Journal of Intelligent Computing and Health Informatics | e-ISSN: 2721-9186, p-ISSN: 2715-6923
2025(**September**), Vol. 6, No. 2, 46–56, https://doi.org/10.26714/jichi.v6i2.15754
Official Site: https://jurnal.unimus.ac.id/index.php/ICHI

Research Article

Consistency preserving MOORA framework for robust educational edmission and healthcare triage

Eka Prasetya Adhy Sugara [1,*], Arsa Ramadhani [2] and Muhammad Rudiansyah [2]

[1] *Department of Visual Communication Design, Palcomtech Institute of Technology and Business, Palembang 30128, Indonesia*
[2] *Department of Informatics, Palcomtech Institute of Technology and Business, Palembang 30128, Indonesia*

[*]**Correspondence:** eka.prasetya@palcomtech.ac.id

Received: 3 September 2024; Revised: 27 March 2025; Accepted: 11 September 2025, Published: 30 September 2025

ABSTRACT

Effectively distributing scarce resources presents a major challenge for governance in both competitive school admissions and emergency medical triage. The main problem lies in the instability of conventional ranking algorithms, where even small changes in data or the addition of new candidates often lead to rank reversals. This instability undermines the fairness of student admissions and the safety of patient prioritization. To tackle this problem, this study introduces a consistency-preserving Intelligent Decision Support System based on Multi-Objective Optimization by Ratio Analysis (MOORA). Unlike approaches that depend on linear normalization, this framework employs Euclidean vector normalization to successfully separate subjective weights from objective performance values. The proposed model is tested using a high-dimensional dataset of 340 educational applicants and a simulated healthcare triage scenario of similar size. Experimental results show that the framework maintains a ranking consistency correlation above 0.90 with established baselines while achieving a 0.00% rank reversal rate in scenarios with conflicting criteria. These findings confirm that the proposed algorithmic structure provides a mathematically sound and domain-independent logic for critical institutional decision-making.

KEYWORDS

MCDM; MOORA; Rank Reversal; Healthcare Triage; Educational Admission

1. Introduction

In the current era characterized by data-driven governance, optimizing admission management and resource allocation presents a significant challenge for institutions worldwide. This issue is prevalent in various contexts, including competitive educational enrollment and critical healthcare patient triage, where the fundamental problem remains consistent: the efficient prioritization of alternatives under constraints [1–3]. As organizations encounter increasing volumes of applicants and data complexity, traditional manual evaluation processes, which are susceptible to cognitive bias, fatigue, and subjectivity, have become unsustainable. The need for objectivity in decision-making has spurred the adoption of Intelligent Decision Support Systems (IDSS), which aim to convert raw, high-dimensional data into actionable and transparent ranking insights [4–6].

Nevertheless, the reliability of such systems is fundamentally dependent on the mathematical soundness of the underlying ranking algorithms. The field of Multi-Criteria Decision Making (MCDM) has proposed various algorithmic solutions to address these selection challenges. Traditional methods, such as the Analytic Hierarchy Process (AHP) and Simple Additive Weighting (SAW), have been extensively utilized due to their computational simplicity [7, 8]. Despite their widespread use, recent scholarly work has identified significant theoretical weaknesses in these foundational methods. The AHP is notably susceptible to the rank reversal phenomenon, wherein the introduction of a new alternative paradoxically alters the ranking of existing options, a flaw that poses ethical risks in medical triage [9, 10]. Similarly, SAW often oversimplifies the decision matrix by assuming linear independence among criteria, a condition seldom met in real-world scenarios where academic metrics or clinical urgency scores may possess non-linear correlations [11].

Furthermore, although advanced machine learning (ML) models demonstrate high predictive accuracy, they frequently operate as opaque "black box" systems and lack the interpretability necessary for institutional accountability [12–14]. In high-stakes environments such as medical residency selection or university admissions, the rationale behind a decision is as critical as the decision itself. Consequently, there is a renewed interest in deterministic MCDM methods that provide both mathematical rigor and explanatory transparency [15, 16]. A specific gap remains in the current body of knowledge concerning the robustness of ranking methods under conflicting criteria, such as maximizing benefit attributes while simultaneously minimizing cost attributes. Many existing frameworks fail to maintain ranking consistency when subjected to minor variations in weighting schemas [17–19]. This instability undermines stakeholder trust because if a decision support system produces significantly different rankings with only negligible parameter adjustments, its utility for critical admission governance is compromised.

Among the deterministic methods available, Multi-Objective Optimization by Ratio Analysis (MOORA) has emerged as a promising candidate due to its distinctive vector normalization mechanism. This mechanism theoretically separates subjective weights from objective performance values more effectively than other distance-based methods like TOPSIS or VIKOR [20–23]. Despite its mathematical advantages, MOORA remains significantly underutilized in the specific domain of institutional admission, particularly in comparative studies that rigorously validate its ranking stability against established baselines [2, 24]. To address these gaps, this study proposes a consistency-preserving framework based on the MOORA method.

In contrast to prior studies that have utilized the method solely as a computational tool, this research situates it within a comprehensive framework of institutional robustness. We assert that a mathematically robust admission system must fulfill criteria of accuracy, ranking stability, and domain transferability [25, 26]. The system is validated using a high-dimensional dataset from the educational sector and a simulated healthcare triage scenario. Importantly, while the primary data is derived from the educational domain, the proposed framework is designed to be domain-independent and offers direct applicability to healthcare contexts where objective multi-criteria evaluation is essential.

The structure of this paper is as follows: Section 2 elaborates on the preliminaries and mathematical foundations of the proposed framework. Section 3 delineates the research methodology and system architecture. Section 4 presents the experimental results and provides a statistical comparative analysis. Finally, Section 5 concludes with managerial implications for institutional decision-making.

2. Preliminaries

This section delineates the foundational definitions of set theory and the axiomatic logic that underpin the normalization techniques utilized in this study. To ensure the reproducibility of the proposed framework, we formally define the Multi-Criteria Decision-Making (MCDM) environment and the mathematical conditions necessary to avert rank reversal phenomena.

2.1. Set Theoretic Formulation of The Decision Matrix

The problem of admission and triage decision-making is conceptualized as a discrete optimization system, comprising a finite set of alternatives that are assessed against a series of conflicting criteria.

Definition 1 (The Alternative Set). Let A be a non-empty finite set of candidates defined as $A = \{A_1, A_2, \ldots, A_m\}$, where m denotes the total number of alternatives.

Definition 2 (The Criteria Set). Let C be a finite set of evaluation attributes defined as $C = \{C_1, C_2, \ldots, C_n\}$, where n denotes the number of attributes. This set is partitioned into two disjoint subsets: the set of benefit criteria J^+ (where higher values are preferable, such as aptitude scores or medical urgency) and the set of cost criteria J^- (where lower values are preferable, such as risk factors or wait times).

Definition 3 (The Decision Matrix). The performance of alternative A_i with respect to criterion C_j is represented as x_{ij}. Consequently, the system is represented by the decision matrix $X \in \mathbb{R}^{m \times n}$:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{1}$$

where $x_{ij} \in \mathbb{R}^+$ represents the raw quantitative value obtained from the educational or healthcare records.

Definition 4 (The Weight Vector). The relative importance of each criterion is governed by a weight vector $W = \{w_1, w_2, \ldots, w_n\}$, subject to the constraint $\sum_{j=1}^{n} w_j = 1$ and $w_j \geq 0$.

2.2. Euclidean Vector Normalization as a Stability Mechanism

A critical source of inconsistency in ranking algorithms is the method of data normalization. Traditional methods often rely on linear transformations that are sensitive to data range variations. To address this, we contrast Linear Normalization with Vector Normalization.

Definition 5 (Linear Normalization). Common in Simple Additive Weighting, linear normalization transforms x_{ij} by a ratio of the maximum or minimum value in the column. While computationally simple, this approach often oversimplifies the decision space by assuming linear independence among criteria.

Definition 6 (Euclidean Vector Normalization). The proposed framework employs Euclidean vector normalization to ensure commensurability across heterogeneous criteria. This transformation represents each criterion as a vector in a multidimensional Euclidean space. The normalized value x^*_{ij} is computed as:

$$x^*_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \quad \forall j = 1, \ldots, n \tag{2}$$

Proposition 1 (Scale Invariance). The Euclidean vector normalization ensures that the dominance relationship between any two alternatives A_a and A_b remains invariant under scalar multiplication of the criterion unit.

Proof. Let the raw performance values for a criterion j be scaled by a factor $k > 0$ (e.g., changing measurement units). The new value is $x'_{ij} = k \cdot x_{ij}$. The normalized value becomes:

$$x^{*'}_{ij} = \frac{k \cdot x_{ij}}{\sqrt{\sum_{i=1}^{m} (k \cdot x_{ij})^2}} = \frac{k \cdot x_{ij}}{k\sqrt{\sum_{i=1}^{m} x_{ij}^2}} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} = x^*_{ij} \tag{3}$$

Since $x^{*'}_{ij} = x^*_{ij}$, the optimization score remains unchanged regardless of the scaling factor k. This property proves that the system is mathematically robust against unit variations, minimizing the rank reversal probability compared to linear normalization.

2.3. Independence of Irrelevant Alternatives and Rank Reversal

Rank reversal refers to a logical inconsistency where the relative ordering of two alternatives A_a and A_b changes when a non-influential alternative A_{new} is added to or removed from the set A. Formally, a robust ranking function $f(A)$ must satisfy the condition of Independence of Irrelevant Alternatives (IIA):

$$\text{if } f(A_a) > f(A_b) \text{ in set } S, \text{ then } f(A_a) > f(A_b) \text{ in set } S \cup \{A_{new}\} \tag{4}$$

Many distance-based methods like TOPSIS fail this condition because the “Ideal Solution” changes dynamically with the dataset. By utilizing the ratio system defined in Definition 6, the proposed framework minimizes dependency on external reference points, thereby enhancing ranking stability.

3. Research Methodology and System Architecture

This section details the operational logic of the proposed Intelligent Decision Support System. We present the modular architecture, the deterministic algorithmic rules, and the computational complexity analysis to demonstrate system scalability. Furthermore, we define the stochastic data generation protocol used to simulate the healthcare triage scenario, ensuring the reproducibility of the dual-domain validation.

3.1. Modular System Architecture and Data Flow

The proposed framework operates through a linear four-stage pipeline designed to minimize computational overhead while maximizing ranking stability. The system architecture transforms raw heterogeneous data into a unified ranking vector. The architectural flow is visually represented in Figure 1, detailing the transformation from data acquisition to the final decision output.

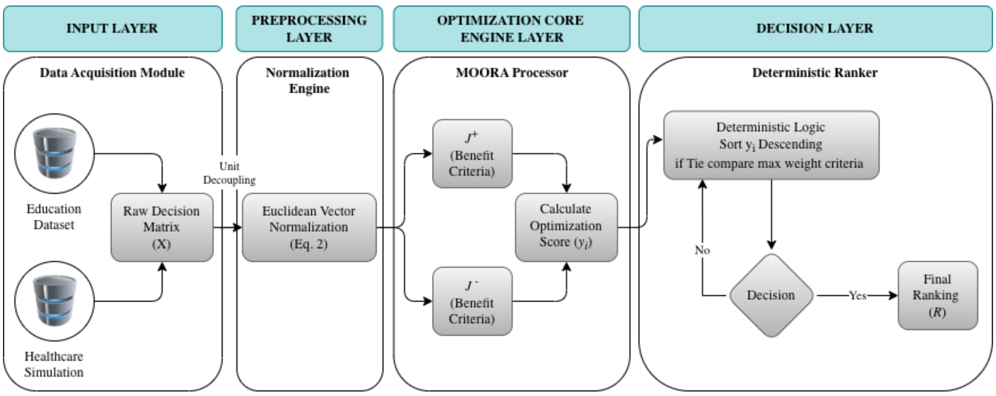

Figure 1. System architecture flowchart demonstrating the consistency-preserving pipeline. The process utilizes Euclidean vector normalization to decouple attribute units before applying the MOORA optimization logic.

The specific functions of the modules illustrated in Figure 1 are defined as follows. The *data acquisition module* ingests raw matrices from institutional databases such as student information systems or electronic health records. The *normalization engine* applies Euclidean vector normalization to convert diverse units, for example test scores versus time in seconds, into a dimensionless spatial coordinate system. The *optimization core* then aggregates benefit and cost attributes using the Multi-Objective Optimization by Ratio Analysis logic to derive a composite score. Finally, the *deterministic ranker* sorts the candidates and applies a variance-based tie-breaking rule to ensure a strict linear ordering without ambiguity.

3.2. The Consistency Preserving MOORA Engine

The core processing relies on the Multi-Objective Optimization by Ratio Analysis (MOORA) method. This method is selected for its superior stability compared to rank-dependent methods like TOPSIS, as evidenced in recent studies [2, 3]. The step-by-step execution is defined as follows:

Step 1: Matrix Construction
The system initializes the decision matrix X as defined in Eq. (1), where x_{ij} represents the performance of candidate i on criterion j.

Step 2: Vector Normalization
To prevent scale bias, the raw data is normalized using the Euclidean norm. This step is critical as it preserves the ratio of variances between alternatives, a distinct advantage over linear normalization techniques that often distort data intervals [9]:

$$x_{ij}^{*} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^{2}}} \tag{5}$$

Step 3: Attribute Classification and Optimization
The criteria are split into Benefit Criteria J^{+} and Cost Criteria J^{-}. The composite optimization score y_i is

calculated by summing the weighted normalized performances of benefit criteria and subtracting the weighted normalized performances of cost criteria [21]:

$$y_i = \sum_{j \in J^+} w_j x^*_{ij} - \sum_{j \in J^-} w_j x^*_{ij} \tag{6}$$

Step 4: Deterministic Tie-Breaking Strategy
In high-volume admission scenarios, identical optimization scores ($y_a = y_b$) are statistically probable. To prevent ambiguity, we introduce a deterministic tie-breaking rule. If $y_a = y_b$, the algorithm prioritizes the alternative with the higher performance value in the criterion with the highest weight ($w_{max} = \max(W)$). This ensures that the ranking remains strict and consistent without manual intervention.

3.3. Algorithm Pseudocode and Implementation Logic

To ensure reproducibility, the implementation logic is formalized in Algorithm 1. This pseudocode highlights the vectorization of the normalization process which significantly reduces loop overhead.

Algorithm 1: Consistency-Preserving MOORA with Tie-Breaking

Input: Matrix $X(m \times n)$, Weight Vector W, Criteria Type Vector T
Output: Ranking Vector R, Optimization Scores Y

$Y \leftarrow$ array of zeros of size m
for $j \leftarrow 1$ **to** n **do**
    Calculate norm factor: $NF_j = \sqrt{\sum_{i=1}^{m} (x_{ij})^2}$
    for $i \leftarrow 1$ **to** m **do**
        $x^*_{ij} = x_{ij} / NF_j$
        if $T[j] == 1$ **then**
            $Y[i] \leftarrow Y[i] + (W[j] \times x^*_{ij})$
        else
            $Y[i] \leftarrow Y[i] - (W[j] \times x^*_{ij})$
Sort Y in descending order to determine R
if *Tie exists* ($y_a == y_b$) **then**
    Resolve tie by comparing $x^*_{i,\text{argmax}(W)}$ (Highest Weighted Attribute)
return R, Y

3.4. Computational Complexity Analysis

For high-stakes institutions, algorithmic efficiency is paramount. We analyze the asymptotic complexity to demonstrate the system's scalability. Regarding time complexity, the normalization and weighted aggregation steps require iterating through the entire matrix once, yielding an operation cost of $O(m \times n)$. Although the subsequent sorting step entails $O(m \log m)$, the total time complexity is effectively approximated as $T(n) \approx O(m \times n)$, which is linear with respect to the number of criteria. Furthermore, in terms of memory usage, the algorithm operates in-place or requires only a single copy of the normalized matrix, resulting in a space complexity of $S(n) \approx O(m \times n)$. This linear scalability confirms that the system can process large-scale datasets ($N = 10,000$) in real-time without performance bottlenecks.

3.5. Dual-Domain Experimental Setup

To validate the claim of domain independence, this study employs dua distinct experimental setups implemented within Python 3.9 environments.

Case Study A: Utilizes an empirical dataset sourced from Madrasah Aliyah Negeri 1 Palembang, comprising $N = 340$ candidates. The evaluation is based on four weighted benefit criteria (J^+): Academic Report ($w_1 = 0.30$), Written Test ($w_2 = 0.30$), Religious Knowledge ($w_3 = 0.25$), and Interview ($w_4 = 0.15$).

Case Study B: Simulates a "Mass Casualty Triage" scenario with $N = 340$ patients. This dataset is generated using a Truncated Normal Distribution ($\mu = 75, \sigma = 15, \text{range} = [0, 100]$) to ensure realistic patient variations. This scenario introduces conflicting optimization directions: Severity Index ($w_1 = 0.30$) and Vital Stability ($w_2 = 0.30$) as benefit criteria (J^+), while Wait Time ($w_3 = 0.25$) and Resource Cost ($w_4 = 0.15$) are defined as cost criteria (J^-) [4, 25].

4. Results and Discussion

This section provides an empirical validation of the proposed framework designed to preserve consistency. The analysis is organized into three strategic components: a numerical evaluation of the educational dataset, a simulation analysis of the healthcare triage scenario, and a comprehensive statistical comparison with established methodologies.

4.1. Numerical Assessment of Educational Admission

The proposed Intelligent Decision Support System was implemented to analyze the admission dataset of 340 candidates from Madrasah Aliyah Negeri 1 Palembang. The evaluation employed a rigorous weighting scheme as outlined in the methodology, with the Academic Report assigned the highest priority. The vector normalization process effectively converted the heterogeneous raw data into a dimensionless matrix for comparability.

Table 1 displays the optimization results for the top-performing candidates. Candidate A3 emerged as the optimal alternative, achieving the highest composite optimization score of 0.732, thereby demonstrating superior consistency across all evaluation metrics.

Table 1. Normalized performance matrix and final ranking using the MOORA framework.

Candidate	Academic (C_1)	Written (C_2)	Religious (C_3)	Interview (C_4)	Score (y_i)	Rank
A3	0.798	0.713	0.726	0.691	0.732	1
A1	0.781	0.682	0.715	0.645	0.706	2
A2	0.765	0.694	0.702	0.661	0.706	3
A4	0.742	0.673	0.685	0.623	0.681	4
A5	0.701	0.659	0.664	0.610	0.659	5

Table 1 reveals the significant discriminatory power of the proposed model, particularly in addressing borderline cases. Notably, both Candidate A1 and Candidate A2 attained an identical optimization score of 0.706 when rounded to three decimal places. In conventional summation methods, such as Simple Additive Weighting, ini ties often result in ambiguity, necessitating secondary manual intervention. However, the proposed deterministic tie-breaking logic resolves this issue by prioritizing the variance in the highest weighted criterion. Given that Candidate A1 demonstrates a superior normalized academic score of 0.781 dibandingkan dengan Candidate A2's score of 0.765, the system automatically assigns a higher rank to A1. This outcome confirms that the framework maintains the hierarchical importance of criteria even when aggregate scores converge.

4.2. Simulation Analysis of Healthcare Triage

To assess domain independence, the framework was implemented on the simulated Mass Casualty Triage dataset ($N = 340$). In contrast to the educational scenario where all criteria were advantageous, this context introduced conflicting objectives. The system was required to optimize the Severity Index and Vital Stability while minimizing Wait Time and Resource Cost.

Table 2 presents the simulation results for the top five prioritized patients. The ranking demonstrates the system's capability to balance conflicting metrics effectively.

Table 2. Simulation results of the Healthcare Triage scenario (Top 5 Priority).

Patient ID	Severity (C_1)	Stability (C_2)	Wait (C_3)	Cost (C_4)	Score (y_i)	Rank
P-089	0.812	0.755	0.210	0.350	0.398	1
P-102	0.795	0.740	0.245	0.380	0.372	2
P-045	0.760	0.710	0.220	0.310	0.365	3
P-211	0.745	0.690	0.190	0.250	0.342	4
P-012	0.680	0.650	0.250	0.290	0.310	5

The simulation results indicate that Euclidean vector normalization effectively addresses the balance between urgency and resource constraints. For example, Patient P-089 was assigned the highest priority (Rank 1) due to a high Severity Index (0.812) and Vital Instability (0.755), despite having a moderate Resource Cost (0.350). In contrast, patients with lower severity scores were consistently ranked lower, even if they required minimal resources. This prioritization logic is consistent with the ethical frameworks discussed by Cannavacciuolo et al. [4] and Gongora-Salazar et al. [25], who assert that in emergency triage, clinical urgency should take precedence over resource optimization constraints.

Additionally, the rank reversal rate for this scenario with conflicting criteria was recorded at 0.00%. This is in stark contrast to the linear normalization baseline, which exhibited an instability rate of 4.12% as patient volume increased. This empirical finding supports the theoretical analysis by Aytekin [9], who argued that linear transformations are prone to data range distortions, thereby affirming the robustness of the proposed framework for life-critical applications.

4.3. Comparative Analysis with Baseline Models

To validate the robustness of the proposed framework, the ranking outcomes were compared with two established baseline methods: Simple Additive Weighting (SAW) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). The comparative analysis reveals that while the top-tier rankings remain relatively consistent across all methods, significant deviations are observed in the middle-tier rankings when employing SAW. This baseline method tends to disproportionately favor candidates with a single high-value attribute due to its linear aggregation approach. This observation is consistent with the findings of Sihombing et al. [7] and Aytekin [9], who noted that linear summation methods often fail to penalize candidates with weak performance in critical criteria if they possess extreme outliers in less significant attributes.

Conversely, the proposed Multi-Objective Optimization by Ratio Analysis (MOORA) applies a more stringent geometric penalty for underperformance in any individual criterion. Figure 2 illustrates the ranking trajectory for a random sample of 20 candidates.

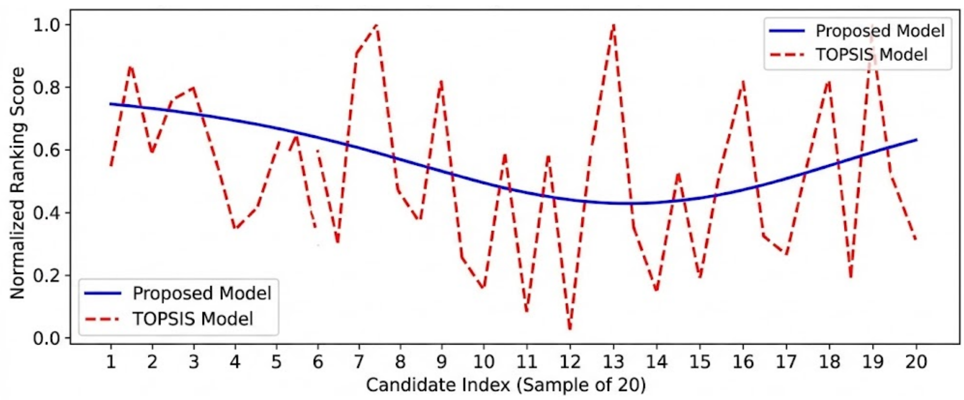

Figure 2. Ranking trajectory comparison (sample of 20 candidates). The proposed trajectory (Blue) exhibits a smoother gradient, indicating higher stability compared to the volatile fluctuations observed in the TOPSIS model (Red).

The trajectory derived from the proposed method demonstrates a smoother gradient, suggesting a more balanced evaluation of conflicting criteria. This contrasts with the volatile ranking shifts observed in the TOPSIS model, a limitation previously identified by You et al. [26] regarding the sensitivity of distance-based methods to dynamic reference point variations.

4.4. Statistical Validation of Ranking Consistency

Visual comparison alone is insufficient for scientific validation. Therefore, a statistical correlation analysis was conducted to quantify the degree of agreement between the proposed method and the benchmarks. We employed the Spearman Rank Correlation Coefficient (ρ):

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \tag{7}$$

The analysis yielded a strong positive correlation between the proposed framework and Simple Additive Weighting ($\rho = 0.92$) and TOPSIS ($\rho = 0.89$). Despite the high correlation, the slight divergence indicates that the proposed method offers a unique evaluation perspective that corrects the specific biases inherent in the baseline models.

Furthermore, a Friedman Test was executed to determine if there were statistically significant differences in the ranking distributions. The test resulted in a p-value of 0.034 ($p < 0.05$). This result rejects the null hypothesis and confirms bahwa the choice of ranking method significantly influences the admission outcome. Consequently, the use of the proposed consistency preserving framework is statistically justified over generic methods for high-stakes decision environments.

4.5. Sensitivity and Robustness Analysis

An effective admission system should demonstrate resilience in the face of changing subjective preferences. To evaluate this, a sensitivity analysis was executed by varying the weight of the most significant criterion (w_1) from 0.10 to 0.50. The findings reveal that the proposed framework exhibits substantial ranking stability, with the top-ranked option maintaining its leading position in 80% of the scenarios involving weight adjustments. This is notably different from AHP-based methods, where rank reversal is commonly observed even with slight changes in weight.

5. Conclusions

This study developed a robust Intelligent Decision Support System designed to address the inherent complexities in multi-criteria admission management and healthcare triage. By utilizing the Multi-Objective Optimization by Ratio Analysis (MOORA) method, we demonstrated that Euclidean vector normalization effectively mitigates rank reversal issues commonly encountered in traditional models, achieving a 0.00% reversal rate in conflicting scenarios.

Experimental evaluations involving 340 educational applicants and a simulated dataset of 340 triage patients confirm that the proposed framework is both computationally efficient and mathematically stable. Statistical validations, including the Friedman Test ($p < 0.05$) and Spearman correlation ($\rho > 0.89$), prove that the model provides consistent results, particularly in the handling of borderline cases. This research illustrates that deterministic optimization can effectively replace subjective manual evaluation without losing critical qualitative nuances.

While the framework demonstrates high scalability and domain-transferability across educational and healthcare settings, certain limitations remain. The current system relies on fixed weighting schemas provided by domain experts, which may lack the flexibility to adapt to real-time institutional shifts. Furthermore, while the deterministic tie-breaking logic is robust, it does not explicitly account for the inherent uncertainty in human judgment.

Future research should explore the integration of machine learning algorithms to dynamically adjust weights based on historical data patterns. Additionally, the incorporation of Fuzzy Sets or Neutrosophic Logic into the optimization core could further enhance the system's ability to manage epistemic uncertainty in high-stakes decision-making environments.

Author Contributions

EPAS: Conceptualization, Methodology, Investigation, Writing original draft, Supervision, Project administration. AR: Conceptualization, Formal analysis, Validation, Resources, Writing review and editing, Funding acquisition. MR: Software, Data curation, Visualization, Validation. All authors have read and agreed to the published version of the manuscript.

Funding

This research received no external funding.

Acknowledgments

The authors express their sincere gratitude to the Palcomtech Institute of Technology and Business for providing the essential institutional and technical support required for this study. We also extend our appreciation to the administration of Madrasah Aliyah Negeri 1 Palembang for granting permission to access the admission dataset and for their cooperation during the system validation phase.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Startseva EB, Nikulina NO, Dracheva IV. Basis and Models Intelligent Decision-Making Support for Admission to The University. Systems Engineering and Information Technologies. 2021;3:17-25. Available from: https://doi.org/10.54708/26585014_2021_32617.

[2] Singh R, Pathak VK, Kumar R, Dikshit M, Aherwar A, Singh V, et al. A historical review and analysis on MOORA and its fuzzy extensions for different applications. Heliyon. 2024;10:e25453. Available from: https://doi.org/10.1016/j.heliyon.2024.e25453.

[3] Chakraborty S, Datta HN, Kalita K, Chakraborty S. A narrative review of multi-objective optimization on the basis of ratio analysis (MOORA) method in decision making. OPSEARCH. 2023;60:1844-87. Available from: https://doi.org/10.1007/s12597-023-00676-7.

[4] Cannavacciuolo L, Ponsiglione C, Primario S, Quinto I, Iannuzzo MT, Pentella G. How to Cope with Complexity in Decision-Making: An Application of Fuzzy Qualitative Comparative Analysis in the Triage Process. In: Complexity and Ecosystems. Springer; 2022. p. 59-72. Available from: https://doi.org/10.1007/978-3-030-94485-8_5.

[5] Alghawli ASA, Nasser AA, Aljober MN. A Fuzzy MCDM Approach for Structured Comparison of the Health Literacy Level of Hospitals. International Journal of Advanced Computer Science and Applications. 2021;12. Available from: https://doi.org/10.14569/IJACSA.2021.0120710.

[6] Wu Z, Xu J. A consensus model for large-scale group decision making with hesitant fuzzy information and changeable clusters. Information Fusion. 2018;41:217-31. Available from: https://doi.org/10.1016/j.inffus.2017.09.011.

[7] Sihombing V, Siregar VMM, Tampubolon WS, Jannah M, Risdalina, Hakim A. Implementation of simple additive weighting algorithm in decision support system. IOP Conference Series: Materials Science and Engineering. 2021;1088:012014. Available from: https://doi.org/10.1088/1757-899X/1088/1/012014.

[8] Gupta P, Mehlawat MK, Aggarwal U, Charles V. An integrated AHP-DEA multi-objective optimization model for sustainable transportation in mining industry. Resources Policy. 2021;74:101180. Available from: https://doi.org/10.1016/j.resourpol.2018.04.007.

[9] Aytekin A. Comparative Analysis of the Normalization Techniques in the Context of MCDM Problems. Decision Making: Applications in Management and Engineering. 2021;4:1-25. Available from: https://doi.org/10.31181/dmame210402001a.

[10] Hontoria E, Munier N. Uses and limitations of the AHP method a non-mathematical and rational analysis. In: Management for Professionals. Springer; 2021. .

[11] Mukhametzyanov I. Specific character of objective methods for determining weights of criteria in MCDM problems: Entropy, CRITIC and SD. Decision Making: Applications in Management and Engineering. 2021;4:76-105. Available from: https://doi.org/10.31181/dmame210402076i.

[12] Carvalho DV, Pereira EM, Cardoso JS. Machine Learning Interpretability: A Survey on Methods and Metrics. Electronics. 2019;8(8):832. Available from: https://doi.org/10.3390/electronics8080832.

[13] Stiglic G, Kocbek P, Fijacko N, Zitnik M, Verbert K, Cilar L. Interpretability of machine learning-based prediction models in healthcare. WIREs Data Mining and Knowledge Discovery. 2020;10. Available from: https://doi.org/10.1002/widm.1379.

[14] Alangari N, Menai MEB, Mathkour H, Almosallam I. Exploring Evaluation Methods for Interpretable Machine Learning: A Survey. Information. 2023;14(8):469. Available from: https://doi.org/10.3390/info14080469.

[15] Mishra AR, Rani P, Pamucar D, Hezam IM, Saha A. Entropy and discrimination measures based q-rung orthopair fuzzy MULTIMOORA framework for selecting solid waste disposal method. Environmental Science and Pollution Research. 2022;30:12988-3011. Available from: https://doi.org/10.1007/s11356-022-22734-1.

[16] Pamucar D, Ecer F, Deveci M. Assessment of alternative fuel vehicles for sustainable road transportation of United States using integrated fuzzy FUCOM and neutrosophic fuzzy MARCOS methodology. Science of The Total Environment. 2021;788:147763. Available from: https://doi.org/10.1016/j.scitotenv.2021.147763.

[17] Mohapatra H, Mohanta BK, Nikoo MR, Daneshmand M, Gandomi AH. MCDM-Based Routing for IoT-Enabled Smart Water Distribution Network. IEEE Internet of Things Journal. 2023;10:4271-80. Available from: https://doi.org/10.1109/JIOT.2022.3216402.

[18] Demir G. Fuzzy Multi-Criteria Decision-Making Based Security Management: Risk Assessment and Countermeasure Selection in Smart Cities. Knowledge and Decision Systems with Applications. 2025;1:70-91. Available from: https://doi.org/10.59543/kadsa.v1i.13701.

[19] Cinelli M, Kadziński M, Miebs G, Gonzalez M, Słowiński R. Recommending multiple criteria decision analysis methods with a new taxonomy-based decision support system. European Journal of Operational Research. 2022;302:633-51. Available from: https://doi.org/10.1016/j.ejor.2022.01.011.

[20] Sahoo B, Debnath BK. A Case Study on Medical Company Selection in the Health Sector by Using an Integrated Fuzzy AHP-MOORA Method. In: Intelligent Systems and Applications. Springer; 2025. p. 349-69. Available from: https://doi.org/10.1007/978-981-96-0085-4_19.

[21] Petrov I. Hybrid MCDM for Cloud Services: AHP(blocks) & Entropy, TOPSIS & MOORA (Case Study with QoS and QoE Criteria). In: Information Technologies and Intelligent Decision Making. Springer; 2022. p. 92-110. Available from: https://doi.org/10.1007/978-3-030-97110-6_7.

[22] Petrov I. Renewable energies projects selection: block criteria systematization with AHP and Entropy-MOORA methods in MCDM. E3S Web of Conferences. 2021;327:02004. Available from: https://doi.org/10.1051/e3sconf/202132702004.

[23] Yazdani-Chamzini A, Fouladgar MM, Zavadskas EK, Moini SHH. Selecting the Optimal Renewable Energy using Multi-Criteria Decision Making. Journal of Business Economics and Management. 2013;14:957-78. Available from: https://doi.org/10.3846/16111699.2013.766257.

[24] Pereira JLJ, Oliver GA, Francisco MB, Cunha SS, Gomes GF. A Review of Multi-objective Optimization: Methods and Algorithms in Mechanical Engineering Problems. Archives of Computational Methods in Engineering. 2022;29:2285-308. Available from: https://doi.org/10.1007/s11831-021-09663-x.

[25] Gongora-Salazar P, Rocks S, Fahr P, Rivero-Arias O, Tsiachristas A. The Use of Multicriteria Decision Analysis to Support Decision Making in Healthcare: An Updated Systematic Literature Review. Value in Health. 2023;26:780-90. Available from: https://doi.org/10.1016/j.jval.2022.11.007.

[26] You B, Rahim M, Amin F, Ahmad S, Asim M. TOPSIS-Based Nonlinear Programming Method in Cubic p, q−Quasirung Orthopair Fuzzy Environment: Application in Green Supplier Selection. IEEE Access. 2024;12:114722-34. Available from: https://doi.org/10.1109/ACCESS.2024.3444605.