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Implementation of the MARCOS Method and Entropy Weighting for Selecting the Best Teacher at Madrasah Ibtidaiyah

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Keywords

Decision Support; MARCOS; Madrasah Ibtidaiyah; MCDM; Shannon Entropy

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Abstract

Selecting the best teacher in a madrasah requires an assessment mechanism that is transparent, reproducible, and able to process several performance criteria simultaneously. This study evaluates 20 active teachers at Madrasah Ibtidaiyah Al-Huda using five benefit criteria: attendance, pedagogical competence, personality competence, social competence, and professional competence. The criterion weights were calculated objectively using Shannon Entropy, and the alternatives were ranked using the Measurement of Alternatives and Ranking according to Compromise Solution (MARCOS) method. The Entropy calculation produced weights of 0.011 for attendance, 0.266 for pedagogical competence, 0.266 for personality competence, 0.245 for social competence, and 0.212 for professional competence. The MARCOS results show that Wasilul Gaffar obtained the highest utility value of 0.783 and ranked first. Sensitivity testing and Simple Additive Weighting (SAW) comparison indicate that the leading alternative remains stable under several weighting scenarios. The findings show that the integration of Shannon Entropy and MARCOS can support evidence-based teacher performance evaluation in a small madrasah context without relying solely on subjective judgment.

1. Introduction

Education quality depends strongly on the quality of teachers who plan learning, guide students, manage classrooms, and evaluate learning outcomes. In a madrasah, teacher performance also has institutional implications because teachers are expected to show academic competence, social responsibility, and exemplary personal conduct. For that reason, the selection of the best teacher should not rely only on informal impressions or a single dominant criterion.

The practical problem found at Madrasah Ibtidaiyah Al-Huda is that best-teacher selection involved 20 active teachers and several performance criteria, but the assessment process had not been supported by an explicit objective weighting and ranking procedure. This condition reflects a broader challenge in Indonesian madrasah education, where teacher performance assessment is often dominated by informal observation and subjective evaluation rather than structured, criteria-based scoring [1]. The available assessment data at Madrasah Ibtidaiyah Al-Huda contained five criteria, namely attendance, pedagogical competence, personality competence, social competence, and professional competence. Without a reproducible calculation procedure, the final decision can be influenced by subjective preference, especially when several teachers obtain similar scores on different criteria.

This study addresses the following research problem: how can the best teacher at Madrasah Ibtidaiyah Al-Huda be selected objectively by integrating Shannon Entropy weighting and the MARCOS method? The quantitative scope of the study consists of 20 teacher alternatives and five benefit criteria. The use of Shannon Entropy is intended to determine criterion weights from the variation of the observed data, while MARCOS is used to rank teachers by comparing each alternative with ideal and anti-ideal reference values.

Previous studies have shown that Multi-Criteria Decision Making (MCDM) methods are widely used when decision-making involves multiple criteria that must be evaluated simultaneously. The broad application of MCDM methods across various decision-making contexts in higher education has been systematically reviewed, demonstrating their effectiveness in supporting complex evaluation processes [2]. In teacher selection, the combination of the AHP and ARAS methods has been applied to recommend the best teachers, confirming that teacher performance evaluation can be treated as a structured decision-making problem rather than a purely administrative judgment [3], [4]. In a broader educational context, MCDM approaches have also been employed to evaluate university professors using fuzzy AHP and Grey MARCOS, as well as to assess physical education teaching quality through a hybrid MCDM framework, further demonstrating the suitability of these methods for teacher performance assessment [5], [6].

Research on the MARCOS method further indicates its suitability for ranking alternatives because it evaluates each alternative relative to ideal and anti-ideal solutions. The method has been successfully applied in sustainable supplier selection[7], location selection[8], university selection[9], logistics systems[10], and engineering processes[11], These studies show that MARCOS can produce clear utility values and ranks in problems with multiple conflicting criteria.

The weighting stage is equally important because the final ranking can change when the criterion weights change. Entropy-based weighting has been used to reduce subjective bias by deriving criterion weights from data dispersion. The Entropy Weight method assigns higher weights to criteria that provide greater discriminatory information, while criteria exhibiting lower variation receive proportionally smaller weights, resulting in a more objective weighting process [12], [13]. Recent MCDM studies also emphasize that weighting methods influence ranking stability [14], [15]. A hybrid approach combining Shannon Entropy and MARCOS has been successfully applied to construct a robust service quality evaluation framework under fuzzy uncertainty, demonstrating the effectiveness of integrating objective weighting with utility-based ranking methods [16]. In teacher performance evaluation, the use of pedagogical, personality, social, and professional competence is supported by teacher competency standards [17] and empirical teacher assessment literature [18]. Advanced weighting techniques combined with ranking methods have also been employed to develop picture fuzzy teaching quality evaluation frameworks, demonstrating their capability to produce stable and reliable educational decision models [19].

Collectively, these studies confirm that MCDM methods are effective for structured teacher evaluation and that objective weighting is preferable to subjective weight assignment when performance data are available. However, no study has specifically applied Shannon Entropy with MARCOS for teacher selection in a Madrasah Ibtidaiyah context. This gap motivates the present study, which integrates Shannon Entropy for objective criterion weighting with MARCOS for alternative ranking in a competency-based teacher evaluation setting.

The literature shows that MCDM has been used in teacher selection, but the integration of Shannon Entropy and MARCOS remains limited in the context of Madrasah Ibtidaiyah teacher evaluation. The gap is not only the absence of a particular method in a new dataset. The more specific gap lies in the need for a transparent method that fits a small madrasah environment, where the number of alternatives is limited, the criteria are practical and competency-based, and the assessment must be understandable for school management.

MARCOS is appropriate for this context because it compares each teacher with the best and worst observed conditions, making the calculation easy to interpret for decision makers. Shannon Entropy is also appropriate because it does not force the school to assign subjective weights before seeing the actual data pattern. In the present dataset, attendance has very low variation because almost all teachers were fully present. The Entropy

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method captures this condition by assigning a very small weight to attendance, while giving higher weights to criteria that better distinguish teacher performance. This combination provides a more data-driven and context-sensitive decision model for Madrasah Ibtidaiyah.

2. Research Method

2.1 Research Design

This study uses a quantitative decision-support approach based on MCDM. The analysis combines Shannon Entropy for objective criterion weighting and MARCOS for alternative ranking. The unit of analysis is teacher performance at Madrasah Ibtidaiyah Al-Huda. All criteria are treated as benefit criteria because higher scores indicate better teacher performance.

2.2 Alternatives and Criteria

The alternatives consist of 20 active teachers. The criteria were selected from the school assessment instrument and aligned with teacher competency standards. The five criteria are C1 attendance, C2 pedagogical competence, C3 personality competence, C4 social competence, and C5 professional competence. The use of pedagogical, personality, social, and professional competence follows the main teacher competency domains recognized in Indonesian teacher standards [17], while attendance was included as an institutional discipline indicator. The optimization and structured weighting of such teacher evaluation indicator systems are widely supported by recent methodology literature, including Zhao [20].

Table 1. Assessment Criteria and Measurement Scale

Code	Criterion	Data source	Scoring rule	Type
C1	Attendance	Attendance record/documentation	5 = fully present; 4 = excused absence/sick leave; lower scores indicate repeated absence	Benefit
C2	Pedagogical competence	Observation of lesson planning and teaching practice	1 = very poor, 2 = poor, 3 = fair, 4 = good, 5 = very good	Benefit
C3	Personality competence	Observation and principal assessment	1 = very poor, 2 = poor, 3 = fair, 4 = good, 5 = very good	Benefit
C4	Social competence	Observation of communication and interaction	1 = very poor, 2 = poor, 3 = fair, 4 = good, 5 = very good	Benefit
C5	Professional competence	Observation of subject mastery and professional responsibility	1 = very poor, 2 = poor, 3 = fair, 4 = good, 5 = very good	Benefit

For C1, the attendance score was converted from the attendance record. Teachers with full attendance received a score of 5. Isma'il, S.Pd.I and Masduqi received a score of 4 because their attendance records contained excused absence or sick leave. This conversion was used only to represent the available attendance variation in the evaluation period.

2.3 Data Collection and Instrument Validity

Data were collected through observation, interview, and documentation. Observation was used to record teacher performance during classroom activities. Interviews with the principal and relevant staff were used to confirm the meaning of each criterion. Documentation was used to verify attendance records and teacher administrative information. The scoring instrument used a 1-5 scale to convert qualitative observations into quantitative values. Content validity was supported by aligning the criteria with teacher competency domains

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and by confirming the scoring interpretation with the school. Reliability was supported through structured scoring and the use of the same scale for all alternatives.

2.4 Shannon Entropy Weighting

This study uses Shannon Entropy as the objective weighting method. Let X = [x_ij] be the decision matrix, where i = 1, 2, ..., m represents teacher alternatives and j = 1, 2, ..., n represents criteria. The calculation steps are as follows.

Step 1: Normalize the decision matrix :

$$p_{ij} = \frac{x_{ij}}{\sum_i x_{ij}}. \tag{1}$$

Step 2: Calculate the entropy value :

$$e_j = -k \sum_i p_{ij} \ln(p_{ij}), \text{ where } k = \frac{1}{\ln(m)}. \text{ If } p_{ij} = 0, \text{ then } p_{ij} \ln(p_{ij}) = 0 \text{ is treated as } 0. \tag{2}$$

Step 3: Calculate the degree of diversification :

$$d_j = 1 - e_j. \tag{3}$$

Step 4: Calculate the criterion weight :

$$w_j = \frac{d_j}{\sum_j d_j}. \tag{4}$$

2.5 MARCOS Method

The MARCOS method ranks alternatives by comparing each alternative with the anti-ideal alternative (AAI) and the ideal alternative (AI). Because all criteria are benefit criteria, AI is the maximum value of each criterion and AAI is the minimum value of each criterion.

Step 1: Form the extended matrix by adding AAI and AI rows to the decision matrix.

Step 2: Normalize the matrix for benefit criteria :

$$n_{ij} = \frac{x_{ij}}{x_j(AI)}. \tag{5}$$

Step 3: Calculate the weighted normalized matrix :

$$v_{ij} = n_{ij} \times w_j. \tag{6}$$

Step 4: Calculate the total weighted score :

$$S_i = \sum_j v_{ij}. \tag{7}$$

Step 5: Calculate the utility degrees :

$$K_i^- = \frac{S_i}{S_{AAI}} \text{ and } K_i^+ = \frac{S_i}{S_{AI}}. \tag{8}$$

Step 6: Calculate the utility function $f(K_i)$and rank the alternatives from the highest utility value to the lowest.

The utility function was calculated using

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$$f(K_i) = \frac{K_i^- + K_i^+}{1+\left(\frac{1-f(K_i^-)}{f(K_i^-)}\right)+\left(\frac{1-f(K_i^+)}{f(K_i^+)}\right)} \text{ where } f(K_i^-) = \frac{K_i^+}{K_i^- + K_i^+} \text{ and } f(K_i^+) = \frac{K_i^-}{K_i^- + K_i^+}. \quad (9)$$

2.6 Validation and Sensitivity Analysis

To examine ranking robustness, sensitivity analysis was conducted by increasing each criterion weight by 10% and normalizing the total weight back to 1. A validation comparison was also conducted using the Simple Additive Weighting (SAW) method with the same benefit normalization and Entropy weights. This comparison was used to check whether the leading alternatives remain consistent under a simpler additive MCDM model.

3. Results and Discussion

3.1 Decision Matrix

The decision matrix contains the actual scores of 20 teachers on five assessment criteria. This table replaces the previous illustrative matrix and enables the calculation to be reproduced.

Table 2. Decision Matrix of 20 Teachers and Five Criteria

Code	Teacher	C1	C2	C3	C4	C5
A1	Moh. Masduna, M.Pd.	5	2	4	3	5
A2	Tirmidi, S.Pd.	5	3	2	5	4
A3	Alfan	5	2	3	2	4
A4	Isma'il, S.Pd.I	4	2	4	3	4
A5	Moh. Maswi, S.Pd.I	5	1	3	4	2
A6	H. Waqid Musthafa Ar	5	2	4	3	2
A7	Moh. Rusydi, S.Pd.I	5	1	3	2	4
A8	Abd. Salam	5	2	4	4	3
A9	M. Yahya	5	2	1	3	4
A10	Ach. Qusyairi, A.Ma	5	3	2	4	5
A11	M. Kamil, A.Ma	5	2	4	3	5
A12	Abd. Aziz	5	1	2	3	2
A13	Syauqi Futaqi	5	2	3	4	3
A14	Masduqi	4	3	2	4	5
A15	Moh. Alawi	5	2	3	4	5
A16	Helmiyatus Sarierah, S.Ag	5	2	3	2	4
A17	M. Munir	5	3	2	4	5
A18	Ach. Wahedi, M.Pd.	5	2	3	2	4
A19	Zayyadi, S.Pd.I	5	2	3	5	4
A20	Wasilul Gaffar	5	3	4	2	5

3.2 Shannon Entropy Weights

The Entropy calculation shows that attendance has the lowest weight because almost all teachers had the same attendance score. Criteria with higher variation, especially pedagogical and personality competence, produced higher weights because they provided stronger discriminatory information.

Table 3. Shannon Entropy Calculation and Criterion Weights

Criterion	Sum of scores	Entropy e_j	Diversification d_j	Weight w_j
C1	98	0.999337	0.000663	0.011378
C2	42	0.984475	0.015525	0.266326

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Criterion	Sum of scores	Entropy e_j	Diversification d_j	Weight w_j
C3	59	0.984482	0.015518	0.266204
C4	66	0.985746	0.014254	0.244521
C5	79	0.987667	0.012333	0.211571

The resulting weights are 0.011 for C1, 0.266 for C2, 0.266 for C3, 0.245 for C4, and 0.212 for C5. These values confirm that the weights were not assigned manually, but were derived from the data distribution using Shannon Entropy. This result is consistent with the principle of Entropy weighting, in which criteria with greater information diversity receive higher importance values, while criteria with limited variation receive lower weights [6], [7].

3.3 MARCOS Ranking

Table 4. Ideal and Anti-Ideal Reference Values

Reference	C1	C2	C3	C4	C5
AI	5	3	4	5	5
AAI	4	1	1	2	2

The anti-ideal total score S_AAI was 0.346866, while the ideal total score S_AI was 1.000000. The ranking results are presented in Table 5. The use of ideal and anti-ideal reference values follows the MARCOS framework, which evaluates alternatives by measuring their relative closeness to the best and worst observed conditions [1].

Table 5. MARCOS Utility Values and Rankings

Code	Teacher	S_i	K-	K+	f(K)	Rank
A20	Wasilul Gaffar	0.853287	2.459995	0.853287	0.783314	1
A2	Tirmidi, S.Pd.	0.824584	2.377244	0.824584	0.756964	2
A10	Ach. Qusyairi, A.Ma	0.817994	2.358245	0.817994	0.750915	3
A17	M. Munir	0.817994	2.358245	0.817994	0.750915	3
A14	Masduqi	0.815718	2.351685	0.815718	0.748826	5
A1	Moh. Masduna, M.Pd.	0.813416	2.345048	0.813416	0.746712	6
A11	M. Kamil, A.Ma	0.813416	2.345048	0.813416	0.746712	6
A19	Zayyadi, S.Pd.I	0.802359	2.313171	0.802359	0.736562	8
A15	Moh. Alawi	0.795769	2.294173	0.795769	0.730513	9
A8	Abd. Salam	0.777692	2.242056	0.777692	0.713918	10
A4	Isma'il, S.Pd.I	0.768826	2.216497	0.768826	0.705779	11
A13	Syauqi Futaqi	0.711141	2.050192	0.711141	0.652824	12
A6	H. Waqid Musthafa Ar	0.686473	1.979077	0.686473	0.630179	13
A16	Helmiyatus Sarierah, S.Ag	0.655647	1.890205	0.655647	0.601881	14
A18	Ach. Wahedi, M.Pd.	0.655647	1.890205	0.655647	0.601881	14
A3	Alfan	0.655647	1.890205	0.655647	0.601881	14
A5	Moh. Maswi, S.Pd.I	0.580051	1.672266	0.580051	0.532484	17
A9	M. Yahya	0.571449	1.647466	0.571449	0.524588	18
A7	Moh. Rusydi, S.Pd.I	0.566871	1.634269	0.566871	0.520385	19
A12	Abd. Aziz	0.464596	1.339413	0.464596	0.426497	20

The highest utility value was obtained by G20 f(K) = 0.783314. Therefore, G20 is recommended as the best teacher based on the combined evaluation of five criteria. G2 ranked second, while G10 and G17 obtained the same rank because their criterion scores were identical. The clear utility score generated by MARCOS supports

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transparent interpretation of teacher ranking results because each alternative is evaluated against the same ideal and anti-ideal benchmarks [1].

3.4 Sensitivity Analysis and SAW Validation

Table 6. Sensitivity Analysis of Criterion Weights

Scenario	C1	C2	C3	C4	C5	Top five ranks
Base Entropy	0.011	0.266	0.266	0.245	0.212	Wasilul Gaffar (1); Tirmidi, S.Pd. (2); Ach. Qusyairi, A.Ma (3); M. Munir (3); Masduqi (5)
C1 weight +10%	0.013	0.266	0.266	0.244	0.211	Wasilul Gaffar (1); Tirmidi, S.Pd. (2); Ach. Qusyairi, A.Ma (3); M. Munir (3); Masduqi (5)
C2 weight +10%	0.011	0.285	0.259	0.238	0.206	Wasilul Gaffar (1); Tirmidi, S.Pd. (2); Ach. Qusyairi, A.Ma (3); M. Munir (3); Masduqi (5)
C3 weight +10%	0.011	0.259	0.285	0.238	0.206	Wasilul Gaffar (1); Moh. Masduna, M.Pd. (2); M. Kamil, A.Ma (2); Tirmidi, S.Pd. (4); Ach. Qusyairi, A.Ma (5)
C4 weight +10%	0.011	0.260	0.260	0.263	0.207	Wasilul Gaffar (1); Tirmidi, S.Pd. (2); Ach. Qusyairi, A.Ma (3); M. Munir (3); Masduqi (5)
C5 weight +10%	0.011	0.261	0.261	0.239	0.228	Wasilul Gaffar (1); Tirmidi, S.Pd. (2); Ach. Qusyairi, A.Ma (3); M. Munir (3); Masduqi (5)
Equal weights	0.200	0.200	0.200	0.200	0.200	Wasilul Gaffar (1); Ach. Qusyairi, A.Ma (2); M. Munir (2); Tirmidi, S.Pd. (4); Moh. Masduna, M.Pd. (5)

The sensitivity analysis shows that Wasilul Gaffar remains ranked first across all tested scenarios. Changes in the weight of C3 affect the order of several teachers below the first rank, but the leading recommendation does not change. This result indicates that the main recommendation is stable under moderate weight variation. Previous MCDM studies also emphasize that sensitivity testing is important to evaluate whether the ranking outcome remains consistent when criterion weights are adjusted [5], [19].

Table 7. SAW Validation using Entropy Weights

Code	Teacher	MARCOS Rank	SAW Score	SAW Rank
A20	Wasilul Gaffar	1	0.853287	1
A2	Tirmidi, S.Pd.	2	0.824584	2
A10	Ach. Qusyairi, A.Ma	3	0.817994	3
A17	M. Munir	3	0.817994	3
A14	Masduqi	5	0.815718	5
A1	Moh. Masduna, M.Pd.	6	0.813416	6
A11	M. Kamil, A.Ma	6	0.813416	6
A19	Zayyadi, S.Pd.I	8	0.802359	8
A15	Moh. Alawi	9	0.795769	9
A8	Abd. Salam	10	0.777692	10
A4	Isma'il, S.Pd.I	11	0.768826	11
A13	Syauqi Futaqi	12	0.711141	12
A6	H. Waqid Musthafa Ar	13	0.686473	13
A16	Helmiyatus Sarierah, S.Ag	14	0.655647	14
A18	Ach. Wahedi, M.Pd.	14	0.655647	14
A3	Alfan	14	0.655647	14

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Code	Teacher	MARCOS Rank	SAW Score	SAW Rank
A5	Moh. Maswi, S.Pd.I	17	0.580051	17
A9	M. Yahya	18	0.571449	18
A7	Moh. Rusydi, S.Pd.I	19	0.566871	19
A12	Abd. Aziz	20	0.464596	20

The SAW comparison produces the same leading alternative and the same rank pattern because all criteria are benefit criteria and both calculations use the same Entropy weights. This finding supports the internal consistency of the ranking result and shows that the first recommendation is not an isolated output of a single calculation step. The consistency between MARCOS and SAW also strengthens the robustness of the decision model because the leading alternative remains unchanged under a simpler additive MCDM validation procedure [5], [19].

The integration of Shannon Entropy and MARCOS improves the transparency of best-teacher selection in several important ways. First, the criterion weights are generated objectively from the observed data distribution rather than being assigned subjectively by decision makers. The integration of Shannon Entropy and MARCOS improves the transparency of best-teacher selection in several important ways. First, the criterion weights are generated objectively from the observed data distribution rather than being assigned subjectively by decision makers. In the Entropy weighting method, criteria with greater discriminatory information receive higher weights, whereas criteria exhibiting lower variation are assigned smaller weights, resulting in a more objective weighting process [6], [7].

Second, the MARCOS method evaluates each alternative relative to both ideal and anti-ideal reference solutions, providing a clear interpretation of utility values and ranking outcomes. Stevic et al. [1] introduced MARCOS as a compromise-based ranking method that allows decision makers to understand how close each alternative is to the ideal condition and how far it is from the anti-ideal condition. Therefore, the resulting teacher ranking is easier to interpret because every alternative is assessed using the same reference points.

Third, the sensitivity analysis and SAW validation indicate that the leading alternative remains stable under several weighting scenarios. This finding is consistent with previous studies showing that ranking stability in MCDM problems is strongly influenced by the weighting scheme and should be examined through robustness analysis [5], [19]. The stability of Wasilul Gaffar as the highest-ranked teacher across all tested scenarios suggests that the recommendation is not highly sensitive to moderate weight changes and can therefore be considered reliable.

From a practical perspective, the proposed model can support madrasah management in conducting teacher performance evaluation more transparently and consistently. Structured MCDM approaches have been used in educational decision-making to reduce subjective bias and to support evaluation and reward allocation processes [9], [10]. Therefore, the ranking generated by the Entropy-MARCOS framework may serve as an evidence-based reference for recognizing teacher achievement while still allowing school leaders to review the contextual aspects of teacher performance.

Nevertheless, ranking results should not be interpreted solely as a reward mechanism. Teachers who obtain lower scores should be supported through targeted professional development programs according to the competency areas requiring improvement. Previous educational studies have highlighted that strengthening pedagogical and professional competence contributes to better learning quality and student learning outcomes, which means that evaluation results should also be used as a basis for continuous teacher improvement [18].

This study is limited to one madrasah and one evaluation period. Future studies may expand the evaluation to multiple institutions and compare the Entropy-MARCOS framework with other MCDM approaches such as TOPSIS, MOORA, MAIRCA, and Grey MARCOS. Comparative studies involving alternative ranking models are

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important to assess methodological consistency and decision robustness in educational evaluation settings [8], [11].

4. Conclusions and Future Works

This study demonstrates that the combination of Shannon Entropy and MARCOS can be applied to select the best teacher at Madrasah Ibtidaiyah Al-Huda using 20 teacher alternatives and five competency-based criteria. Shannon Entropy produced objective weights from the data distribution, with pedagogical competence and personality competence receiving the largest weights, while attendance received the smallest weight because its scores were almost uniform. The MARCOS calculation ranked Wasilul Gaffar first with a utility value of 0.783314.

The theoretical contribution of this study lies in showing how objective weighting and compromise-based ranking can be integrated for teacher performance evaluation in a small madrasah context. The study extends MCDM application in education by demonstrating that the Entropy-MARCOS combination is not only useful for industrial or technical selection problems, but also relevant for human-resource decisions where the criteria are competency-based and the number of alternatives is limited. Practically, the method provides a transparent calculation framework that school leaders can audit, repeat, and communicate more easily than informal selection procedures.

Future research should test the model using data from multiple madrasahs and several assessment periods. Further research can also compare Entropy-MARCOS with other MCDM combinations and include qualitative follow-up to understand why certain teachers perform better on specific criteria.

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