



HIVE Weighting: A Novel Heterogeneity-Aware Approach for Criteria Weighting in Multi-Criteria Decision Making

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ABSTRACT

Keywords:

HIVE Weighting;
Objective
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Objective criterion weighting plays an important role in multi-criteria decision-making (MCDM), particularly when decision outcomes depend on how differences among criteria are represented. However, conventional objective weighting approaches may emphasize specific statistical characteristics of the decision matrix without explicitly considering criterion heterogeneity as an integrated concept. This study proposes Heterogeneity-Informed Value Emphasis (HIVE) Weighting, a Heterogeneity-Informed Value Emphasis approach, for objective criterion weighting in MCDM. The method incorporates the mean, standard deviation, and relative variability of normalized criterion values to construct a heterogeneity-based measure of criterion importance. The resulting weights are then integrated with established MCDM methods to examine their applicability in alternative evaluation. A comparative analysis is conducted against Entropy, WENSLO, LOGSTA, CRITIC, and MEREC, followed by evaluations using the SAW and MOORA methods. Sensitivity analysis is further performed by varying criterion weights across multiple perturbation scenarios to examine the stability of the resulting rankings. The findings indicate that HIVE generates a more balanced representation of criterion importance than several comparative weighting approaches while preserving compatibility with different MCDM aggregation procedures. The ranking results obtained through SAW and MOORA show consistent patterns, while the sensitivity analysis indicates that the overall ranking structure is relatively stable under changes in criterion weights. These results demonstrate that HIVE provides an interpretable and flexible framework for incorporating criterion heterogeneity into objective weighting. The proposed approach offers a basis for further research on heterogeneity-aware weighting across diverse MCDM datasets and decision-making contexts, supporting more



reliable and transparent weighting practices in complex decision environments.

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I. Introduction

Multi-Criteria Decision Making (MCDM) is a systematic decision-making framework designed to evaluate and rank multiple alternatives based on several criteria simultaneously[1]-[3]. In real-world decision problems, alternatives are rarely assessed from a single perspective, as each alternative may exhibit different levels of performance across various dimensions. MCDM provides a structured mechanism for integrating these diverse criteria into a comprehensive evaluation process, enabling decision makers to compare alternatives and determine their relative performance. The MCDM process generally involves several stages, including the construction of a decision matrix, data normalization, determination of criterion weights, aggregation of criterion values, and ranking of alternatives. Among these stages, criterion weighting plays a particularly important role because it determines the relative contribution of each criterion to the overall evaluation. Consequently, the effectiveness of an MCDM approach is influenced not only by the ranking or aggregation technique employed but also by the extent to which the weighting procedure can appropriately represent the information contained within the criteria[4]-[6]. Differences in data variability, distribution, discriminatory power, and relationships among criteria may further affect the contribution of individual criteria to the decision process. Therefore, developing MCDM approaches that can appropriately accommodate the diverse characteristics of criteria is essential for producing decision outcomes that are objective, consistent, and representative of the underlying structure of the decision data.

Criterion weights determine the relative influence of each criterion on the overall evaluation and ranking of alternatives[7]-[9]. In an MCDM process, the weight assigned to a criterion represents its contribution to the final decision relative to the other criteria[10], [11]. A criterion with a higher weight has a greater influence on the aggregated performance of an alternative, whereas a criterion with a lower weight contributes comparatively less to the overall evaluation. Consequently, the weighting structure can substantially affect the final



scores and the resulting ranking of alternatives, particularly when alternatives exhibit different performance patterns across criteria. An appropriate weighting mechanism is therefore essential to ensure that the relative contribution of each criterion is represented consistently with the information contained in the decision matrix.

Conventional criterion weighting methods face several limitations that can affect the representation of criterion importance in MCDM[12], [13]. Subjective weighting methods generally rely on expert judgment or decision-maker preferences, making the resulting weights potentially dependent on individual perceptions, experience, and knowledge. Although this approach can incorporate contextual expertise, it may introduce a degree of subjectivity and reduce consistency across different decision-making settings[4], [14]. In contrast, objective weighting methods derive weights from the information contained in the decision matrix, but many existing approaches primarily emphasize statistical characteristics such as dispersion, variance, entropy, correlation, or information content. Focusing predominantly on these characteristics may not fully capture the broader structural differences among criteria. In addition, certain weighting procedures can produce highly concentrated or extreme weights, causing a small number of criteria to dominate the evaluation while the contribution of other criteria becomes relatively limited. Such an outcome may not always reflect the overall structure of the decision data. Another important limitation is that the heterogeneous characteristics of criteria are not always explicitly considered. Criteria may differ in terms of variability, distribution, range, discriminatory capability, and relationships with other criteria, yet these differences may be insufficiently represented when weighting is based on a single statistical property. These limitations indicate the need for a more comprehensive weighting approach that can objectively recognize and incorporate the heterogeneity of criteria when determining their relative importance.

The concept of criterion heterogeneity refers to the differences in characteristics exhibited by individual criteria within a decision matrix[15]. In an MCDM context, criteria may differ substantially in terms of their variability, distribution, range, discriminatory capability, and overall data behavior across alternatives. Some criteria may display considerable variation among alternatives, allowing them to distinguish alternative performance more clearly, while others may contain relatively similar values and therefore provide less differentiation. Differences may also occur in the shape and distribution of criterion values, the magnitude of their ranges, and the extent to which they contribute unique information to the decision process. Consequently, criteria cannot necessarily be assumed to possess comparable statistical characteristics simply because they are included within the same decision matrix. Criterion heterogeneity provides a means of recognizing these differences as an inherent property of the decision data. By explicitly considering such heterogeneity, the weighting process can move beyond evaluating criteria according to a single characteristic and instead examine the distinctive information



associated with each criterion. This perspective is particularly relevant for objective weighting because the resulting weights can be derived according to the observed structure and differences within the decision matrix rather than being determined solely by predefined preferences or a single measure of information content.

The increasing recognition of criterion heterogeneity highlights the need for a weighting approach that can explicitly identify and incorporate differences among criteria into the determination of their relative importance. A weighting method should not rely solely on a single statistical property, such as variance or information content, because the characteristics of a criterion may be reflected through multiple dimensions of the decision matrix. Differences in variability, distribution, range, discriminatory capability, and relationships among criteria can provide complementary information about how each criterion contributes to the differentiation of alternatives. Therefore, an appropriate weighting framework should be capable of adapting to the specific structure of the available data while maintaining an objective basis for weight determination. By incorporating heterogeneity information into the weighting process, the resulting weights can provide a more comprehensive representation of the distinctive characteristics of each criterion and reduce the possibility of assigning disproportionate importance based on only one aspect of the data. Such an approach can also support more transparent interpretation of why criteria receive different weights and provide a stronger foundation for subsequent evaluation and ranking within MCDM.

Existing objective weighting methods have generally been developed by exploiting specific statistical properties of the decision matrix, such as information content, variance, correlation, and dispersion[16], [17]. Although these approaches provide objective mechanisms for determining criterion weights, their reliance on particular characteristics may limit their ability to capture the broader structural differences that exist among criteria. In particular, the heterogeneity structure among criteria has not been sufficiently modeled as an explicit component of the weighting process. Criteria may exhibit different levels of variability, distributional patterns, discriminatory capabilities, and relationships with other criteria, and these differences may not be adequately represented when criterion importance is determined from only one statistical characteristic. As a result, the resulting weights may emphasize certain criteria disproportionately while providing a less balanced representation of the overall information structure of the decision matrix. This situation indicates the need for a more comprehensive weighting approach that can recognize the distinctive characteristics of individual criteria while preserving an objective basis for weight determination. Such an approach should be objective, so that the weights are derived from the decision data rather than subjective preferences; heterogeneity-aware, so that structural differences among criteria are explicitly incorporated; adaptive, so that the weighting mechanism can respond to different data configurations; interpretable, so that the contribution of each



criterion to the resulting weight can be clearly understood; and robust, so that reasonable changes in the underlying data do not lead to disproportionate changes in the weights or subsequent decision outcomes.

The primary objective of this study is to develop Heterogeneity-Informed Value Emphasis (HIVE) Weighting as a novel objective criterion-weighting method that explicitly incorporates heterogeneity among criteria into the weighting process. The proposed method aims to quantify the heterogeneity of individual criteria based on the statistical and structural characteristics of the decision matrix and subsequently transform this information into objective and adaptive criterion weights. Through this approach, HIVE Weighting is intended to capture differences in the characteristics of criteria while providing an interpretable mechanism for determining their relative importance. The study further aims to compare HIVE Weighting with established weighting methods to examine differences in the resulting weights and their effects on alternative evaluation and ranking. The stability and robustness of both the generated criterion weights and alternative rankings will also be evaluated under variations in the decision data. The main contributions of the study are the introduction of the Heterogeneity-aware Criterion Weighting concept, the development of quantitative indicators for measuring criterion heterogeneity, and the integration of heterogeneity information into the weighting mechanism. In addition, the proposed framework provides a general weighting procedure that accounts for differences in criterion characteristics and can be integrated with various MCDM methods, thereby extending the applicability of objective weighting to decision problems involving heterogeneous criteria.

II. Literature Review

2.1. Multi-Criteria Decision Making

MCDM is a methodological framework for solving decision problems involving multiple alternatives evaluated according to several criteria. In practical decision environments, alternatives are rarely comparable using a single attribute because different criteria may represent different dimensions of performance, requirements, or preferences. MCDM provides a structured mechanism for organizing these heterogeneous evaluation dimensions and combining them into an overall assessment of alternatives[18], [19]. The general structure of an MCDM problem consists of a set of alternatives, a collection of evaluation criteria, and a decision matrix containing the performance of each alternative with respect to each criterion. Depending on the characteristics of the problem, criteria may represent either benefit or cost attributes and may be measured using different units and scales.

A typical MCDM procedure involves several interconnected stages, including the construction of the decision matrix, normalization of criterion values, determination of criterion weights, aggregation of the weighted performance values, and ranking of alternatives[20], [21].



Normalization is required to transform criteria with different measurement units into comparable scales, while weighting is used to represent the relative contribution of each criterion to the decision process. The weighted criteria are subsequently incorporated into an aggregation or ranking mechanism to obtain the overall performance of each alternative. Consequently, the final ranking is influenced by both the performance data and the weighting structure used in the decision model.

The weighting stage is particularly important because criteria may not contribute equally to the discrimination of alternatives[22]. A criterion exhibiting substantial differences among alternatives may provide different informational characteristics from a criterion whose values are relatively homogeneous. Furthermore, criteria may differ in their distributions, ranges, variability, and relationships with other criteria. These characteristics create a heterogeneous structure within the decision matrix that may influence the interpretation of criterion importance. Therefore, the selection of an appropriate weighting mechanism represents an important methodological consideration in MCDM, particularly when the objective is to derive criterion importance directly from the available decision data.

MCDM methods have subsequently been developed across a wide range of decision-making contexts, including supplier selection, sustainability assessment, risk evaluation, technology selection, resource allocation, and performance evaluation. Different MCDM techniques employ different mechanisms for aggregating criterion performance and producing alternative rankings. However, regardless of the specific ranking technique, the criterion-weighting mechanism remains an important component because it determines how much each criterion contributes to the overall evaluation. This has motivated extensive research into alternative approaches for determining criterion weights, including both subjective and objective weighting methods.

2.2. Objective Weighting Methods

Objective weighting methods determine criterion weights primarily from the information contained in the decision matrix rather than directly relying on the subjective preferences of decision makers[23]-[25]. The fundamental rationale is that the characteristics of the observed data can provide evidence regarding the relative contribution of criteria to the differentiation of alternatives. This characteristic distinguishes objective weighting from subjective approaches, in which weights are generally obtained through expert judgment, pairwise comparisons, preference statements, or predefined priorities. By deriving weights from the decision matrix, objective methods aim to reduce the influence of individual preferences and provide a reproducible mechanism for determining criterion importance.

Several objective weighting approaches have been developed based on different interpretations of information contained in the decision matrix[26]. Statistical dispersion-based methods generally associate greater importance with criteria that exhibit greater variation among



alternatives, based on the assumption that greater differentiation provides more information for decision making. Variance and standard deviation are examples of measures that can be used to quantify such variation. Similarly, entropy-based approaches assess the degree of uncertainty or information contained in the distribution of criterion values. A criterion with a more diverse distribution may produce a different entropy value from a criterion whose values are more uniformly distributed, leading to differences in the resulting weights.

Other approaches incorporate correlation among criteria to account for redundancy in the information they provide. When two criteria exhibit a strong relationship, their information may partially overlap, and a weighting mechanism may reduce the relative contribution associated with redundant information. This perspective differs from purely dispersion-based approaches because it considers not only the internal variability of an individual criterion but also its relationship with other criteria. Consequently, objective weighting methods can produce substantially different weights when they rely on different definitions of informational importance.

Information-content-based methods provide another important perspective in objective weighting. These approaches attempt to quantify the amount of useful information associated with each criterion based on characteristics of the decision matrix. The resulting weights are then normalized so that they can be incorporated into subsequent MCDM procedures. Although the mathematical formulations vary considerably across methods, their common principle is to derive criterion importance from observable properties of the data rather than requiring explicit preference assignments.

The diversity of objective weighting methods demonstrates that there is no single universally adopted definition of criterion importance. Different methods emphasize different characteristics, such as variability, uncertainty, correlation, or information content. Consequently, the same decision matrix may produce different weighting structures depending on the objective weighting principle employed. This methodological diversity is important because it indicates that the interpretation of criterion importance is closely related to the type of information selected as the basis for weighting.

2.3. Limitations of Objective Weighting Methods

Despite their advantages, objective weighting methods also present several methodological limitations. A major issue concerns the dependence of many methods on a particular statistical characteristic of the decision matrix[27]-[29]. For example, a dispersion-based method may assign greater importance to criteria exhibiting greater variability, whereas an entropy-based method may emphasize differences in the distribution of criterion values. Correlation-based approaches, in contrast, focus on the degree of redundancy between criteria. Each perspective provides useful information, but a single characteristic may not fully represent the complexity of criterion behavior within a heterogeneous decision matrix.



The reliance on a specific information characteristic can become problematic when criteria exhibit substantially different structural properties. Two criteria may have similar levels of variance but different distributions, ranges, or discriminatory patterns. Conversely, criteria with different levels of dispersion may contribute similar amounts of distinctive information when their relationships with other criteria are taken into account. Therefore, the use of a single statistical property does not necessarily provide a comprehensive description of the differences among criteria. This issue suggests that criterion importance may need to be interpreted through a broader representation of the structural characteristics of the decision matrix.

Another concern is the possibility of imbalanced or concentrated weights. When a weighting method strongly responds to a particular statistical characteristic, criteria exhibiting extreme values of that characteristic may receive disproportionately high weights, while other criteria may receive relatively small contributions. Such a weighting structure can cause the subsequent MCDM evaluation to become highly dependent on a limited number of criteria. Although this outcome may be mathematically consistent with the assumptions of a particular method, it may not always represent the broader informational structure of the decision matrix.

Furthermore, existing objective weighting methods do not always explicitly model criterion heterogeneity as a separate structural concept. The heterogeneity of criteria encompasses differences in variability, distribution, range, discriminatory capability, and relationships among criteria. These dimensions may exist simultaneously and may interact with one another. When weighting is derived from only one dimension, some of the structural differences between criteria may remain unrepresented. Thus, there is a methodological opportunity to develop an objective weighting mechanism that treats heterogeneity among criteria as an explicit source of weighting information rather than as an incidental consequence of another statistical measure.

These limitations do not imply that existing objective weighting methods are inappropriate. Rather, they indicate that different weighting principles capture different aspects of the decision matrix. The methodological challenge is therefore to develop a weighting framework capable of incorporating multiple characteristics of criteria while maintaining objectivity, interpretability, adaptability, and robustness. Such a framework could provide a more comprehensive representation of criterion importance, particularly in decision problems characterized by substantial differences among criteria.

2.4. Research Positioning

The present study is positioned within the development of objective criterion-weighting methods for MCDM, with particular emphasis on the explicit treatment of heterogeneity among criteria. Existing research has established several approaches for deriving objective weights from statistical properties of the decision matrix, including dispersion, variance, entropy, correlation, and information content.



These approaches provide different perspectives on the informational contribution of criteria and have been successfully incorporated into various MCDM models. However, their weighting mechanisms generally emphasize specific characteristics of the data rather than explicitly modeling the broader structural heterogeneity that distinguishes one criterion from another.

Based on this methodological context, the proposed HIVE Weighting is positioned as a heterogeneity-aware objective weighting approach. Rather than defining criterion importance exclusively through one statistical property, HIVE Weighting is designed to identify and quantify differences in criterion characteristics and incorporate the resulting heterogeneity information into the weighting process. The central distinction lies in treating heterogeneity itself as a meaningful source of information for determining criterion weights. In this framework, the objective is not simply to identify which criterion has greater dispersion or information content, but to characterize how each criterion differs within the overall structure of the decision matrix.

The positioning of HIVE Weighting can therefore be understood through five methodological characteristics: objectivity, heterogeneity awareness, adaptiveness, interpretability, and robustness. Objectivity refers to deriving weights from the decision data rather than requiring direct expert assignment. Heterogeneity awareness concerns the explicit representation of differences among criteria. Adaptiveness refers to the ability of the weighting mechanism to respond to changes in the underlying data structure. Interpretability concerns the extent to which the resulting weights can be explained through measurable characteristics of the criteria. Robustness refers to the stability of the weighting and subsequent ranking results when reasonable changes occur in the input data. Through these characteristics, the proposed approach seeks to extend the existing objective weighting literature by introducing a weighting perspective centered on the structural heterogeneity of criteria.

III. Proposed HIVE Weighting Method

The proposed HIVE Weighting method is developed to provide an objective criteria-weighting mechanism that accounts for differences in the statistical characteristics and heterogeneity of decision-making data. Unlike weighting approaches that primarily emphasize a single source of information, HIVE integrates multiple data characteristics to obtain a more comprehensive representation of criterion importance. The method is formulated to capture both the magnitude and dispersion of normalized criterion values while incorporating relative variation as an indicator of heterogeneity. Based on these characteristics, HIVE generates information measures that are subsequently transformed into normalized criteria weights, providing a consistent basis for their application in multi-criteria decision-making problems.



3.1. Conceptual Framework of HIVE Weighting

The conceptual framework of HIVE Weighting provides a general representation of the proposed approach for determining criteria importance from the inherent characteristics of decision-making data. The framework emphasizes the integration of informational characteristics, data variability, and heterogeneity to generate criteria weights that are responsive to differences in the underlying data structure. By considering these characteristics jointly, HIVE Weighting seeks to provide a more informative representation of criterion importance without relying on subjective preferences. The overall conceptual relationship underlying the proposed weighting approach is illustrated in Figure 1.

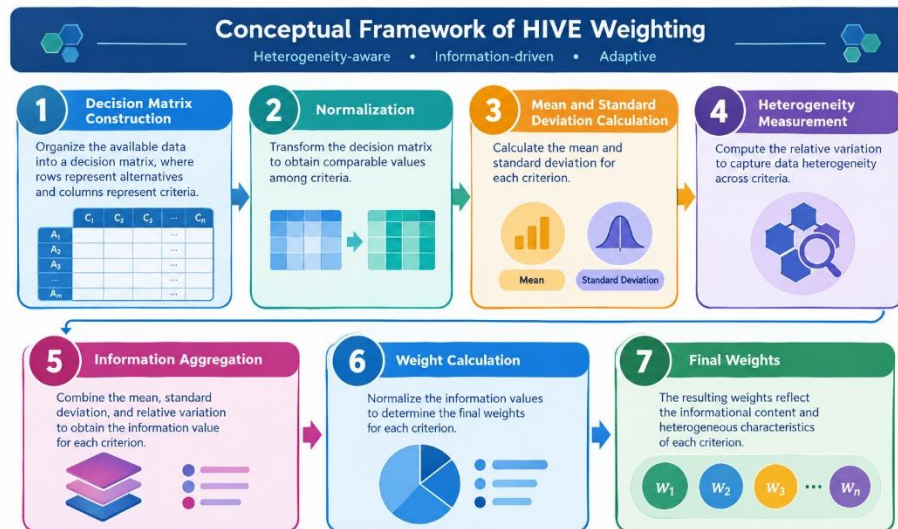


Figure 1. Framework of HIVE Weighting

The HIVE Weighting framework is designed to derive criteria weights by integrating the statistical characteristics and heterogeneity of the available decision data. The framework represents the transformation of the original decision information into a normalized form, from which the central tendency and dispersion of each criterion are evaluated. These characteristics are subsequently used to quantify relative variation and construct an information measure that reflects the combined contribution of criterion magnitude, variability, and heterogeneity. The resulting information measures are then converted into normalized weights, producing a weight vector in which criteria with greater informational contribution receive correspondingly higher weights. Through this structure, HIVE Weighting provides a data-driven mechanism for representing differences among criteria while maintaining a consistent and interpretable weighting scale.

3.2. HIVE Weighting Method

The determination of criteria weights using the HIVE Weighting method consists of a series of systematic stages designed to identify



the relative importance of each criterion while accounting for the heterogeneous characteristics of the decision data. Each stage is performed sequentially, beginning with the construction of the decision matrix and data normalization, followed by the measurement of information variation, heterogeneity, and the relative contribution of each criterion. The resulting information is then processed through an adaptive weighting mechanism to ensure that the final weights reflect both the informational content and the distinctive characteristics of the criteria. The criteria-weighting procedure of HIVE Weighting can be described through the following stages:

The first step in determining criterion weights using the HIVE weighting method is to construct a decision matrix that represents the performance values of each alternative with respect to all criteria considered in the decision-making process. The matrix consists of a set of alternatives and criteria, where each element represents the performance of a particular alternative under a specific criterion using (1). The decision matrix serves as the primary input for the HIVE weighting method, as the information contained within the matrix regarding the performance characteristics and differences among alternatives across criteria is subsequently used to determine the degree of heterogeneity and the corresponding objective criterion weights.

$$X = [x_{ij}]_{m \times n} \quad (1)$$

The second step involves normalizing the decision matrix using the Euclidean normalization approach. This process aims to transform the original criterion values into a comparable scale so that differences in measurement units and numerical magnitudes do not disproportionately influence the weighting process using (2). The normalization process preserves the relative relationships among alternatives within each criterion while producing standardized values that can be consistently used in the subsequent statistical calculations. Therefore, normalization provides a common basis for analyzing the distributional characteristics of different criteria.

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

The third step in the HIVE weighting procedure is to calculate the mean value of the normalized data for each criterion. The mean represents the central tendency and provides an indication of the general performance characteristics of alternatives with respect to each criterion using (3). This measure constitutes an important component of the HIVE method because it is considered together with measures of variation to characterize the heterogeneity of each criterion. Accordingly, this step establishes the average performance level of each criterion before its degree of dispersion is further examined.

$$\mu_j = \frac{1}{m} \sum_{i=1}^m r_{ij} \quad (3)$$



The fourth step is to calculate the standard deviation for each criterion in order to measure the dispersion of alternative performance values around their respective mean values. Standard deviation indicates the extent to which the performance of alternatives varies within a particular criterion using (4). A higher standard deviation indicates greater differences in performance among alternatives, whereas a lower standard deviation indicates that the performance values tend to be more homogeneous. This variation information provides an important basis for the HIVE method in identifying the degree of heterogeneity associated with each criterion.

$$\sigma_j = \sqrt{\frac{1}{m} \sum_{i=1}^m (r_{ij} - \mu_j)^2} \quad (4)$$

The fifth step involves calculating the Relative Variability to obtain a measure of variation that accounts for the mean level of each criterion. This approach enables the variability of a criterion to be assessed proportionally rather than solely on the basis of its absolute dispersion using (5). Consequently, criteria with different mean levels can be evaluated more consistently in terms of their relative variation. A small parameter is incorporated into the calculation to maintain numerical stability when the mean value of a criterion approaches zero. The resulting Relative Variability provides additional information regarding the relative dispersion of each criterion and complements the information obtained from the standard deviation.

$$RV_j = \frac{\sigma_j}{\mu_j + \varepsilon} \quad (5)$$

The sixth step represents the core of the HIVE Weighting method, namely the construction of the Heterogeneity Index for each criterion. The index integrates information on the mean value, absolute variability, and Relative Variability to provide a more comprehensive representation of the heterogeneity characteristics of each criterion using (6). Through this formulation, HIVE considers not only the general performance level of a criterion but also the extent of variation and relative differences observed among alternatives. The resulting Heterogeneity Index therefore provides the primary basis for determining the relative importance of each criterion within the proposed weighting framework.

$$H_j = \mu_j + \sigma_j + RV_j \quad (6)$$

The final step is to determine the HIVE criterion weights based on the Heterogeneity Index values obtained in the preceding stage. Each Heterogeneity Index is converted into a relative criterion weight by normalizing it against the total Heterogeneity Index across all criteria using (7). This normalization ensures that the resulting criterion weights collectively sum to one. The final HIVE weights represent the relative contribution of each criterion based on the characteristics of the observed data and the degree of heterogeneity identified across the alternatives. These weights can subsequently be incorporated into an MCDM method to support the evaluation and ranking of alternatives.



$$w_j = \frac{H_j}{\sum_{j=1}^n H_j} \quad (7)$$

Overall, the HIVE Weighting method provides a systematic and data-driven procedure for determining objective criterion weights by incorporating the central tendency, absolute variability, and relative variability of normalized performance data. Through the sequential calculation of the Heterogeneity Index, the method captures differences in the characteristics of alternatives across criteria and transforms these characteristics into normalized criterion weights. The resulting weights reflect the relative contribution of each criterion based on the information contained in the decision matrix, thereby reducing the dependence on subjective weight assignments. The final HIVE weights can subsequently be integrated with various MCDM methods to support the objective evaluation and ranking of alternatives in complex decision-making problems.

3.3. Research Design

Research design is a structured framework that defines how a research study is planned, conducted, and evaluated to address the research objectives systematically. It establishes the overall research strategy, data sources, analytical procedures, and evaluation techniques used throughout the study. In methodological research, the research design provides a clear structure for developing the proposed method, applying it to decision-making data, and evaluating its performance through comparative and robustness analyses. The research design adopted in this study is illustrated in Figure 2.

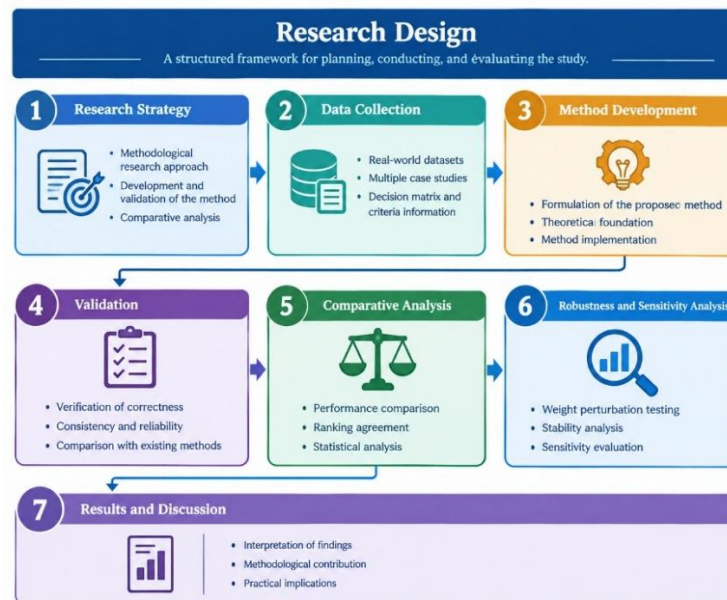
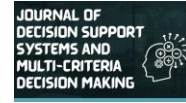


Figure 2. Research Design

The research design presented in Figure 2 illustrates the overall structure of the study from its methodological foundation to the



interpretation of the resulting findings. It integrates the research strategy, data collection, method development, validation, comparative analysis, and robustness and sensitivity evaluation within a connected analytical framework. The design emphasizes a systematic progression in which the proposed method is developed from an established methodological basis, examined using relevant decision-making datasets, and subsequently evaluated through multiple forms of empirical assessment. The final stage focuses on interpreting the findings and identifying the methodological and practical implications, thereby providing a coherent framework for assessing the applicability and reliability of the proposed approach.

IV. Experimental Design

The experimental design is developed to systematically evaluate the effectiveness and applicability of the proposed HIVE Weighting method in MCDM problems. The evaluation is conducted by applying HIVE Weighting to a representative decision matrix and integrating the resulting criterion weights with several established MCDM methods to examine their influence on alternative evaluation and ranking. To provide a comprehensive assessment, the experimental design includes comparisons with other objective weighting methods, cross-method ranking analysis, and sensitivity and robustness evaluations. This experimental setting enables the proposed HIVE Weighting method to be examined from multiple perspectives, particularly in terms of criterion weight distribution, ranking consistency, and stability under different weighting and MCDM configurations.

4.1. Dataset

The dataset consists of performance assessment data representing a set of alternatives evaluated across several predefined decision criteria. Each alternative is described by a series of numerical values corresponding to its performance on each criterion, forming a structured decision matrix. The dataset is organized systematically to ensure that each alternative has a complete and comparable set of assessment values across all criteria. These data provide a comprehensive representation of the differences in performance among alternatives and serve as the basis for subsequent analysis and evaluation.

The dataset used in this study consists of decision-making data designed to evaluate alternatives across multiple criteria within the context of fair decision making. The dataset includes a set of alternatives assessed according to predefined criteria representing the relevant attributes and performance dimensions of each alternative. The assessment data are presented in Table 1, which contains the performance values of all alternatives across the selected criteria. The dataset is organized as a structured decision matrix, where each row represents an alternative and each column represents an evaluation criterion, providing a comprehensive representation of the differences in



alternative performance and the trade-offs among criteria considered in the decision-making process.

Table 1. Performance Assessment Data of Lecturer Candidates [30]

Alternatives	CM10	CM11	CM12	CM13	CM14
SA-C	620	750	12	90	9
CF-C	600	720	15	88	8
RF-C	650	800	10	93	8
TR-C	580	670	14	85	7
IH-C	630	790	13	91	9
AK-C	610	740	11	87	8
GM-C	590	650	9	84	6
MF-C	640	770	16	89	9
SH-C	600	700	11	86	7
DG-C	610	680	13	88	8

The criteria used to evaluate prospective lecturers consist of five indicators representing academic qualifications, language proficiency, research productivity, and teaching capabilities. CM10 (TOEFL Score) represents the candidate's English language proficiency based on the TOEFL assessment. CM11 (TKDA Score) reflects the candidate's academic aptitude and general reasoning ability as measured through the TKDA assessment. CM12 (Number of Publications) indicates the candidate's research productivity and academic contribution based on the number of scientific publications produced. CM13 (Interview Score) represents the candidate's communication skills, academic suitability, motivation, and overall performance during the interview process. Finally, CM14 (Teaching Ability Score) reflects the candidate's pedagogical competence, instructional skills, and ability to effectively deliver learning materials. Collectively, these criteria provide a multidimensional representation of the qualifications and capabilities of prospective lecturers considered in the lecturer admission process.

4.2. Implementation HIVE Weighting Method

The HIVE Weighting method is implemented to determine the relative importance of the criteria used in the evaluation of branch manager candidates. The implementation involves a series of systematic procedures that process the assessment data and produce a set of criterion weights. Each stage contributes to the transformation of the initial assessment data into final weights that can be used in the subsequent decision-making process. The detailed stages of the HIVE Weighting implementation are presented in the following sections.

The first step in determining weights using HIVE weighting is to build a decision matrix that represents the performance values of each alternative based on all the criteria using (1), the general form of the decision matrix in the HIVE weighting method are as follows.



$$X = \begin{bmatrix} x_{11} & x_{12} & x_{13} & x_{14} & x_{15} \\ x_{21} & x_{22} & x_{23} & x_{24} & x_{25} \\ x_{31} & x_{32} & x_{33} & x_{34} & x_{35} \\ x_{41} & x_{42} & x_{43} & x_{44} & x_{45} \\ x_{51} & x_{52} & x_{53} & x_{54} & x_{55} \\ x_{61} & x_{62} & x_{63} & x_{64} & x_{65} \\ x_{71} & x_{72} & x_{73} & x_{74} & x_{75} \\ x_{81} & x_{82} & x_{83} & x_{84} & x_{85} \\ x_{91} & x_{92} & x_{93} & x_{94} & x_{95} \\ x_{101} & x_{102} & x_{103} & x_{104} & x_{105} \end{bmatrix}$$

The results of the decision matrix for the assessment data based on Table 1 are as follows.

$$X = \begin{bmatrix} 620 & 750 & 12 & 90 & 9 \\ 600 & 720 & 15 & 88 & 8 \\ 650 & 800 & 10 & 93 & 8 \\ 580 & 670 & 14 & 85 & 7 \\ 630 & 790 & 13 & 91 & 9 \\ 610 & 740 & 11 & 87 & 8 \\ 590 & 650 & 9 & 84 & 6 \\ 640 & 770 & 16 & 89 & 9 \\ 600 & 700 & 11 & 86 & 7 \\ 610 & 680 & 13 & 88 & 8 \end{bmatrix}$$

The second step in determining weights using HIVE weighting is to normalize the decision matrix using (2). The results of the normalization calculation in the HIVE weighting method are as follows.

$$\begin{aligned} r_{11} &= \frac{x_{11}}{\sqrt{\sum_{i=1}^{10} x_{i1}^2}} = \frac{x_{11}}{\sqrt{x_{11}^2 + x_{21}^2 + x_{31}^2 + x_{41}^2 + x_{51}^2 + x_{61}^2 + x_{71}^2 + x_{81}^2 + x_{91}^2 + x_{101}^2}} \\ &= \frac{620}{\sqrt{620^2 + 600^2 + 650^2 + 580^2 + 630^2 + 610^2 + 590^2 + 640^2 + 600^2 + 610^2}} \\ &= \frac{620}{\sqrt{3762100}} = \frac{620}{1939.6134} = 0.320 \end{aligned}$$

The overall normalization results that have been calculated are shown in the following Table 2.

Table 2. Normalization Results of the HIVE Weighting Method

Alternatives	CM10	CM11	CM12	CM13	CM14
SA-C	0.320	0.325	0.302	0.323	0.358
CF-C	0.309	0.312	0.377	0.316	0.318
RF-C	0.335	0.347	0.251	0.334	0.318
TR-C	0.299	0.291	0.352	0.305	0.278
IH-C	0.325	0.343	0.327	0.326	0.358
AK-C	0.314	0.321	0.277	0.312	0.318
GM-C	0.304	0.282	0.226	0.301	0.238
MF-C	0.330	0.334	0.402	0.319	0.358
SH-C	0.309	0.304	0.277	0.309	0.278
DG-C	0.314	0.295	0.327	0.316	0.318



The third step in determining weights using HIVE weighting is calculating the average value from the normalized data using (3). The result of the average value calculation in the HIVE weighting method is as follows.

$$\begin{aligned}\mu_1 &= \frac{1}{10} \sum_{i=1}^{10} r_{i1} = \frac{1}{9} (r_{11} + r_{21} + r_{31} + r_{41} + r_{51} + r_{61} + r_{71} + r_{81} + r_{91} + r_{101}) \\ &= \frac{1}{10} (0.320 + 0.309 + 0.335 + 0.299 + 0.325 + 0.314 + 0.304 + 0.330 + 0.309 + 0.314) \\ &= \frac{1}{10} (3.1604) = 0.3160\end{aligned}$$

The overall average value results that have been calculated are shown in the following Table 3.

Table 3. Average Value Results of the HIVE Weighting Method

CM10	CM11	CM12	CM13	CM14
0.3160	0.3155	0.3118	0.3161	0.3140

The fourth stage in determining the weight using HIVE weighting is to calculate the standard deviation on each criterion using (4), the result of the calculation of the standard deviation value in the HIVE weighting method as follows.

$$\begin{aligned}\sigma_1 &= \sqrt{\frac{1}{10} \sum_{i=1}^{10} (r_{i1} - \mu_1)^2} \\ &= \sqrt{\frac{1}{10} \left((r_{11} - \mu_1)^2 + (r_{21} - \mu_1)^2 + (r_{31} - \mu_1)^2 + (r_{41} - \mu_1)^2 + (r_{51} - \mu_1)^2 + \right. \\ &\quad \left. + (r_{61} - \mu_1)^2 + (r_{71} - \mu_1)^2 + (r_{81} - \mu_1)^2 + (r_{91} - \mu_1)^2 + (r_{101} - \mu_1)^2 \right)} \\ &= \sqrt{\frac{1}{10} \left((0.320 - 0.3160)^2 + (0.309 - 0.3160)^2 + (0.335 - 0.3160)^2 + (0.299 - 0.3160)^2 + \right. \\ &\quad \left. (0.325 - 0.3160)^2 + (0.314 - 0.3160)^2 + (0.304 - 0.3160)^2 + (0.330 - 0.3160)^2 + (0.309 - 0.3160)^2 + (0.314 - 0.3160)^2 \right)} = 0.0108\end{aligned}$$

The overall standard deviation value results that have been calculated are shown in the following Table 4.

Table 4. Standard Deviation Results of the HIVE Weighting Method

CM10	CM11	CM12	CM13	CM14
0.0108	0.0213	0.0530	0.0094	0.0375

The fifth step in determining weights using HIVE weighting is calculating relative variability to get a measure of variation that considers the average level of each criterion with (5), the calculation results of relative variability in the HIVE weighting method are as follows.

$$RV_1 = \frac{\sigma_1}{\mu_1 + \varepsilon} = \frac{0.0108}{0.3160 + 10^{-10}} = \frac{0.0108}{0.3160} = 0.0343$$

The overall relative variability results that have been calculated are shown in the following Table 5.

**Table 5. Relative Variability Results of the HIVE Weighting Method**

CM10	CM11	CM12	CM13	CM14
0.0343	0.0674	0.1699	0.0298	0.1194

The sixth step in determining weights using HIVE weighting is the formation of a heterogeneity index for each criterion using (6), the results of the heterogeneity index calculation in the HIVE weighting method are as follows.

$$H_1 = \mu_1 + \sigma_1 + RV_1 = 0.3160 + 0.0108 + 0.0343 = 0.3611$$

The overall heterogeneity index results that have been calculated are shown in the following Table 6.

Table 6. Heterogeneity Index Results of the HIVE Weighting Method

CM10	CM11	CM12	CM13	CM14
0.3611	0.4042	0.5347	0.3553	0.4709

The final stage in determining the weights using HIVE weighting is to calculate the weight values for all criteria using (7). The results of the weight value calculations in the HIVE weighting method are as follows.

$$\begin{aligned}
 w_1 &= \frac{H_1}{\sum_{j=1}^n H_j} = \frac{H_1}{H_1 + H_2 + H_3 + H_4 + H_5} \\
 &= \frac{0.3611}{0.3611 + 0.4042 + 0.5347 + 0.3553 + 0.4709} \\
 &= \frac{0.3611}{2.1262} = 0.1698
 \end{aligned}$$

The overall weight values results that have been calculated are shown in the following Table 7.

Table 7. Weight Values Results of the HIVE Weighting Method

CM10	CM11	CM12	CM13	CM14
0.1698	0.1901	0.2515	0.1671	0.2215

Table 7 presents the weight values generated by the HIVE Weighting method for the five criteria used in the lecturer admission assessment, namely CM10 (TOEFL Score), CM11 (TKDA Score), CM12 (Number of Publications), CM13 (Interview Score), and CM14 (Teaching Ability Score). The obtained weights indicate differences in the relative contribution of each criterion to the decision-making process. CM12 (Number of Publications) receives the highest weight of 0.2515, indicating its relatively greater informational contribution, followed by CM14 (Teaching Ability Score) with a weight of 0.2215 and CM11 (TKDA Score) with 0.1901. Meanwhile, CM10 (TOEFL Score) and CM13 (Interview Score) obtain weights of 0.1698 and 0.1671, respectively. Overall, the variation in weight values demonstrates that HIVE Weighting differentiates the relative importance of each criterion according to the characteristics of the assessment data and their contributions to the evaluation of prospective lecturers.



The HIVE Weighting results demonstrate that the proposed method produces differentiated weight values across criteria CM10 to CM14, reflecting variations in their underlying data characteristics. CM12 (Number of Publications) obtains the highest weight at 0.2515, followed by CM14 (Teaching Ability Score) at 0.2215 and CM11 (TKDA Score) at 0.1901. Meanwhile, CM10 (TOEFL Score) receives a weight of 0.1698, while CM13 (Interview Score) records the lowest weight at 0.1671. The differences among the resulting weights indicate that HIVE is able to distinguish the relative informational contribution of each criterion rather than assigning uniform importance. These findings support the use of HIVE Weighting as a data-driven approach for capturing differences in criterion characteristics and translating them into differentiated weighting values for subsequent multi-criteria decision-making analysis.

V. Result

5.1. Comparative Analysis of Criterion Weights

The comparison with existing objective weighting methods is conducted to examine the characteristics of the weights generated by HIVE Weighting in relation to other established data-driven weighting approaches. This evaluation focuses exclusively on the distribution, magnitude, and relative importance of the criteria produced by each method. By comparing the resulting weight values, the analysis aims to identify similarities and differences in how each approach interprets the informational characteristics and variability contained in the dataset. Particular attention is given to the ability of HIVE Weighting to produce differentiated and meaningful weight distributions while accounting for the heterogeneous nature of the criteria. This comparison provides an objective basis for understanding the distinctive behavior of the proposed weighting method and clarifies its contribution to the development of alternative objective weighting techniques.

The comparison involves six objective weighting methods, namely Entropy, WENSLO, LOGSTA, CRITIC, MEREC, and the proposed HIVE Weighting method. The resulting weight distributions reveal differences in how each approach assigns relative importance to the evaluated criteria. Entropy determines weights based on the degree of information diversification[31], while WENSLO and LOGSTA employ their respective mathematical formulations to capture criterion-specific characteristics[31], [32]. CRITIC considers the contrast intensity and correlation structure among criteria, whereas MEREC evaluates the influence of criteria through the effect of their removal from the decision framework[33], [34]. In contrast, HIVE Weighting incorporates central tendency, dispersion, and relative variation to represent the heterogeneous characteristics of the data. The comparative results of the six objective weighting methods are presented in Table 8, providing a direct overview of the resulting weight values and the differences in criterion importance identified by each approach.

**Table 8. Comparison of Criteria Weights**

Method	CM10	CM11	CM12	CM13	CM14
Entropy	0.0233	0.0906	0.5769	0.0176	0.2915
WENSLO	0.0247	0.0805	0.6025	0.0197	0.2726
LOGSTA	0.0929	0.0874	0.2924	0.3101	0.2171
CRITIC	0.1663	0.1607	0.3744	0.1515	0.1470
MEREC	0.0951	0.1570	0.4419	0.0876	0.2184
HIVE	0.1698	0.1901	0.2515	0.1671	0.2215

The comparison of the criteria weights presented in Table 8 shows the weighting results generated by Entropy, WENSLO, LOGSTA, CRITIC, MEREC, and HIVE for criteria CM10 to CM14. The results reveal substantial differences in the weighting patterns produced by the six methods, indicating that each approach responds differently to the information characteristics of the lecturer admission criteria. Entropy assigns its highest weight to CM12 (Number of Publications) at 0.5769, followed by CM14 (Teaching Ability Score) at 0.2915, whereas CM13 (Interview Score) receives the lowest weight of 0.0176. WENSLO exhibits a similar pattern, assigning the largest weights to CM12 at 0.6025 and CM14 at 0.2726, while CM13 again obtains the smallest weight at 0.0197.

LOGSTA produces a different distribution compared with Entropy and WENSLO. Its highest weight is assigned to CM13 (Interview Score) at 0.3101, followed by CM12 (Number of Publications) at 0.2924 and CM14 (Teaching Ability Score) at 0.2171. In contrast, CM11 (TKDA Score) and CM10 (TOEFL Score) receive relatively lower weights of 0.0874 and 0.0929, respectively. CRITIC generates another distinctive weighting structure, with CM12 obtaining the highest weight at 0.3744, followed by CM10 at 0.1663 and CM11 at 0.1607. Meanwhile, CM14 and CM13 receive weights of 0.1470 and 0.1515, respectively, indicating a more distributed weighting pattern than those produced by Entropy and WENSLO.

MEREC produces a weighting distribution in which CM12 (Number of Publications) remains the most influential criterion, with a weight of 0.4419. CM14 (Teaching Ability Score) follows with 0.2184, while CM11 (TKDA Score) obtains 0.1570. The lowest weights are assigned to CM10 (TOEFL Score) and CM13 (Interview Score), with values of 0.0951 and 0.0876, respectively. In comparison, HIVE generates a comparatively balanced distribution across the five criteria. Its highest weight is assigned to CM12 at 0.2515, followed by CM14 at 0.2215 and CM11 at 0.1901. CM10 and CM13 obtain weights of 0.1698 and 0.1671, respectively. This distribution indicates that HIVE avoids excessive concentration on a single criterion while still differentiating the relative contribution of each criterion.

Overall, the comparison demonstrates that CM12 (Number of Publications) is consistently assigned a substantial weight by Entropy, WENSLO, CRITIC, MEREC, and HIVE, although the magnitude varies considerably across methods. LOGSTA differs from these methods by assigning its highest weight to CM13 (Interview Score). HIVE exhibits the most balanced weighting structure among the compared methods, with its values ranging from 0.1671 to 0.2515. In contrast, Entropy and WENSLO produce considerably wider weight distributions, particularly by



assigning very high weights to CM12 and substantially lower weights to CM13. These differences illustrate the distinctive weighting behavior of each objective weighting method and demonstrate how alternative approaches can produce different interpretations of the relative importance of criteria in prospective lecturer evaluation.

5.2. MCDM Ranking Results Using HIVE Weighting

The implementation of HIVE Weighting with MCDM integrates the objective criterion weights generated by HIVE Weighting with selected MCDM methods to evaluate and rank the alternatives. In this framework, the HIVE Weighting method is first applied to determine the relative importance of the criteria based on the characteristics of the assessment data. The resulting weights are then incorporated into the MCDM process to assess the performance of each alternative across the considered criteria and obtain the final ranking. This integration enables the evaluation process to consider both the objective characteristics of the criteria and the overall performance of the alternatives, providing a systematic framework for multi-criteria decision analysis[35], [36].

The implementation of HIVE Weighting with the Simple Additive Weighting (SAW) method integrates the objective criterion weights generated by HIVE Weighting with the SAW approach to evaluate and rank branch manager candidates. In this framework, HIVE Weighting is first applied to determine the relative importance of each criterion based on the characteristics of the assessment data. The resulting HIVE weights are subsequently incorporated into the SAW process, where the performance values of each candidate are normalized according to the type of criterion and aggregated using the corresponding criterion weights. The final preference values obtained from the SAW process are then used to determine the ranking of the branch manager candidates. The overall implementation process, including the HIVE Weighting stages, SAW evaluation, and the resulting ranking of alternatives, is illustrated in Figure 3.

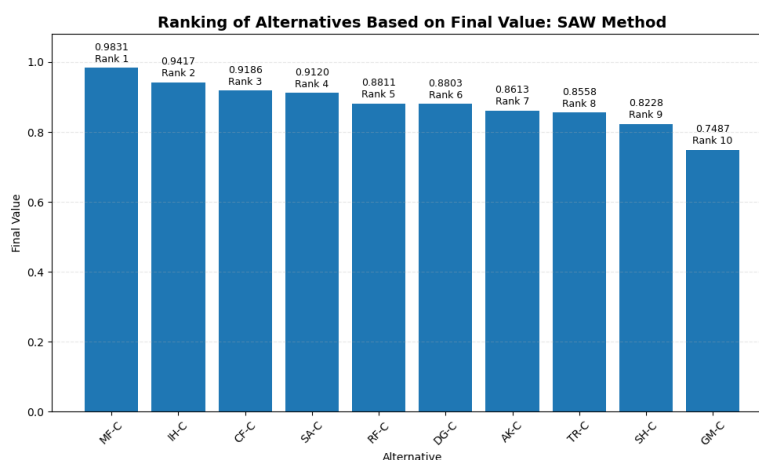


Figure 3. Ranking Results from the Combination of HIVE Weighting with the SAW Method



The SAW method produces a clear ranking of the lecturer candidates based on their final preference values. MF-C achieves the highest final value of 0.9831 and is ranked first, followed by IH-C with 0.9417 and CF-C with 0.9186 in the second and third positions, respectively. SA-C occupies the fourth position with a value of 0.9120, while RF-C and DG-C rank fifth and sixth with values of 0.8811 and 0.8803. The subsequent positions are occupied by AK-C (0.8613), TR-C (0.8558), SH-C (0.8228), and GM-C (0.7487), which ranks tenth. Overall, the ranking demonstrates a gradual decrease in final values across the alternatives, with MF-C showing the highest aggregated performance and GM-C obtaining the lowest final value under the SAW evaluation.

The implementation of HIVE Weighting with the Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA) method integrates the objective criterion weights generated by HIVE Weighting with the MOORA approach to evaluate and rank branch manager candidates. In this framework, HIVE Weighting is first applied to determine the relative importance of each criterion based on the characteristics of the assessment data. The resulting HIVE weights are subsequently incorporated into the MOORA process, where the performance values of each candidate are normalized and evaluated according to the corresponding benefit and cost criteria. The weighted normalized values are then aggregated to obtain the overall optimization value for each candidate, which is used to determine the final ranking. The overall implementation process, including the HIVE Weighting stages, MOORA evaluation, and the resulting ranking of alternatives, is illustrated in Figure 4.

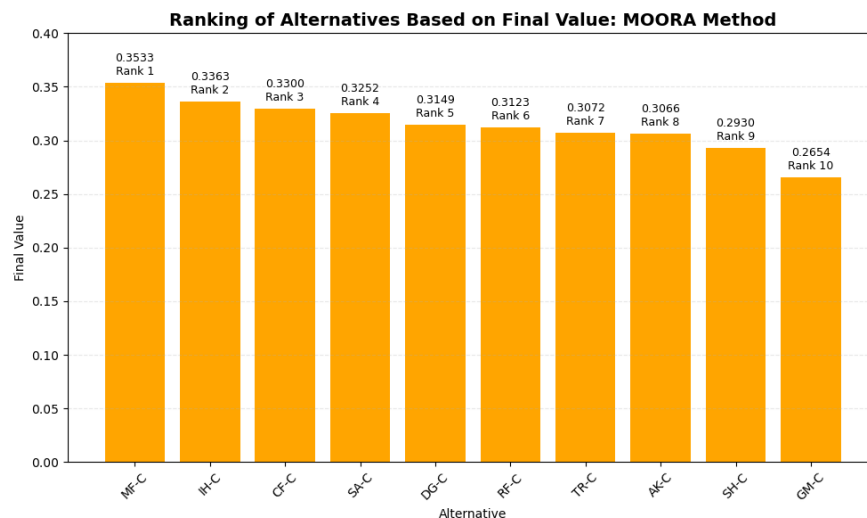


Figure 4. Ranking Results from the Combination of HIVE Weighting with the MOORA Method

The MOORA method generates a ranking in which MF-C achieves the highest final value of 0.3533, placing it in first position, followed by IH-C with 0.3363 and CF-C with 0.3300 in the second and third positions. SA-



C ranks fourth with a final value of 0.3252, while DG-C and RF-C occupy the fifth and sixth positions with values of 0.3149 and 0.3123, respectively. The remaining alternatives are ranked as TR-C (0.3072), AK-C (0.3066), SH-C (0.2930), and GM-C (0.2654), which occupies the tenth position. Overall, the MOORA results show a consistent ordering pattern in which the alternatives are differentiated according to their final preference values, with MF-C obtaining the highest value and GM-C the lowest.

The ranking results obtained from the SAW and MOORA methods show an identical ordering of the ten alternatives. Both methods place MF-C in the first position, followed by IH-C, CF-C, SA-C, and RF-C in the second to fifth positions, respectively. The subsequent positions are occupied by DG-C, TR-C, AK-C, SH-C, and GM-C. Although the numerical final values differ between the two methods, with SAW producing values ranging from 0.9831 to 0.7487 and MOORA generating values from 0.3533 to 0.2654, the resulting rankings remain completely consistent. This agreement indicates that the relative ordering of the alternatives is stable across the two MCDM approaches for the evaluated lecturer admission dataset, with MF-C maintaining the highest position and GM-C occupying the lowest position in both analyses.

5.3. Ranking Comparison with Objective Weighting

The ranking comparison with objective weighting is conducted to examine how differences in criteria weights influence the resulting order of alternatives. In this analysis, HIVE Weighting is compared with several established objective weighting methods by applying the same decision matrix and ranking procedure to ensure a consistent basis for evaluation. The comparison focuses on the resulting preference values and alternative rankings generated under different weight distributions, allowing the stability of the ranking outcomes to be observed across weighting schemes. Particular attention is given to whether changes in criterion importance lead to substantial changes in the relative positions of the alternatives. The comparative ranking results provide further insight into the behavior of HIVE Weighting when its derived weights are applied within the subsequent decision-making analysis.

The ranking comparison is performed by combining six objective weighting methods, namely Entropy, WENSLO, LOGSTA, CRITIC, MEREC, and the proposed HIVE Weighting method, with the SAW method. This analysis aims to examine how different criteria-weight distributions affect the preference values and ranking positions of the alternatives when the same SAW procedure is applied. Each weighting method generates a distinct set of criteria weights based on the characteristics of the decision data, while SAW is consistently used to calculate the final preference values and determine the alternative rankings. This structure allows the ranking outcomes associated with HIVE Weighting to be examined alongside those obtained from established objective weighting approaches under the same ranking mechanism. The resulting preference values and ranking positions are presented to identify the differences and similarities produced by the six weighting schemes. The comparative ranking results



obtained from the six objective weighting methods combined with SAW are presented in Figure 7, providing a visual representation of the ranking positions generated by each weighting scheme.

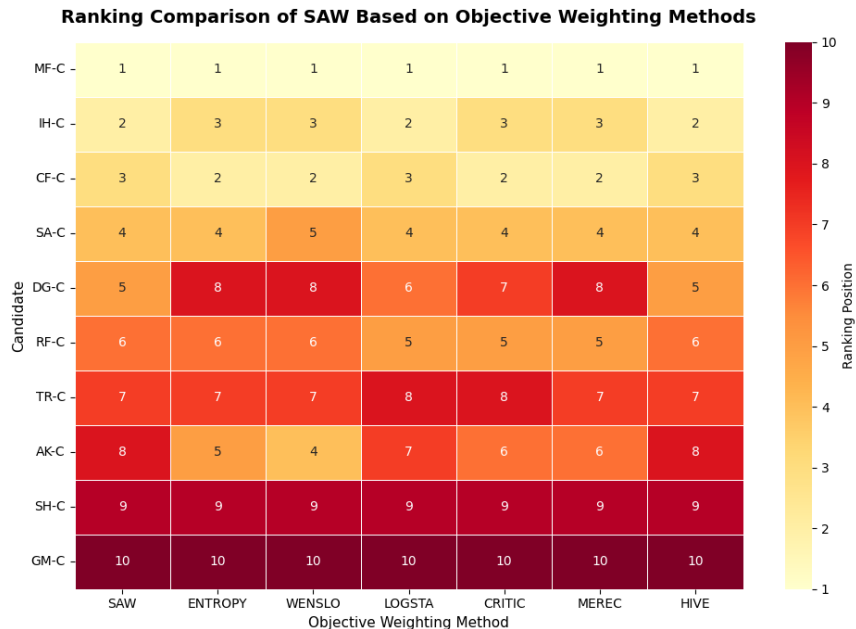


Figure 5. Ranking Comparison using the SAW Method

Figure 5 presents the ranking comparison obtained using the SAW method with six objective weighting approaches, namely Entropy, WENSLO, LOGSTA, CRITIC, MEREC, and HIVE Weighting. The heatmap shows that MF-C consistently occupies the first position across all weighting methods, while SH-C and GM-C remain in the ninth and tenth positions, respectively. IH-C and CF-C exchange the second and third positions under several weighting schemes, whereas SA-C consistently remains in fourth position except under WENSLO, where it moves to fifth. The most noticeable variations occur among DG-C, RF-C, TR-C, and AK-C. DG-C ranges from fifth to eighth, RF-C from fifth to sixth, TR-C from seventh to eighth, and AK-C from fourth to eighth depending on the weighting method. In contrast, the relative positions of the leading and lowest-ranked alternatives remain highly stable. Overall, the heatmap indicates that changes in objective weighting affect several middle-ranked alternatives, but do not substantially alter the overall ranking structure of the lecturer candidates.

The ranking comparison is performed by combining six objective weighting methods, namely Entropy, WENSLO, LOGSTA, CRITIC, MEREC, and the proposed HIVE Weighting method, with the MOORA method. This analysis aims to examine how different criteria-weight distributions affect the preference values and ranking positions of the alternatives when the same MOORA procedure is applied. Each weighting method generates a distinct set of criteria weights based on the characteristics of the decision data, while MOORA is consistently used to calculate the final



preference values and determine the alternative rankings. This structure allows the ranking outcomes associated with HIVE Weighting to be examined alongside those obtained from established objective weighting approaches under the same ranking mechanism. The resulting preference values and ranking positions are presented to identify the differences and similarities produced by the six weighting schemes. The comparative ranking results obtained from the six objective weighting methods combined with MOORA are presented in Figure 6, providing a visual representation of the ranking positions generated by each weighting scheme.

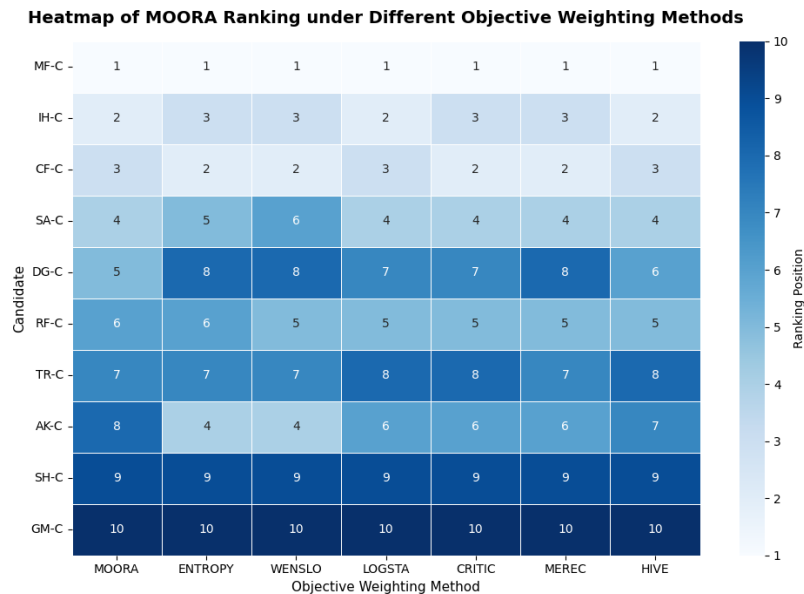


Figure 6. Ranking Comparison using the MOORA Method

Figure 6 presents the ranking comparison obtained by applying the MOORA method with six objective weighting approaches, namely Entropy, WENSLO, LOGSTA, CRITIC, MEREC, and HIVE Weighting. The results show that MF-C consistently occupies the first position across all weighting methods, while SH-C and GM-C remain in the ninth and tenth positions, respectively. IH-C and CF-C alternate between the second and third positions across the weighting schemes, indicating minor changes among the top-ranked alternatives. Greater variations are observed among the middle-ranked alternatives, particularly SA-C, DG-C, RF-C, TR-C, and AK-C. SA-C ranges from fourth to sixth, DG-C from fifth to eighth, RF-C from fifth to sixth, TR-C from seventh to eighth, and AK-C from fourth to eighth across the different weighting methods. These changes indicate that variations in criterion weights can affect the relative positions of several middle-ranked alternatives, while the leading and lowest-ranked alternatives remain comparatively stable under the MOORA procedure.

The comparative analysis demonstrates that the six objective weighting methods, namely Entropy, WENSLO, LOGSTA, CRITIC, MEREC, and



HIVE Weighting, produce highly consistent ranking patterns when integrated with the MOORA method. MF-C consistently occupies the first position across all weighting schemes, while SH-C and GM-C remain in the ninth and tenth positions, respectively. IH-C and CF-C alternate between the second and third positions, whereas the middle-ranked alternatives exhibit greater variation. In particular, SA-C ranges from fourth to sixth position, DG-C from fifth to eighth, RF-C from fifth to sixth, TR-C from seventh to eighth, and AK-C from fourth to eighth. These variations indicate that differences in the objective weights primarily affect the relative ordering of the middle-ranked alternatives, while the highest- and lowest-ranked candidates remain stable. Overall, the results show that HIVE Weighting produces a ranking pattern that remains broadly consistent with the other objective weighting approaches when applied within the MOORA framework.

5.4. Sensitivity Analysis

Sensitivity analysis is conducted to examine the stability of the ranking results obtained from the integration of HIVE Weighting and the SAW method under variations in criterion weights. The analysis systematically modifies the weights of the selected criteria while maintaining the total weight equal to one, and subsequently evaluates the changes in the preference values and ranking positions of the alternatives. This process provides an assessment of the extent to which the SAW ranking results are affected by changes in the relative importance of the criteria. A stable ranking across different weight scenarios indicates that the decision results remain consistent despite variations in criterion weights, whereas considerable changes in ranking positions indicate a higher sensitivity to the corresponding criteria. The sensitivity analysis therefore provides additional evidence regarding the robustness and stability of the proposed HIVE-SAW decision-making framework.

Sensitivity analysis is conducted to evaluate the stability of the criterion weighting results obtained using HIVE Weighting by systematically varying the original criterion weights. The sensitivity scenarios are established by increasing and decreasing each original HIVE weight by 0.05, 0.10, 0.15, and 0.20, respectively, to examine the effect of progressively larger weight variations on the resulting weight distribution. The resulting criterion weights for each sensitivity scenario, including the original weights and the corresponding positive and negative variations of ± 0.05 , ± 0.10 , ± 0.15 , and ± 0.20 , are presented in Table 9. These scenarios provide a systematic basis for assessing how changes in the relative importance of individual criteria affect the overall distribution of HIVE criterion weights.

Table 9. Comparison of Criteria Weights

Case	Changed Criteria	Changes	CM10	CM11	CM12	CM13	CM14
Test 1	CM10	-0.1500	0.0198	0.2244	0.2969	0.1973	0.2615
Test 2	CM10	-0.1000	0.0698	0.213	0.2818	0.1872	0.2482



Test 3	CM10	-0.0500	0.1198	0.2015	0.2666	0.1772	0.2348
Test 4	CM10	0.0500	0.2198	0.1787	0.2364	0.157	0.2082
Test 5	CM10	0.1000	0.2698	0.1672	0.2212	0.147	0.1948
Test 6	CM10	0.1500	0.3198	0.1558	0.2061	0.1369	0.1815
Test 7	CM10	0.2000	0.3698	0.1443	0.1909	0.1268	0.1681
Test 8	CM11	-0.1500	0.2012	0.0401	0.2981	0.198	0.2625
Test 9	CM11	-0.1000	0.1908	0.0901	0.2826	0.1877	0.2488
Test 10	CM11	-0.0500	0.1803	0.1401	0.267	0.1774	0.2352
:	:	:	:	:	:	:	:
:	:	:	:	:	:	:	:
Test 35	CM14	0.1000	0.1480	0.1657	0.2192	0.1456	0.3215
Test 36	CM14	0.1500	0.1371	0.1535	0.2030	0.1349	0.3715
Test 37	CM14	0.2000	0.1262	0.1413	0.1869	0.1242	0.4215

For each scenario, the adjusted criterion weights are applied to the SAW evaluation, and the resulting preference values and rankings are compared with the original results to identify changes in the positions of the alternatives under different weight conditions. The sensitivity analysis results, including the changes in ranking positions across the weight variation scenarios, are presented in Figure 7. This analysis provides an assessment of the stability of the HIVE-SAW results and indicates the extent to which the ranking is affected by changes in the relative importance of the criteria.

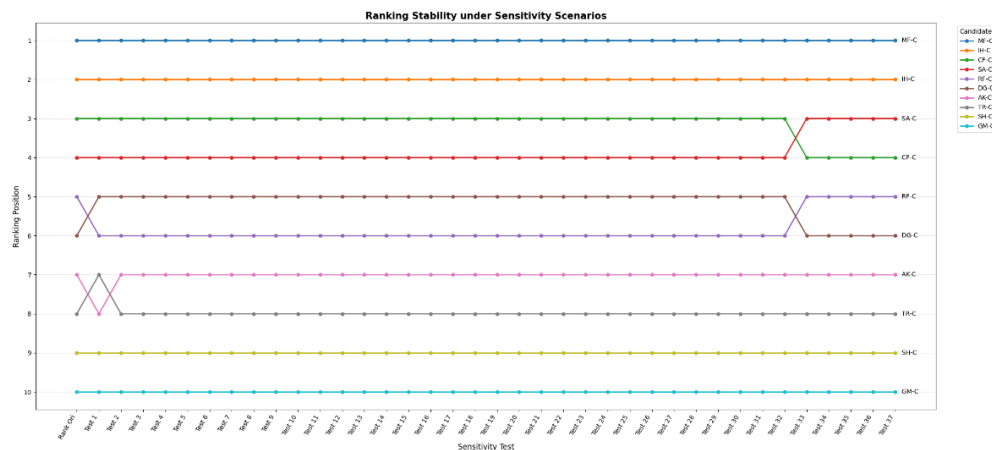


Figure 7. Comparison of Alternative Rankings using SAW Method

Figure 7 illustrates the ranking stability of the alternatives under the 37 sensitivity test scenarios generated from variations in the HIVE criterion weights and evaluated using the SAW method. The results show that MF-C and IH-C consistently maintain the first and second positions, respectively, throughout all scenarios, while SH-C and GM-C remain stable at ninth and tenth positions. DG-C and RF-C exhibit a consistent exchange of positions, with DG-C ranked fifth and RF-C sixth across Tests 1-33, before reversing to sixth and fifth, respectively, in Tests 34-37. A similar pattern is observed for CF-C and SA-C, which maintain third and fourth positions through Test 33 and then exchange positions in Tests 34-37. AK-C and TR-C show a minor change at Test 1, where their positions



are temporarily reversed, after which their original seventh and eighth positions are maintained. Overall, the limited number of ranking changes across the 37 sensitivity scenarios indicates that the ranking structure remains highly stable despite variations in the criterion weights.

For each scenario, the adjusted criterion weights are applied to the MOORA method, and the resulting preference values and rankings are compared with the original results to identify changes in the positions of the alternatives under different weight conditions. The sensitivity analysis results, including the changes in ranking positions across the weight variation scenarios, are presented in Figure 8. This analysis provides an assessment of the stability of the HIVE-MOORA results and indicates the extent to which the ranking is affected by changes in the relative importance of the criteria.

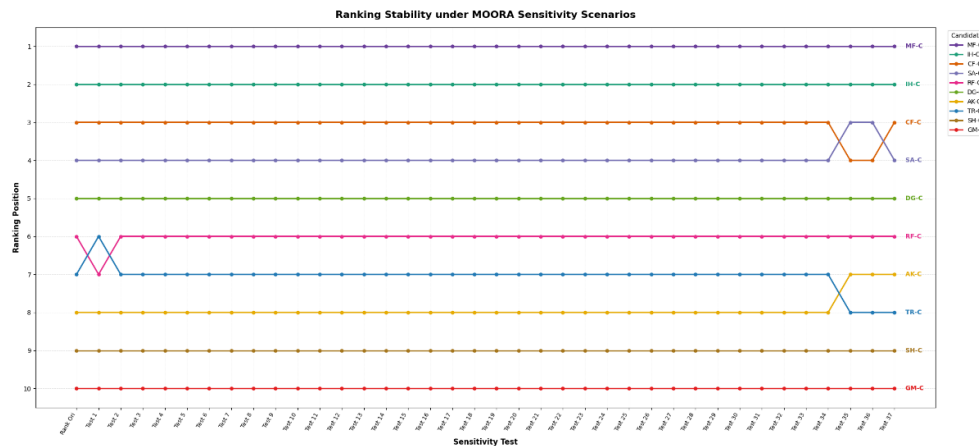


Figure 8. Comparison of Alternative Rankings using MOORA Method

Figure 8 presents the ranking stability of the alternatives under the MOORA sensitivity scenarios. The results indicate that MF-C and IH-C consistently maintain the first and second positions throughout all test scenarios, while DG-C, SH-C, and GM-C remain stable at fifth, ninth, and tenth positions, respectively. RF-C experiences a temporary shift from sixth to seventh position in Test 1 before returning to sixth in the subsequent scenarios, while TR-C changes from seventh to sixth in Test 1 and subsequently returns to seventh until Test 34. More noticeable changes occur in Tests 35-37, where CF-C moves from third to fourth position and SA-C moves from fourth to third position in Tests 35-36 before both return to their original positions in Test 37. During the same scenarios, AK-C improves from eighth to seventh position, whereas TR-C moves from seventh to eighth position. Overall, the limited ranking changes across the sensitivity scenarios indicate that the MOORA ranking structure remains stable under the tested variations in criterion weights.

The sensitivity analysis using SAW and MOORA demonstrates that the resulting rankings remain highly stable across the tested weight variation scenarios of ± 0.05 , ± 0.10 , ± 0.15 , and ± 0.20 . In both approaches, MF-C and IH-C consistently occupy the first and second



positions, while SH-C and GM-C remain at the ninth and tenth positions, respectively. Only limited rank shifts are observed among the middle-ranked candidates, particularly CF-C, SA-C, RF-C, AK-C, and TR-C, with most changes occurring in specific sensitivity scenarios rather than throughout the entire analysis. The overall consistency of the ranking patterns indicates that variations in the relative importance of the criteria have only a limited effect on the ordering of alternatives, supporting the robustness of the HIVE-based weighting results when integrated with both SAW and MOORA.

VI. Discussion

6.1. HIVE as a Heterogeneity-Aware Weighting Approach

The findings demonstrate that HIVE Weighting provides an objective mechanism for translating differences in criterion characteristics into relative criterion importance. Unlike weighting procedures that primarily emphasize a single statistical property, HIVE combines the central tendency, absolute variability, and relative variability of normalized criterion values to construct a heterogeneity-based representation of each criterion. This formulation allows the weighting process to recognize that criteria may differ not only in their average performance but also in the degree and proportion of variation observed across alternatives. Such a design is consistent with the underlying concept of criterion heterogeneity, where differences in variability, distribution, discriminatory capability, and data behavior are treated as relevant information for objective weighting.

The empirical weighting results further illustrate this characteristic. HIVE assigns weights of 0.1698, 0.1901, 0.2515, 0.1671, and 0.2215 to CM10, CM11, CM12, CM13, and CM14, respectively. CM12 receives the largest weight, but its contribution is substantially lower than the values generated by Entropy, WENSLO, CRITIC, and MEREC, which assign 0.5769, 0.6025, 0.3744, and 0.4419, respectively. At the same time, HIVE provides relatively substantial contributions to the remaining criteria, particularly CM11 and CM14. This distribution suggests that the method does not allow one criterion to dominate the weighting structure solely because it exhibits a particular statistical characteristic. Instead, the resulting weights represent a more distributed interpretation of the information contained in the decision matrix.

From a methodological perspective, this behavior is important because highly concentrated objective weights can cause subsequent MCDM rankings to become excessively dependent on a limited number of criteria. HIVE addresses this issue by incorporating multiple dimensions of criterion heterogeneity before producing the final normalized weights. The approach therefore provides an interpretable connection between the observed structure of the decision matrix and the resulting criterion importance. In this sense, HIVE extends objective weighting from simply measuring how much a criterion varies toward examining how different



characteristics jointly describe the informational behavior of a criterion.

6.2. Comparative Analysis with Objective Weighting Methods

The comparison with Entropy, WENSLO, LOGSTA, CRITIC, and MEREC reveals that HIVE generates a distinct weighting profile rather than reproducing the weighting tendencies of existing objective methods. Entropy and WENSLO strongly emphasize CM12, assigning more than half of the total weight to this criterion, while MEREC also gives CM12 a substantially dominant contribution. CRITIC produces a more distributed structure but still places CM12 as the most influential criterion. LOGSTA differs by assigning its largest weight to CM13. In contrast, HIVE distributes the weights more evenly across the five criteria, with CM12 remaining the largest contributor at 0.2515, followed by CM14 at 0.2215 and CM11 at 0.1901.

This difference is theoretically meaningful because the weighting method directly affects how information from the decision matrix is transmitted to the subsequent ranking stage. Objective methods based primarily on entropy, dispersion, correlation, or information loss may respond strongly to a particular characteristic of the data. Consequently, a criterion with a pronounced statistical feature can receive a disproportionately large weight. HIVE instead evaluates heterogeneity through a combination of mean level, standard deviation, and relative variability. The resulting weighting structure can therefore be interpreted as a compromise between the magnitude of criterion performance and the extent to which that criterion differentiates alternatives. This provides a broader representation of criterion behavior than approaches that rely predominantly on one statistical dimension.

The ranking results provide additional evidence that differences in objective weights do not necessarily translate into substantially different alternative rankings. When HIVE is integrated with SAW, MF-C, IH-C, CF-C, and SA-C occupy the first four positions, while RF-C, DG-C, AK-C, TR-C, SH-C, and GM-C follow in the subsequent positions. MOORA produces the same ordering despite generating different numerical preference values. Thus, the comparison indicates that HIVE can generate a distinct weighting structure while still producing a coherent alternative ordering when integrated with established MCDM procedures.

6.3. Cross-MCDM Consistency of HIVE

The consistency between SAW and MOORA provides evidence that the ranking outcomes are not strongly dependent on a single aggregation mechanism. Both methods produce an identical ordering of the ten candidates, with MF-C ranked first and GM-C ranked tenth, despite differences in their mathematical procedures and the resulting preference-value scales. SAW produces preference values ranging from 0.9831 to 0.7487, whereas MOORA produces values from 0.3533 to 0.2654. The preservation of the same ordering despite these differences suggests that the ranking pattern is supported by the underlying performance



structure and HIVE-derived weights rather than being an artifact of one specific MCDM formulation.

The sensitivity analysis provides a further perspective on this consistency. Under weight variations of ± 0.05 , ± 0.10 , ± 0.15 , and ± 0.20 , the ranking structures obtained through both SAW and MOORA exhibit only limited changes. MF-C and IH-C remain in the first and second positions, while SH-C and GM-C maintain their positions at the lower end of the ranking. The changes that do occur are concentrated mainly among middle-ranked alternatives and appear only under particular perturbation scenarios. For SAW, changes are observed among CF-C, SA-C, RF-C, DG-C, AK-C, and TR-C, while MOORA exhibits similarly limited movements, particularly in the later sensitivity tests.

The cross-method sensitivity evidence is particularly relevant because robustness in MCDM should not be interpreted solely as the absence of any rank change. Rather, a robust weighting structure should prevent reasonable perturbations in criterion importance from producing widespread or disproportionate changes in the decision outcome. In this study, the limited rank shifts across 37 sensitivity scenarios indicate that moderate and relatively large changes in criterion weights do not substantially disrupt the overall ranking structure. The consistency observed across SAW and MOORA therefore strengthens the interpretation that HIVE provides weights that are sufficiently stable for subsequent MCDM applications.

6.4. Theoretical and Practical Implications

The theoretical implication of the findings is that criterion heterogeneity can be operationalized as an explicit component of objective weighting rather than being treated only as a descriptive characteristic of the decision matrix. HIVE establishes a framework in which the average level, absolute dispersion, and relative variability of each criterion jointly contribute to its final importance. This extends the conceptual basis of objective weighting by recognizing that the informational contribution of a criterion may emerge from multiple statistical characteristics simultaneously. The approach is therefore aligned with the broader need for objective, heterogeneity-aware, adaptive, interpretable, and robust weighting mechanisms in MCDM.

From a practical perspective, the results indicate that HIVE can be integrated with different MCDM methods without requiring modifications to the subsequent ranking procedures. The identical rankings produced by HIVE-SAW and HIVE-MOORA demonstrate that the weighting mechanism can be transferred across different aggregation frameworks while maintaining the same ordering in the examined case. This characteristic is useful for decision-support applications in which analysts may wish to verify whether conclusions remain consistent across alternative MCDM procedures rather than relying on a single ranking technique.

The sensitivity results also have practical significance for decision-makers because criterion importance is rarely known with absolute certainty. The stability observed under systematic



perturbations indicates that the decision structure is not excessively dependent on precise weight specifications. Consequently, HIVE can provide a useful basis for decision environments where criteria exhibit heterogeneous data characteristics and where the relative importance of criteria may reasonably fluctuate. Nevertheless, the findings should be interpreted within the scope of the examined dataset and candidate-selection context. Further validation using datasets with different numbers of alternatives, criterion types, distributions, and benefit-cost configurations would be necessary to determine how consistently the observed properties of HIVE generalize across broader MCDM applications.

VII. Conclusion

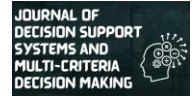
This study concludes that HIVE Weighting provides a structured framework for incorporating heterogeneity into objective criterion weighting within MCDM. Rather than treating criteria through a single statistical characteristic, the approach establishes a unified weighting mechanism that reflects differences in the distributional characteristics of the decision data. This formulation strengthens the connection between the information contained in the decision matrix and the resulting criterion importance, while maintaining a relatively straightforward computational procedure.

The proposed approach also contributes a complementary perspective to objective weighting research by treating heterogeneity as an explicit consideration in weight construction. Its formulation allows HIVE to be incorporated into established MCDM procedures without altering their underlying decision rules. This makes the method suitable as a weighting component rather than as a replacement for existing ranking techniques, allowing researchers and practitioners to retain familiar evaluation frameworks while adopting a heterogeneity-oriented weighting perspective.

From a methodological standpoint, HIVE establishes a basis for further investigation into how differences among criteria can be represented more systematically in objective weighting. Future research can extend this direction by testing alternative formulations of heterogeneity, examining the behavior of the method across datasets with different structural characteristics, and investigating its applicability to larger and more diverse decision-making problems. Such extensions can help determine the broader scope of HIVE and further develop heterogeneity-aware weighting as a research direction in MCDM.

CRedit Authorship Contribution Statement

Nirwana Hendrastuty: Conceptualization, Methodology, Visualization, Writing – Original Draft Preparation. **Aditia Yudhistira:** Investigation, Writing – Original Draft Preparation, Writing – Review & Editing. **Ari Sulistiyawati:** Data Curation, Formal Analysis, Writing – Original Draft



Preparation. **Ahmad Ari Aldino:** Validation, Visualization, Writing - Review & Editing.

Declaration of Competing 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.

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Data Availability

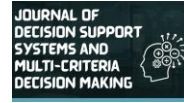
The data used to support the findings of this study are available from the corresponding author upon request.

Declaration of Generative AI and AI-assisted Technologies in The Writing Process

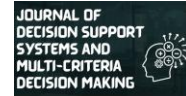
The authors used Generative Artificial Intelligence to improve the writing clarity of this paper. They reviewed and edited the AI-assisted content and take full responsibility for the final publication.

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