Analysis of normalization technique on multi objective preference analysis method

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ABSTRACT

Normalization is a critical step in multi-criteria decision analysis (MCDA) because it influences ranking consistency and decision reliability. This study evaluates the effects of four normalization techniques linear max, linear max-min, linear sum, and semi-linear vector, within the multi objective preference analysis (MOPA) framework using a tourism development case involving 18 alternatives and 8 decision criteria with both cost and benefit attributes. The techniques were compared based on ranking behavior, discriminative capability, and robustness using statistical and non-parametric validation. The results show that linear max-min normalization provides the strongest discriminative performance and the most significant statistical results, while semi-linear vector demonstrates high ranking stability and balanced sensitivity. In contrast, linear sum and linear max exhibit lower discriminative capability under the evaluated conditions. Kendall's tau and robustness analyses further confirm that normalization choice significantly affects ranking consistency and decision reliability. These findings provide practical guidance for selecting appropriate normalization techniques and support the development of more reliable MCDA-based decision-making models for complex applications, including sustainable tourism planning.

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1. INTRODUCTION

Complex decision-making often involves multiple interacting criteria that must be evaluated simultaneously [1]. Multi-criteria decision analysis (MCDA) provides a structured approach to assess alternatives and generate interpretable rankings [2]. In practice, decision data usually come from different scales, making normalization a crucial step to ensure fair comparison across criteria [3].

MCDA has been widely applied in tourism and hospitality, including halal tourism planning, where decision-making must balance economic, social, and environmental considerations within multi-stakeholder contexts [4]. Recent halal (sharia) tourism studies and reviews also emphasize that destination development must reconcile Islamic compliance requirements with market competitiveness and sustainability considerations, which naturally leads to multi-criteria evaluation settings [5]–[8]. Decision making using the MCDA method goes through several stages such as defining the problem that needs to be solved and the purpose of decision making [9], [10], identifying relevant criteria for evaluating alternatives [11], [12], collecting the necessary data for each alternative based on the predetermined criteria [13], normalizing the data to transform different measurement scales so that the data can be compared fairly [14], determining criteria weights [15], evaluating alternatives [16], ranking alternatives [17], conducting sensitivity analysis to understand how changes in criteria weights or alternative values may affect the results [18], and finally supporting decision making [19].

Among these, normalization plays a critical role in preventing scale dominance and reducing bias, thereby ensuring proportional contribution of each criterion [20]. In addition, this process reduces bias from unbalanced data, ensuring each criterion contributes proportionally to the final decision [21], [22]. The choice of normalization method significantly affects alternative rankings and, consequently, the final decision [19]. However, the choice of normalization technique can significantly influence ranking results and may even lead to inconsistencies such as rank reversal [23], [24]. Thus, normalization ensures consistent and structured evaluation, supporting decision validity [25]. It is a critical component affecting reliability, with studies confirming its significant impact across contexts, including green supplier selection [26].

Different normalization techniques (e.g., max-min and z-score) can significantly influence ranking results [27]. Studies show that method selection may produce different outcomes and inconsistencies [28], [29], while recent research highlights its role in rank reversal and interaction with distance measures in MCDA methods such as technique for order preference by similarity to ideal solution (TOPSIS) [23], [24]. Additionally, sustainability-focused studies emphasize the need for normalization choices that are robust, interpretable, and comparable across contexts [30].

Despite extensive studies on normalization in MCDA, consistency and systematic evaluation frameworks remain limited [31]–[33]. This highlights the need for integrated approaches that assess techniques based on accuracy, consistency, and sensitivity [11], supported by recent sustainability-focused research emphasizing structured evaluation and reporting [30]. In sharia tourism site selection, choosing the right normalization technique is crucial due to the need to balance social, economic, and environmental criteria [34]. Additional factors, such as competitiveness and governance, further increase complexity [5]–[8]. Prior studies show that appropriate normalization improves decision effectiveness, highlighting the importance of systematic frameworks in sustainable tourism planning [14], [35]. Sustainability-oriented tourism development requires integrated evaluation approaches capable of balancing environmental protection, visitor engagement, and destination competitiveness within increasingly complex tourism ecosystems [36].

Multi-objective preference analysis (MOPA) has been proposed as an MCDA method to support evaluation and ranking in complex, multi-objective decisions [16]. However, variability in normalization can affect the credibility and reproducibility of results, especially in stakeholder-driven contexts such as tourism and sustainability [23], [24], [30]. While normalization in MCDA has been widely studied, its systematic evaluation within the MOPA framework remains limited. This study addresses this gap by examining how normalization techniques influence ranking behavior in MOPA, including an application to sharia tourism site selection. This research contributes by providing a comparative evaluation of normalization methods in MOPA, supported by statistical validation analysis of variance (ANOVA) and non-parametric tests, as well as ranking stability analysis using Kendall's tau. It also demonstrates practical applicability in a real-world case, offering more reliable and interpretable decision-making insights.

2. METHOD

Several normalization methods have been introduced and proposed in the literature and can be used for various problems in MCDA. Vafaei *et al.* [28] proposed a general evaluation framework that includes several metrics to assess different normalization techniques using MCDA methods. Figure 1 shows the evaluation framework, adapted from [28]. This research method will focus on selecting the most appropriate normalization technique in the context of MCDA with the MOPA method, using a case study of tourism development location selection taken from the literature [27]. The dataset comprises 18 alternatives (A1–A18) and 8 criteria (C1–C8), where C1 represents a cost criterion, and the remaining criteria are benefit criteria. The selection of this dataset is based on its relevance in representing a real-world MCDA problem, the presence of both cost and benefit criteria, and its use in previous studies, which supports the reproducibility and comparability of the results.

Previous studies mainly relied on the linear max normalization method. In this research, additional normalization approaches, namely linear max-min, linear sum, and semi-linear vector, are incorporated to facilitate comparative analysis and evaluate their influence on the resulting rankings. Table 1 summarizes the formulas of the selected normalization techniques for both benefit and cost criteria used in this comparative assessment, adapted from [28].

The normalization process is illustrated step-by-step for alternative A1 using C1 (cost) and C2 (benefit), with reference bounds min =2 and max =4. First, under linear max–min normalization, the benefit value for C2 is computed as $\frac{2-2}{4-2} = 0$, while the cost value for C1 is obtained as $\frac{4-3}{4-2} = 0.5$. Second, using linear max normalization, the benefit value becomes $2/4 = 0.5$, and cost value is calculated as $2/3 \approx 0.667$. Third, under linear sum normalization, assuming the total value of criterion C2 across all alternatives is 52, the normalized score is $2/52 = 0.0385$, reflecting a compressed scale. Finally, using vector normalization, with $\sqrt{\sum x_{i2}^2} = 14.42$, the normalized value is $2/14.42 \approx 0.139$. This descending, stepwise computation demonstrates how each normalization technique transforms the same raw data into different scales, highlighting their varying sensitivity and impact on subsequent ranking results.

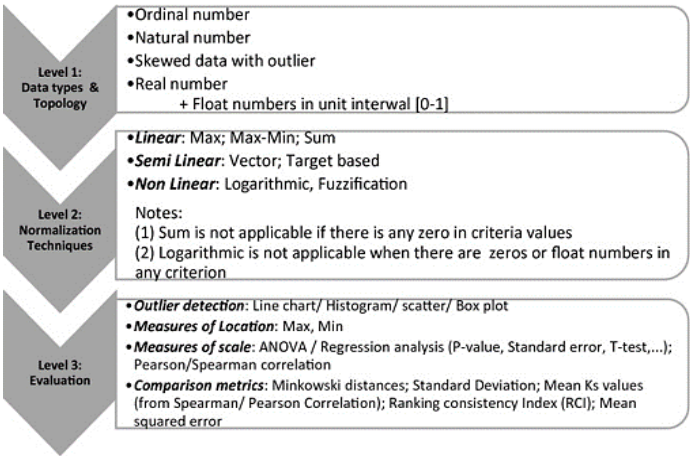

Figure 1. Three levels of the evaluation framework

Table 1. Selected normalization techniques

Normalization technique	Conditions of use	Formulation
Linear: max	Benefits	$n_{ij}^{+} = \frac{r_{ij}}{r_{max}}$
	Cost	$n_{ij}^{-} = 1 - \frac{r_{ij}}{r_{max}}$
Linear: max-min	Benefits	$n_{ij}^{+} = \frac{r_{ij} - r_{min}}{r_{max} - r_{min}}$
	Cost	$n_{ij}^{-} = \frac{r_{max} - r_{ij}}{r_{max} - r_{min}}$
Linear: sum	Benefits	$n_{ij}^{+} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}}$
	Cost	$n_{ij}^{-} = \frac{1/r_{ij}}{\sum_{i=1}^{m} 1/r_{ij}}$
Semi-linear: vector	Benefits	$n_{ij}^{+} = \frac{r_{ij}}{\sqrt{\sum_{i=1}^{m} r_{ij}^2}}$
	Cost	$n_{ij}^{-} = 1 - \frac{r_{ij}}{\sqrt{\sum_{i=1}^{m} r_{ij}^2}}$

3. RESULTS AND DISCUSSION

Selecting an appropriate normalization technique is essential to ensure accurate and relevant decision analysis. This study applies a benchmarking framework using a case study to evaluate four normalization methods and identify the most suitable approach for sharia tourism development using the MOPA method [27]. The MOPA method was first introduced by Riandari *et al.* [27] for multidimensional issues. The related formula for determining the ranking of alternatives is determined by (1).

$$AC_i = \sum_{n=1}^{n} C_{ij} * W_1, W_2, W_3 \dots W_j \quad (1)$$

In the proposed model, AC_{ij} refers to the value of an alternative positioned in a row $i$and column j, whereas $\sum_{n=1}^{m} C_{ij}$ describes the alternative score associated with each criterion. Meanwhile, w_j reflects the priority weight of every criterion according to its importance level. The case study evaluates eight criteria (C1–C8), where C1 functions as a cost attribute with smaller values considered more favorable, while the other criteria represent benefit attributes where larger values are preferred. A total of 18 alternatives, ranging from A1 to A18, are assessed in the study, and their corresponding criterion weights are summarized in Table 2.

Table 2. Decision matrix input data and weights from the borrowed case study [27]

Alt.	C1	C2	C3	C4	C5	C6	C7	C8
A1	3	2	3	3	3	4	3	4
A2	4	4	2	3	4	2	3	3
A3	3	3	4	2	2	4	2	2
A4	4	2	4	3	4	2	3	4
A5	4	3	4	2	2	4	4	2
A6	2	3	2	3	2	3	2	4
A7	4	4	4	4	3	2	2	4
A8	3	3	4	4	2	4	4	4
A9	4	2	4	2	4	3	4	3
A10	3	2	3	4	2	2	4	3
A11	3	2	2	3	4	4	3	4
A12	4	3	3	4	3	3	3	2
A13	4	3	3	2	4	3	4	3
A14	3	4	4	4	2	4	2	2
A15	3	2	2	4	4	2	2	3
A16	3	3	4	2	3	3	2	3
A17	3	4	3	3	3	4	3	3
A18	2	2	3	3	4	4	3	2

The results of the analysis with four selected normalization techniques, namely linear-max, linear-max-min, linear-sum, and semi-linear-vector normalization for the related case study, obtained the final results of the MOPA method, with alternative rankings for each selected normalization technique presented in Table 3. This table shows that linear max-min and semi-linear vectors produce more discriminative and stable ranking patterns, while linear sum yields compressed score distributions, reducing differentiation among alternatives. The slope chart, as in Figure 2, shows how alternative rankings change across normalization techniques. Several alternatives, such as A1, A8, and A11, remain stable, indicating robustness to normalization choice. In contrast, some alternatives exhibit ranking shifts, particularly under linear sum, which produces more compressed and less discriminative results. The presence of rank changes confirms that normalization selection can influence final decision outcomes, while linear max–min and semi-linear vector demonstrates more consistent ranking patterns.

Table 3. Comparative ranking scores under different normalization techniques

Alt.	Linear max	Linear max-min	Linear sum	Semi-linear vector
A1	0.846	0.691	0.062	0.843
A2	0.749	0.470	0.055	0.735
A3	0.611	0.221	0.044	0.608
A4	0.835	0.641	0.061	0.821
A5	0.757	0.486	0.055	0.743
A6	0.695	0.418	0.051	0.709
A7	0.762	0.495	0.055	0.748
A8	0.920	0.840	0.067	0.918
A9	0.853	0.677	0.062	0.838
A10	0.762	0.524	0.056	0.760
A11	0.863	0.726	0.063	0.861
A12	0.703	0.377	0.051	0.688
A13	0.845	0.661	0.062	0.830
A14	0.648	0.296	0.047	0.646
A15	0.673	0.346	0.049	0.671
A16	0.680	0.361	0.049	0.678
A17	0.790	0.580	0.058	0.788
A18	0.732	0.492	0.053	0.746

Prior to conducting ANOVA, assumption testing was performed to ensure the validity of the parametric approach. Normality was assessed using the Shapiro-Wilk test, and homogeneity of variances was evaluated using Levene's test. The results indicate that the data are normally distributed ($p > 0.05$) and that variances across groups are homogeneous, satisfying the assumptions required for ANOVA. However, considering the relatively small dataset and the discrete nature of the data, a non-parametric Kruskal-Wallis test was also conducted as a robustness check. The results are consistent with ANOVA, indicating significant differences among normalization techniques. This consistency confirms that the findings are robust and not dependent solely on parametric assumptions.

Next, an analysis is conducted to assess the level of precision of the four normalization techniques by evaluating their robustness in producing consistent ranking results. To find out the concept of the normalization technique weight convincingly, ANOVA was conducted on the actual final selection index (FSI) of the alternatives using a significance level of α =0.05. ANOVA is a statistical technique used to determine whether there is a significant difference between the means of two or more groups. In this context, we compare the results of ANOVA applied to data that has been normalized using four different normalization techniques: linear max normalization, linear max-min normalization, linear sum normalization, and semi-linear vector normalization. The 0.05 (or 5%) level of significance is a commonly used level in statistical analysis. It is based on a well-established convention and is widely used in scientific research. This level of significance indicates that there is a 5% chance that the observed difference is due to chance alone. ANOVA was conducted using python software, ANOVA was conducted for the four selected normalization techniques. ANOVA was tested on the final results conducted with the four selected normalizations against the borrowed case study. The results of the ANOVA test conducted using Python Software obtained the results that can be seen in Table 4.

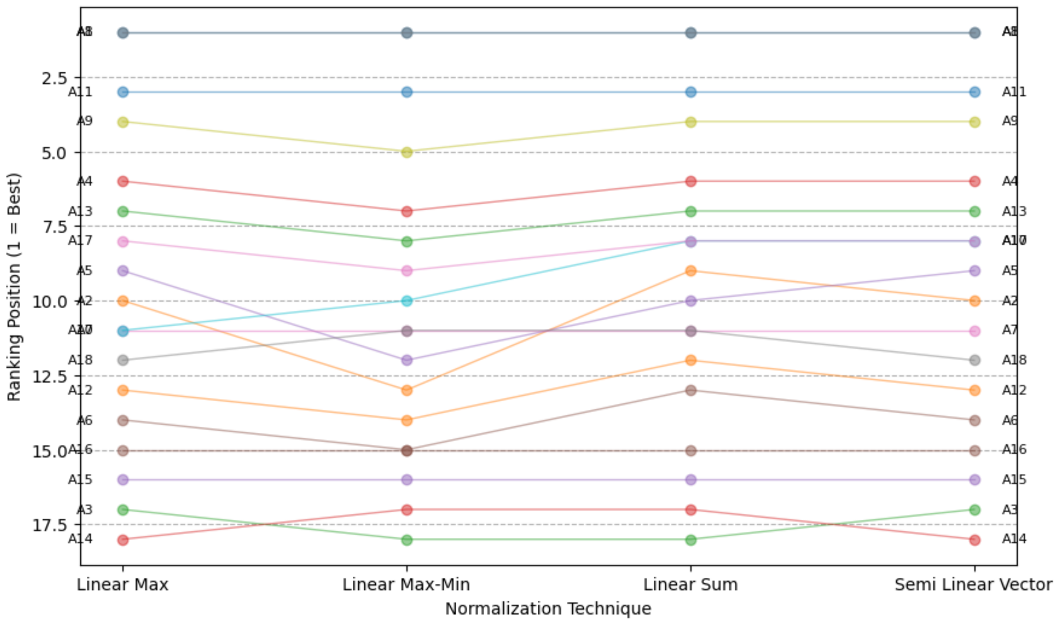

Figure 2. Slope chart of ranking changes across normalization techniques

Table 4. Comparison of ANOVA results

Normalization technique	F-statistic	P – value
Linear max	3.804	0.046
Linear max-min	4.059	0.039
Linear sum	3.703	0.049
Semi-linear vector	3.995	0.041

Normalization ensures comparability and prevents scale dominance, but different techniques can lead to different outcomes. Empirical studies show that choosing an inappropriate method may even degrade model performance compared to unscaled data [37]. This finding helps explain why max normalization produced relatively weaker results in the ANOVA test in this study.

Linear max-min normalization achieved the best results (F =4.060; p =0.039), effectively scaling data for comparison and enhancing the detection of differences, consistent with prior findings [38]. Linear sum normalization also showed significant results with a P-value of 0.049. Although the results are good, this technique tends to be simpler and can ignore critical variations in the data. Chen [39] shows that although sum normalization is easy to apply, it can cause distortions in the analysis, especially when the data is not normally distributed.

Semi-linear vector normalization gives quite good results with a P-value of 0.041. This technique, which combines several approaches, shows the potential to provide more balanced results. Vafaei *et al.* [40] showed that the semi-linear approach can provide advantages in preserving data integrity while still detecting significant differences between groups. The results support this finding, suggesting that this technique has value in the context of ANOVA. To further explain the observed differences among normalization techniques, a theoretical analysis is provided to clarify the underlying mechanisms.

The inferior performance of linear sum normalization can be explained by its mathematical structure, which distributes values proportionally across all alternatives. This tends to compress the range of normalized values, reducing contrast between high- and low-performing alternatives. As a result, the method becomes less sensitive to variations in input data, leading to weaker discrimination power. In contrast, linear max-min normalization preserves relative distances by scaling values within a fixed range, enhancing differentiation. Similarly, semi-linear vector normalization maintains proportional relationships while incorporating magnitude sensitivity, allowing it to better capture performance variations across alternatives.

These results support many previous studies that emphasize the importance of selecting the right normalization technique. For example, Zorov *et al.* [41] found that choosing right normalization technique can significantly affect the results of analysis, including ANOVA. This shows that choosing a normalization method is not just a technical issue, but can also affect data-based decisions and conclusions drawn.

Overall, the variance analysis highlights that normalization choice significantly affects decision accuracy and relevance. Linear max–min is the most recommended technique, showing the best performance in distinguishing alternatives, while semi-linear vector also performs well by balancing robustness and sensitivity. In contrast, linear sum is less discriminative, and linear max shows weaker performance under uneven data conditions. These findings emphasize that normalization selection should be aligned with data characteristics and analysis objectives, and supported by sensitivity analysis to ensure stable and reliable decision outcomes. To further evaluate the robustness of ranking results, sensitivity analysis was conducted.

Ranking stability under different normalization techniques was evaluated using Kendall's tau correlation coefficient. The results show that linear max-min and semi-linear vectors exhibit high stability, while linear sum produces greater rank variability. These findings indicate that normalization choice significantly affects ranking robustness, with linear max-min and semi-linear vector providing more reliable and consistent decision outcomes within the MOPA-based decision-making framework.

The decision-making procedure may utilize various normalization methods depending on the objectives and characteristics of the dataset. To improve the consistency and dependability of ranking results, decision-makers can implement the proposed evaluation framework through the practical model presented in Figure 3. The figure presents a structured framework for evaluating normalization techniques within MCDA, consisting of three phases. Phase 1 establishes the decision model through matrix construction, benefit–cost identification, and weight assignment. Phase 2 assesses normalization techniques based on data characteristics, highlighting their influence on ranking outcomes. Phase 3 validates the results through sensitivity analysis, followed by stability and robustness evaluation to ensure consistent and reliable rankings. This framework emphasizes that normalization is a critical determinant of decision quality and supports reproducible and robust decision-making.

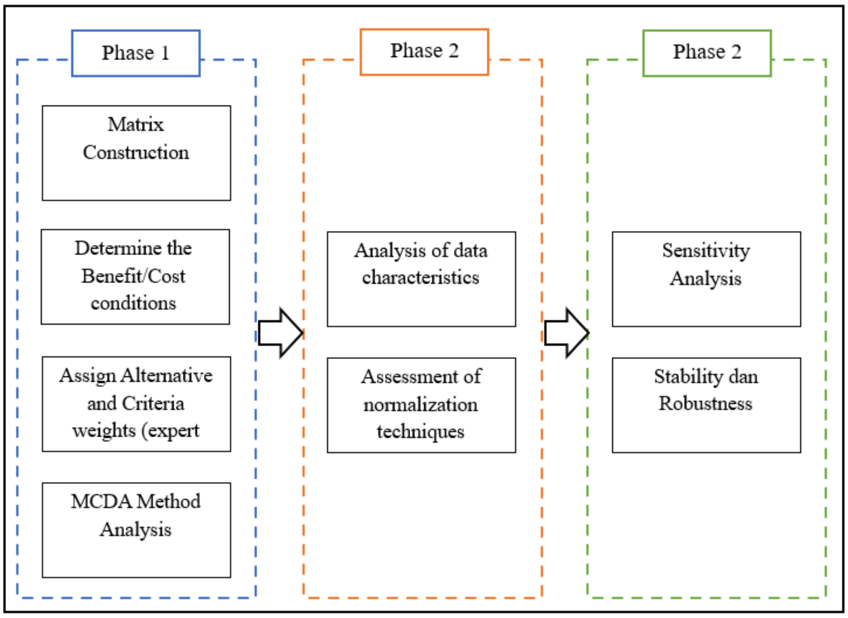

Figure 3. Practical design model for the analysis of normalization techniques on the MCDA model using the proposed framework

4. CONCLUSION

Selecting the appropriate normalization technique is critical for accurate data-driven decision-making. Among the four methods evaluated, linear max-min performs best, effectively distinguishing alternatives and yielding significant ANOVA results. The semi-linear vector also shows strong performance by balancing robustness and sensitivity, while the linear sum and linear max are less discriminative. These findings highlight that normalization choice should align with data characteristics and analysis objectives, supported by sensitivity analysis to ensure stable results. This study provides practical guidance for selecting suitable normalization techniques and contributes to the literature by offering a comparative and validated evaluation framework, with implications across various application domains.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

The author declares that there is no conflict of interest regarding the publication of this paper. The author states that there are no known competing financial interests or personal relationships that could have influenced the work reported in this study.

DATA AVAILABILITY

The data supporting the findings of this study are available within the article. Additional processed data and analysis results are available from the corresponding author upon reasonable request.

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