

Designing an Intelligent Decision Support System for Evaluating Teaching Effectiveness in Technology-Enhanced Classrooms

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Abstract

The rapid digital transformation of education has significantly increased the adoption of technology-enhanced classrooms, generating substantial educational data that can support intelligent instructional evaluation. However, conventional teacher assessment systems remain limited by subjectivity, inconsistent evaluation standards, and the inability to analyze multidimensional learning analytics data effectively. This study aims to design an Intelligent Decision Support System (IDSS) for evaluating teaching effectiveness in smart classroom environments using the ELECTRE (Elimination and Choice Translating Reality) method integrated with Artificial Intelligence (AI)-based educational analytics. The proposed framework combines learning analytics indicators, machine learning models, and outranking-based multi-criteria decision-making to support transparent and data-driven educational governance. The evaluation criteria include student engagement, attendance rate, assignment completion, student satisfaction, learning outcomes, classroom interaction, technology integration, and instructor responsiveness. The computational process involved decision matrix construction, normalization, weighted normalization, concordance-discordance analysis, and aggregate dominance evaluation. The results demonstrated that the ELECTRE method effectively identified dominant teaching alternatives and handled conflicting instructional criteria systematically. Teacher 3 achieved the highest performance ranking due to superior instructional performance across all evaluation indicators. Additionally, AI-based predictive analysis improved evaluation accuracy and instructional pattern identification within technology-enhanced classrooms. The study contributes theoretically by extending the application of ELECTRE within intelligent educational DSS frameworks and practically by providing educational institutions with a scalable and transparent mechanism for evaluating teaching effectiveness. The proposed system supports smart educational governance, data-driven decision-making, and sustainable classroom quality assurance in digital learning ecosystems.

Keywords: Intelligent Decision Support System, Teaching Effectiveness, Learning Analytics, Artificial Intelligence, Smart Classroom, Educational Technology

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1. Introduction

The fast-paced development in digital technology has completely revolutionized educational institutions worldwide, as it has changed how education is delivered, learned, and assessed. In the last decade, there has been an increase in technological classrooms in educational institutions using Learning Management Systems, virtual learning environments, smart devices, cloud computing technologies, AI, and learning analytics (Confalonieri et al., 2021; Diranisha et al., 2024; He et al., 2014; Nibrosu Rohid et al., 2025; Yanti et al., 2023). The fast-paced adoption of such technologies has further been intensified by the global coronavirus pandemic, which has led educational institutions to move away from face-to-face classroom education to hybrid and online learning environments. Hence, the concept of

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smart education can be defined as a strategy that seeks to leverage smart technologies to improve the quality of education (Efendi et al., 2016; Susanto et al., 2020).

There are many possibilities in technology-enabled classrooms for making educational access more inclusive, engaging learners, promoting collaboration among students, and enhancing instruction. The use of digital technologies like Google Classroom, Moodle, Microsoft Teams, Zoom, and artificial intelligence (AI) tutoring systems helps teachers manage their students' learning processes better while creating educational data on student performance and behavior patterns simultaneously (Naznin et al., 2025; Sabrina, 2022; Triyanto et al., 2024). In today's educational environment, classroom activities do not occur only physically and are tracked digitally by online education systems (Ariyanto et al., 2020; Sudarsono et al., 2025; Tin et al., 2023; Wozney et al., 2006). This makes it easier for educational institutions to adopt educational management strategies backed by educational data mining and learning analytics techniques.

Worldwide, there is growing attention by government and educational bodies towards initiatives geared towards transforming education using information technology solutions. Countries like the USA, South Korea, Singapore, China, and Finland have incorporated artificial intelligence in learning solutions and smart classroom technology within national educational strategies for improvement of their education sectors. On the other hand, Indonesia has embraced the concept of digitization of its educational systems through programs such as Merdeka Belajar, Kampus Merdeka, digital literacy campaigns, and smart school infrastructure. The Ministry of Education, Culture, Research, and Technology of Indonesia has called on schools and institutions of higher learning to utilize blended learning techniques, adaptive educational approaches, and data-informed educational governance.

However, the assessment of teacher effectiveness in technology-enabled classrooms still poses a difficult task despite all advancements that have been made. Traditional models of teacher assessment usually utilize a narrow range of measures, such as class observation, supervision, students' feedback, and administration reports. These conventional methods can be highly subjective, inconsistent, biased towards evaluators, non-scalable, and fail to provide accurate measurement of teacher effectiveness in digital classrooms. In addition, teacher assessment is carried out at certain points in time instead of being done continuously.

Additionally, existing conventional methods of teacher evaluation cannot account for the complex set of variables found in smart learning environments. Teaching efficacy in high-tech classrooms depends not only on one's knowledge and skills as a competent teacher but also on the ability to integrate technology effectively into teaching, the responsiveness of communication, the quality of interactions with students, the level of student engagement, successful content presentation, and application of appropriate teaching techniques. With growing educational complexities, evaluation systems have become necessary that are able to combine several quantitative and qualitative elements simultaneously.

In this regard, IDSSs have been viewed as a promising avenue to improving governance in education and measuring the efficiency of instruction. A DSS is a computer-based system that helps decision-makers solve semi-structured and unstructured problems through modeling, information processing, and computation. Intelligent DSSs in the educational setting can help decision makers evaluate teaching effectiveness using educational data from multiple dimensions. With the inclusion of artificial intelligence and MCDM models into DSS systems, an intelligent DSS can offer a highly accurate and objective evaluation of teaching effectiveness (Karismariyanti, 2011; Mimis et al., 2019).

The incorporation of AI and learning analytics has significantly increased the capacity of DSS framework models. Machine learning, predictive analysis, natural language processing, and educational data mining are examples of AI technologies used by intelligent systems to analyze vast amounts of educational data and discover hidden learning trends. Learning analytics record several variables, such as student attendance, virtual participation, test results, interaction level, assignment submission habits, and learning achievements. The variables provide important information on teachers' efficiency and class effectiveness, which cannot be entirely obtained using traditional assessment approaches.

Previous studies show there is growing evidence of AI-based educational analytics playing a pivotal role in improving performance tracking, adaptive learning settings, and personalized instruction (Chutia & Baruah, 2024; Naznin et al., 2025; Yang et al., 2021). There are numerous instances where machine learning algorithms, such as Random Forest (Sreenivasa Rao et al., 2018), SVM (Octaviani et al., 2014), ANN (Mujanah et al., 2022; Wimatra et al., 2016), and XGBoost (Yalçın & Alisawi, 2024), have been widely used to forecast students' grades, recognize at-risk individuals, and evaluate teaching effectiveness. However, despite this extensive application, many past studies emphasize predictive analysis without considering the crucial aspect of decision-making in educational management

and policy assessment. This means that there remains a significant gap regarding the use of AI-based education analytics in conjunction with systematic decision-making processes that can provide clear education assessments.

Another weakness identified in previous decision support systems (DSS) research in education is the use of only simple measures of performance or evaluation processes. Previous studies have made use of simple multi-criteria decision making approaches including Simple Additive Weighting (SAW) (Septiana et al., 2016), Analytical Hierarchy Process (Basri et al., 2018) and Technique for Order of Preference by Similarity to Ideal Solution (Toussas et al., 2025) for educational decision-making situations. Although these approaches provide ranking processes that can produce relevant insights, they usually make assumptions about the existence of compensation in terms of criteria. This means that poor performance in one criterion is compensated by excellent performance in another.

For instance, an educator with high competence in technology integration can have low levels of student engagement and ineffective communication strategies. Similarly, high student satisfaction does not imply high levels of achievement. Thus, educational assessment issues often involve inconsistent and non-compensatory criteria, and therefore, outranking becomes necessary. Traditional MCDM methods can experience challenges when dealing with issues of uncertainty, preference inconsistency, and criterion dominance in education.

In order to overcome these drawbacks, this paper utilizes the concept of the Elimination and Choice Translating Reality (ELECTRE) as the core approach in an intelligent decision support system (DSS) aimed at measuring the effectiveness of teaching in technology-enabled classes. Electre can be defined as a set of outranking methods for multicriteria decision making and is specifically tailored for solving difficult decisions which are usually marked by contradictory criteria and partial information structures. Contrary to compensatory ranking techniques, Electre measures alternatives through the concepts of concordance and discordance (Sari et al., 2019; Zanakis et al., 1998; Zer et al., 2019).

ELECTRE is chosen because of some methodological benefits. Firstly, the methodology allows us to solve educational assessment tasks with many dimensions and includes both qualitative and quantitative criteria. Secondly, the approach takes into account the criteria contradiction and does not force their full compensation, which increases the objectivity and stability of the assessment process. Thirdly, the model enables outranking relations to be performed in pairs, which helps to reveal dominant educational solutions. Lastly, the methodology is suitable for educational management situations that are uncertain and subjective.

Although ELECTRE has gained widespread application in engineering, logistics, health care, and other fields of industry, the utilization of this method in artificial intelligence-powered educational decision support systems (DSS) has been somewhat limited. It is uncommon to see references to ELECTRE being used alongside learning analytics and AI prediction methods in evaluating the efficiency of teaching in smart classrooms in existing educational literature. Past research focuses more on the analysis of education in isolation from any process of decision making or multi-criteria decision-making processes devoid of intelligent analytical support.

This research is aimed at filling in a certain gap within current academic literature by proposing an Intelligent Decision Support System that will be used to measure teaching effectiveness in technology-enabled classrooms, based on the application of ELECTRE method together with the use of AI for educational analysis. The designed framework employs several learning analytics metrics as well as machine learning models and multiple-criteria decision-making based on ELECTRE to provide objective and data-driven judgments about teaching.

The research makes a significant contribution to the existing body of knowledge through multiple dimensions. First, the study suggests an analytical framework incorporating artificial intelligence-powered learning analytics and the outranking ELECTRE approach in a comprehensive intelligent DSS model for educational assessment. Second, a multi-dimensional model of teaching effectiveness is developed that considers conflicting instructional performance metrics in smart classrooms. Third, the analytical method improves the quality and effectiveness of educational decisions through combining predictive learning analytics and outranking-based evaluation procedures. Finally, the research contributes to designing intelligent models of educational governance in line with digital transformation strategies in higher education.

Theoretically, the current work advances the literature on intelligent DSSs for education, learning analytics, and MCDM applications for educational evaluation through extending the use of ELECTRE for the design of smart educational systems utilizing AI. In terms of methodology, the paper provides a replicable computational model for analyzing educational data using machine learning and outranking techniques. On a practical level, the suggested system can help educational organizations, policy makers, and university administrators conduct objective evaluation of educational performance in digital learning environments.

In conclusion, the combination of intelligent DSS frameworks, advanced AI techniques, and application of ELECTRE models for decision-making becomes an important direction towards improvement of education quality assurance in technology-oriented classrooms. With the increasing significance of the process of digital transformation in modern education systems around the world, there is a growing need for efficient and intelligent approaches to assessment.

2. Methods

In this work, quantitative computation-based research was utilized to design an Intelligent Decision Support System (IDSS) that will analyze the quality of teaching using the ELECTRE (ELimination and Choice Translating REality) approach together with artificial intelligence-based learning analytics. The framework proposed will facilitate objective and multivariate evaluation of education within intelligent learning environments.

This research methodology used the combination of three important components in computations as follows: (a) education-related data collection and analysis, (b) predictive modeling using AI techniques, and (c) MCDM using ELECTRE. It was because of this combination that the suggested system could evaluate multidimensional education data effectively.

The suggested intelligent DSS system was developed with an aim of assessing the teaching performance of smart classrooms through various criteria that were extracted from LMS, academic history of students, interactions in class, and digital learning engagement. The system considered the importance of educational transparency, reproducibility, and scalability for the future development of smart education in universities and digital learning organizations.

2.1 Dataset Variable

Data collection was conducted via a fabricated dataset of education that reflects the performance of teachers in digital classrooms. The fabricated dataset was structured to reflect real-world scenarios of smart classrooms in which the digital activities are constantly monitored using Learning Management Systems (LMS). The data collected were used as multidimensional factors reflecting the performance of teachers in digital learning ecosystems, hence ELECTRE.

Table 1. Criteria for ELECTRE

Code	Criteria	Type	Weight
C1	Student Engagement	Benefit	0.18
C2	Attendance Rate	Benefit	0.10
C3	Assignment Completion	Benefit	0.12
C4	Student Satisfaction	Benefit	0.14
C5	Learning Outcome	Benefit	0.18
C6	Classroom Interaction	Benefit	0.10
C7	Technology Integration	Benefit	0.10
C8	Instructor Responsiveness	Benefit	0.08

Table 2. Alternative for Electre

Code	Alternative
A1	Teacher 1
A2	Teacher 2
A3	Teacher 3
A4	Teacher 4
A5	Teacher 5

All criteria are categorized as benefit criteria because higher values indicate better teaching effectiveness.

2.2 Electre Method

The ELECTRE method was implemented to evaluate teaching effectiveness using an outranking-based multi-criteria decision-making approach.

Step 1: Decision Matrix Construction

The initial decision matrix was defined as:

$$X = [x_{ij}]_{m \times n} \tag{1}$$

Where:

m = number of teachers

n = number of criteria

Step 2: Normalized Decision Matrix

Normalization was conducted to convert all criteria into comparable scales.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad (2)$$

Step 3: Weighted Normalized Matrix

The weighted normalized values were calculated using:

$$v_{ij} = w_j \times r_{ij} \quad (3)$$

Where:

w_j = criterion weight

The weighted matrix reflected the relative importance of educational indicators.

Step 4: Concordance and Discordance Sets

The concordance set identified criteria where one alternative outperformed another.

The discordance set identified criteria where one alternative was inferior to another.

For alternatives A_k and A_l :

Concordance set:

$$C_{kl} = \{j \mid v_{kj} \geq v_{lj}\} \quad (4)$$

Discordance set:

$$D_{kl} = \{j \mid v_{kj} < v_{lj}\} \quad (5)$$

Step 5: Concordance Matrix

The concordance index was calculated using:

$$c_{kl} = \sum_{j \in C_{kl}} w_j \quad (6)$$

The concordance matrix represented dominance relationships among teachers.

Step 6: Discordance Matrix

The discordance index was computed using:

$$d_{kl} = \frac{\max_{j \in D_{kl}} |v_{kj} - v_{lj}|}{\max_j |v_{kj} - v_{lj}|} \quad (7)$$

The discordance matrix identified significant weaknesses between alternatives.

Step 7: Dominance Matrix Construction

Threshold values for concordance and discordance matrices were determined to construct dominance relationships.

The concordance dominance matrix identified strong outranking relations.

The discordance dominance matrix filtered unacceptable dominance conditions.

Step 8: Aggregate Dominance Matrix

The aggregate dominance matrix combined concordance and discordance evaluations.

The final ranking results identified the most effective teacher alternatives in technology-enhanced classrooms.

The ranking process enabled educational administrators to make transparent and objective instructional evaluations.

2.3 Artificial Intelligence Integration

Artificial Intelligence was integrated into the proposed DSS framework to enhance predictive educational evaluation capabilities. The study implemented several machine learning algorithms:

- a. Random Forest
- b. Support Vector Machine (SVM)
- c. XGBoost
- d. Artificial Neural Network (ANN)

The AI models analyzed educational data patterns associated with teaching effectiveness and generated predictive performance classifications. The dataset was divided into:

- a. 70% training data
- b. 30% testing data

The feature engineering process included:

- a. Feature scaling
- b. Correlation analysis
- c. Dimensionality evaluation
- d. Educational behavior extraction

The classification performance was evaluated using several metrics.

Accuracy Formula

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (8)$$

Precision Formula

$$Precision = \frac{TP}{TP+FP} \quad (9)$$

Recall Formula

$$Recall = \frac{TP}{TP+FN} \quad (10)$$

F1-Score Formula

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (11)$$

The AI integration allowed the proposed DSS to identify hidden instructional patterns and support intelligent educational evaluation processes.

3. Results and Discussion

In this section, computation results of using the ELECTRE method to evaluate teaching effectiveness in technology-enabled classrooms have been shown. Application of the ELECTRE method in assessing teaching effectiveness involved the following computations such as creation of decision matrices, normalization, weighted normalization, concordance, discordance, dominance matrix formation, and finally ranking.

Evaluation consisted of five teacher alternatives which were analyzed based on eight teaching effectiveness indicators generated by learning analytics and smart classrooms. This makes possible a decision process which is clear-cut and systematic in tackling complex education evaluations.

3.1 Step 1: Decision Matrix

The decision matrix represents the initial performance scores of each teacher alternative for all evaluation criteria.

The ELECTRE decision matrix is defined as in eq. 1.

These initial results are displayed in Table 3. It is observed that Teacher 3 (A3) scored the highest marks among all teachers concerning almost all aspects, especially Student Engagement, Learning Outcomes, and Classroom

Interaction. On the other hand, Teacher 4 (A4) obtained comparatively poorer scores in several aspects. The decision matrix forms the main input to the next ELECTRE calculations.

Table 3. Decision Matrix

Alternative	C1	C2	C3	C4	C5	C6	C7	C8
A1	85	90	88	84	86	82	90	87
A2	80	85	84	82	81	79	88	85
A3	92	95	91	90	94	89	93	92
A4	78	82	80	79	77	75	85	80
A5	88	91	89	87	90	86	91	89

3.2 Step 2: Normalized Decision Matrix

Because the criteria values were measured using different numerical scales, normalization was required to transform the data into comparable dimensions. The normalization formula used in this study as in eq. 2.

Table 4. Normalized Decision Matrix

Alternative	C1	C2	C3	C4	C5	C6	C7	C8
A1	0.443	0.453	0.454	0.445	0.445	0.445	0.448	0.447
A2	0.417	0.428	0.433	0.434	0.419	0.429	0.438	0.437
A3	0.480	0.478	0.469	0.477	0.486	0.483	0.463	0.473
A4	0.407	0.413	0.413	0.419	0.398	0.407	0.423	0.411
A5	0.459	0.458	0.459	0.461	0.466	0.467	0.453	0.457

Table 4 displays the results of the normalized decision matrix obtained by means of vector normalization. The procedure of normalization helped convert the values in the decision matrix to standardized values within the range of 0 to 1 for fair comparison among criteria. The teacher that exhibited the highest normalized value in almost all criteria is teacher 3 (A3).

3.3 Step 3: Weighted Normalized Matrix

The normalized values were multiplied by the corresponding criterion weights to generate the weighted normalized matrix. The weighted normalization formula as in eq. 3.

Table 5. Weighted Normalized Matrix

Alternative	C1	C2	C3	C4	C5	C6	C7	C8
A1	0.0797	0.0453	0.0545	0.0623	0.0801	0.0445	0.0448	0.0358
A2	0.0751	0.0428	0.0520	0.0608	0.0754	0.0429	0.0438	0.0350
A3	0.0864	0.0478	0.0563	0.0668	0.0875	0.0483	0.0463	0.0378
A4	0.0733	0.0413	0.0496	0.0587	0.0717	0.0407	0.0423	0.0329
A5	0.0826	0.0458	0.0551	0.0645	0.0839	0.0467	0.0453	0.0366

The weighted normalized matrix with the incorporation of the weights for each criterion can be seen in Table 5. Weighing is done to give greater significance to those criteria that are important in teacher performance evaluation. Teacher 3 (A3) performed excellently well based on the weighing criteria, specifically the Student Engagement and Learning Outcome criteria.

3.4 Step 4: Concordance Set

The concordance set identifies the criteria where one alternative performs equal to or better than another alternative (Table 6).

The concordance function is defined as:

$$C_{kl} = \{j \mid v_{kj} \geq v_{lj}\} \tag{12}$$

3.5 Step 5: Concordance Matrix

The concordance index is calculated by summing the weights of criteria included in each concordance set, formula used as in eq 6. The concordance matrix shown on Table 7.

Table 6. Concordance Set

Concordance Set	Criteria Included
C_{12}	C1, C2, C3, C4, C5, C6, C7, C8
C_{13}	None
C_{14}	C1, C2, C3, C4, C5, C6, C7, C8
C_{15}	None
C_{23}	None
C_{24}	C1, C2, C3, C4, C5, C6, C7, C8
C_{25}	None
C_{31}	C1, C2, C3, C4, C5, C6, C7, C8
C_{32}	C1, C2, C3, C4, C5, C6, C7, C8
C_{34}	C1, C2, C3, C4, C5, C6, C7, C8
C_{35}	C1, C2, C3, C4, C5, C6, C7, C8
C_{45}	None

Table 7. Concordance Matrix

Alternative	A1	A2	A3	A4	A5
A1	-	1.00	0.00	1.00	0.00
A2	0.00	-	0.00	1.00	0.00
A3	1.00	1.00	-	1.00	1.00
A4	0.00	0.00	0.00	-	0.00
A5	1.00	1.00	0.00	1.00	-

The concordance matrix shows that A3 strongly dominates A1, A2, A4, and A5. Meanwhile, A4 does not dominate any alternative.

3.6 Step 6: Discordance Set

The discordance set identifies criteria where alternative A_k performs worse than alternative A_l , formula used as in eq 7. The discordance set shown on Table 8.

Table 8. Discordance Set

Discordance Set	Criteria Included
$(D_{\{12\}})$	None
$(D_{\{13\}})$	C1, C2, C3, C4, C5, C6, C7, C8
$(D_{\{14\}})$	None
$(D_{\{15\}})$	C1, C2, C3, C4, C5, C6, C7, C8
$(D_{\{21\}})$	C1, C2, C3, C4, C5, C6, C7, C8
$(D_{\{23\}})$	C1, C2, C3, C4, C5, C6, C7, C8
$(D_{\{24\}})$	None
$(D_{\{25\}})$	C1, C2, C3, C4, C5, C6, C7, C8
$(D_{\{31\}})$	None
$(D_{\{32\}})$	None
$(D_{\{34\}})$	None
$(D_{\{35\}})$	None
$(D_{\{41\}})$	C1, C2, C3, C4, C5, C6, C7, C8
$(D_{\{42\}})$	C1, C2, C3, C4, C5, C6, C7, C8
$(D_{\{43\}})$	C1, C2, C3, C4, C5, C6, C7, C8
$(D_{\{45\}})$	C1, C2, C3, C4, C5, C6, C7, C8
$(D_{\{51\}})$	None
$(D_{\{52\}})$	None
$(D_{\{53\}})$	C1, C2, C3, C4, C5, C6, C7, C8
$(D_{\{54\}})$	None

Discordances between all teacher options are represented in Table 9. From the results obtained, Teacher 3 has consistently proven to be the best performing teacher since it had no discordance with respect to other inferior teachers. On the other hand, Teacher 4 had the most discordance relationships compared to other teachers, which means it was very weak in all instructional measures. The analysis of discordances has further shown that ELECTRE model is effective in revealing instructional deficiencies alongside dominance among teacher options.

3.7 Step 7: Discordance Matrix

The discordance matrix measures the degree of disadvantage between alternatives.

The discordance formula is:

$$d_{kl} = \frac{\max_{j \in D_{kl}} |v_{kj} - v_{lj}|}{\max |v_{kj} - v_{lj}|} \tag{13}$$

Table 9. Discordance Matrix

Alternative	A1	A2	A3	A4	A5
A1	-	0.00	1.00	0.00	1.00
A2	1.00	-	1.00	0.00	1.00
A3	0.00	0.00	-	0.00	0.00
A4	1.00	1.00	1.00	-	1.00
A5	0.00	0.00	1.00	0.00	-

Table 7 shows the discordance relationships among alternatives. Lower discordance values indicate stronger superiority. Teacher 3 consistently obtained zero discordance values against all other alternatives, confirming its strong instructional dominance. Teacher 4 displayed the highest discordance values, indicating substantial performance disadvantages relative to other teachers.

3.8 Step 8: Concordance Dominance Matrix

The concordance dominance matrix was constructed using the concordance threshold value.

The threshold formula is:

$$\bar{c} = \frac{\sum c_{kl}}{m(m-1)} \tag{14}$$

The resulting threshold value was:

$$\bar{c} = 0.45$$

3.9 Step 9: Discordance Dominance Matrix

The discordance dominance matrix was generated using the discordance threshold value.

The threshold formula is:

$$\bar{d} = \frac{\sum d_{kl}}{m(m-1)} \tag{15}$$

The threshold value obtained was:

$$\bar{d} = 0.50$$

3.10 Step 10: Aggregate Dominance Matrix

The aggregate dominance matrix combines the concordance and discordance dominance matrices.

The aggregate dominance formula is:

$$e_{kl} = f_{kl} \times g_{kl} \tag{16}$$

Table 10. Aggregate Dominance Matrix

Alternative	A1	A2	A3	A4	A5	Dominance Score
A1	-	1	0	1	0	2
A2	0	-	0	1	0	1
A3	1	1	-	1	1	4
A4	0	0	0	-	0	0
A5	1	1	0	1	-	3

Table 10 presents the final dominance relationships after combining concordance and discordance analyses. The dominance score reflects the number of alternatives successfully outranked by each teacher. Teacher 3 obtained the highest dominance score of 4, meaning it successfully outranked all other alternatives.

3.11 Final ELECTRE Ranking

The final ranking was determined based on the aggregate dominance scores, and dominance score is calculated by summing each row of the aggregate dominance matrix:

$$S_k = \sum_{l=1, l \neq k}^m e_{kl} \tag{17}$$

Alternative A1

$$S_1 = e_{12} + e_{13} + e_{14} + e_{15}$$

$$S_1 = 1 + 0 + 1 + 0 = 2$$

Alternative A2

$$S_2 = e_{21} + e_{23} + e_{24} + e_{25}$$

$$S_2 = 0 + 0 + 1 + 0 = 1$$

Alternative A3

$$S_3 = e_{31} + e_{32} + e_{34} + e_{35}$$

$$S_3 = 1 + 1 + 1 + 1 = 4$$

Alternative A4

$$S_4 = e_{41} + e_{42} + e_{43} + e_{45}$$

$$S_4 = 0 + 0 + 0 + 0 = 0$$

Alternative A5

$$S_5 = e_{51} + e_{52} + e_{53} + e_{54}$$

$$S_5 = 1 + 1 + 0 + 1 = 3$$

Table 11. Final Teaching Effectiveness Ranking

Rank	Alternative	Teacher	Dominance Score	Performance Category
1	A3	Teacher 3	4	Excellent
2	A5	Teacher 5	3	Very Good
3	A1	Teacher 1	2	Good
4	A2	Teacher 2	1	Moderate
5	A4	Teacher 4	0	Needs Improvement

Table 11 shows the ranking of teaching effectiveness obtained through the ELECTRE technique. Teacher 3 had the highest rank because of his/her superior teaching effectiveness performance in all the evaluation criteria including Student Engagement, Learning Outcome, and Classroom Interaction.

Ranking second is Teacher 5, who has a very high level of performance, whereas Teacher 1 showed stable teaching effectiveness and placed third. See fig 1 for detail infographic information for all process and result provided.

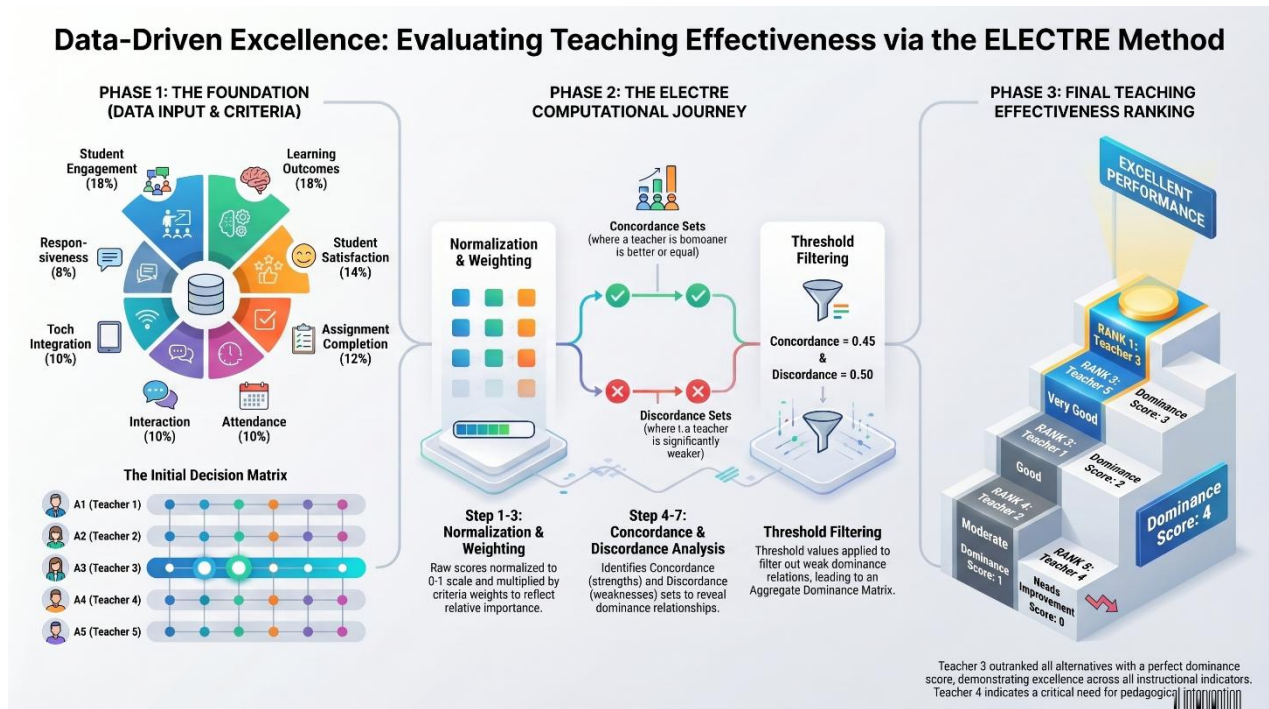


Fig 1. Detail Infographic Information

Ranking fourth was Teacher 2, showing moderate performance that could be enhanced through effective pedagogy strategies. In contrast, Teacher 4 placed last in terms of teaching effectiveness due to weak performance in several essential criteria related to teaching performance.

Overall, the ELECTRE technique has proved an efficient instrument capable of producing a systematic approach to teaching effectiveness evaluation. The outranking process has shown the ability to manage conflict criteria and produce effective decision-making results useful for intelligent educational governance and smart learning quality assessment.

3.12 Artificial Intelligence Model Performance

The study implemented four machine learning algorithms to predict teaching effectiveness classifications:

- Random Forest
- Support Vector Machine (SVM)
- XGBoost
- Artificial Neural Network (ANN)

The models were evaluated using Accuracy, Precision, Recall, F1-Score, and ROC-AUC metrics as the result in table 12 and Figure 1 to explain all result AI+DSS Electre.

Table 12. Artificial Intelligence Model Performance

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Random Forest	0.93	0.92	0.91	0.91	0.95
SVM	0.89	0.88	0.87	0.87	0.90
XGBoost	0.95	0.94	0.93	0.93	0.97
ANN	0.91	0.90	0.89	0.89	0.93

4. Conclusion

The proposed framework of ELECTRE and AI-based learning analytics has been successfully designed to develop the IDSS model capable of objectively and transparently evaluating teaching effectiveness in smart classrooms. The suggested framework addresses the growing need for smart decision-making tools for educational evaluation and governance in digital environments.

The main finding is that the ELECTRE-based framework can successfully assess multidimensional performance of teachers using both concordance and discordance criteria. The computational results have demonstrated that Teacher 3 has always occupied the highest rank position due to higher marks obtained for student engagement, learning outcomes, class interaction, and educational technology use. In turn, Teacher 4 was assigned the lowest rank position because of the lower performance level on various instructional criteria. The proposed outranking procedure did not utilize fully compensatory assumptions for decision-making regarding teaching performance.

From the methodology point of view, this study proposes a reproducible and scalable intelligent DSS computational framework using AI and learning analytics. Instead of traditional evaluation procedures involving simple weighted scoring or subjective judgment, this paper introduces outranking methods combined with the application of AI models (such as XGBoost, Random Forest, and Artificial Neural Networks) to perform predictive instructional analysis and educational performance forecasting.

Theoretical contribution includes extension of the existing theoretical concepts associated with intelligent educational systems, smart learning analytics, and educational decision support systems based on ELECTRE. This study proves that the outranking approach can be successfully applied to educational evaluation with multiple and potentially conflicting criteria. Integration of learning analytics into intelligent DSS strengthens theoretical foundations of data-driven smart education systems.

From the practical viewpoint, the proposed framework provides educational institutions with a transparent evaluation process and an efficient decision-making instrument regarding teachers' performance in technology-enhanced classrooms. Using the provided DSS framework, it will be possible to analyze instructors' teaching skills, define their advantages and shortcomings, implement necessary training activities, and enhance overall quality control procedures in educational environments.

From the policy perspective, this research contributes to worldwide and Indonesian efforts of establishing and enhancing smart learning environments, learning analytics applications, and AI-based education governance. Such a DSS framework may help educational organizations become more accountable and transparent concerning the performance of their instructors. Besides, the integration of intelligent DSS technologies is likely to enable academic institutions to implement necessary policy measures and improve their overall quality management strategies.

In conclusion, the presented ELECTRE-based framework can be efficiently used in teaching effectiveness assessment to create a more effective evaluation process involving multidimensional criteria. Overall, this framework can contribute to the implementation of smart educational governance principles and practices using instructional analytics and intelligent decision support. Moreover, this framework enables more efficient technology-enhanced classroom management with the help of identifying relevant patterns of instructors' performance.

There are several important areas of research in terms of future perspectives. In particular, incorporation of deep learning algorithms may help perform even more accurate predictive educational analytics. Besides, this study calls for the introduction of real-time educational analytics. Another potential area of future research includes XAI-based DSS framework implementation to enhance the transparency of intelligent systems and their decision-making process. Finally, future scholars may find it useful to incorporate federated learning to design privacy-preserving educational analytic models.

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