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Comparative Analysis of Objective Weighting Approaches in Multi-Criteria Decision Making Using WASPAS

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ABSTRACT

Selecting the best-performing honorary employee is a multi-criteria decision-making problem because employee performance is influenced by several criteria with different levels of importance. This study aims to conduct a comparative analysis of objective weighting approaches in the Weighted Aggregated Sum Product Assessment (WASPAS) method for evaluating honorary employee performance and examining the stability of the resulting rankings. Eight alternatives, namely HE-A to HE-H, were evaluated using five criteria: Work Performance, Discipline, Cooperative Ability, Initiatives and Problem Solving, and Communication Skills. Twelve objective weighting methods, namely Entropy, G2M, RECA, LOPCOW, CRITIC, MEREC, WENSLO, LOGSTA, LODECI, ITARA, SITDE, and DAM, were independently applied to determine criterion weights. The resulting weights were then integrated into WASPAS to generate alternative rankings under different weighting scenarios. The results show that HE-F consistently achieved the first rank across all objective weighting approaches, while HE-E consistently occupied the eighth position. The ranking comparison further indicates that most methods produce ranking patterns close to the original ranking, although MEREC introduces greater changes in several alternative positions. Spearman rank correlation analysis confirms a strong consistency of the resulting rankings, with the highest correlation obtained by LODECI, SITDE, and DAM at 0.9524, followed by G2M and CRITIC at 0.9286 and MEREC at 0.9048. Overall, the findings demonstrate that the combination of objective weighting approaches and WASPAS provides a reliable framework for employee performance evaluation, while comparative correlation analysis can be used to

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assess ranking stability and robustness across different weighting perspectives.

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I. Introduction

Decision-making in various fields often involves situations in which alternatives must be evaluated based on more than one criterion [1]. These criteria may represent different aspects of a decision problem and may have different characteristics and levels of importance, making the process of selecting the best alternative more complex than decision-making based on a single indicator. In such situations, Multi-Criteria Decision Making (MCDM) has become an important approach for supporting decision-makers in evaluating and prioritizing multiple alternatives based on several criteria in a systematic manner [2], [3]. MCDM provides a structured framework for integrating the performance of alternatives across different criteria into a decision model, allowing the final decision to consider multiple relevant dimensions rather than relying on a single performance measure. Through MCDM, multidimensional information can be transformed into preference values that facilitate the comparison and ranking of alternatives [4]. Therefore, the effectiveness of an MCDM application is not determined solely by the selection of the ranking method but also by the accuracy of the components involved in the decision-making process, particularly the determination of the relative importance or weights assigned to each criterion.

Criterion weighting plays a critical role in MCDM because weights represent the relative importance of individual criteria in determining the overall preference of an alternative [5], [6]. When a criterion is assigned a higher weight, its contribution to the final evaluation becomes greater than that of a criterion with a lower weight. Consequently, changes in criterion weights can affect the aggregate value of each alternative and, under certain conditions, may lead to changes in the final ranking. This issue becomes particularly important when criteria have different levels of variation, measurement scales, or data distributions. Inappropriate weighting may cause certain criteria to exert excessive or insufficient influence on the decision outcome, whereas an appropriate weighting scheme can provide a more proportional representation of the contribution of each criterion to the overall

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evaluation. Therefore, criterion weighting cannot be separated from the quality of MCDM results, as differences in weights at the initial stage may produce different preference values and final rankings even when the same alternatives, criteria, and ranking method are used [7].

In general, criterion weighting methods in MCDM can be classified into subjective weighting and objective weighting approaches [8], [9]. Subjective weighting determines the importance of criteria based on the judgments, experience, knowledge, or preferences of decision-makers or experts [10]–[12]. This approach has the advantage of incorporating human perspectives that may not be fully captured by quantitative data. However, its dependence on human judgment can result in different weighting outcomes when the process is conducted by different decision-makers. The resulting weights may be influenced by individual perceptions, experience, understanding of the decision problem, and preferences toward particular criteria. Such dependence may become a limitation when a study requires a weighting process that is more consistent, measurable, and reproducible based on available data. Furthermore, subjective weighting may make it difficult to determine whether differences in criterion importance genuinely reflect the information contained in the decision matrix [13], [14]. These limitations have encouraged the adoption of objective weighting methods, which do not directly rely on the preferences of decision-makers but determine criterion weights based on the mathematical characteristics and information contained in the dataset.

Objective weighting methods have increasingly been adopted as an approach for determining criterion importance based on measurable characteristics of the data [15], [16]. Various objective weighting techniques may utilize information such as data variability, dispersion, inter-criterion relationships, conflict among criteria, or the amount of information contained within each criterion to determine the corresponding weights. Although these methods share the principle of deriving weights from the data, each objective weighting approach may employ different mathematical principles, formulations, and computational mechanisms. These differences may cause a criterion to receive a relatively high weight under one method but a lower weight under another method when both are applied to the same dataset. Therefore, objective weighting does not necessarily produce a single universal distribution of criterion weights. Instead, the resulting distribution may depend on both the characteristics of the data and the mathematical approach adopted by the weighting method. This issue is important in MCDM because different weight distributions lead to different levels of contribution from each criterion during the aggregation of alternative performance. Consequently, comparing multiple objective weighting methods is necessary to determine the extent to which differences in weighting mechanisms produce variations in criterion weights and how these variations may affect subsequent decision-making outcomes.

One MCDM method that can be used to evaluate and rank alternatives across multiple criteria is the Weighted Aggregated Sum Product

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Assessment (WASPAS) method. WASPAS integrates the concepts of the Weighted Sum Model (WSM) and the Weighted Product Model (WPM) to obtain preference values for alternatives [17]–[19]. This integration allows the evaluation process to incorporate the characteristics of both weighted summation and weighted multiplication in aggregating the performance of alternatives into preference scores that can subsequently be used for ranking. In the WASPAS framework, criterion weights represent one of the fundamental components of the calculation because they determine the contribution of each criterion to the final preference value of an alternative [20], [21]. Therefore, when the weights used in WASPAS are obtained from different objective weighting methods, variations may occur in both the preference values and the resulting ranking of alternatives. Such differences may not be limited to numerical changes in the weights themselves but may also affect the relative positions of alternatives, particularly when several alternatives have similar performance levels. Consequently, WASPAS provides a relevant framework for examining the effects of different objective weighting approaches on the outcomes of multi-criteria decision-making.

The research problem arises when different objective weighting methods produce different weight distributions and these weights are subsequently incorporated into the WASPAS method. Variations in criterion weights may alter the contribution of individual criteria to the preference values of alternatives and consequently affect their ranking positions. However, the magnitude and pattern of these changes may vary depending on the characteristics of the dataset and the weighting methods employed. In some cases, several weighting methods may produce highly similar rankings despite differences in their weight distributions, whereas in other cases, relatively substantial differences in weights may lead to significant changes in the ranking of alternatives. This condition indicates that the selection of an objective weighting method may become an important factor influencing the stability of decision outcomes obtained through WASPAS. Although objective weighting methods have been widely applied in MCDM research, a comprehensive comparison focusing specifically on how variations in objective weights affect ranking stability and consistency within the WASPAS framework remains important. This research gap raises a fundamental question regarding whether certain objective weighting methods are capable of producing more stable and consistent rankings than others and to what extent changes in weight distributions influence the final ranking of alternatives. Therefore, an evaluation is required not only to compare the resulting weights but also to examine the relationship between weight variations, changes in preference values, and changes in alternative rankings.

The present study aims to compare several objective weighting approaches and apply the resulting weights within the WASPAS framework. The analysis focuses on comparing the weight distributions generated by each objective weighting method and subsequently evaluating their effects on alternative preference values and ranking outcomes. Changes in ranking across different weighting approaches are further examined

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to identify the degree of ranking stability and consistency. Statistical measures can be employed to quantify the similarity and variation of rankings across approaches, while visualizations can provide a clearer representation of changes in criterion weights, preference values, and alternative rankings. Through this approach, the study is expected to provide several contributions to the MCDM literature. First, it provides a systematic comparison of multiple objective weighting methods within a common WASPAS framework. Second, it analyzes differences in weight distributions generated by the respective objective weighting approaches. Third, it evaluates the effects of weighting variations on alternative rankings. Fourth, it assesses ranking stability and consistency using appropriate statistical measures and visualizations. The findings are expected to provide empirical evidence regarding the robustness of WASPAS rankings to different objective weighting approaches and to support a more informed selection of objective weighting methods when ranking stability and consistency are important considerations in multi-criteria decision-making.

II. Methodology

2.1. Research Framework

A research framework is a structured representation that illustrates the logical flow of a research study, including the relationships among the research problem, variables, methods, analytical procedures, and expected outcomes [22]. It serves as a conceptual and methodological guide that helps researchers organize the stages of the study in a systematic and coherent manner. The research framework of this study is presented in Figure 1.

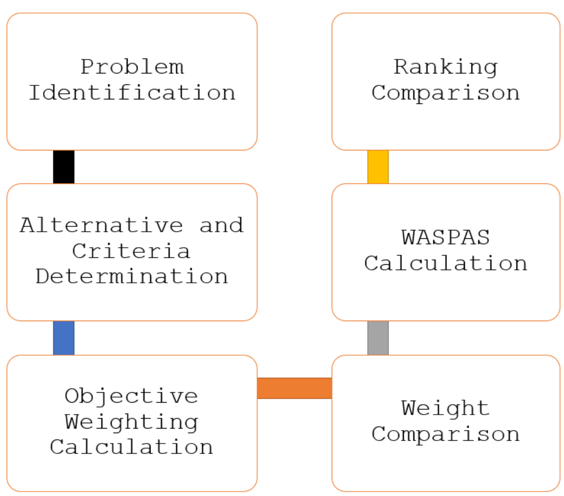

Figure 1. Research Stages

The research framework begins with Problem Identification, which defines the decision-making problem and establishes the main issues to be addressed in the study. This stage is followed by Alternative and

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Criteria Determination, where the alternatives to be evaluated and the criteria used as the basis for assessment are identified and defined. The next stage is Objective Weighting Calculation, in which several objective weighting methods are applied to determine the relative importance of each criterion based on the characteristics of the available data. The resulting weights are then examined through Weight Comparison to identify differences in weight distribution across the objective weighting approaches. Subsequently, the calculated weights are incorporated into the WASPAS Calculation to obtain the preference values of each alternative. The results are then evaluated through Ranking Comparison to determine differences in the ordering of alternatives generated by each weighting approach. Finally, Sensitivity and Stability Analysis is conducted to assess the extent to which changes in criterion weights affect the preference values and ranking results, as well as to determine the stability and consistency of the rankings across the different objective weighting methods.

2.2. Objective Weighting

Objective weighting is a criterion weighting approach in MCDM that determines the relative importance of criteria based on the mathematical characteristics and information contained in the decision data, rather than relying directly on the subjective judgments or preferences of decision-makers [23]. The resulting weights are generally derived from statistical properties such as data variability, dispersion, correlation, contrast, or the amount of information provided by each criterion. The main purpose of objective weighting is to provide a more data-driven and reproducible representation of criterion importance, allowing the weighting process to be applied consistently across decision-making problems. Different objective weighting methods may use different mathematical principles and therefore can produce different weight distributions from the same decision matrix. These differences in weight distribution may subsequently influence the preference values and ranking of alternatives when the weights are incorporated into an MCDM method.

The Entropy method is one of the objective weighting methods in MCDM used to determine the importance level of each criterion based on the level of variation or uncertainty of the information contained in the data [24], [25]. The greater the variation in a criterion's values across alternatives, the greater the criterion's ability to provide information to differentiate alternatives, so the resulting weight becomes higher. Conversely, criteria with relatively uniform values have a lower level of information and receive a smaller weight. The steps in the entropy method are: the decision matrix is created using (1). The decision matrix is normalized using (2). The entropy value of each criterion is calculated using (3). The level of information diversification of each criterion is determined using Equation (4). The objective weight of each criterion is calculated using (5).

$$X = [x_{ij}]_{mxn} \tag{1}$$

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$$k_{ij} = \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}} \quad (2)$$

$$E_j = -\frac{1}{\ln m} \sum_{i=1}^{n} k_{ij} \ln(k_{ij}) \quad (3)$$

$$D_j = 1 - E_j \quad (4)$$

$$w_j = \frac{D_j}{\sum_{j=1}^{n} D_j} \quad (5)$$

The Entropy method produces objective weights for each criterion based on the level of information variation in the data. Criteria with a higher level of information variation will get a higher weight because they are better at distinguishing between alternatives, while criteria with low information variation will get a smaller weight.

The Grey Geometric Mean (G2M) method is an objective weighting method used to determine the relative importance of criteria based on the geometric mean and grey system theory[26], [27]. This method is suitable for decision-making problems involving uncertain, incomplete, or limited information, as it transforms the original decision data into grey values and uses their distribution to determine the objective weights of the criteria. The steps in the G2M method are as follows: the geometric mean of each criterion is calculated using (6). The geometric mean values are normalized using (7). The grey value of each criterion is determined using (8). The objective weight of each criterion is calculated using (9).

$$GM_i = \left(\prod_{i=1}^{j} x_i\right)^{1/n} \quad (6)$$

$$R_{ij} = \frac{x_{ij}}{GM_i} \quad (7)$$

$$GRG_j = \frac{1}{n} \sum_{j=1}^{n} R_{ij} \quad (8)$$

$$w_j = \frac{GRG_j}{\sum_{i=1}^{j} GRG_j} \quad (9)$$

The G2M method produces objective weights that represent the relative importance of each criterion based on the information contained in the decision data. The resulting weights reflect the contribution of each criterion after considering the geometric mean, normalized values, and grey values. The objective weights obtained from the G2M method are subsequently used in the WASPAS method to calculate the preference values and determine the ranking of the alternatives.

The Respond to Criteria Weighting (RECA) method is an objective weighting method used to determine the importance of each criterion based on the relationship between the criteria and the distribution and stability of their values [28], [29]. This method evaluates the contribution of each criterion by considering its preference value, normalized value, standard value, dispersion of values, and stability measure. The steps in the RECA method are as follows: the preference value of each criterion is determined using (10). The preference values are normalized using (11). The standard value of each criterion is calculated using (12). The dispersion of values for each criterion is determined using (13). The measure of the stability of each criterion is calculated using (14). The objective weight of each criterion is calculated using (15).

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$$PV_{ij} = \frac{x_{ij}}{\sqrt[n]{\prod_{j=1}^{n} x_{ij}}} \quad (10)$$

$$R_{ij} = \frac{PV_{ij}}{PV_j^{max}} \quad (11)$$

$$N_i = \frac{1}{N}\sum R_{ij} \quad (12)$$

$$\emptyset_j = \sum_{i=1}^{m}\left[R_{ij} - N_i\right]^2 \quad (13)$$

$$\Omega_j = \left|1 - \emptyset_j\right| \quad (14)$$

$$w_j = \frac{\Omega_j}{\sum_{j=1}^{n}\Omega_j} \quad (15)$$

The RECA method produces objective weights that represent the relative importance of each criterion based on its preference, normalized value, dispersion, and stability. Criteria that provide greater information and demonstrate stronger stability in the decision data obtain higher weights, while criteria with lower information contribution receive smaller weights. The objective weights obtained from the RECA method are subsequently used in the WASPAS method to calculate the preference values and determine the ranking of the alternatives.

The Logarithmic Percentage Change-Driven Objective Weighting (LOPCOW) method is an objective weighting method used to determine the relative importance of criteria based on the logarithmic percentage changes in the normalized decision data [30]-[32]. This method evaluates the degree of variation among alternatives for each criterion, allowing criteria with greater discriminatory information to obtain higher objective weights. The steps in the LOPCOW method are as follows: the decision matrix is normalized using (15), the preference value of each criterion is calculated using (16). The objective weight of each criterion is calculated using (17).

$$n_{ij} = \frac{x_{ij}}{m + \sum_{i=1}^{m} {x_{ij}}^2} \quad (16)$$

$$PV_i = 100 * \left|\frac{\sqrt{\sum_{i=1}^{m} {n_{ij}}^2}}{\ln\frac{m}{\sigma}}\right| \quad (17)$$

$$w_j = \frac{PV_i}{\sum_{j=1}^{n} PV_i} \quad (18)$$

The LOPCOW method produces objective weights for each criterion based on the magnitude of logarithmic percentage changes in the decision data. Criteria with greater variation and stronger discriminatory capability obtain higher weights, while criteria with lower variation receive smaller weights. The objective weights obtained from the LOPCOW method are subsequently used in the WASPAS method to calculate the preference values and determine the ranking of the alternatives.

The Criteria Importance Through Intercriteria Correlation (CRITIC) method is an objective weighting method used to determine the relative importance of criteria by considering the contrast intensity and correlation among criteria [33], [34]. This method evaluates the amount of information provided by each criterion based on its variability and the degree of correlation with other criteria. A criterion with

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greater variability and lower correlation with other criteria provides more unique information and therefore receives a higher weight. The steps in the CRITIC method are as follows: the decision matrix is normalized using (19). The standard deviation of each criterion is calculated using (20). The correlation coefficient between criteria is determined using (21). The information value of each criterion is calculated using (22). The objective weight of each criterion is calculated using (23).

$$d_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}} \tag{19}$$

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{n}\left(d_{ij} - \bar{d}_j\right)^2}{n}} \tag{20}$$

$$R_{ij} = \frac{\sum_{i=1}^{n}\left(d_{ij} - \bar{d}_j\right) * \left(d_{ij} - \bar{d}_h\right)}{\sqrt{\sum_{i=1}^{n}\left(d_{ij} - \bar{d}_j\right)^2} * \sqrt{\sum_{i=1}^{n}\left(d_{ij} - \bar{d}_h\right)^2}} \tag{21}$$

$$C_j = \sigma_j \sum_{j=1}^{n}\left(1 - R_{ij}\right) \tag{22}$$

$$W_j = \frac{C_j}{\sum C_j} \tag{23}$$

The CRITIC method produces objective weights that reflect the information content of each criterion by considering both the variability and intercriteria correlation. Criteria with greater contrast intensity and lower correlation with other criteria obtain higher weights because they provide more independent information, while criteria with lower variability or greater correlation contribute less unique information and receive smaller weights.

The Method Based on the Removal Effects of Criteria (MEREC) is an objective weighting method used to determine the relative importance of criteria based on the effect of removing each criterion from the decision-making process [35], [36]. This method evaluates the influence of each criterion by measuring the change in the overall performance of alternatives when a particular criterion is excluded. A criterion that causes a greater change in the overall performance when removed is considered more influential and therefore receives a higher weight. The steps in the MEREC method are as follows: the decision matrix is normalized using (24). The overall performance level of each alternative is calculated using (25). The effect of removing each criterion is determined using (26). The magnitude of the influence or deletion effect of each criterion is calculated using (27). The objective weight of each criterion is calculated using (28).

$$n_{ij} = \begin{cases} \dfrac{\min x_{kj}}{x_{ij}} & (for\ benefical\ criteria) \\ \dfrac{x_{ij}}{\max x_{kj}} & (for\ non-benefical\ criteria) \end{cases} \tag{24}$$

$$S_i = \ln\left(1 + \left(\frac{1}{m}\sum\left|\ln\left(n_{ij}\right)\right|\right)\right) \tag{25}$$

$$S'_{ij} = \ln\left(1 + \left(\frac{1}{m}\sum_{k,k\neq j}\left|\ln\left(n_{ij}\right)\right|\right)\right) \tag{26}$$

$$E_j = \sum\left|S'_{ij} - S_i\right| \tag{27}$$

$$w_j = \frac{E_j}{\sum_k E_k} \tag{28}$$

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The MEREC method produces objective weights based on the magnitude of the influence of each criterion on the overall performance of the alternatives. Criteria that have a greater deletion effect obtain higher weights because their removal results in a more substantial change in the overall performance, while criteria with smaller deletion effects receive lower weights.

The Weights by Envelope and Slope (WENSLO) method is an objective weighting method in MCDM that determines the relative importance of criteria based on the geometric characteristics of normalized decision data [37], [38]. The method evaluates the distribution pattern of each criterion through envelope and slope measures, allowing criteria with greater variability and consistency across alternatives to obtain higher weights. The steps in the WENSLO method are as follows: the decision matrix is normalized using (29). The class interval of each criterion is calculated using (30). The envelope value of each criterion is determined using (31). The slope of each criterion is calculated using (32). The envelope-slope ratio is determined using (33). The objective weight of each criterion is calculated using (34).

$$z_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{29}$$

$$\Delta Z_j = \frac{\max_j z_{ij} - \min_j z_{ij}}{1+3.322*\log(m)} \tag{30}$$

$$\varphi_j = \frac{\sum_{i=1}^{m} z_{ij}}{(m-1)*\Delta Z_j} \tag{31}$$

$$E_j = \sum_{i=1}^{m-1} \sqrt{\left(z_{i+1j} - z_{ij}\right)^2 + \Delta Z_j{}^2} \tag{32}$$

$$q_j = \frac{E_j}{\varphi_j} \tag{33}$$

$$w_j = \frac{q_j}{\sum_{j=1}^{n} q_j} \tag{34}$$

The WENSLO method produces objective weights based on the structural characteristics of the normalized data, particularly the envelope and slope of each criterion. Criteria with a greater envelope-slope ratio obtain higher weights because they provide stronger information through their distribution across alternatives.

The Logarithmic Standard Deviation (LOGSTA) method is an objective weighting method used to determine the relative importance of criteria based on the logarithmic transformation and standard deviation of the decision data [39]. This method considers the variability of each criterion after logarithmic normalization, allowing criteria with greater dispersion to provide greater discriminatory information and receive higher weights. The steps in the LOGSTA method are as follows: the logarithmic normalization of the decision matrix is performed using (35). The logarithmic normalization for the corresponding criterion type is determined using (36). The standard deviation of each criterion is calculated using (37). The objective weight of each criterion is calculated using (38).

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$$n_{ij} = \begin{cases} \left|\frac{\ln x_{ij}}{\ln(\prod_{i=1}^{m} x_{ij})}\right|; benefit \\ \left|\frac{1-\frac{\ln x_{ij}}{\ln(\prod_{i=1}^{m} x_{ij})}}{n-1}\right|; cost \end{cases} \tag{35}$$

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{n}(n_{ij}-\overline{n_j})^2}{n}} \tag{36}$$

$$g_j = \sigma_j * \left(\left|\sum_{i=1}^{n}(\ln(n_{ij}))\right|\right)^{-1} \tag{37}$$

$$w_j = \frac{g_j}{\sum_{j=1}^{n} g_j} \tag{38}$$

The LOGSTA method produces objective weights based on the degree of dispersion represented by the standard deviation of the logarithmically transformed data. Criteria with greater variability obtain higher weights because they provide more information for distinguishing alternatives, while criteria with lower variability receive smaller weights.

The Logarithmic Decomposition of Criteria (LODECI) method is an objective weighting method used to determine the relative importance of criteria based on the differences among alternatives [40], [41]. The method identifies the maximum difference between an alternative and its competing alternatives for each criterion and then applies a logarithmic transformation to obtain a balanced measure of information contribution. The steps in the LODECI method are as follows: the decision matrix is normalized using (39). The decomposition value of each criterion is determined using (40). The logarithmic decomposition value of each criterion is calculated using (41). The objective weight of each criterion is calculated using (42).

$$d_{ij} = \begin{cases} \frac{x_{ij}}{\max_j x_{ij}}; benefit\ criteria \\ 1 - \frac{x_{ij}}{\max_j x_{ij}}; cost\ criteria \end{cases} \tag{39}$$

$$SD_{ij} = \max\{\left|d_{ij} - d_r\right|\} r \neq i \tag{40}$$

$$LSD_j = \ln\left(1 + \frac{\sum_{i=1}^{m} SD_{ij}}{m}\right) \tag{41}$$

$$w_j = \frac{LSD_j}{\sum_{j=1}^{n} LSD_j} \tag{42}$$

The LODECI method produces objective weights based on the magnitude of differences among alternatives for each criterion. Criteria with greater decomposition values provide stronger discriminatory information and therefore obtain higher weights, while criteria with smaller decomposition values receive lower weights. The logarithmic transformation helps moderate excessive differences in the resulting weights.

The Indifference Threshold-based Attribute Ratio Analysis (ITARA) method is an objective weighting method used to determine the relative importance of criteria by considering the differences between ordered alternatives and the indifference threshold associated with each criterion [42]–[44]. The method evaluates how changes in criterion values

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contribute to the discrimination of alternatives while accounting for a threshold below which differences are considered insignificant. The steps in the ITARA method are as follows: the decision matrix is normalized using (43). The alternatives are ordered according to the values of each criterion using (44). The differences between consecutive alternatives are determined using (45). The indifference-threshold-adjusted differences are calculated using (46). The objective weight of each criterion is calculated using (47).

$$e_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}};\ NIT_j = \frac{IT_j}{\sum_{i=1}^{m} x_{ij}} \tag{43}$$

$$\gamma_{ij} = \beta_{i+1,j} - \beta_{ij} \tag{44}$$

$$\varepsilon_{ij} = \begin{cases} \gamma_{ij} - NIT_j; for\ \gamma_{ij} > NIT_j \\ 0 \qquad\qquad ; for\ \gamma_{ij} \le NIT_j \end{cases} \tag{45}$$

$$v_j = \left(\sum_{i=1}^{m-1} {\varepsilon_{ij}}^{p}\right)^{1/p} \tag{46}$$

$$w_j = \frac{v_j}{\sum_{j=1}^{n} v_j} \tag{47}$$

The ITARA method produces objective weights based on the effective differences between alternatives after considering the indifference threshold. Criteria that demonstrate greater meaningful variation among alternatives obtain higher weights because they provide stronger discriminatory information, while criteria with smaller effective differences receive lower weights.

The Skewness Impact Through Distributional Evaluation (SITDE) method is an objective weighting method in MCDM that determines the relative importance of criteria by considering the distributional characteristics and skewness of criterion values [45], [46]. Unlike conventional objective weighting methods that primarily focus on variability or correlation, SITDE incorporates the asymmetry of the data distribution to evaluate the discriminatory information provided by each criterion. The method is particularly useful for decision-making problems involving asymmetric or skewed datasets. The steps in the SITDE method are as follows: the decision matrix is normalized using (48). The skewness value of each criterion is calculated using (49). The normalized skewness value of each criterion is determined using (50). The objective weight of each criterion is calculated using (51).

$$z_{ij} = \begin{cases} \dfrac{\min_i x_{ij}}{x_{ij}}; cost \\ \dfrac{x_{ij}}{\max_i x_{ij}}; benefit \end{cases} \tag{48}$$

$$K_j = \frac{m}{(m-1)(m-2)} \sum_{j=1}^{m} \left(\frac{z_{ij} - \bar{z}_j}{\sigma_j}\right)^3 \tag{49}$$

$$LK_j = \log\left|\left((K_j + 1) + \left(\left|\min(K_j)\right| + 1\right)\right)\right| \tag{50}$$

$$w_j = \frac{LK_j}{\sum_{j=1}^{n} LK_j} \tag{51}$$

The SITDE method produces objective weights based on the distributional characteristics and skewness of each criterion. Criteria with greater skewness impact provide stronger discriminatory information regarding the distribution of alternatives and therefore obtain higher

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weights, while criteria with lower skewness impact receive smaller weights.

Data Assessment Method Weighting (DAM Weighting) is a method for weighting criteria used in MCDM to determine the relative importance of each criterion based on the characteristics and information contained in the alternative data [47]. Unlike subjective weighting methods that rely on the decision maker's judgment, DAM Weighting can be used as an objective approach, since the weights are derived from the patterns, variations, and contributions of data in each criterion. The steps in the LOPCOW method are as follows: the decision matrix is normalized using (52), the preference value of each criterion is calculated using (53). The objective weight of each criterion is calculated using (54).

$$t_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{52}$$

$$PV_j = 100 * \left| \frac{\sqrt{\sum_{i=1}^{m} {t_{ij}}^2}}{\ln\frac{m}{\sigma}} \right| \tag{53}$$

$$w_j = \frac{PV_j}{\sum_{j=1}^{n} PV_j} \tag{54}$$

The DAM Weighting provides an objective approach to determining criterion weights by utilizing the information contained in the alternative data. This method helps reduce subjectivity in determining the importance level of criteria, so the resulting weights better represent the actual characteristics of the data. Therefore, DAM Weighting can be a relevant method for supporting multi-criteria decision-making processes, especially when combined with ranking methods to produce decisions that are more systematic, objective, and accountable.

2.3. WASPAS Method

The WASPAS method is a MCDM method used to evaluate and rank alternatives based on multiple criteria by combining the WSM and WPM approaches. WASPAS integrates the additive characteristics of WSM with the multiplicative characteristics of WPM to obtain a more comprehensive preference value for each alternative [48], [49]. The method uses criterion weights and normalized decision data to calculate the performance of each alternative, where a higher preference value indicates a more favorable alternative. By combining the two aggregation approaches, WASPAS provides a systematic basis for comparing alternatives and determining the best alternative in multi-criteria decision-making problems. The steps in the WASPAS method are as follows: the decision matrix is normalized using (55), the final WASPAS preference value for each alternative is calculated using (56).

$$N_{ij} = \begin{cases} \frac{x_{ij}}{x{j^{max}}}; benefit \\ \frac{x{j^{min}}}{x_{ij}}; cost \end{cases} \tag{55}$$

$$Q_i = 0.5 \sum n_{ij} w_j + 0.5\, \Pi_{j=1}^{n} {n_{ij}}^{w_j} \tag{56}$$

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The WASPAS method produces a preference value for each alternative by combining the results of the WSM and WPM approaches. Alternatives with higher preference values are considered more desirable and consequently obtain higher rankings, while alternatives with lower preference values receive lower rankings. The final ranking obtained from the WASPAS method is used to identify the best alternative based on the objective weights generated by the weighting methods.

2.4. Alternative Evaluation Data

Alternative Evaluation Data is the assessment data used to describe the performance level of each alternative against a number of criteria determined in the decision-making process. This data is arranged in a decision matrix, with rows representing the evaluated alternatives and columns showing the evaluation criteria, while each value in the matrix indicates the performance of an alternative against a specific criterion. Assessment values can be obtained from quantitative data or the results of converting qualitative assessments into a numerical scale so they can be processed mathematically. In MCDM-based research, Alternative Evaluation Data forms the basis for normalization, weighting, preference value calculation, and ranking of alternatives using the chosen method. The accuracy and consistency of the assessment data are very important because changes in a criterion's value can affect the final ranking results and decision stability.

The evaluation data used in this study refers to data obtained from research [50]. This data is used as alternative evaluation data, which shows the performance value of each alternative based on the criteria that have been set. Each value in the evaluation data represents the level of achievement of an alternative against certain criteria and is then used as the initial data in the decision-making process shown in Table 1.

Table 1. Alternative Evaluation Data

Alterative	C1	C2	C3	C4	C5
HE-A	85	9	4	3	5
HE-B	92	8	4	4	3
HE-C	75	7	5	4	4
HE-D	88	8	4	5	4
HE-E	95	6	3	3	4
HE-F	78	9	5	4	5
HE-G	82	7	4	5	3
HE-H	90	9	3	4	4

The assessment data used to evaluate each alternative against the set criteria is then processed to get the preference value for each alternative. The processing of this assessment data produces a ranking of alternatives based on performance level or obtained preference value. The ranking results are then presented in Table 2, showing the position of each alternative based on the evaluation results using the applied method.

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Table 2. Rank Alternative

Alterative	Rank
HE-F	1
HE-A	2
HE-D	3
HE-H	4
HE-C	5
HE-G	6
HE-B	7
HE-E	8

Thus, the assessment data used becomes the basis for the evaluation and ranking of alternatives. The data is then processed using weighting and decision-making methods to obtain preference values for each alternative, so that the order of alternatives based on their performance can be known. The final results of this process are presented as a ranking in Table 2 as the basis for determining the best alternative.

III. Result and Discussion

Comparative analysis of objective weighting approaches in MCDM using WASPAS is an analysis stage aimed at comparing the influence of various objective weighting approaches on decision-making results using the WASPAS method. Each weighting approach is used to determine the relative importance of each criterion based on the characteristics of the evaluation data, which can result in different criteria weights across approaches. The obtained weights are then used in the WASPAS calculation process to determine the preference value and ranking of each alternative. Comparing these results allows researchers to identify ranking consistency, changes in alternative positions, and the stability of decision outcomes when different weighting approaches are applied.

3.1. Decision Matrix and Problem Description

This subsection presents the results obtained from data processing, method implementation, or system outputs generated during the study. The findings may be presented in the form of tables, figures, charts, or other visualizations that facilitate readers' understanding of the research outcomes.

All presented results must be properly referenced and systematically explained within the narrative. The discussion should focus on the key findings and their significance rather than repeating the entire content of tables or figures. The presentation of results should clearly demonstrate the relationship between the research procedures undertaken and the objectives of the study The decision-making problem in this study concerns the comparative evaluation of eight honorary employees based on multiple performance-related criteria. The alternatives are represented by HE-A, HE-B, HE-C, HE-D, HE-E, HE-F, HE-G, and HE-H. Employee evaluation represents a typical multi-criteria decision-making problem because overall performance cannot be adequately

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represented by a single indicator. Each employee may demonstrate different levels of performance across several evaluation dimensions, meaning that an alternative with the highest score in one criterion does not necessarily represent the best overall alternative. Therefore, a systematic multi-criteria decision-making approach is required to integrate the available performance information and determine the relative position of each honorary employee objectively.

The evaluation process considers five criteria, namely Work Performance (C1), Discipline (C2), Cooperative Ability (C3), Initiatives and Problem Solving (C4), and Communication Skills (C5). Work Performance represents the overall achievement of an employee in completing assigned tasks and responsibilities. Discipline reflects the consistency of employees in complying with organizational rules and work-related obligations. Cooperative Ability measures the capacity of employees to collaborate effectively with colleagues and contribute to team activities. Initiatives and Problem Solving evaluates the ability to identify problems, develop appropriate solutions, and take constructive actions when necessary. Meanwhile, Communication Skills represent the ability of employees to exchange information effectively and maintain productive interactions within the working environment. Collectively, these criteria provide a comprehensive representation of employee performance by considering both task-related achievement and behavioral competencies.

The decision matrix consists of eight alternatives, denoted as HE-A to HE-H, and five evaluation criteria. All criteria are treated as benefit criteria, indicating that higher values represent better performance. The alternatives exhibit different performance patterns across the evaluated criteria. For example, HE-E achieves the highest score in Work Performance, while HE-F demonstrates strong performance in Discipline, Cooperative Ability, and Communication Skills. In addition, HE-D and HE-G obtain the highest scores in Initiatives and Problem Solving. These differences indicate that no single alternative consistently dominates all criteria. Consequently, the evaluation process requires an aggregation mechanism capable of combining performance across multiple criteria while simultaneously considering the relative importance assigned to each criterion. Since the criteria are measured on different numerical scales, normalization is required before the weighting and ranking processes are performed.

The normalized decision matrix subsequently serves as the primary input for the comparative analysis of objective weighting approaches and the application of the WASPAS method. Different objective weighting methods may generate different importance levels for the same criteria because each method evaluates the information contained in the decision matrix according to a different mathematical principle. Consequently, variations in the resulting criterion weights may influence the overall utility values and ranking positions of HE-A to HE-H. By applying the same decision matrix to several objective weighting approaches and subsequently using WASPAS to rank the alternatives, this study examines the extent to which differences in criterion weights affect the final

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decision results. This comparative analysis is important for determining whether the resulting ranking remains stable across different objective weighting perspectives or whether the selection of a particular weighting approach substantially influences the evaluation of honorary employee performance.

3.2. Comparative Analysis of Objective Criterion Weights

The comparative analysis of objective criterion weights was conducted to examine how different weighting approaches interpret the importance of the five evaluation criteria based solely on the information contained in the decision matrix. Unlike subjective weighting approaches, objective weighting methods do not require direct judgments from decision-makers regarding the relative importance of the criteria. Instead, the weights are determined mathematically according to the characteristics of the evaluation data. In this study, the same normalized decision matrix for alternatives HE-A to HE-H was used as the basis for each objective weighting approach. Although the methods were applied to identical data, differences in their underlying principles may result in different weight distributions. For example, some methods emphasize the degree of variation among alternative performances, while others consider the relationships between criteria or the impact of removing a criterion from the overall evaluation. Therefore, the resulting weights provide different perspectives regarding which criteria contribute most significantly to distinguishing the performance of the evaluated honorary employees.

The comparison of the obtained criterion weights is important because the weighting stage directly affects the subsequent WASPAS evaluation and final alternative ranking. A criterion assigned a higher weight will have a greater influence on the overall performance value of each alternative, potentially changing the relative ranking of HE-A to HE-H. Differences in weight distributions among the objective approaches may therefore reveal whether the importance of the criteria remains consistent or depends on the mathematical mechanism used to calculate the weights. If a particular criterion receives a relatively high weight across multiple approaches, its importance can be considered more consistently supported by the characteristics of the decision data. Conversely, substantial differences in criterion weights indicate that the perceived importance of the criteria is sensitive to the selected objective weighting method. This comparative analysis consequently provides an essential basis for understanding how variations in criterion importance may influence the robustness and consistency of the final WASPAS ranking results.

To obtain a comprehensive comparison of criterion importance, this study applies 12 objective weighting methods, namely Entropy, G2M, RECA, LOPCOW, CRITIC, MEREC, WENSLO, LOGSTA, LODECI, ITARA, SITDE, and DAM. The Entropy evaluates the information contained in the distribution of criterion values, while G2M and RECA provide alternative mechanisms for deriving objective importance from the characteristics of the decision matrix. LOPCOW emphasizes relative variations in the data, whereas CRITIC

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considers both the contrast intensity and correlation among criteria. MEREC determines importance based on the effect of removing individual criteria from the evaluation process. The other approaches, namely WENSLO, LOGSTA, LODECI, ITARA, SITDE, and DAM, are included to broaden the comparative perspective and identify differences in the resulting weight structures. The resulting weights are subsequently incorporated into the WASPAS method, producing 13 separate WASPAS ranking scenarios. This design makes it possible to determine not only which criteria receive the greatest importance under each method, but also whether changes in objective weights lead to meaningful changes in the ranking alternatives. The comparative results of the 13 objective weighting methods are presented in Table 3. The table reports the weight obtained for each criterion under every weighting approach, allowing the differences and similarities between methods to be examined systematically.

Table 3. Comparison Results of Criteria Weights

Method	C1	C2	C3	C4	C5
Entropy	0.0488	0.1540	0.2657	0.2657	0.2657
G2M	0.1982	0.1995	0.2008	0.2008	0.2008
RECA	0.2201	0.2036	0.1921	0.1921	0.1921
LOPCOW	0.0094	0.1356	0.2850	0.2850	0.2850
CRITIC	0.2406	0.1618	0.1967	0.2116	0.1893
MEREC	0.0613	0.5387	0.1324	0.1342	0.1335
WENSLO	0.0567	0.1620	0.2571	0.2571	0.2672
LOGSTA	0.0044	0.1455	0.2834	0.2834	0.2834
LODECI	0.1280	0.2070	0.2217	0.2217	0.2217
ITARA	0.0525	0.1432	0.2681	0.2681	0.2681
SITDE	0.2311	0.1982	0.1902	0.1902	0.1902
DAM	0.1795	0.1971	0.2078	0.2078	0.2078

The results indicate considerable variation in the criterion weights generated by the twelve objective weighting methods. The Entropy method assigns the lowest importance to C1 (0.0488), while C3, C4, and C5 obtain identical and substantially higher weights of 0.2657. A similar pattern can be observed in LOPCOW and LOGSTA, where C1 receives extremely low weights of 0.0094 and 0.0044, respectively, while C3, C4, and C5 become the dominant criteria. In contrast, MEREC produces a markedly different distribution, assigning the highest weight to C2 (0.5387), which is considerably greater than the weights of the remaining criteria. This indicates that the weighting methods interpret the information contained in the decision matrix differently. Meanwhile, CRITIC provides a comparatively balanced distribution, although C1 receives the highest weight at 0.2406, followed by C4 at 0.2116 and C3 at 0.1967.

The remaining methods demonstrate varying degrees of weight concentration and balance. G2M produces the most uniform distribution, with weights ranging from 0.1982 to 0.2008, indicating that all five criteria contribute almost equally to the decision. RECA and SITDE place relatively greater emphasis on C1, with weights of 0.2201 and 0.2311, respectively, while assigning comparatively lower weights to C3, C4, and

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C5. Conversely, WENSLO, LODECI, ITARA, and DAM generally assign greater importance to C3, C4, and C5 than to C1 and C2. These differences are important because the resulting weights are subsequently incorporated into the WASPAS method. Therefore, changes in the weighting structure can influence the contribution of each criterion to the final WASPAS score and potentially alter the ranking of alternatives HE-A to HE-H. The comparison demonstrates that objective weighting method selection is an important factor in MCDM analysis, particularly when the objective is to evaluate the stability and reliability of the resulting alternative rankings.

3.3. Subchapter on Evaluation and Comparison of Results

The WASPAS is employed because it combines two well-established aggregation approaches, namely the WSM and the WPM, allowing the performance of each alternative to be assessed from both additive and multiplicative perspectives. In this study, the WASPAS procedure is applied separately using the weights generated by Entropy, G2M, RECA, LOPCOW, CRITIC, MEREC, WENSLO, LOGSTA, LODECI, ITARA, SITDE, and DAM. The use of these twelve weighting scenarios makes it possible to observe how differences in objective criterion importance affect the final performance scores and ranking positions of HE-A to HE-H. The resulting comparison provides an empirical basis for examining the consistency of the alternative rankings and identifying whether the selection of an objective weighting method has a substantial influence on the final decision.

The WASPAS method was subsequently applied to determine the ranking of the eight honorary employees, namely HE-A to HE-H, using the criterion weights obtained from the twelve objective weighting methods. The application of WASPAS enables the individual performance of each alternative to be aggregated across the five evaluation criteria. Since all criteria are categorized as benefit criteria, higher normalized values indicate better employee performance. For each weighting method, the corresponding criterion weights were incorporated into the WASPAS calculation to obtain the WSM component and WPM component. These two components were then combined to produce the final WASPAS score for each alternative. Thus, twelve independent ranking scenarios were generated, with each scenario representing a different objective weighting perspective.

The comparative WASPAS results are presented in Figure 2. The figure provides the final WASPAS score and ranking position of each alternative under the Entropy, G2M, RECA, LOPCOW, CRITIC, MEREC, WENSLO, LOGSTA, LODECI, ITARA, SITDE, and DAM weighting approaches. The comparison is intended to identify whether the ranking of HE-A to HE-H remains consistent despite substantial differences in criterion weights. An alternative that consistently obtains a high WASPAS score across several weighting methods can be considered to have relatively strong overall performance and greater ranking stability. Conversely, an alternative whose position changes considerably between weighting methods may be more sensitive to the distribution of criterion

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importance. This comparison therefore provides an important basis for assessing the robustness of the employee evaluation results and determining whether the final decision is dependent on a particular objective weighting approach.

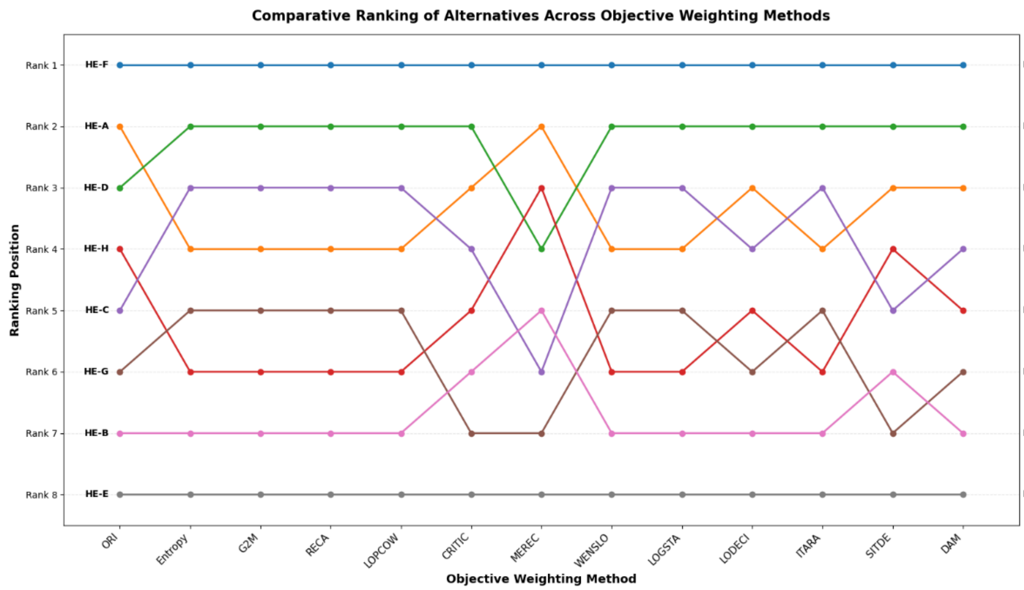

Figure 2. Comparison of Alternative Rankings

The comparison chart of the rankings shows the stability of the rankings of alternatives HE-A to HE-H across all twelve objective weighting approaches compared to the ORI ranking. The results show that HE-F consistently maintains the first position across all weighting methods, indicating highly stable superior performance regardless of the objective weighting approach applied. HE-E also demonstrates complete stability by remaining in the eighth position throughout all scenarios. HE-D generally occupies the second position, except under MEREC, where it moves to fourth, while HE-A shows moderate variation, ranging from second to fourth position. The most noticeable ranking changes occur under MEREC, where HE-H improves from fourth to third, HE-C declines from fifth to sixth, and HE-B improves from seventh to fifth compared with the ORI ranking. In contrast, most other methods produce ranking patterns that are highly similar to the ORI results, particularly Entropy, G2M, RECA, LOPCOW, WENSLO, LOGSTA, and ITARA. Overall, the bump chart indicates that the alternative rankings are relatively stable across the objective weighting methods, with MEREC producing the greatest ranking deviations, while the consistently high position of HE-F confirms its robustness as the best-performing alternative.

To further evaluate the consistency of the ranking results, a Spearman rank correlation analysis was conducted by comparing the ranking produced by each objective weighting approach with the ORI ranking. Spearman's correlation coefficient measures the degree of monotonic association between two ranking sequences, where a value close to 1 indicates a very strong positive correlation and consequently a high

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level of ranking agreement. In this study, the correlation analysis uses the rankings of HE-A to HE-H generated by Entropy, G2M, RECA, LOPCOW, CRITIC, MEREC, WENSLO, LOGSTA, LODECI, ITARA, SITDE, and DAM as the comparison basis. The results are presented visually in Figure 3, allowing the degree of similarity between the ORI ranking and each objective weighting approach to be examined.

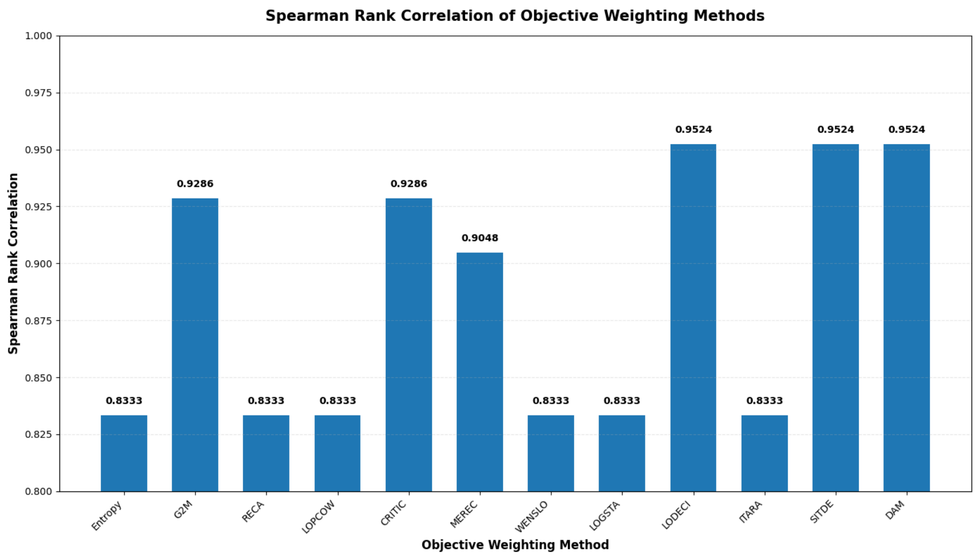

Figure 3. Comparison of Correlation Values

The Spearman rank correlation analysis presented in Figure 3 shows a high level of agreement between the ranking results generated by the different objective weighting methods and the ORI ranking. The highest correlation value is obtained by LODECI, SITDE, and DAM, each with a coefficient of 0.9524, indicating that their resulting alternative rankings are highly consistent with the ORI ranking. G2M and CRITIC also demonstrate a strong correlation of 0.9286, followed by MEREC with a correlation coefficient of 0.9048. Meanwhile, Entropy, RECA, LOPCOW, WENSLO, LOGSTA, and ITARA produce correlation coefficients of 0.8333, which still indicate a strong positive association between the ranking structures. Overall, all weighting approaches achieve correlation coefficients above 0.80, demonstrating that the ranking of alternatives is relatively stable despite differences in the objective weighting mechanisms. The results further indicate that LODECI, SITDE, and DAM provide the closest ranking agreement with the ORI benchmark, suggesting greater consistency in the resulting WASPAS-based alternative rankings.

IV. Conclusion

This study presented a comparative analysis of objective weighting approaches in a MCDM framework using the WASPAS method for evaluating honorary employee performance. Eight alternatives, namely HE-A to HE-H, were assessed using five criteria: Work Performance, Discipline,

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Cooperative Ability, Initiatives and Problem Solving, and Communication Skills. Twelve objective weighting methods, namely Entropy, G2M, RECA, LOPCOW, CRITIC, MEREC, WENSLO, LOGSTA, LODECI, ITARA, SITDE, and DAM, were applied to determine the relative importance of the evaluation criteria. The comparison demonstrated that the weighting methods generated different weight distributions, reflecting the distinct mathematical characteristics used by each approach to measure the information contained in the decision matrix.

The WASPAS-based ranking results showed that HE-F consistently obtained the first position across all objective weighting approaches, while HE-E consistently occupied the eighth position. This consistency indicates that the performance of HE-F is relatively robust and is not substantially affected by changes in the objective weighting method. Most methods also produced ranking patterns that were highly similar to the ORI ranking, although some changes were observed, particularly when the MEREC weighting method was applied. The bump chart further confirmed that the majority of alternatives maintained relatively stable ranking positions across the different weighting scenarios, while MEREC generated comparatively greater changes in several alternative positions.

The ranking stability analysis using Spearman rank correlation further confirmed the consistency of the results. LODECI, SITDE, and DAM achieved the highest correlation coefficient of 0.9524, followed by G2M and CRITIC with 0.9286, and MEREC with 0.9048. Entropy, RECA, LOPCOW, WENSLO, LOGSTA, and ITARA each obtained a correlation coefficient of 0.8333. Since all approaches produced correlation values above 0.80, the findings indicate a strong level of agreement among the resulting rankings and demonstrate that the overall decision is relatively stable across different objective weighting approaches. These results suggest that combining objective weighting methods with WASPAS can provide a reliable framework for comparative employee evaluation while also allowing the sensitivity and robustness of the resulting ranking to be examined.

Overall, the study demonstrates that the choice of objective weighting method influences criterion importance and can affect alternative ranking, but the general ranking structure remains relatively stable for the evaluated dataset. The consistent first position of HE-F provides strong evidence of its superior overall performance across the five criteria, while the high Spearman correlations indicate that the decision results are not highly dependent on a single weighting approach. Future studies may extend this analysis by incorporating larger datasets, additional employee performance criteria, alternative MCDM ranking methods, and statistical or sensitivity-analysis techniques to provide a broader assessment of ranking robustness across different decision-making environments.

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CRediT Authorship Contribution Statement

Sanriomi Sintaro: Writing – review & editing, Writing – original draft, Validation, Methodology, Conceptualization. **Pritasari Palupiningsih:** Writing – original draft, Formal analysis, Visualization. **Junhai Wang:** Writing – original draft, Software, Investigation

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 ChatGPT-5 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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