



# Logarithmic Normalization and Standard Deviation Modification for Enhanced Sensitivity in Objective Criteria Weighting

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## ABSTRACT

### Keywords:

LOGSTA-D;  
Objective  
Weighting;  
Dispersion  
Compression;  
Logarithmic  
Normalization;  
Robustness  
Analysis;

Objective weighting methods are essential in multi-criteria decision-making (MCDM) because criterion weights directly influence alternative rankings. However, dispersion-based weighting approaches may assign excessive importance to criteria with high variability, resulting in an imbalanced weighting structure. This study proposes LOGSTA-D, an extension of the Logarithmic Normalization and Standard Deviation (LOGSTA) method that introduces a Dispersion Compression Transformation based on the square root of standard deviation. The transformation is designed to moderate differences in criterion dispersion before logarithmic dispersion is used to derive the final criterion weights. The proposed method is evaluated using a supplier selection dataset consisting of nine alternatives and eight criteria and is integrated with four MCDM methods, namely SAW, MOORA, WP, and WASPAS. The results show that LOGSTA-D produces a more moderated distribution of criterion weights by reducing the dominance of highly dispersed criteria and redistributing importance toward criteria with lower initial weights. Across the evaluated MCDM methods, the resulting rankings exhibit a high degree of consistency, with limited changes among intermediate alternatives. The robustness analysis shows that the LOGSTA-D with MCDM framework achieves a robustness value of 0.9875, compared with 0.9604 for the LOGSTA with MCDM framework, indicating a higher level of ranking consistency under the evaluated conditions. These findings demonstrate that LOGSTA-D provides a controlled dispersion-based weighting



mechanism that can support robust decision-making in supplier selection problems.

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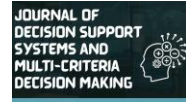
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## I. Introduction

Objective criteria weighting constitutes a fundamental component of Multi-Criteria Decision Making (MCDM), as the assigned weights determine the relative contribution of individual criteria to the overall evaluation of alternatives[1]-[3]. In contrast to subjective weighting schemes that rely primarily on the preferences or judgments of decision makers, objective approaches derive criterion importance from the intrinsic characteristics of the decision matrix, such as data distribution, variability, information content, and inter-criterion relationships. This data-driven perspective is particularly relevant in decision environments involving heterogeneous criteria, where differences in measurement scales and statistical characteristics can affect the resulting weighting structure[4]-[6]. Consequently, the development of objective weighting methods that can extract criterion information consistently while avoiding excessive concentration of weights remains an important research issue in MCDM.

Among dispersion-oriented objective weighting approaches, Logarithmic Normalization and Standard Deviation (LOGSTA) provides a mechanism for combining logarithmic normalization with statistical dispersion to derive criterion importance[7]-[9]. Logarithmic normalization is particularly useful for decision matrices containing substantially different numerical magnitudes, including monetary values, performance scores, quantities, and other heterogeneous measurements. By compressing the scale of larger observations, logarithmic transformation can moderate the influence of numerical magnitude while preserving the relative ordering of observations. The normalized decision matrix can subsequently be analyzed using standard deviation to quantify the degree of variation associated with each criterion. Through this combination, LOGSTA establishes a direct relationship between the statistical characteristics of normalized observations and the objective determination of criterion weights.

The standard deviation component plays a central role in this framework because it represents the extent to which a criterion differentiates alternatives after normalization[10], [11]. A criterion

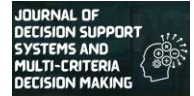


with greater dispersion indicates a larger degree of observable differentiation among alternatives, whereas a criterion with highly concentrated observations provides comparatively less variation for distinguishing alternatives. This characteristic makes standard deviation an intuitive and computationally efficient information measure for objective weighting. Nevertheless, the resulting dispersion values remain strongly dependent on the distributional characteristics of individual criteria. Consequently, logarithmic normalization does not necessarily produce dispersion values with comparable magnitudes across all criteria. The transformation may reduce differences in the original scale while still allowing substantial disparities in the variability of the transformed observations to persist.

This condition gives rise to a dispersion imbalance problem in which standard deviation values may differ considerably across criteria. For instance, dispersion values of 0.0019 and 0.0381 indicate a substantial difference in the amount of variation captured by two criteria, with the latter being approximately twenty times greater than the former. When such values are directly used as information measures, the criterion with greater dispersion can obtain a disproportionately large contribution to the final weighting structure. Conversely, criteria characterized by very limited variation may receive extremely small weights. Although such a result is mathematically consistent with the principle that greater variability represents greater discriminatory information, an excessive disparity may produce a highly concentrated weight distribution in which a limited number of criteria dominate the decision model. This issue is particularly relevant when the objective is to construct a weighting structure that reflects data variability without allowing extreme dispersion differences to disproportionately determine criterion importance.

The problem is not unique to LOGSTA but reflects a broader methodological issue in objective weighting. Existing approaches employ different mechanisms to quantify criterion information. Standard Deviation-based methods primarily emphasize variability, Entropy-based methods assess the information characteristics of normalized distributions, CRITIC incorporates contrast intensity and correlations among criteria, while MEREC evaluates criterion significance through the effect of removing individual criteria from the decision process. Although these approaches provide alternative mechanisms for extracting objective information, the subsequent normalization of information measures does not necessarily resolve substantial disparities among the underlying measures. Conventional weight normalization ensures that the weights sum to one, but it does not fundamentally reduce the relative distance between extremely high and extremely low information values. Therefore, when the underlying dispersion measures are highly heterogeneous, normalization alone may preserve a concentrated weighting structure.

This observation identifies a methodological gap in the application of LOGSTA. The principal limitation does not necessarily originate from the use of logarithmic normalization or standard deviation



individually, but from the direct propagation of highly unequal dispersion values into the criterion weighting stage. Logarithmic normalization addresses differences in the numerical magnitude of the original observations, while standard deviation captures variability after transformation. However, the framework does not inherently provide an additional mechanism for moderating extreme disparities among the resulting dispersion measures. As a consequence, criteria exhibiting substantially higher variability may continue to dominate the weighting structure even after conventional weight normalization. Addressing this issue requires an additional transformation at the dispersion level rather than merely applying another normalization procedure to the final weights.

To address this methodological gap, this study proposes an extension of the LOGSTA framework through a Dispersion Compression Transformation based on the square root of standard deviation. The proposed transformation is introduced before the generation of final criterion weights to compress excessive differences among dispersion measures while retaining their relative ordering. The underlying rationale is that a controlled compression of dispersion can reduce the disproportionate influence of extremely large variability values without eliminating the information represented by differences among criteria. Accordingly, the proposed approach seeks to establish a more balanced relationship between criterion variability and final weight generation while preserving the data-driven nature of LOGSTA.

The contribution of this study lies in extending a dispersion-based objective weighting framework rather than replacing its fundamental mechanism. The proposed approach retains logarithmic normalization as a means of handling heterogeneous numerical scales and preserves dispersion as the primary indicator of criterion differentiation, while introducing a compression mechanism between dispersion calculation and weight generation. This extension is intended to provide an alternative strategy for handling dispersion imbalance in objective weighting and to examine whether controlling the magnitude of dispersion differences can produce a more balanced weighting structure. The proposed method is subsequently evaluated through an MCDM application and comparative analysis with established objective weighting approaches to examine its weighting behavior and implications for decision ranking.

Overall, the study is motivated by the need to reconcile two objectives in data-driven criterion weighting: preserving the discriminatory information contained in criterion variability and preventing excessive dispersion disparities from dominating the weighting structure. By introducing Dispersion Compression Transformation into the LOGSTA framework, this research develops an extended objective weighting approach that explicitly addresses this trade-off. The resulting framework provides a basis for investigating how controlled dispersion compression affects criterion weights and subsequent MCDM outcomes, thereby contributing to the methodological development of objective weighting for heterogeneous decision-making environments.



### 1.1. Research Gap

Despite the availability of various objective weighting methods, several methodological gaps remain in handling substantial differences in criterion dispersion. Existing approaches generally assume that the statistical characteristics extracted from the decision matrix can be directly converted into criterion importance after normalization. In dispersion-based methods, this assumption may become problematic when the variability of one criterion is considerably larger than that of other criteria. Under such circumstances, the resulting weights may become concentrated on criteria with relatively high dispersion, while criteria with limited variability receive considerably smaller contributions. Although this behavior reflects the statistical characteristics of the data, it does not explicitly address the potential imbalance caused by extreme differences in dispersion magnitude.

A further gap concerns the distinction between scale normalization and dispersion compression. Normalization procedures primarily aim to transform heterogeneous observations into a comparable numerical representation[12], [13]. However, achieving comparable normalized observations does not necessarily imply that the resulting dispersion measures will be proportionally balanced. Similarly, conventional normalization of information measures constrains their total contribution but does not modify the relative disparity among the measures themselves. Therefore, an objective weighting framework may require an additional transformation specifically designed to moderate extreme differences in dispersion before the final weights are generated.

The existing literature also provides limited attention to the use of nonlinear transformations for controlling dispersion imbalance in standard-deviation-based weighting. Established objective methods employ different information mechanisms, including variability, entropy, correlation, and criterion-removal effects, but the problem of excessively unequal dispersion is generally addressed indirectly or remains dependent on the characteristics of the resulting data. This creates an opportunity to investigate whether a controlled nonlinear compression of dispersion can improve the balance of criterion contributions while preserving the ordering implied by the original variability. Such an approach differs conceptually from replacing the dispersion measure itself because the objective is to retain the information contained in variability while reducing its excessive magnitude differences.

Accordingly, the research gap addressed in this study can be summarized in three aspects. First, existing LOGSTA-based weighting does not explicitly incorporate a mechanism for controlling extreme disparities among standard deviation values. Second, conventional normalization does not necessarily resolve imbalance originating from the underlying dispersion measures. Third, the potential of square-root-based compression as an intermediate transformation between dispersion calculation and final weight generation has not been sufficiently incorporated into the LOGSTA framework. These gaps motivate the



development of an extended LOGSTA approach that introduces a dedicated dispersion compression mechanism.

## 1.2. Research Contributions and Novelty

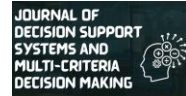
To address the identified gaps, this study develops an extended objective weighting method referred to as LOGSTA with Dispersion Compression Transformation (LOGSTA-D). The proposed method retains the fundamental structure of LOGSTA, consisting of logarithmic normalization and standard deviation-based information measurement, while introducing a square-root transformation at the dispersion stage[14], [15]. The transformation is designed to reduce excessive differences among standard deviation values before they are converted into criterion weights. In this way, the proposed method preserves the data-driven foundation of LOGSTA while providing an additional mechanism for controlling dispersion imbalance.

The first contribution of this study is the development of a dispersion compression mechanism specifically integrated into an objective weighting framework. Unlike conventional normalization, which primarily ensures comparability or constrains the sum of final weights, the proposed transformation operates directly on the dispersion measures. This positioning allows the method to address the source of imbalance before the dispersion information is propagated into the final weighting structure. The square-root transformation provides a nonlinear compression effect in which larger dispersion values are reduced proportionally more than smaller values, while the ordinal relationship among criteria is maintained.

The second contribution is the formulation of an extended LOGSTA weighting framework that establishes a sequential relationship between logarithmic normalization, dispersion measurement, dispersion compression, and final weight generation. This structure provides a transparent methodological pathway for examining how each stage contributes to the resulting criterion weights. The proposed framework therefore does not discard the discriminatory information represented by standard deviation; instead, it modifies the magnitude of dispersion before weight normalization to reduce the potential dominance of criteria with exceptionally high variability.

The third contribution is an empirical examination of the proposed weighting mechanism through comparative MCDM analysis. The resulting criterion weights are compared with those generated by established objective weighting approaches to examine differences in weight distribution and criterion contribution. The analysis is further extended to the resulting alternative rankings to determine how changes in criterion weighting propagate into the MCDM decision process. This provides an empirical basis for evaluating whether the proposed dispersion compression produces meaningful differences in decision outcomes rather than assessing the weighting mechanism solely from its mathematical formulation.

Finally, this study contributes to the broader development of objective weighting methods by introducing dispersion imbalance as an



explicit methodological consideration in the design of statistical weighting schemes. The proposed LOGSTA-D framework offers an alternative perspective in which objective weighting is not limited to extracting information from data but also considers how the magnitude of extracted information should be controlled before determining final criterion importance. The proposed contribution is therefore positioned at the intersection of statistical dispersion measurement and balanced objective weighting, providing a foundation for further research on nonlinear transformation strategies in MCDM weighting.

## II. Related Work

### 2.1. Objective Criteria Weighting in MCDM

Objective criteria weighting is an essential component of Multi-Criteria Decision Making (MCDM) because it determines the relative contribution of individual criteria to the evaluation of alternatives[16], [17]. In practical decision-making environments, criteria often differ in measurement units, numerical ranges, and distributional characteristics. Consequently, assigning weights directly from raw observations can produce an inappropriate representation of criterion importance. Objective weighting methods address this issue by deriving criterion importance from the information contained in the decision matrix, thereby reducing the dependence on subjective judgments from decision makers. The resulting weights can subsequently be integrated with an MCDM method to generate alternative scores and rankings.

A wide range of objective weighting techniques has been developed based on different interpretations of information contained in decision data. Some methods emphasize statistical dispersion, while others measure uncertainty, contrast intensity, correlation, or the influence of individual criteria on the overall evaluation. This methodological diversity reflects the fact that criterion importance can be represented from different perspectives. Therefore, the selection or development of an objective weighting method should consider not only the mathematical procedure used to calculate weights but also how effectively the method represents meaningful differences among alternatives[18], [19].

From a methodological perspective, objective weighting can generally be represented as a sequence consisting of decision-matrix normalization, information extraction, and weight generation. Normalization transforms heterogeneous observations into a comparable scale, whereas the subsequent information measure determines the relative importance of each criterion. The final weights are then obtained by normalizing the information measures. This structure makes the information extraction stage particularly important because any disproportion among the calculated information values can directly affect the resulting weighting distribution.



## 2.2. Dispersion-Based Objective Weighting

Dispersion-based weighting methods determine criterion importance according to the degree of variation observed among alternatives[20], [21]. The underlying principle is that criteria with greater variability provide more discriminatory information because they differentiate alternatives more strongly. Standard deviation is one of the most commonly used statistical measures for representing this variability because it provides a direct indication of how far observations deviate from their central tendency.

In an objective weighting framework, standard deviation can therefore be used as an information measure in which criteria with larger dispersion obtain larger weights. This approach has several practical advantages, including conceptual simplicity, straightforward computation, and transparent interpretation[22], [23]. Unlike methods requiring complex inter-criterion relationships, standard-deviation-based weighting can derive criterion importance directly from the distribution of observations for each criterion.

However, the direct use of standard deviation also introduces an important consideration. Dispersion values are inherently dependent on the distribution of each criterion. When criteria exhibit substantially different levels of variability, the resulting information measures can become highly unequal. After weight normalization, these differences may translate into a concentrated weighting structure. Thus, although greater dispersion can reasonably be interpreted as greater discriminatory information, extreme dispersion differences may cause certain criteria to exert disproportionately large influence on the final decision model.

This characteristic distinguishes dispersion-based methods from approaches that explicitly incorporate other forms of information. The usefulness of standard deviation weighting therefore depends not only on the existence of variability but also on the relative magnitude of dispersion across criteria. This issue becomes more relevant when the decision matrix contains heterogeneous criteria with substantially different statistical distributions.

## 2.3. LOGSTA and the Need for Dispersion Compression

LOGSTA combines logarithmic normalization and standard deviation to derive objective criterion weights. Its methodological structure provides two complementary functions: logarithmic normalization reduces differences in numerical magnitude, while standard deviation quantifies the variability remaining after transformation. This combination provides a relatively direct mechanism for extracting criterion importance from heterogeneous decision data.

However, the two operations address different levels of the decision matrix. Logarithmic normalization operates on the observations, whereas standard deviation operates on the distribution of transformed observations[24], [25]. As a result, reducing numerical magnitude differences does not necessarily eliminate differences in dispersion.



Two criteria can exhibit comparable normalized scales while still producing substantially different standard deviations. If these standard deviations are directly converted into information measures, the resulting weights may remain highly concentrated.

This observation suggests that an additional transformation can be positioned between standard deviation calculation and final weight generation. Rather than modifying the logarithmic transformation or replacing standard deviation, dispersion compression can be introduced specifically to control the magnitude of the resulting variability measures. Such a strategy preserves the basic information logic of LOGSTA while addressing the potential imbalance arising from highly unequal dispersion values.

#### **2.4. Dispersion Compression as a Methodological Extension**

Nonlinear transformations provide a general mechanism for reducing differences in the magnitude of numerical values while preserving their ordinal relationships. In the context of objective weighting, such transformations can potentially be applied to information measures rather than directly to the original decision observations. This creates a distinction between data normalization and information-measure transformation.

The proposed Dispersion Compression Transformation follows this second perspective. Instead of attempting to eliminate variability differences, the transformation reduces the magnitude gap between high and low dispersion values before final weights are calculated. A square-roots transformation is particularly relevant because it is monotonic for non-negative dispersion values and therefore preserves their ordering while producing a compression effect. Consequently, criteria with larger dispersion remain relatively more important, but the magnitude of their advantage over criteria with smaller dispersion can be moderated.

This approach provides a different methodological perspective from conventional objective weighting. The objective is not to assume that all criteria should receive similar weights, nor to eliminate the discriminatory information represented by variability. Rather, the objective is to investigate whether excessive dispersion disparities should be moderated before they determine the final weighting structure. This distinction forms the conceptual basis for the proposed LOGSTA-D method.

### **III. Methodology**

The Results and Discussion section presents the research findings obtained from the implementation of the proposed method, model, or approach. Research results may be presented in the form of tables, figures, charts, or other visualizations to facilitate readers' understanding. Every table and figure must be properly referenced and



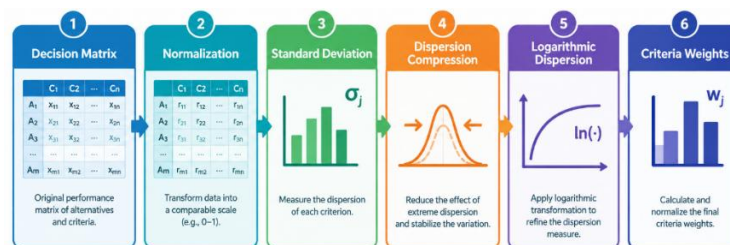
explained within the narrative, highlighting the purpose of the presented data and its relationship to the research objectives.

The discussion should focus on analyzing and interpreting the obtained results rather than merely repeating the information already presented in tables or figures. Authors are expected to explain the significance of the findings, the factors influencing the results, and their relationship to relevant theories, concepts, or previous studies. The analysis should clearly demonstrate the contribution of the research to problem-solving or to the advancement of knowledge in the relevant field.

In addition, authors are encouraged to evaluate the performance of the proposed method, model, or system through testing, comparison, or other appropriate analytical procedures aligned with the research objectives. The evaluation results should be discussed critically by highlighting the strengths, limitations, and implications of the findings. This section should be written in a systematic, logical, and evidence-based manner to provide a comprehensive and convincing discussion.

### 3.1. Conceptual Framework of LOGSTA-D

The proposed LOGSTA-D (Logarithmic Normalization and Standard Deviation with Dispersion Compression Transformation) framework is designed to address the potential imbalance of criterion importance arising from substantially different dispersion values in objective MCDM weighting. The framework extends the conventional LOGSTA procedure by introducing an additional transformation between the calculation of standard deviation and the generation of final criterion weights. The overall process begins with the construction of the decision matrix containing alternatives and evaluation criteria, followed by logarithmic normalization to reduce differences in numerical magnitude across heterogeneous criteria. The normalized observations are then analyzed using standard deviation to quantify the variability of each criterion. Instead of directly converting these dispersion values into criterion weights, LOGSTA-D applies a dispersion compression transformation based on the square root of standard deviation. This transformation is intended to reduce excessive differences between high- and low-dispersion criteria while preserving their relative ordering. The compressed dispersion values are subsequently used to generate and normalize the final criterion weights. The complete conceptual framework is illustrated in Figure 1.



**Figure 1. LOGSTA-D Framework**



The LOGSTA-D Framework presents a sequential procedure for objective criteria weighting, beginning with the Decision Matrix, which contains the original performance values of alternatives across multiple criteria. The matrix is then transformed through Normalization to obtain comparable criterion values, followed by Standard Deviation to quantify the dispersion of each criterion. The resulting dispersion measure is processed using Dispersion Compression to reduce the influence of excessively large variations and improve the stability of the weighting process. Subsequently, Logarithmic Dispersion applies a logarithmic transformation to refine and adjust the dispersion information, producing a more controlled representation of criterion variability. Finally, the adjusted dispersion values are normalized to generate the Criteria Weights, which represent the relative importance of each criterion and can subsequently be used in the decision-making process.

### 3.2. LOGSTA-D Method

LOGSTA-D is a modified objective criteria-weighting framework developed from the LOGSTA approach by incorporating an additional Dispersion Compression mechanism. In the original LOGSTA, criterion importance is derived from the standard deviation of normalized data and subsequently adjusted through a logarithmic transformation to regulate the magnitude of dispersion. LOGSTA-D extends this procedure by introducing Dispersion Compression before the logarithmic adjustment, allowing excessively large dispersion values to be compressed while retaining the relative information contained in criterion variability. The resulting compressed dispersion is then processed using the logarithmic transformation and normalized to obtain the final criterion weights. Thus, the principal modification of LOGSTA-D lies in the addition of the Dispersion Compression stage, which is intended to reduce the disproportionate influence of extreme dispersion and provide a more controlled representation of criterion variability.

The first stage involves constructing the decision matrix, which represents the performance of all alternatives across the evaluation criteria. The matrix contains the original observations obtained from the decision problem and may involve criteria with different measurement units, numerical scales, and data magnitudes[26], [27]. This stage establishes the empirical basis for the subsequent weighting process while preserving the original characteristics of the observations before normalization is applied. The formulation of the decision matrix is presented in (1).

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

The normalization stage transforms the original decision data into a comparable representation. In the proposed LOGSTA-D framework, logarithmic normalization is applied to reduce excessive differences in numerical magnitude among observations while maintaining their relative ordering. This transformation is particularly useful for heterogeneous decision data involving different measurement scales and numerical characteristics[28], [29]. The resulting normalized data provide the



basis for measuring the variability of each criterion in the subsequent stage. The normalization procedure is presented in (2).

$$n_{ij} = \begin{cases} \left| \frac{\ln(x_{ij})}{\ln(\prod_{i=1}^m x_{ij})} \right|; \text{benefit} \\ \left| \frac{1 - \frac{\ln(x_{ij})}{\ln(\prod_{i=1}^m x_{ij})}}{n-1} \right|; \text{cost} \end{cases} \quad (2)$$

The standard deviation stage measures the variability of observations associated with each criterion after normalization[25]. This stage identifies the degree of differentiation among alternatives based on the normalized data. A higher dispersion indicates greater variation among alternatives, whereas a lower dispersion reflects more concentrated observations. The resulting dispersion values serve as the initial information measures in the proposed weighting framework. The standard deviation calculation is presented in (3).

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^m (n_{ij} - \bar{n}_j)^2}{n}} \quad (3)$$

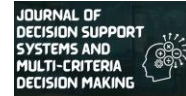
The dispersion compression stage represents the main methodological extension introduced by LOGSTA-D. The standard deviation values obtained for different criteria may exhibit substantial differences in magnitude, potentially causing certain criteria to receive disproportionately high importance. To address this condition, a square-root-based compression is applied to the dispersion values[30]. This transformation reduces the magnitude gap between high and low dispersion while preserving the relative ordering of the criteria. Thus, criteria with greater variability continue to contribute more information, while excessive differences in dispersion are moderated. The dispersion compression procedure is presented in (4).

$$D_j = \sqrt{\sigma_j} \quad (4)$$

The logarithmic dispersion stage transforms the compressed dispersion values into information measures used in the subsequent weighting process. The logarithmic transformation further moderate differences in the magnitude of the compressed dispersion values and provides a more controlled representation of criterion variability[31]. This stage is intended to prevent criteria with exceptionally large dispersion from exerting an excessive influence on the resulting weighting structure. The logarithmic dispersion procedure is presented in (5).

$$S_j = D_j * (|\sum_{i=1}^m (\ln(n_{ij}))|)^{-1} \quad (5)$$

The final stage generates the objective criterion weights based on the logarithmic dispersion values. The information contribution of each criterion is normalized against the total information contribution of all criteria, resulting in weights that represent the relative importance of the evaluation criteria. The resulting weights can subsequently be integrated with an appropriate MCDM method for evaluating



and ranking alternatives. The criteria weighting procedure is presented in (6).

$$w_j = \frac{s_j}{\sum_{j=1}^n s_j} \quad (6)$$

Overall, the LOGSTA-D framework provides a systematic procedure for deriving objective criterion weights from heterogeneous decision data. The integration of normalization, standard deviation, dispersion compression, and logarithmic dispersion enables the framework to capture criterion variability while controlling excessive differences in dispersion magnitude. The dispersion compression stage represents the principal extension of the proposed approach by moderating disproportionate dispersion without eliminating the relative differentiation among criteria. Through this sequential process, LOGSTA-DCT produces a balanced set of objective criterion weights that can be incorporated into subsequent MCDM procedures for alternative evaluation and ranking. The framework therefore establishes the methodological foundation for examining whether dispersion compression can improve the distribution and stability of criterion weights in heterogeneous decision-making environments.

## IV. Experimental Result

The Results and Discussion section presents the research findings obtained from the implementation of the proposed method, model, or approach. Research results may be presented in the form of tables, figures, charts, or other visualizations to facilitate readers' understanding. Every table and figure must be properly referenced and explained within the narrative, highlighting the purpose of the presented data and its relationship to the research objectives.

### 4.1. Dataset

The dataset used in this study represents a multi-criteria decision-making problem involving the evaluation of several alternatives across a set of heterogeneous criteria. The data were selected to provide a representative decision matrix containing different numerical ranges and distributional characteristics, thereby enabling the proposed LOGSTA-D method to be examined under conditions where dispersion differences among criteria may occur. Each alternative is evaluated according to the predefined criteria, with the resulting observations serving as the primary input for logarithmic normalization, standard deviation calculation, dispersion compression, and logarithmic dispersion processing. The dataset is subsequently used to generate objective criterion weights and evaluate the resulting alternative rankings through the selected MCDM approach. This experimental setting enables the study to examine both the weighting behavior of LOGSTA-DCT and its implications for comparative, sensitivity, and robustness analyses.



The dataset used in this study represents a supplier selection problem involving nine supplier alternatives evaluated according to eight criteria. The dataset is designed to reflect a heterogeneous decision environment in which the criteria have different numerical scales and characteristics. The alternatives are represented by supplier codes S01-S09, while the evaluation criteria consist of Cost (CS001), Quality (CS002), Delivery (CS003), Reliability (CS004), Flexibility (CS005), Capacity (CS006), Sustainability (CS007), and Service (CS008). The inclusion of criteria with substantially different numerical ranges, particularly Cost, Delivery, and Capacity compared with the score-based criteria, provides an appropriate setting for examining the capability of LOGSTA-D to process heterogeneous decision data and control differences in criterion dispersion. The complete alternative assessment data are presented in Table 1.

**Table 1. Dataset Supplier**

| Supplier | CS001 | CS002 | CS003 | CS004 | CS005 | CS006 | CS007 | CS008 |
|----------|-------|-------|-------|-------|-------|-------|-------|-------|
| S01      | 82    | 91    | 14    | 88    | 76    | 820   | 72    | 84    |
| S02      | 95    | 86    | 18    | 81    | 83    | 1050  | 65    | 79    |
| S03      | 68    | 94    | 11    | 92    | 71    | 680   | 88    | 91    |
| S04      | 110   | 79    | 24    | 74    | 90    | 1280  | 59    | 73    |
| S05      | 76    | 88    | 16    | 85    | 79    | 760   | 81    | 86    |
| S06      | 125   | 83    | 21    | 78    | 94    | 1450  | 54    | 77    |
| S07      | 61    | 96    | 10    | 95    | 68    | 590   | 93    | 94    |
| S08      | 88    | 89    | 17    | 87    | 85    | 910   | 75    | 82    |
| S09      | 103   | 81    | 22    | 76    | 88    | 1190  | 62    | 75    |

The dataset presented in Table 1 provides a heterogeneous evaluation environment for examining the proposed LOGSTA-DCT weighting framework. The nine supplier alternatives exhibit different performance patterns across the eight criteria. The differences in measurement ranges and performance distributions provide sufficient variation for identifying criterion-specific dispersion and evaluating the effect of the proposed dispersion compression transformation. Accordingly, this dataset serves as the basis for subsequent normalization, dispersion analysis, objective criterion weighting, MCDM ranking, sensitivity analysis, and robustness evaluation.

#### 4.2. Calculating Criteria Weights Using LOGSTA-D

The calculation of criterion weights using LOGSTA-D is conducted to transform the information contained in the normalized decision matrix into objective importance values for each criterion. The procedure applies the characteristics of criterion dispersion to identify the extent to which each criterion contributes to differentiating the evaluated alternatives, while the proposed transformation is used to moderate excessive differences in dispersion among criteria. Through this process, the resulting weights reflect the relative information content of the criteria while maintaining a more balanced distribution of importance. The calculated weights are subsequently used as inputs for the MCDM evaluation stage, enabling the contribution of each



criterion to the final alternative assessment to be determined systematically and consistently.

The first stage in determining the objective criterion weights using the LOGSTA-D method is the construction of the decision matrix, which contains the performance of all alternatives based on the evaluation criteria. The decision matrix is formulated based on Equation (1), and the resulting decision matrix is presented as follows.

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{13} & x_{14} & x_{15} & x_{16} & x_{17} & x_{18} \\ x_{21} & x_{22} & x_{23} & x_{24} & x_{25} & x_{26} & x_{27} & x_{28} \\ x_{31} & x_{32} & x_{33} & x_{34} & x_{35} & x_{36} & x_{37} & x_{38} \\ x_{41} & x_{42} & x_{43} & x_{44} & x_{45} & x_{46} & x_{47} & x_{48} \\ x_{51} & x_{52} & x_{53} & x_{54} & x_{55} & x_{56} & x_{57} & x_{58} \\ x_{61} & x_{62} & x_{63} & x_{64} & x_{65} & x_{66} & x_{67} & x_{68} \\ x_{71} & x_{72} & x_{73} & x_{74} & x_{75} & x_{76} & x_{77} & x_{78} \\ x_{81} & x_{82} & x_{83} & x_{84} & x_{85} & x_{86} & x_{87} & x_{88} \\ x_{91} & x_{92} & x_{93} & x_{94} & x_{95} & x_{96} & x_{97} & x_{98} \end{bmatrix}$$

The decision matrix results from the alternative evaluation data are as follows.

$$X = \begin{bmatrix} 82 & 91 & 14 & 88 & 76 & 820 & 72 & 84 \\ 95 & 86 & 18 & 81 & 83 & 1050 & 65 & 79 \\ 68 & 94 & 11 & 92 & 71 & 680 & 88 & 91 \\ 110 & 79 & 24 & 74 & 90 & 1280 & 59 & 73 \\ 76 & 88 & 16 & 85 & 79 & 760 & 81 & 86 \\ 125 & 83 & 21 & 78 & 94 & 1450 & 54 & 77 \\ 61 & 96 & 10 & 95 & 68 & 590 & 93 & 94 \\ 88 & 89 & 17 & 87 & 85 & 910 & 75 & 83 \\ 103 & 81 & 22 & 76 & 88 & 1190 & 62 & 75 \end{bmatrix}$$

The second stage in determining the objective criterion weights using the LOGSTA-D method is data normalization using logarithmic normalization. This stage transforms the original data into a comparable scale while reducing differences in numerical magnitude among observations. The normalization process is performed based on Equation (2), and the normalized results are presented as follows.

$$n_{11} = \left| \frac{1 - \frac{\ln(x_{11})}{\ln(\prod_{i=1}^9 x_{i1})}}{9 - 1} \right| = \left| \frac{1 - \frac{\ln(x_{11})}{\ln(x_{11} * x_{21} * x_{31} * x_{41} * x_{51} * x_{61} * x_{71} * x_{81} * x_{91})}}{9 - 1} \right|$$

$$= \left| \frac{1 - \frac{\ln(82)}{\ln(82 * 95 * 68 * 110 * 76 * 125 * 61 * 88 * 103)}}{8} \right| = \left| \frac{0.8906}{8} \right| = 0.1113$$

Table 2 shows the overall results of the normalization calculations using the LOGSTA-D method.

**Table 2. Normalization Results of the LOGSTA-D Method.**

| Supplier | CS001  | CS002  | CS003  | CS004  | CS005  | CS006  | CS007  | CS008  |
|----------|--------|--------|--------|--------|--------|--------|--------|--------|
| S01      | 0.1113 | 0.1122 | 0.1119 | 0.1124 | 0.1095 | 0.1090 | 0.1115 | 0.1117 |
| S02      | 0.1109 | 0.1107 | 0.1106 | 0.1103 | 0.1117 | 0.1131 | 0.1088 | 0.1102 |
| S03      | 0.1119 | 0.1130 | 0.1131 | 0.1135 | 0.1077 | 0.1060 | 0.1167 | 0.1137 |



|     |        |        |        |        |        |        |        |        |
|-----|--------|--------|--------|--------|--------|--------|--------|--------|
| S04 | 0.1104 | 0.1086 | 0.1092 | 0.1080 | 0.1137 | 0.1163 | 0.1063 | 0.1082 |
| S05 | 0.1116 | 0.1113 | 0.1112 | 0.1115 | 0.1104 | 0.1078 | 0.1145 | 0.1123 |
| S06 | 0.1100 | 0.1099 | 0.1099 | 0.1093 | 0.1148 | 0.1183 | 0.1040 | 0.1095 |
| S07 | 0.1122 | 0.1135 | 0.1136 | 0.1143 | 0.1066 | 0.1037 | 0.1181 | 0.1145 |
| S08 | 0.1111 | 0.1116 | 0.1109 | 0.1121 | 0.1123 | 0.1107 | 0.1125 | 0.1111 |
| S09 | 0.1106 | 0.1093 | 0.1096 | 0.1087 | 0.1132 | 0.1151 | 0.1076 | 0.1088 |

The third stage in determining the objective criterion weights using the LOGSTA-D method is the calculation of the standard deviation, which measures the variability of each criterion based on the normalized data. A higher standard deviation indicates greater differentiation among alternatives. The calculation is performed based on (3), and the resulting values are presented as follows.

$$\sigma_1 = \sqrt{\frac{\sum_{i=1}^9 (n_{i1} - \bar{n}_1)^2}{9}} = \sqrt{\frac{(n_{11} - \bar{n}_1)^2 + (n_{21} - \bar{n}_1)^2 + (n_{31} - \bar{n}_1)^2 + (n_{41} - \bar{n}_1)^2 + (n_{51} - \bar{n}_1)^2 + (n_{61} - \bar{n}_1)^2 + (n_{71} - \bar{n}_1)^2 + (n_{81} - \bar{n}_1)^2 + (n_{91} - \bar{n}_1)^2}{9}}$$

$$= 0.000679$$

Table 3 shows the overall results of the standard deviation calculations using the LOGSTA-D method.

**Table 3. Standard Deviation Results of the LOGSTA-D Method.**

| CS001    | CS002    | CS003    | CS004    | CS005    | CS006    | CS007    | CS008    |
|----------|----------|----------|----------|----------|----------|----------|----------|
| 0.000679 | 0.001551 | 0.001418 | 0.002045 | 0.002606 | 0.004651 | 0.004555 | 0.002044 |

The fourth stage in determining the objective criterion weights using the LOGSTA-D method is dispersion compression. This stage applies a square-root transformation to the standard deviation values to reduce excessive differences in dispersion magnitude while preserving their relative order. The process is performed based on (4), and the resulting dispersion compression values are presented as follows.

$$D_1 = \sqrt{\sigma_1} = \sqrt{0.000679} = 0.0261$$

Table 4 shows the overall results of the dispersion compression calculations using the LOGSTA-D method.

**Table 4. Dispersion Compression Results of the LOGSTA-D Method.**

| CS001  | CS002  | CS003  | CS004  | CS005  | CS006  | CS007  | CS008  |
|--------|--------|--------|--------|--------|--------|--------|--------|
| 0.0261 | 0.0394 | 0.0377 | 0.0452 | 0.0510 | 0.0682 | 0.0675 | 0.0452 |

The fifth stage in determining the objective criterion weights using the LOGSTA-D method is logarithmic dispersion. This stage applies a logarithmic transformation to the compressed dispersion values to further control magnitude differences and obtain the information values of each criterion. The calculation is performed based on (5), and the resulting logarithmic dispersion values are presented as follows.

$$S_1 = D_1 * \left( \left| \sum_{i=1}^9 (\ln(n_{ij})) \right| \right)^{-1}$$



$$= D_1 * (|\ln(n_{11}) + \ln(n_{21}) + \ln(n_{31}) + \ln(n_{41}) + \ln(n_{51}) + \ln(n_{61}) + \ln(n_{71}) + \ln(n_{81}) + \ln(n_{91})|)^{-1}$$

$$= 0.0261 * 0.05057 = 0.0013$$

Table 5 shows the overall results of the logarithmic dispersion calculations using the LOGSTA-D method.

**Table 5. Logarithmic Compression Results of the LOGSTA-D Method.**

| CS001  | CS002  | CS003  | CS004  | CS005  | CS006  | CS007  | CS008  |
|--------|--------|--------|--------|--------|--------|--------|--------|
| 0.0013 | 0.0020 | 0.0019 | 0.0023 | 0.0026 | 0.0034 | 0.0034 | 0.0023 |

The final stage derives the objective criterion weights by normalizing the logarithmic dispersion values against their total. The resulting weights reflect the relative importance of each criterion and can be integrated into an MCDM method, as presented in (6), and the resulting criterion weights values are presented as follows.

$$w_1 = \frac{S_1}{\sum_{j=1}^8 S_j} = \frac{S_1}{S_1 + S_2 + S_3 + S_4 + S_5 + S_6 + S_7 + S_8} = \frac{0.0013}{0.0192} = 0.0685$$

Table 6 shows the overall results of the criterion weights calculations using the LOGSTA-D method.

**Table 6. Criterion Weights Results of the LOGSTA-D Method.**

| CS001  | CS002  | CS003  | CS004  | CS005  | CS006  | CS007  | CS008  |
|--------|--------|--------|--------|--------|--------|--------|--------|
| 0.0685 | 0.1036 | 0.0990 | 0.1189 | 0.1343 | 0.1793 | 0.1774 | 0.1189 |

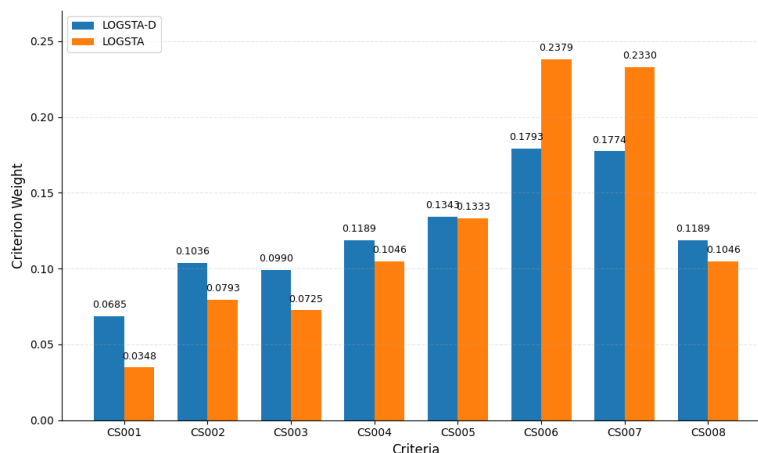
Table 6 presents the criterion weights obtained using the proposed LOGSTA-D method. The results show that CS006 has the highest weight at 0.1793, followed closely by CS007 at 0.1774, indicating their relatively greater contribution to the decision process. In contrast, CS001 has the lowest weight at 0.0685. The remaining criteria have weights ranging from 0.0990 to 0.1343, with CS005 receiving a weight of 0.1343, while CS004 and CS008 both obtain 0.1189. Overall, the weights indicate that LOGSTA-D assigns differentiated importance to the criteria based on their dispersion characteristics.

### 4.3. Comparison of Criteria Weights

The comparison of criterion weights between LOGSTA and LOGSTA-D is conducted to investigate the effect of the proposed methodological modification on the distribution of objective weights. Both methods are applied to the same decision matrix and evaluation criteria, allowing the differences in the resulting weights to be attributed primarily to the modification introduced in LOGSTA-D. The analysis particularly examines the changes resulting from the incorporation of the Dispersion Compression mechanism, which is designed to regulate the dispersion information before the final criterion weights are determined. As shown in Figure 2, the criterion weights generated by LOGSTA and LOGSTA-D exhibit noticeable differences across several criteria, indicating that the proposed modification affects the relative contribution of the criteria. The comparison further shows that LOGSTA-D modifies the weighting pattern by compressing the dispersion values, thereby reducing



the influence of excessively large dispersion differences while maintaining the relative information contained in the decision matrix. These changes can be observed from the variations in the weight values between the two methods, particularly for criteria with relatively high or low dispersion. Therefore, the results presented in Figure 2 demonstrate the direct effect of the Dispersion Compression mechanism and provide a basis for examining the distinctive weighting behavior of LOGSTA-D compared with the original LOGSTA method.



**Figure 2. Comparison of Weights between LOGSTA and LOGSTA-D**

Figure 2 illustrates the comparison of criterion weights generated by the LOGSTA and LOGSTA-D methods. LOGSTA assigns the highest weights to CS006 (0.2379) and CS007 (0.2330), whereas LOGSTA-D produces lower values of 0.1793 and 0.1774, respectively. Conversely, LOGSTA-D increases the weights of CS001, CS002, CS003, CS004, and CS008, with the most notable increase observed for CS001, from 0.0348 to 0.0685. The weight of CS005 remains relatively stable, changing only slightly from 0.1333 to 0.1343. Overall, the comparison indicates that the Dispersion Compression mechanism in LOGSTA-D reduces the dominance of criteria with relatively high dispersion while redistributing part of their weight toward criteria with lower weights, resulting in a more balanced criterion-weight distribution.

## V. Result and Discussion

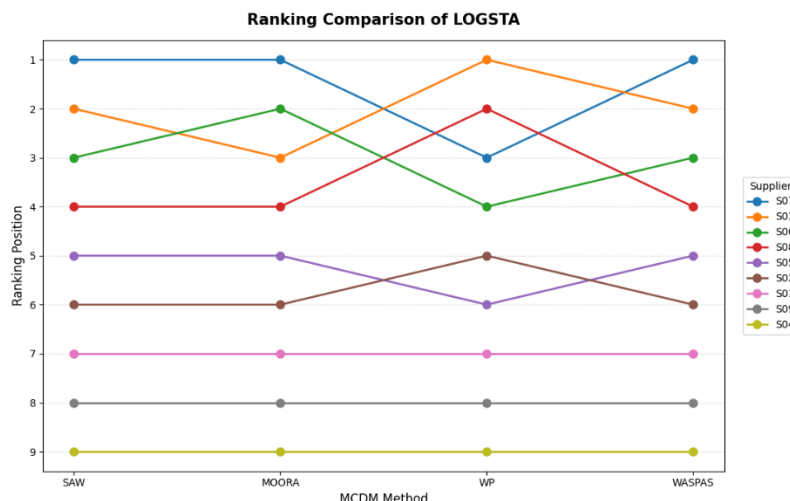
### 5.1. The Combination of LOGSTA with the MCDM Method

The integration of LOGSTA with an MCDM framework offers a structured approach for solving decision problems in which alternatives must be assessed according to several criteria with different characteristics. In this framework, LOGSTA functions as an objective weighting technique that extracts the relative significance of criteria from the information contained in the decision matrix. Its weighting procedure employs logarithmic normalization and standard deviation to



capture differences in the distribution and variability of criterion values. The weights obtained from LOGSTA are then transferred to the subsequent evaluation stage, where they determine the contribution of each criterion to the overall assessment of alternatives. Such integration establishes a direct relationship between the statistical properties of the available data and the final decision-making process. Consequently, the framework can be used to examine how data-driven criteria importance affects the relative position of competing alternatives. This approach also provides a basis for assessing the consistency of the resulting decisions when the same LOGSTA-derived weights are applied within different MCDM procedures.

To further examine the applicability of LOGSTA-based weighting, the generated criteria weights are combined with SAW, MOORA, WP, and WASPAS for alternative assessment and ranking. Each method processes the weighted decision information according to its own aggregation mechanism, thereby providing several perspectives on the resulting priority structure. The comparison among these approaches allows the influence of LOGSTA-derived weights to be observed across different MCDM formulations. In particular, variations or similarities in the obtained rankings can be used to identify the extent to which alternative priorities remain consistent despite differences in the underlying ranking procedures. This comparative analysis is also useful for revealing potential rank changes that may arise from the mathematical characteristics of each MCDM method. The resulting ranking profiles therefore provide empirical evidence for examining the behavior of LOGSTA when coupled with different decision-making techniques. The comparative ranking outcomes generated from the LOGSTA-based framework are illustrated in Figure 3.



**Figure 3. Comparison of LOGSTA and MCDM Rankings**

Figure 3 presents the ranking comparison of nine suppliers obtained by integrating LOGSTA-derived criteria weights with SAW, MOORA, WP, and WASPAS. The results show that SAW and WASPAS produce an identical ranking

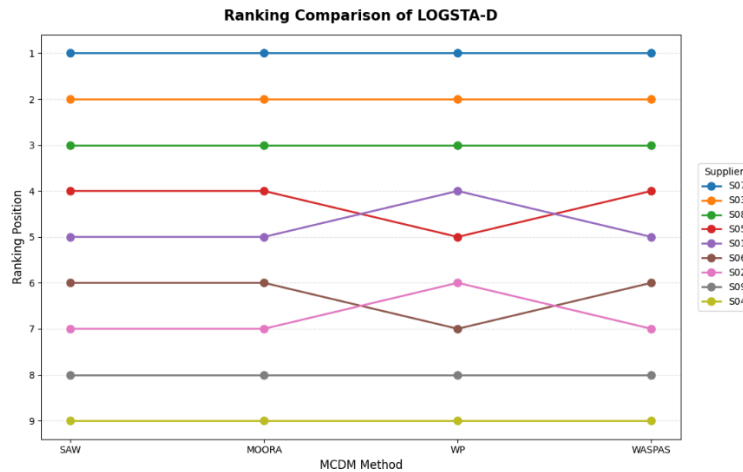


order, with S07, S03, S06, and S08 occupying the first four positions, while MOORA introduces a minor change by placing S06 above S03. A more noticeable variation appears under WP, where S03 moves to the first position, followed by S08, S07, and S06, indicating greater rank changes among the leading suppliers. Meanwhile, S01, S09, and S04 maintain the same seventh, eighth, and ninth positions across all four methods, respectively. Overall, the figure demonstrates that most suppliers retain relatively stable positions, although differences in the aggregation mechanisms of the MCDM methods can produce noticeable changes in the ordering of the highest-ranked alternatives.

## 5.2. The Combination of LOGSTA-D with the MCDM Method

The combination of LOGSTA-D with the MCDM method establishes an integrated framework for addressing decision-making problems involving multiple and potentially conflicting criteria. LOGSTA-D serves as the objective weighting component by processing the decision matrix through logarithmic transformation, standard deviation, and dispersion compression to determine the relative importance of each criterion. The resulting criteria weights provide an objective foundation for the subsequent evaluation of alternatives within the MCDM framework. This integration is important because the weighting process directly affects how the performance of alternatives is interpreted and compared across different criteria. By incorporating LOGSTA-D, the decision-making process can account for the distribution and variability of criterion values while reducing excessive differences in dispersion that may distort the resulting weights. The framework therefore connects the statistical characteristics of the decision matrix with the evaluation stage, creating a coherent sequence from data processing to alternative prioritization. In this context, the combination of LOGSTA-D and MCDM provides a methodological structure for examining whether the proposed weighting mechanism can produce meaningful and stable decision outcomes.

The combination of LOGSTA-D with SAW, MOORA, WP, and WASPAS provides an integrated framework for addressing multi-criteria decision-making problems through objective criteria weighting and systematic alternative ranking. In this framework, LOGSTA-D is employed to determine the relative importance of criteria by incorporating logarithmic transformation, standard deviation, and dispersion compression into the weighting process. The resulting weights are subsequently integrated into SAW, MOORA, WP, and WASPAS to evaluate the performance of alternatives based on their respective computational mechanisms. The use of multiple MCDM methods enables the decision process to be examined from different ranking perspectives rather than relying on a single evaluation procedure. This combination also makes it possible to investigate whether the criteria weights generated by LOGSTA-D consistently influence the prioritization of alternatives across different MCDM approaches. Furthermore, the resulting ranking outcomes provide a basis for comparing the consistency of alternative priorities across the four methods. The final ranking results obtained from the LOGSTA-D-based MCDM framework are presented in Figure 4.



**Figure 4. Comparison of LOGSTA-D and MCDM rankings**

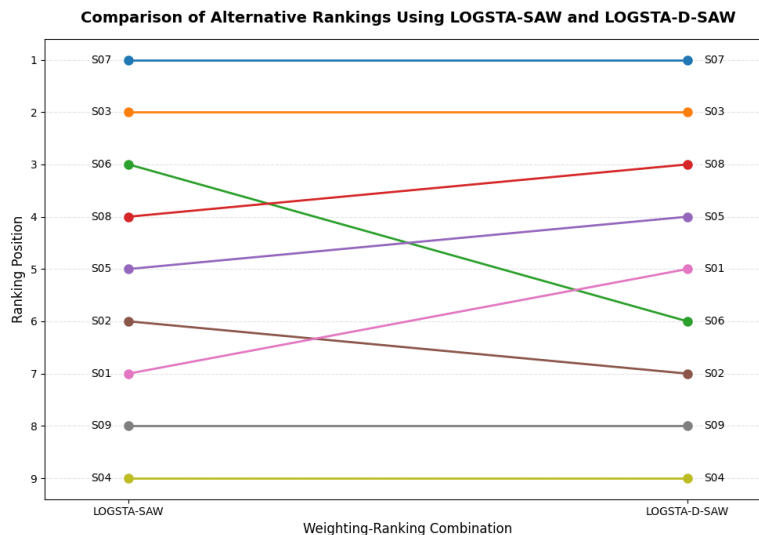
Figure 4 presents the ranking comparison of suppliers obtained by combining LOGSTA-D weighting with four MCDM methods, namely SAW, MOORA, WP, and WASPAS. The results indicate a highly consistent ranking pattern across the methods, with S07, S03, and S08 maintaining the first, second, and third positions, respectively. S04 and S09 also retain their positions at ranks 9 and 8 across all methods, indicating stable prioritization at the lower end of the ranking. The most noticeable variations occur under WP, where S05 moves from fourth to fifth position while S01 moves from fifth to fourth position. Similarly, S06 shifts from sixth to seventh position, whereas S02 moves from seventh to sixth position under WP. In contrast, the rankings produced by SAW, MOORA, and WASPAS remain identical for all suppliers. Overall, the figure illustrates a strong degree of ranking consistency among the MCDM methods when using LOGSTA-D as the criteria weighting approach, with only limited rank reversals observed in the WP results.

### 5.3. Comparison of Alternative Rankings

The comparison of alternative rankings is performed to examine the consistency of decision outcomes generated using the criteria weights obtained from LOGSTA and its modified version, LOGSTA-D. Both weighting approaches are applied within the same MCDM framework to determine whether the additional dispersion compression procedure introduced in LOGSTA-D affects the relative positions of the evaluated alternatives. By comparing the ranking results produced under both weighting schemes, the analysis identifies similarities and differences in alternative priorities and provides insight into the influence of the weighting formulation on the final decision structure. This comparison also enables the stability of alternative rankings to be examined across different combinations of weighting and MCDM procedures, thereby providing a basis for evaluating the practical behavior of LOGSTA and LOGSTA-D in multi-criteria decision-making.



The comparison of alternative rankings using SAW is conducted to examine the effect of LOGSTA and LOGSTA-D weighting schemes on the final prioritization of alternatives. In this analysis, the SAW method is applied consistently to both sets of criteria weights, allowing the resulting rankings to be compared under an identical aggregation procedure. This design isolates the influence of the weighting approach and provides a clearer assessment of whether the dispersion compression transformation incorporated into LOGSTA-D changes the relative importance of criteria and, consequently, the positions of the evaluated alternatives. The comparison focuses on the degree of ranking consistency between LOGSTA-SAW and LOGSTA-D-SAW, including alternatives that maintain, improve, or decline in position. The resulting ranking patterns provide an empirical basis for examining the effect of the proposed LOGSTA-D modification on decision outcomes while maintaining the same SAW-based evaluation mechanism. Figure 5 shows a ranking comparison between LOGSTA and SAW, and LOGSTA-D and SAW.



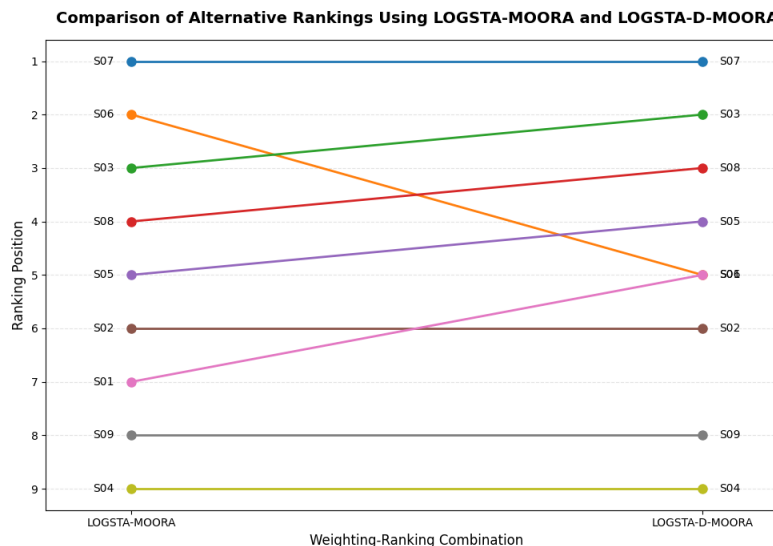
**Figure 5. Ranking Comparison between LOGSTA and LOGSTA-D using the SAW method**

The ranking results obtained from LOGSTA-SAW and LOGSTA-D-SAW show a high degree of consistency among the evaluated suppliers, particularly for the leading and lowest-ranked alternatives. S07 and S03 retain the first and second positions in both approaches, while S09 and S04 consistently occupy the eighth and ninth positions, respectively. Several changes occur in the middle-ranking group following the incorporation of the dispersion compression transformation in LOGSTA-D. S08 improves from fourth to third position, S05 moves from fifth to fourth, and S01 rises from seventh to fifth. In contrast, S06 declines from third to sixth position, while S02 decreases from sixth to seventh. These changes indicate that the modification introduced by LOGSTA-D affects the relative contribution of the criteria during the SAW aggregation process, particularly for alternatives positioned in the



middle of the ranking structure. Nevertheless, the unchanged positions of S07, S03, S09, and S04 indicate that the modification does not alter the overall ordering boundaries of the highest- and lowest-ranked alternatives.

The ranking comparison under MOORA is used to investigate how the alternative priorities respond to the use of LOGSTA and LOGSTA-D criteria weights. Unlike a direct comparison of the weighting procedures, this analysis examines their consequences within the MOORA ranking mechanism, where the normalized performance of each alternative is aggregated according to the corresponding criteria weights and criterion orientations. Applying the same decision matrix and evaluation procedure to both weighting schemes ensures that any observed differences in ranking are primarily associated with the weighting formulation. The resulting LOGSTA-MOORA and LOGSTA-D-MOORA rankings are then compared to identify changes in alternative positions, ranking consistency, and the extent to which the dispersion compression transformation influences the final ordering. This analysis provides further evidence of the behavioral differences between the original LOGSTA approach and the modified LOGSTA-D framework when implemented in a ratio-based MCDM method. Figure 6 shows a ranking comparison between LOGSTA and MOORA, and LOGSTA-D and MOORA.



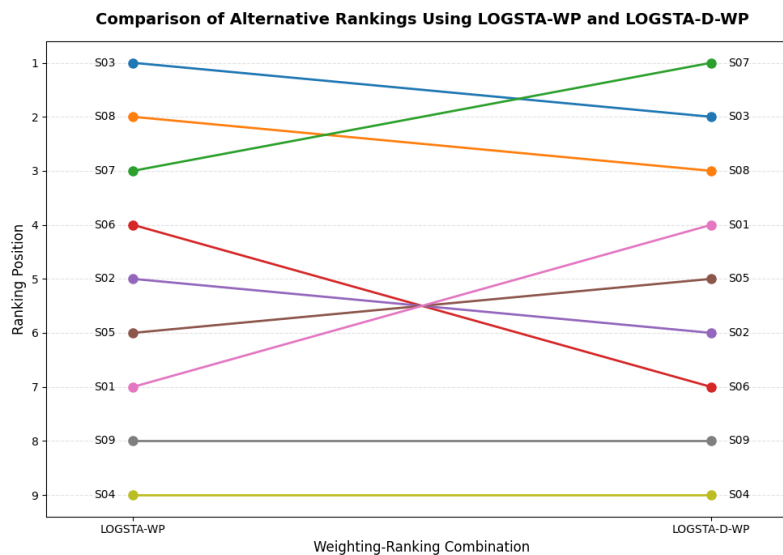
**Figure 6. Ranking Comparison between LOGSTA and LOGSTA-D using the MOORA Method**

The comparison between LOGSTA-MOORA and LOGSTA-D-MOORA reveals several changes in the relative positions of the evaluated suppliers following the introduction of the dispersion compression transformation. S07 maintains the first position under both weighting schemes, while S09 and S04 consistently remain in the eighth and ninth positions. The most notable changes occur among the intermediate-ranked suppliers. S06 declines from second to fifth position, whereas S03 improves from third to second and S08 moves from fourth to third. S05 also advances from fifth to fourth, while S01 improves from seventh to fifth position. In



contrast, S02 retains its sixth position across both approaches. These changes indicate that the LOGSTA-D weighting scheme modifies the relative influence of the criteria within the MOORA aggregation process, resulting in a redistribution of several middle-ranking alternatives while preserving the positions of some suppliers at the upper and lower boundaries of the ranking.

The application of the Weighted Product (WP) method provides a further perspective for assessing the effect of LOGSTA and LOGSTA-D on alternative prioritization. In contrast to additive aggregation, WP determines the overall preference of each alternative through a multiplicative formulation in which the weighted performance values are combined according to the corresponding criterion weights and orientations. The use of LOGSTA and LOGSTA-D weights within the same WP procedure enables the resulting rankings to be examined under comparable decision conditions. Particular attention is given to changes in the relative positions of alternatives, since differences in criteria weights can propagate through the multiplicative aggregation process and alter the final preference values. The comparison between LOGSTA-WP and LOGSTA-D-WP therefore illustrates how the incorporation of dispersion compression in LOGSTA-D may influence alternative prioritization when evaluated using a multiplicative MCDM mechanism. Figure 7 shows a ranking comparison between LOGSTA and WP, and LOGSTA-D and WP.



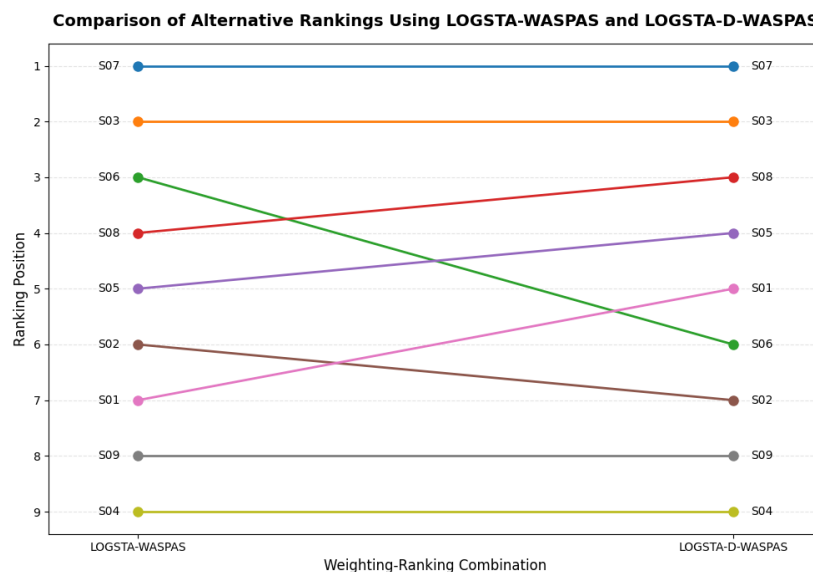
**Figure 7. Ranking Comparison between LOGSTA and LOGSTA-D using the WP Method**

The comparison of LOGSTA-WP and LOGSTA-D-WP shows that the incorporation of the dispersion compression transformation produces several changes in supplier priorities, particularly within the upper and middle positions. S07 records the most prominent improvement, moving from third position under LOGSTA-WP to first position under LOGSTA-D-WP. Meanwhile, S03 shifts from first to second position and S08 moves from second to

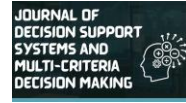


third, indicating a moderate downward adjustment among the highest-ranked suppliers. In the middle-ranking group, S01 improves substantially from seventh to fourth position, while S05 moves from sixth to fifth. Conversely, S06 declines from fourth to seventh position and S02 decreases from fifth to sixth. S09 and S04 retain their eighth and ninth positions, respectively, under both approaches, demonstrating stable rankings at the lower end of the alternatives. Overall, the ranking changes illustrate that the LOGSTA-D weighting scheme can modify the relative preference structure when processed through the multiplicative WP mechanism, with the most pronounced effects occurring among suppliers in the higher and intermediate ranking positions.

The WASPAS-based comparison is performed to determine whether the use of LOGSTA-D weights produces different alternative priorities from those obtained with the original LOGSTA weights. WASPAS combines the Weighted Sum Model and Weighted Product Model within a unified assessment procedure, allowing alternative performance to be evaluated from both additive and multiplicative perspectives. By maintaining the same alternatives, decision matrix, and criterion classifications, the comparison between LOGSTA-WASPAS and LOGSTA-D-WASPAS primarily reflects the effect of the two weighting schemes on the final preference structure. The resulting rankings are examined to identify changes in alternative positions and the degree of consistency between the two approaches. This comparison further demonstrates how the dispersion compression transformation incorporated into LOGSTA-D interacts with a hybrid aggregation mechanism and whether its influence is reflected in the final ordering of alternatives. Figure 8 shows a ranking comparison between LOGSTA and WASPAS, and LOGSTA-D and WASPAS.



**Figure 8. Ranking Comparison between LOGSTA and LOGSTA-D using the WASPAS Method**



The comparison between LOGSTA-WASPAS and LOGSTA-D-WASPAS indicates that the incorporation of the dispersion compression transformation produces several changes in the ranking positions while preserving the overall structure of the highest- and lowest-ranked alternatives. S07 and S03 maintain their first and second positions, respectively, whereas S09 and S04 remain consistently ranked eighth and ninth. Among the intermediate alternatives, S08 improves from fourth to third position and S05 moves from fifth to fourth, while S01 shows a notable improvement from seventh to fifth position. In contrast, S06 declines from third to sixth position and S02 shifts from sixth to seventh. The observed changes indicate that LOGSTA-D modifies the relative contribution of the criteria within the WASPAS aggregation process, leading to a redistribution of supplier priorities in the middle portion of the ranking. Despite these changes, the stability of several alternatives demonstrates that the modification does not uniformly alter the ranking structure, but primarily affects alternatives whose preference values are more sensitive to changes in the criteria weights.

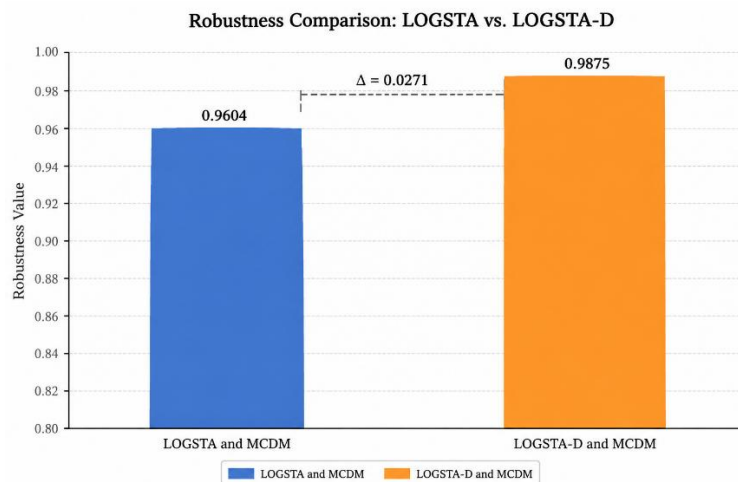
Overall, the comparative analysis demonstrates that both LOGSTA and LOGSTA-D provide consistent criteria weighting inputs while producing differences in alternative rankings when integrated with SAW, MOORA, WP, and WASPAS. The ranking comparisons show that several suppliers maintain their positions across the two weighting schemes, particularly those located at the upper and lower ends of the ranking structure, whereas greater variations occur among the intermediate alternatives. These changes reflect the influence of the dispersion compression transformation introduced in LOGSTA-D on the relative importance of criteria and its subsequent effect on alternative evaluation. The consistency and variation observed across the four MCDM methods provide complementary evidence for understanding the behavior of the proposed modification under different aggregation mechanisms. Therefore, the comparative results establish a basis for further examining ranking stability and the sensitivity of alternative priorities to changes in objective weighting formulations.

#### 5.4. Robustness Analysis

Robustness analysis is performed to evaluate the stability and reliability of the decision-making results obtained using the LOGSTA and LOGSTA-D weighting approaches. The analysis focuses on examining how consistently both methods produce alternative rankings when applied under the same decision-making conditions[32]-[34]. By comparing the ranking results generated from LOGSTA and its modified LOGSTA-D version, the analysis provides insight into whether the proposed LOGSTA-D approach can maintain stable decision outcomes while incorporating its distinctive weighting mechanism. This comparison is important for identifying potential variations in alternative rankings and assessing the extent to which the weighting strategy influences the final decision-making results[35], [36]. Consequently, the robustness analysis serves as an additional evaluation of the consistency of LOGSTA-D relative to the original LOGSTA approach.



To further assess the consistency of the ranking results, a correlation analysis based on Spearman's Rank Correlation Coefficient ( $\rho$ ) was conducted to compare the rankings obtained using the LOGSTA and LOGSTA-D weighting approaches across the MCDM methods, namely SAW, MOORA, WP, and WASPAS. This analysis aims to examine the extent to which the modification introduced in LOGSTA-D affects the resulting alternative rankings compared with the original LOGSTA approach. Spearman's correlation was selected to measure the degree of association between the two ranking structures, where a coefficient closer to one indicates greater consistency between the rankings. The comparative correlation results between LOGSTA and LOGSTA-D across the evaluated MCDM methods are presented in Figure 9.

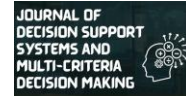


**Figure 9. Comparison of Correlation Values**

The robustness comparison shows that the LOGSTA-D and MCDM approach achieves a robustness value of 0.9875, while the LOGSTA and MCDM approach obtains 0.9604. The difference of 0.0271 indicates that the ranking results generated using LOGSTA-D exhibit a different degree of stability compared with those obtained using the original LOGSTA weighting approach. Overall, the results demonstrate that both approaches produce high robustness values, while the proposed LOGSTA-D framework maintains a robustness value closer to 1.00, indicating greater consistency of the resulting rankings under the conditions evaluated.

### 5.5. Interpretation of the Dispersion Compression Mechanism

The Dispersion Compression mechanism is the principal modification introduced in LOGSTA-D to regulate the influence of criterion variability before the final objective weights are generated. In the original LOGSTA procedure, the standard deviation obtained after logarithmic normalization is directly incorporated into the subsequent weighting calculation, allowing criteria with relatively large dispersion to exert a stronger influence on the resulting weights. LOGSTA-D modifies this process by applying a square-root transformation to the standard



deviation values. This transformation reduces the magnitude of dispersion differences while preserving their relative ordering, allowing the information associated with criterion variability to remain represented without allowing highly dispersed criteria to dominate the weighting structure.

The results in Table 3 and Table 4 illustrate this compression effect. Before compression, CS006 and CS007 exhibit the largest standard deviations, with values of 0.004651 and 0.004555, respectively, whereas CS001 has the smallest value of 0.000679. After applying the square-root transformation, the corresponding dispersion values become 0.0682, 0.0675, and 0.0261. Although CS006 and CS007 remain the two criteria with the highest dispersion values, the transformation changes the scale on which their differences are expressed. For example, the difference between CS006 and CS001 is 0.003972 before compression, whereas it becomes 0.0421 after transformation; however, relative to the original dispersion magnitudes, the square-root operation reduces the proportional dominance of the larger values. Thus, the mechanism does not eliminate dispersion differences, but instead reshapes their magnitude so that the subsequent weighting process is less dependent on extreme variability.

The effect becomes more apparent when the compressed dispersion values are incorporated into the logarithmic dispersion calculation. As shown in Table 5, CS006 and CS007 still obtain the highest information values, at 0.0034 and 0.0034, respectively, but their resulting weights decrease to 0.1793 and 0.1774 in Table 6. In contrast, criteria with initially lower dispersion receive relatively greater contributions, particularly CS001, whose weight increases to 0.0685. The comparison with LOGSTA further demonstrates this redistribution: the weights of CS006 and CS007 decrease from 0.2379 and 0.2330 under LOGSTA to 0.1793 and 0.1774 under LOGSTA-D, while CS001 increases from 0.0348 to 0.0685. These changes indicate that the Dispersion Compression mechanism moderates the direct dominance of highly dispersed criteria and reallocates part of their relative contribution across the remaining criteria.

From a methodological perspective, the Dispersion Compression mechanism therefore changes the weighting behavior from a dispersion-dominant structure toward a more moderated representation of criterion information. The mechanism maintains the ordering of dispersion values while reducing the extent to which large variability differences are propagated into the final weights. This characteristic is particularly relevant for heterogeneous decision matrices such as the supplier-selection dataset, where criteria are measured on different scales and exhibit different distributional patterns. The resulting LOGSTA-D weights provide a more balanced distribution across the eight criteria, while still retaining differentiation based on the information contained in the data. The subsequent ranking and robustness results further indicate that this modified weighting structure can alter intermediate supplier positions while maintaining substantial consistency in the overall ranking pattern.



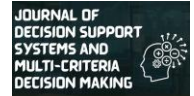
## 5.6. Implications for MCDM Decision Making

The implementation of LOGSTA-D has several implications for multi-criteria decision-making, particularly in situations where evaluation criteria exhibit heterogeneous levels of dispersion. By introducing the Dispersion Compression mechanism, LOGSTA-D moderates the influence of criteria with relatively high variability before the weights are integrated into the MCDM process. This produces a weighting structure in which highly dispersed criteria remain influential but do not disproportionately dominate the decision model. In the supplier-selection case, this behavior is reflected in the reduction of the weights assigned to CS006 and CS007, while criteria with comparatively lower weights under LOGSTA receive greater relative contributions. Consequently, the resulting criterion-weight structure provides an alternative representation of objective information that can be incorporated into different MCDM techniques without relying exclusively on the magnitude of raw dispersion.

The implications are also evident in the ranking results obtained through SAW, MOORA, WP, and WASPAS. The use of LOGSTA-D weights produces highly consistent ranking patterns across these MCDM methods, while differences from the original LOGSTA-based rankings are primarily observed among intermediate-ranked suppliers. This indicates that changes in objective weighting can influence alternative prioritization without necessarily causing substantial changes to the overall ranking structure. The robustness analysis further supports this observation, with the LOGSTA-D and MCDM framework obtaining a Spearman correlation value of 0.9875 compared with 0.9604 for LOGSTA and MCDM. Thus, LOGSTA-D provides a weighting mechanism that can be integrated with multiple MCDM approaches while moderating dispersion effects and maintaining a high degree of ranking consistency under the evaluated decision conditions.

## 5.7. Theoretical and Practical Implications

The findings provide several implications for the development of objective weighting approaches in multi-criteria decision-making. The incorporation of the Dispersion Compression mechanism into LOGSTA-D introduces an additional processing stage between standard deviation and logarithmic dispersion, allowing dispersion information to be moderated before being converted into criterion weights. This modification expands the methodological structure of LOGSTA by addressing the potential dominance of criteria with relatively high dispersion while maintaining the differentiation of criterion importance. The resulting weight distribution demonstrates that the information contained in criterion variability can be preserved without transferring the full magnitude of dispersion differences directly into the final weights. The integration of LOGSTA-D with multiple MCDM methods also demonstrates that the proposed weighting scheme can be used as an objective weighting component within different aggregation structures.



The findings also have implications for practical decision-support applications involving heterogeneous evaluation criteria. The supplier-selection experiment shows that the proposed mechanism changes the relative contribution of criteria, particularly by moderating the weights of CS006 and CS007 while increasing the relative importance of several other criteria. This behavior can help decision-support systems accommodate criteria with different numerical scales and dispersion characteristics without allowing a small number of highly variable criteria to disproportionately determine the evaluation. Furthermore, the LOGSTA-D-based framework produces a robustness value of 0.9875, indicating a high degree of consistency in the evaluated ranking structures. The approach can therefore be incorporated into practical MCDM applications where objective criteria weighting, controlled dispersion influence, and consistent alternative prioritization are important considerations.

### 5.8. Discussion

The findings demonstrate that LOGSTA-D provides a modified weighting mechanism that changes the distribution of criterion importance while maintaining the underlying dispersion-based principle of LOGSTA. The introduction of the dispersion compression stage reduces the influence gap between criteria with different levels of variability. This produces a more balanced weighting structure, particularly by limiting the excessive concentration of weight on criteria with relatively high dispersion. The resulting weights therefore provide a moderated representation of criterion variability rather than directly amplifying the differences observed in the normalized data.

The comparison of the ranking results shows that the weighting modification does not substantially disrupt the overall preference structure of the alternatives. Most changes occur among alternatives positioned relatively close to each other, while several alternatives maintain their positions across the evaluated methods. This indicates that LOGSTA-D remains sensitive to changes in criterion importance, but the effect is generally localized rather than producing extensive rank reversals. Such behavior is relevant in supplier evaluation because moderate changes in criterion weights should be capable of reflecting different importance structures without making the decision outcome excessively unstable.

The integration of LOGSTA-D with SAW, MOORA, WP, and WASPAS also illustrates its applicability across different MCDM aggregation mechanisms. Although each method processes the weighted decision matrix differently, the resulting rankings exhibit a high degree of consistency. The limited variations observed, particularly among intermediate alternatives, indicate that LOGSTA-D can provide a stable weighting input for different decision-making procedures. At the same time, the presence of some rank changes confirms that the proposed weighting mechanism does not eliminate the sensitivity of the MCDM process to criterion importance.



The comparison with the original LOGSTA further highlights the effect of the proposed modification. LOGSTA-D redistributes part of the weight from highly dominant criteria toward criteria with lower initial importance, resulting in a less concentrated weighting structure. Despite this change, the resulting rankings remain strongly associated with those obtained using LOGSTA. The Spearman correlation analysis therefore indicates that the modification changes the weighting behavior without fundamentally altering the overall ranking pattern.

From a decision-making perspective, these findings suggest that LOGSTA-D can be considered a suitable alternative when objective weighting needs to moderate the dominance of highly dispersed criteria. Its combination with several established MCDM methods also demonstrates methodological flexibility. More importantly, the robustness value of 0.9875 obtained by the LOGSTA-D-based framework indicates a high level of ranking consistency under the evaluated conditions. Compared with the corresponding value of 0.9604 for LOGSTA, the results show that the proposed modification can improve the balance of criterion weights while preserving a stable decision structure.

## VI. Conclusion

This study developed LOGSTA-D as an extension of the LOGSTA objective weighting framework by introducing a dispersion compression mechanism based on the square root of standard deviation. The proposed modification provides an additional means of regulating the contribution of dispersion information before criterion weights are generated. The findings indicate that this mechanism can produce a more moderated distribution of criterion importance while retaining the data-driven characteristics of the original framework. The integration of LOGSTA-D with SAW, MOORA, WP, and WASPAS demonstrates that the proposed weighting approach can be applied across different MCDM aggregation mechanisms. The resulting decision structures remain highly consistent, while changes in alternative positions are mainly observed among competing alternatives with relatively close evaluation results. This indicates that the proposed modification can influence decision sensitivity without substantially disrupting the overall ranking structure.

The robustness evaluation further supports the applicability of LOGSTA-D as an objective weighting approach. The high consistency observed in the ranking comparison indicates that modifying the dispersion component does not lead to excessive instability in subsequent MCDM evaluation. Therefore, LOGSTA-D provides a methodological alternative for decision environments where criterion dispersion is heterogeneous and a more controlled weighting distribution is required. Future research can examine LOGSTA-D using larger and real-world datasets from different application domains, as well as investigate alternative nonlinear compression functions and their effects on weighting behavior. Comparative experiments with additional objective weighting and MCDM methods may also provide broader evidence regarding the generalizability and limitations of the proposed framework.



### CRediT Authorship Contribution Statement

**Vederico Pitsalitz Sabandar:** Conceptualization, Writing – Original Draft Preparation. **Yulian Hany Makaruku:** Data Curation, Writing – Original Draft Preparation. **M. Ikbali Siami:** Formal Analysis, Writing – Original Draft Preparation. **Sandi Badiwibowo Atim:** Investigation, Validation, Writing – Review & Editing. **Sanriomi Sintaro:** Methodology, Supervision, 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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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 Gemini AI 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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