subject matter, ability to deliver course material, discipline and punctuality, interaction and communication, teaching methods and media, objectivity and transparency in assessment, and ability to motivate students. The assessment process consists of criterion determination, weighting, decision matrix construction, normalization, and preference value calculation, providing a structured and measurable mechanism for lecturer performance evaluation.

The results demonstrate that the SAW method can effectively transform student evaluation data into a lecturer performance ranking. From 15 lecturer alternatives, V10 obtained the highest preference value of 0.90, followed by V11 with 0.875, while V15 obtained the lowest value of 0.70. The ranking indicates that the proposed DSS is capable of distinguishing performance levels among lecturers based on the criteria and weights established in the study. More importantly, the use of explicit criteria, normalized values, and weighted preference scores improves the transparency and traceability of the assessment process compared with an evaluation process based solely on manual interpretation.

The main contribution of this study is the application of a systematic multi-criteria decision-making framework

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to support the utilization of student evaluation data for lecturer performance assessment. The resulting ranking can provide academic managers and study programs with decision-support information for identifying high-performing lecturers and determining areas requiring instructional improvement. Thus, the proposed approach has practical potential to support evidence-based lecturer evaluation and continuous improvement of teaching quality in higher education.

Nevertheless, the findings should be interpreted within the scope of the criteria, weighting scheme, and evaluation data applied in this study. The resulting ranking is dependent on the predetermined weights and the characteristics of the student evaluation data; therefore, it should be regarded as decision-support information rather than an absolute measure of lecturer quality. Future research should validate the proposed system using larger and more diverse datasets, involve multiple study programs or institutions, and investigate alternative weighting and ranking methods to examine the robustness of the results. Future studies may also integrate additional indicators and develop a web-based or real-time evaluation platform to improve the scalability, usability, and applicability of the system in institutional quality assurance processes.

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