

Modification of the Proximity Indexed Value Method Based on Distance-Based Normalization to Improve the Stability of Alternative Rankings

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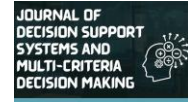
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ABSTRACT

Keywords:

Distance-Based
Normalization;
Proximity Indexed
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Multi-Criteria
Decision-Making;
Ranking Stability;
Sensitivity
Analysis;

The Proximity Indexed Value (PIV) method provides a proximity-based mechanism for ranking alternatives in multi-criteria decision-making; however, its ranking results can be affected by the normalization process and the relative characteristics of criterion values. This study proposes a Distance-Based Proximity Indexed Value (D-PIV) method by incorporating distance-based normalization into the PIV framework to represent the proximity of alternatives to criterion-specific ideal conditions more explicitly. The proposed method was evaluated using an alternative location selection dataset comprising eight alternatives and six criteria, including one cost criterion and five benefit criteria. The evaluation included comparative ranking analysis using 36 systematic criterion-weight perturbation scenarios with changes of ± 0.05 , ± 0.10 , and ± 0.15 . The results show that D-PIV changes the ordering of Loc 3 and Loc 8 compared with conventional PIV, resulting in a ranking that fully corresponds to the reference ranking. The Spearman correlation increased from 0.9762 for PIV to 1.0000 for D-PIV. However, the sensitivity analysis indicates that the distance-based modification does not uniformly improve ranking stability across all alternatives. D-PIV increases the stability of Loc 8 from 69.44% to 72.22%, while lower stability is observed for Loc 3 and Loc 6 compared with PIV. These findings demonstrate that D-PIV contributes a reference-oriented normalization mechanism that improves baseline ranking consistency while redistributing, rather than uniformly eliminating, sensitivity to criterion-weight variations. The study therefore provides both a methodological contribution through the integration of distance-based normalization into PIV and an empirical contribution through systematic



evidence of its effects on ranking agreement and stability.

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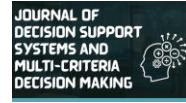
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I. Introduction

Multi-Criteria Decision Making (MCDM) plays an important role in supporting decision-making processes that involve multiple criteria with different characteristics, levels of importance, and measurement scales[1]-[3]. In many real-world decision problems, alternatives cannot be evaluated adequately using a single criterion because each alternative may demonstrate different strengths and weaknesses across several aspects. MCDM provides a systematic framework for integrating these criteria, evaluating the performance of each alternative, and determining the relative preference among available alternatives. Through processes such as criteria weighting, normalization, and alternative ranking, MCDM can transform complex and heterogeneous evaluation data into structured decision information[4]-[6]. This framework enables decision-makers to consider multiple aspects simultaneously while reducing the subjectivity and complexity involved in comparing alternatives, thereby supporting more systematic, transparent, and consistent decision-making.

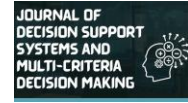
A ranking method plays an important role in MCDM because it determines the final order of alternatives based on their overall performance across multiple criteria. A reliable ranking method should be able to produce an ordering that is consistent with the relative performance of the alternatives and should not change substantially due to minor variations in the input data or evaluation conditions[7], [8]. Ranking consistency is particularly important because the final ranking is often used as the basis for selecting the most appropriate alternative. If small changes in criterion values, normalization results, or weighting parameters can cause substantial changes in the ranking, the reliability of the decision-making process may be reduced. Therefore, the development and application of ranking methods that can maintain stable and interpretable alternative orders are essential for improving the reliability, transparency, and robustness of MCDM-based decision-making.



The Proximity Indexed Value (PIV) method still faces several challenges, particularly its dependence on the normalization process used to transform the original decision matrix into comparable values[9]-[11]. Since the normalization procedure directly affects the magnitude and relative position of the normalized values, changes in the normalization results can subsequently influence the proximity values and the final ranking of alternatives. In addition, differences in the scale, range, and distribution of data across criteria may produce unequal effects on the calculated proximity of alternatives[12], [13]. Criteria with wider ranges or different distribution patterns may contribute differently to the proximity measurement, even when they have been assigned similar weights. Consequently, the resulting ranking may be sensitive to the characteristics of the input data and the normalization procedure applied. These limitations indicate the need for an approach that can better account for variations in data characteristics and reduce the dependence of proximity evaluation on a particular normalization scheme, thereby providing a more consistent and representative basis for alternative ranking in multi-criteria decision-making.

A normalization approach that considers the distance of each alternative from a reference or ideal value is important because it can provide a more meaningful representation of the relative performance of alternatives across different criteria[14]-[16]. Rather than relying solely on the transformation of raw values into a common scale, reference-based normalization can preserve the relative proximity of each alternative to the desired or ideal condition. This consideration is particularly relevant because the normalization process is closely related to the sensitivity of criterion values and the stability of alternative rankings. Small changes in normalized values may alter the calculated proximity between alternatives, especially when their performance values are relatively close. Consequently, variations in the normalization results can propagate through the subsequent evaluation process and lead to changes in ranking positions[17], [18]. Therefore, an appropriate normalization mechanism should not only ensure comparability among criteria but also minimize unnecessary sensitivity to data transformations, allowing the resulting rankings to remain more stable and representative of the underlying performance of the alternatives.

The PIV method provides a proximity-oriented mechanism for representing the relative performance of alternatives; however, there remains an opportunity to strengthen how proximity information is constructed from the decision matrix. In particular, the existing framework does not sufficiently emphasize the role of a reference point or ideal condition as a basis for interpreting the relative position of each alternative. Consequently, the relationship between the transformed criterion values and their corresponding proximity to a desired reference has not been fully explored. This creates an opportunity to develop an enhanced PIV framework in which the normalization and proximity calculation are designed to provide a more direct representation of the



relative position of alternatives with respect to an ideal reference, while maintaining comparability across criteria. The sensitivity of alternative ranking to changes in the decision matrix and criterion weights represents an important aspect that requires further investigation in the PIV framework. Even relatively small adjustments in input values or weighting parameters may alter the relative position of alternatives, particularly when their performance levels are close to one another. This condition highlights the need for a modified PIV approach that explicitly incorporates distance-based normalization to represent the relative position of alternatives with respect to a defined reference and to provide greater control over ranking changes. Furthermore, evaluating the method solely based on the initial ranking is insufficient to determine whether the obtained results remain consistent under variations in input conditions. Therefore, a robustness analysis is required to systematically examine ranking behavior across different data and weight configurations and to assess the consistency of the resulting decision outcomes.

This study aims to develop a modified PIV framework that incorporates distance-based normalization while retaining the fundamental principles of the original PIV method. The proposed modification is intended to provide a more informative representation of the relative distance among alternatives by relating their criterion values to a defined reference condition, thereby improving the ability of the method to capture meaningful differences in alternative performance. The study further seeks to examine how the proposed modification affects the resulting alternative rankings and to determine whether the changes provide consistent decision outcomes under varying input conditions. To support this evaluation, sensitivity analysis and robustness analysis are employed to examine the response of the proposed method to changes in criterion values and weighting configurations, as well as to assess the consistency of ranking outcomes across different evaluation conditions.

The main contributions of this study are the formulation of a distance-based normalization mechanism specifically designed for the PIV framework and its integration into the existing proximity calculation to provide a more reference-oriented representation of alternative performance. The study also develops a ranking procedure that preserves the fundamental computational structure of PIV while incorporating the proposed normalization mechanism into the evaluation process. In addition, a ranking stability evaluation framework is established to examine the consistency of the obtained results under different testing conditions. The proposed approach is further assessed through a systematic comparison between the original PIV and the modified PIV across multiple experimental scenarios, enabling an examination of how the proposed modification affects ranking behavior and the consistency of decision outcomes.



II. Material and Method

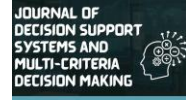
2.1. Research Framework

The research framework provides a systematic structure for organizing the research process and illustrating the relationships among the main stages of the study. It describes the sequence from identifying the research problem and formulating the proposed approach to implementing the method and evaluating its results. The framework also clarifies how the developed approach is examined through alternative ranking, sensitivity analysis, and robustness analysis to determine its behavior under different testing conditions. By presenting these stages in a structured sequence, the research framework provides a clear overview of the research workflow and supports the systematic achievement of the research objectives. The overall research framework is presented in Figure 1.



Figure 1. Research Framework

The research framework, as presented in Figure 1, begins with the identification of the research problem, which establishes the issues and limitations that motivate the study. This stage is followed by a literature and method review to examine relevant concepts, previous studies, and methodological foundations. The research then proceeds to the preparation of the decision matrix, which represents the performance of alternatives across the selected criteria. Based on this matrix, the Modified PIV is implemented to obtain the evaluation and ranking of alternatives using the proposed approach. The resulting outcomes are subsequently subjected to a comparison with the Original PIV to identify differences in ranking and evaluation results. The analysis continues with sensitivity analysis by varying relevant input parameters to observe changes in the resulting rankings, followed by robustness analysis to assess the consistency of the method under different testing conditions. Finally, the research findings are derived from the comparative, sensitivity, and robustness evaluations to provide an overall assessment of the proposed approach.



2.2. Modified PIV Method

The proposed Distance-Based Proximity Indexed Value (D-PIV) method extends the conventional PIV framework through the integration of a distance-based normalization mechanism while retaining its fundamental proximity principle and computational structure. The process starts with the decision matrix, containing the performance values of alternatives across the defined criteria and their corresponding weights. Rather than relying directly on conventional normalization, D-PIV determines the distance of each criterion value from a specified reference or ideal condition and transforms these distances into comparable normalized values. The resulting values are incorporated into the proximity calculation to obtain the weighted proximity of each alternative, which is subsequently aggregated to determine the final ranking. This formulation provides a more explicit representation of the positional relationship between alternative performances and the reference condition while maintaining the essential logic of the original PIV approach.

The process begins by constructing the decision matrix, which represents the performance of each alternative across the evaluated criteria. Each row corresponds to an alternative, while each column represents a criterion used in the decision-making process. The matrix contains the original performance values collected from the dataset and serves as the basis for subsequent normalization and evaluation stages. The decision matrix is represented using (1).

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

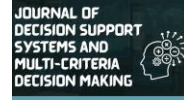
The next stage applies vector normalization to transform the original performance values into comparable values across different criteria. This procedure reduces the influence of differences in measurement scales while maintaining the relative performance of each alternative [19], [20]. Each performance value is normalized against the Euclidean magnitude of the corresponding criterion. The normalized value is calculated using (2).

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

After normalization, the ideal normalized value is determined for each criterion according to its type. For benefit criteria, the maximum normalized value represents the ideal condition, whereas for cost criteria, the minimum normalized value is considered ideal. These values provide the reference points for measuring the distance of each alternative from the ideal performance [21], [22]. The ideal normalized value is determined using (3).

$$n_j^* = \begin{cases} \max(n_{ij}); \text{benefit} \\ \min(n_{ij}); \text{cost} \end{cases} \quad (3)$$

The distance calculation measures the deviation between the normalized performance of each alternative and the corresponding ideal



normalized value. The absolute difference is used to determine how far each alternative is from the ideal condition for every criterion[23], [24]. A smaller distance indicates that the performance of an alternative is closer to the ideal value. The distance is calculated using (4).

$$d_{ij} = |n_{ij} - n_j^*| \quad (4)$$

The calculated distances are subsequently transformed into distance-based normalized values. This stage converts the distance values into a comparable scale in which alternatives with smaller distances from the ideal solution receive higher normalized values. A small positive value is included in the denominator to avoid computational problems when the maximum distance is zero. The distance-based normalized value is calculated using (5).

$$q_{ij} = 1 - \frac{d_{ij}}{\max_i(d_{ij}) + \varepsilon} \quad (5)$$

The normalized distance-based values are then incorporated with the criterion weights to reflect the relative importance of each criterion in the decision-making process[25], [26]. Each normalized value is multiplied by its corresponding criterion weight, producing a weighted distance-based value for every alternative and criterion. The weighted value is calculated using (6).

$$v_{ij} = w_j * q_{ij} \quad (6)$$

The next stage determines the proximity index by considering the relationship between the criterion weight and the weighted distance-based value. This calculation provides an adjusted measure of the contribution of each criterion to the overall performance of an alternative[27], [28]. The proximity index is calculated using (7).

$$u_{ij} = w_j - v_{ij} \quad (7)$$

The final score is obtained by aggregating the proximity index values across all criteria for each alternative. This aggregation produces a single score representing the overall performance of each alternative based on the weighted evaluation process. The final score is calculated using (8).

$$D_i = \sum_{j=1}^n u_{ij} \quad (8)$$

The main modification in D-PIV lies in the refinement of the normalization process and the calculation of distances between the performance values of alternatives and the reference values. Unlike the original PIV, this modification is designed to take into account the characteristics of criteria more consistently by adjusting the normalized values before the weighting and distance measurement processes are carried out. With this mechanism, the impact of differences in scale, criterion type, and weights on the final value can be controlled more systematically, so the ranking results are expected to better reflect the actual data conditions.



2.3. Alternative Assessment Data

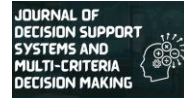
The alternative assessment data represent the performance of each alternative across the selected evaluation criteria and serve as the primary input for the decision-making process. Each alternative is described using a set of criterion values that reflect its performance under the corresponding assessment dimensions. The collected data are organized into a decision matrix to facilitate consistent processing and ensure that the performance of all alternatives can be evaluated within a common analytical structure. Before applying the proposed D-PIV method, the data are examined according to the characteristics and measurement scales of the criteria to ensure their suitability for subsequent normalization and proximity calculations. The resulting decision matrix provides the basis for applying the proposed approach and obtaining the relative ranking of the evaluated alternatives.

The empirical data employed in this study are adapted from a previously published assessment of potential locations for establishing a new store. The dataset comprises eight alternatives described through six evaluation attributes, namely Rental Cost (LS01), Building Area (LS02), Accessibility (LS03), Consumer Traffic (LS04), Parking Availability (LS05), and Infrastructure (LS06). These attributes capture different aspects of location suitability, with LS01 classified as a cost criterion because a lower value is preferred, while the other five attributes are considered benefit criteria in which higher values indicate more favorable conditions. The assessment scores form the initial decision matrix and exhibit variation in magnitude and range among the criteria. Such characteristics provide an appropriate empirical setting for applying the proposed D-PIV procedure, particularly in examining how distance-based normalization represents the relative position of each alternative before the proximity values are determined. The complete dataset used in the analysis is reported in Table 1, with the data adapted from the original source.

Table 1. Alternative Location Assessment Data

Alternatives	LS01	LS02	LS03	LS04	LS05	LS06
Alternative Loc 1	45	120	8	550	10	9
Alternative Loc 2	40	100	7	500	8	8
Alternative Loc 3	55	150	9	600	12	9
Alternative Loc 4	38	90	6	480	6	7
Alternative Loc 5	60	160	8	620	15	10
Alternative Loc 6	42	130	9	570	11	8
Alternative Loc 7	36	110	7	510	9	7
Alternative Loc 8	48	140	8	590	13	9

Next, the results of processing the assessment data produced a ranking of alternatives based on the scores obtained from the applied method. This ranking is used to see the relative position of each alternative and serves as a basis for comparing the results between the approaches used. Overall, the ranking results of the eight alternatives are presented in Table 2.

**Table 2. Alternative Location Assessment Data**

Alternatives	Rank
Alternative Loc 5	1
Alternative Loc 3	2
Alternative Loc 8	3
Alternative Loc 6	4
Alternative Loc 1	5
Alternative Loc 7	6
Alternative Loc 2	7
Alternative Loc 4	8

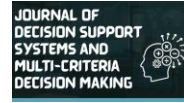
The data used in this study were adopted from the research conducted by [29] because the dataset provides a structured assessment of multiple alternatives across cost and benefit criteria, making it suitable for evaluating the proposed decision-making approach. In addition, the variation in assessment values across alternatives and criteria provides an appropriate basis for examining the behavior of the normalization and proximity calculations. Therefore, the dataset was selected as the empirical basis for the subsequent analysis, ranking process, sensitivity analysis, and robustness evaluation.

III. Result and Discussion

This section presents the results of the proposed D-PIV method and discusses the effect of distance-based normalization on alternative evaluation and ranking stability. The analysis first examines the transformation of the decision matrix into normalized values, distances to the ideal reference, and proximity scores, in order to clarify how the proposed mechanism represents the relative position of each alternative with respect to the reference conditions. The resulting aggregate deviation values and final rankings are then compared with those obtained from the original PIV method, with particular attention to changes in alternative positions and the consistency of ranking patterns. Furthermore, the robustness of the rankings is assessed through sensitivity analysis under variations in the decision matrix, complemented by rank correlation measures. Taken together, these analyses provide an empirical basis for evaluating whether the proposed modification improves ranking stability while preserving the discriminative capability of PIV in multi-criteria decision-making problems.

3.1. Implementation of the PIV Method

The PIV method is applied to evaluate the relative performance of the alternatives across the selected criteria by considering both the characteristics of the decision matrix and the importance of each criterion. The method produces a proximity-based preference value that reflects the overall performance of each alternative in relation to the considered criteria, providing a quantitative basis for alternative comparison and ranking. In this study, the original PIV method serves



as the baseline model for examining the resulting preference values and ranking structure before the proposed distance-based normalization is introduced. The resulting rankings provide a reference for subsequently evaluating the effect of the proposed modification on the consistency and stability of alternative positions.

The original PIV method can be summarized into four main stages. First, the decision matrix is constructed to represent the performance of each alternative across the evaluated criteria, as expressed in (1). The results of the decision matrix are as follows.

$$X = \begin{bmatrix} 45 & 120 & 8 & 500 & 10 & 9 \\ 50 & 100 & 7 & 550 & 8 & 8 \\ 55 & 150 & 9 & 600 & 12 & 9 \\ 38 & 90 & 6 & 480 & 6 & 7 \\ 60 & 160 & 8 & 620 & 15 & 10 \\ 42 & 130 & 9 & 570 & 11 & 8 \\ 36 & 110 & 7 & 510 & 9 & 7 \\ 48 & 140 & 8 & 590 & 13 & 9 \end{bmatrix}$$

Second, vector normalization is applied to convert the original performance values into comparable values across different criteria, as formulated in (2). The normalization results are shown in Table 3.

Table 3. Normalization Results using the PIV Method

Alternatives	LS01	LS02	LS03	LS04	LS05	LS06
Alternative Loc 1	0.3445	0.3338	0.3621	0.3506	0.3262	0.3773
Alternative Loc 2	0.3063	0.2782	0.3169	0.3188	0.2609	0.3354
Alternative Loc 3	0.4211	0.4173	0.4074	0.3825	0.3914	0.3773
Alternative Loc 4	0.2910	0.2504	0.2716	0.3060	0.1957	0.2935
Alternative Loc 5	0.4594	0.4451	0.3621	0.3953	0.4892	0.4192
Alternative Loc 6	0.3216	0.3617	0.4074	0.3634	0.3588	0.3354
Alternative Loc 7	0.2756	0.3060	0.3169	0.3251	0.2935	0.2935
Alternative Loc 8	0.3675	0.3895	0.3621	0.3761	0.4240	0.3773

Third, the normalized values are combined with the corresponding criterion weights to obtain the weighted proximity index, which represents the weighted performance of each alternative. The results of the Weighted Proximity Index calculation are shown in Table 4.

Table 4. Weighted Proximity Index Results using the PIV Method

Alternatives	LS01	LS02	LS03	LS04	LS05	LS06
Alternative Loc 1	0.0118	0.0200	0.0077	0.0059	0.0326	0.0061
Alternative Loc 2	0.0052	0.0300	0.0155	0.0101	0.0456	0.0123
Alternative Loc 3	0.0249	0.0050	0.0000	0.0017	0.0195	0.0061
Alternative Loc 4	0.0026	0.0350	0.0232	0.0117	0.0586	0.0184
Alternative Loc 5	0.0315	0.0000	0.0077	0.0000	0.0000	0.0000
Alternative Loc 6	0.0079	0.0150	0.0000	0.0042	0.0260	0.0123
Alternative Loc 7	0.0000	0.0250	0.0155	0.0092	0.0391	0.0184
Alternative Loc 8	0.0157	0.0100	0.0077	0.0025	0.0130	0.0061

Fourth, the final score is calculated from the weighted proximity index and used to establish the alternative ranking, where the resulting score indicates the relative performance of each alternative. The results of the final score are shown in Table 5.

**Table 5. Final Score Results using the PIV Method**

Alternatives	Final Score
Alternative Loc 1	0.0841
Alternative Loc 2	0.1187
Alternative Loc 3	0.0573
Alternative Loc 4	0.1496
Alternative Loc 5	0.0392
Alternative Loc 6	0.0654
Alternative Loc 7	0.1072
Alternative Loc 8	0.0552

The ranking results obtained using the original PIV method are presented in Table 5, which shows the final scores and positions of each alternative based on evaluations of all the criteria.

Table 6. Ranking Results Using the PIV Method

Alternatives	Rank
Alternative Loc 5	1
Alternative Loc 8	2
Alternative Loc 3	3
Alternative Loc 6	4
Alternative Loc 1	5
Alternative Loc 7	6
Alternative Loc 2	7
Alternative Loc 4	8

Table 6 presents the ranking results obtained using the original Proximity Indexed Value (PIV) method across eight alternative locations. Alternative Loc 5 occupies the first position, indicating the highest overall preference among the evaluated alternatives, followed by Alternative Loc 8 in second place and Alternative Loc 3 in third place. Alternative Loc 6 ranks fourth, while Alternative Loc 1 and Alternative Loc 7 occupy the fifth and sixth positions, respectively. Alternative Loc 2 is ranked seventh, and Alternative Loc 4 occupies the eighth position. The resulting ranking provides the baseline configuration for evaluating the proposed modification of the PIV method, particularly in terms of changes in alternative positions and ranking stability. results using the PIV Method.

3.2. Implementation of the D-PIV Method

The Distance-based Proximity Indexed Value (D-PIV) method is implemented to evaluate the alternatives by incorporating the relative distance of each performance value from the ideal condition into the PIV framework. This modification provides a distance-oriented representation of alternative performance while retaining the weighting structure of the original PIV method. The D-PIV approach is applied to the same decision matrix and criterion weights used in the baseline analysis, allowing the resulting preference values and rankings to be examined under a consistent evaluation setting. The implementation focuses on how distance-based normalization affects the resulting alternative scores and contributes to the stability of the ranking outcomes.



The calculation of the D-PIV method consists of eight stages. First, the decision matrix is constructed to represent the performance of each alternative across the criteria, as given in (1), and the D-PIV decision matrix is the same as the PIV decision matrix. Second, vector normalization is applied to obtain comparable criterion values using (2), the D-PIV normalization result is the same as the PIV normalization result.

Third, the ideal normalized value is determined according to the type of each criterion using (3), and the resulting ideal values are presented in Table 7.

Table 7. Ideal Normalized Results using the D-PIV Method

LS01	LS02	LS03	LS04	LS05	LS06
0.2756	0.4451	0.4074	0.3953	0.4892	0.4192

Fourth, the distance between each normalized value and its corresponding ideal value is calculated using (4), with the results presented in Table 8.

Table 8. Distance Results using the PIV Method

Alternatives	LS01	LS02	LS03	LS04	LS05	LS06
Alternative Loc 1	0.0689	0.1113	0.0453	0.0446	0.1631	0.0419
Alternative Loc 2	0.0306	0.1669	0.0905	0.0765	0.2283	0.0838
Alternative Loc 3	0.1455	0.0278	0.0000	0.0128	0.0978	0.0419
Alternative Loc 4	0.0153	0.1947	0.1358	0.0893	0.2935	0.1258
Alternative Loc 5	0.1838	0.0000	0.0453	0.0000	0.0000	0.0000
Alternative Loc 6	0.0459	0.0835	0.0000	0.0319	0.1305	0.0838
Alternative Loc 7	0.0000	0.1391	0.0905	0.0701	0.1957	0.1258
Alternative Loc 8	0.0919	0.0556	0.0453	0.0191	0.0652	0.0419

Fifth, the distance values are transformed into distance-based normalized values using (5), and the results are presented in Table 9.

Table 9. Distance-based Normalization Results using the PIV Method

Alternatives	LS01	LS02	LS03	LS04	LS05	LS06
Alternative Loc 1	0.6250	0.4286	0.6667	0.5000	0.4444	0.6667
Alternative Loc 2	0.8333	0.1429	0.3333	0.1429	0.2222	0.3333
Alternative Loc 3	0.2083	0.8571	1.0000	0.8571	0.6667	0.6667
Alternative Loc 4	0.9167	0.0000	0.0000	0.0000	0.0000	0.0000
Alternative Loc 5	0.0000	1.0000	0.6667	1.0000	1.0000	1.0000
Alternative Loc 6	0.7500	0.5714	1.0000	0.6429	0.5556	0.3333
Alternative Loc 7	1.0000	0.2857	0.3333	0.2143	0.3333	0.0000
Alternative Loc 8	0.5000	0.7143	0.6667	0.7857	0.7778	0.6667

Sixth, the normalized values are multiplied by the criterion weights to obtain the weighted distance-based values using (6), with the results presented in Table 10.

Table 10. Weighted Distance Results using the PIV Method

Alternatives	LS01	LS02	LS03	LS04	LS05	LS06
Alternative Loc 1	0.1071	0.0771	0.1141	0.0658	0.0887	0.0977
Alternative Loc 2	0.1428	0.0257	0.0570	0.0188	0.0444	0.0489
Alternative Loc 3	0.0357	0.1541	0.1711	0.1128	0.1331	0.0977



Alternative Loc 4	0.1570	0.0000	0.0000	0.0000	0.0000	0.0000
Alternative Loc 5	0.0000	0.1798	0.1141	0.1316	0.1996	0.1466
Alternative Loc 6	0.1285	0.1027	0.1711	0.0846	0.1109	0.0489
Alternative Loc 7	0.1713	0.0514	0.0570	0.0282	0.0665	0.0000
Alternative Loc 8	0.0857	0.1284	0.1141	0.1034	0.1552	0.0977

Seventh, the proximity index is calculated using (7), and the resulting values are presented in Table 11.

Table 11. Proximity Index using the PIV Method

Alternatives	LS01	LS02	LS03	LS04	LS05	LS06
Alternative Loc 1	-0.4537	-0.2488	-0.4956	-0.3684	-0.2448	-0.5201
Alternative Loc 2	-0.6620	0.0369	-0.1622	-0.0113	-0.0226	-0.1867
Alternative Loc 3	-0.0370	-0.6773	-0.8289	-0.7255	-0.4671	-0.5201
Alternative Loc 4	-0.7454	0.1798	0.1711	0.1316	0.1996	0.1466
Alternative Loc 5	0.1713	-0.8202	-0.4956	-0.8684	-0.8004	-0.8534
Alternative Loc 6	-0.5787	-0.3916	-0.8289	-0.5113	-0.3560	-0.1867
Alternative Loc 7	-0.8287	-0.1059	-0.1622	-0.0827	-0.1337	0.1466
Alternative Loc 8	-0.3287	-0.5345	-0.4956	-0.6541	-0.5782	-0.5201

Finally, the proximity index values are aggregated to obtain the final score for each alternative using (8), with the final results presented in Table X.

Table 12. Proximity Index using the PIV Method

Alternatives	Final Value
Alternative Loc 1	-2.331
Alternative Loc 2	-1.008
Alternative Loc 3	-3.256
Alternative Loc 4	0.083
Alternative Loc 5	-3.667
Alternative Loc 6	-2.853
Alternative Loc 7	-1.167
Alternative Loc 8	-3.111

The ranking results obtained using the D-PIV method are presented in Table 13, which shows the final scores and positions of each alternative based on evaluations of all the criteria.

Table 13. Ranking Results Using the D-PIV Method

Alternatives	Rank
Alternative Loc 5	1
Alternative Loc 3	2
Alternative Loc 8	3
Alternative Loc 6	4
Alternative Loc 1	5
Alternative Loc 7	6
Alternative Loc 2	7
Alternative Loc 4	8

Table 13 presents the ranking results obtained using the D-PIV method for eight alternative locations. Alternative Loc 5 ranks first, followed by Alternative Loc 3 in second and Alternative Loc 8 in third. Alternative Loc 6 occupies the fourth position, while Alternative Loc 1



and Alternative Loc 7 rank fifth and sixth, respectively. Alternative Loc 2 is placed seventh, and Alternative Loc 4 remains in the eighth position. Compared with the original PIV results, the main change occurs in the positions of Alternative Loc 3 and Alternative Loc 8, while the other alternatives retain their respective ranking positions.

3.3. Comparison of Alternative Rankings

Comparing alternative rankings is done to check how consistent the decision results are from the method used. Each alternative can end up in a different ranking position because of differences in normalization, weighting, and value aggregation during the decision-making process. That's why comparing rankings is necessary—to spot changes in alternative positions, see how well the methods align, and find out if the method can produce stable ranking patterns. This analysis becomes especially important when several methods are applied to the same decision matrix and criteria weights, because differences in the ranking results can give insights into how sensitive the methods are to the data characteristics and the calculation process.

The ranking comparison was done by comparing the ranking results of alternatives obtained from the PIV method, the D-PIV method, and the original ranking used as a reference. This comparison aims to identify changes in the position of each alternative after applying PIV and its modification through D-PIV. By observing the consistency or shifts in rankings across these three approaches, we can see how much the modification process in D-PIV affects the ranking structure of the alternatives. This analysis also provides an overview of the consistency of the ranking results, especially in checking if alternatives that held high positions in the original ranking still keep their positions after being calculated using PIV and D-PIV. The results of the ranking comparison among the three approaches are shown in Figure 2.

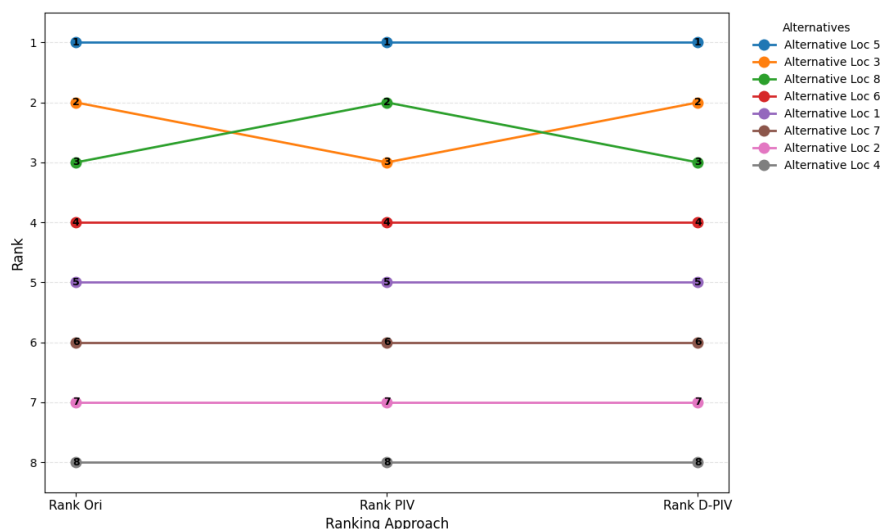


Figure 2. Comparison of Alternative Rankings



Based on the ranking comparison in Figure 2, it looks like out of the eight evaluated alternatives, six of them—Loc 5, Loc 6, Loc 1, Loc 7, Loc 2, and Loc 4—show identical ranking positions across all three approaches (original ranking, PIV, and D-PIV), which suggests that the basic preference structure for these alternatives is relatively stable despite differences in the normalization methods used. However, noticeable differences appear for Loc 3 and Loc 8, where the baseline PIV method causes a rank reversal by placing Loc 8 in 2nd place and Loc 3 in 3rd, whereas the original ranking actually puts Loc 3 in 2nd and Loc 8 in 3rd. Interestingly, the D-PIV method managed to correct those deviations by producing a ranking sequence for Loc 3 and Loc 8 that perfectly matched the original rankings, so overall D-PIV achieved a perfect ranking match (eight out of eight alternatives) compared to the baseline PIV, which was only consistent for six out of eight alternatives.

To strengthen the comparative ranking analysis presented earlier, a rank correlation test was conducted using Spearman's correlation coefficient to quantitatively measure the level of agreement between the rankings produced by the PIV method, the D-PIV method, and the original rankings as a reference. Spearman's correlation coefficient was chosen because it is suitable for measuring the strength and direction of a monotonic relationship between two sets of ordinal data, making it appropriate for assessing the consistency of rank order without requiring the assumption of normal distribution in the data being compared. A coefficient value close to one indicates a high level of agreement between the rankings of the compared methods, while a lower value shows more substantial differences in ranking structure, including the possibility of rank reversal for certain alternatives. This approach provides an objective picture of how far distance-based normalization modifications in D-PIV can improve the stability and validity of ranking results compared to the baseline PIV method. The results of these rank correlation calculations are shown in Figure 3.

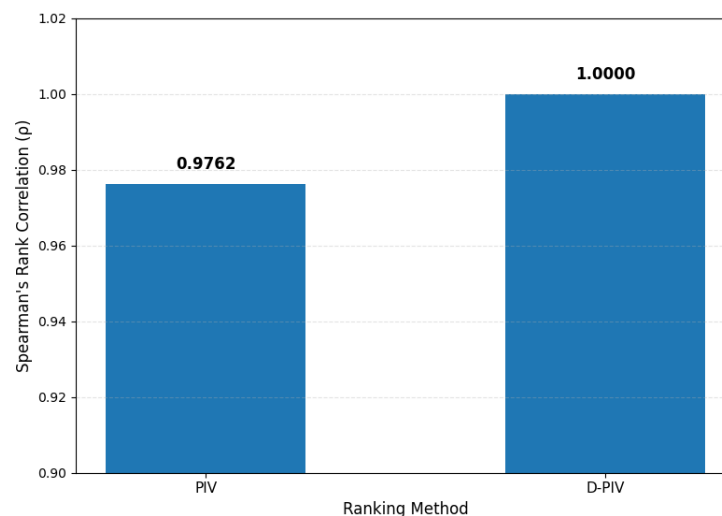
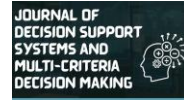


Figure 3. Comparison of Spearman Rank Correlation



Based on the results of the rank correlation calculation shown in Figure 3, the Spearman correlation coefficient between the baseline PIV ranking and the original ranking is 0.9762, indicating a very high level of match even though it hasn't reached a perfect match, which is in line with previous findings that rank reversal occurred for alternatives Loc 3 and Loc 8. On the other hand, the ranking produced by the D-PIV method shows a Spearman correlation coefficient of 1, indicating a perfect correlation between the D-PIV ranking and the original ranking, with no changes in the position of any alternatives. The difference in correlation coefficient values quantitatively confirms that the distance-based normalization modification applied to D-PIV successfully corrected the ranking mismatches that appeared in the conventional PIV method, while also proving that D-PIV is better at maintaining the consistency of alternative ranking structures compared to the reference rankings.

3.4. Sensitivity Analysis

To further evaluate the reliability and accuracy of the developed D-PIV method, a sensitivity analysis was carried out to measure how changes in the criteria weights affect the consistency of the resulting alternative rankings[30]–[32]. Sensitivity analysis is an important step in evaluating MCDM methods since criteria weights can vary depending on the weighting method and the decision-making context used, so testing is needed to ensure that the ranking results do not change drastically (rank reversal) due to these weight fluctuations[33]–[36]. This testing is done by applying a series of weight change scenarios to each criterion and then observing the impact on the ranking order of alternatives produced by both the baseline PIV method and D-PIV. This analysis identifies the robustness of both methods under weight perturbations and provides empirical evidence on how distance-based normalization in D-PIV affects ranking stability under varying criterion weights.

The testing was done by applying weight change scenarios for each criterion through increments and decrements of 0.05, 0.1, 0.15, and 0.2 from the initial weight values, and then observing the impact on the ranking order of alternatives produced by both the baseline PIV method and D-PIV. With this approach, we can identify how robust each method is against weight perturbations at different levels of variation, while also providing empirical evidence on how the distance-based normalization modification in D-PIV helps improve ranking stability under varying criterion weights. The results of this sensitivity analysis are shown in Table 14.

Table 14. Scenario of Sensitivity Analysis of Weight Changes

Testing Scenario	LS01	LS02	LS03	LS04	LS05	LS06
	0.1713	0.1798	0.1711	0.1316	0.1996	0.1466
Test 1: LS01 + 0.05	0.2213	0.1698	0.1611	0.1216	0.1896	0.1366
Test 2: LS02 + 0.05	0.1613	0.2298	0.1611	0.1216	0.1896	0.1366
Test 3: LS03 + 0.05	0.1613	0.1698	0.2211	0.1216	0.1896	0.1366
Test 4: LS04 + 0.05	0.1613	0.1698	0.1611	0.1816	0.1896	0.1366
Test 5: LS05 + 0.05	0.1613	0.1698	0.1611	0.1216	0.2496	0.1366
Test 6: LS06 + 0.05	0.1613	0.1698	0.1611	0.1216	0.1896	0.1966



Test 7: LS01 - 0.05	0.1213	0.1898	0.1811	0.1416	0.2096	0.1566
Test 8: LS02 - 0.05	0.1813	0.1298	0.1811	0.1416	0.2096	0.1566
Test 9: LS03 - 0.05	0.1813	0.1898	0.1211	0.1416	0.2096	0.1566
Test 10: LS04 - 0.05	0.1813	0.1898	0.1811	0.0816	0.2096	0.1566
Test 11: LS05 - 0.05	0.1813	0.1898	0.1811	0.1416	0.1496	0.1566
Test 12: LS06 - 0.05	0.1813	0.1898	0.1811	0.1416	0.2096	0.0966
Test 13: LS01 + 0.1	0.2713	0.1598	0.1511	0.1116	0.1796	0.1266
Test 14: LS02 + 0.1	0.1513	0.2798	0.1511	0.1116	0.1796	0.1266
Test 15: LS03 + 0.1	0.1513	0.1598	0.2711	0.1116	0.1796	0.1266
Test 16: LS04 + 0.1	0.1513	0.1598	0.1511	0.2316	0.1796	0.1266
Test 17: LS05 + 0.1	0.1513	0.1598	0.1511	0.1116	0.2996	0.1266
Test 18: LS06 + 0.1	0.1513	0.1598	0.1511	0.1116	0.1796	0.2466
Test 19: LS01 - 0.1	0.0713	0.1998	0.1911	0.1516	0.2196	0.1666
Test 20: LS02 - 0.1	0.1913	0.0798	0.1911	0.1516	0.2196	0.1666
Test 21: LS03 - 0.1	0.1913	0.1998	0.0711	0.1516	0.2196	0.1666
Test 22: LS04 - 0.1	0.1913	0.1998	0.1911	0.0316	0.2196	0.1666
Test 23: LS05 - 0.1	0.1913	0.1998	0.1911	0.1516	0.0996	0.1666
Test 24: LS06 - 0.1	0.1913	0.1998	0.1911	0.1516	0.2196	0.0466
Test 25: LS01 + 0.15	0.3213	0.1498	0.1411	0.1016	0.1696	0.1166
Test 26: LS02 + 0.15	0.1413	0.3298	0.1411	0.1016	0.1696	0.1166
Test 27: LS03 + 0.15	0.1413	0.1498	0.3211	0.1016	0.1696	0.1166
Test 28: LS04 + 0.15	0.1413	0.1498	0.1411	0.2816	0.1696	0.1166
Test 29: LS05 + 0.15	0.1413	0.1498	0.1411	0.1016	0.3496	0.1166
Test 30: LS06 + 0.15	0.1413	0.1498	0.1411	0.1016	0.1696	0.2966
Test 31: LS01 - 0.15	0.0213	0.2098	0.2011	0.1616	0.2296	0.1766
Test 32: LS02 - 0.15	0.2013	0.0298	0.2011	0.1616	0.2296	0.1766
Test 33: LS03 - 0.15	0.2013	0.2098	0.0211	0.1616	0.2296	0.1766
Test 34: LS04 - 0.15	0.2013	0.2098	0.2011	0.0000	0.2296	0.1766
Test 35: LS05 - 0.15	0.2013	0.2098	0.2011	0.1616	0.0496	0.1766
Test 36: LS06 - 0.15	0.2013	0.2098	0.2011	0.1616	0.2296	0.0000

Following the specified criterion-weight changes, the alternatives were re-ranked using the PIV method under ± 0.05 variations for each criterion. This sensitivity analysis evaluates the effect of weight changes on the ranking order and identifies possible rank shifts among alternatives. By comparing these results with the initial ranking based on the original weights, the stability of the PIV method under-weight variation can be assessed. The ranking results for the ± 0.05 scenarios are presented in Figure 4.

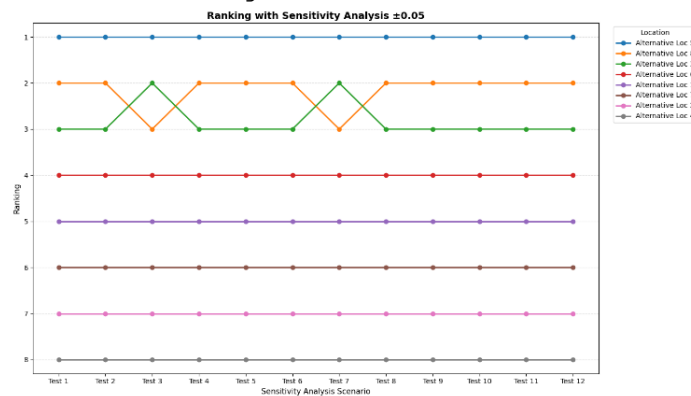


Figure 4. Sensitivity Analysis Ranking of 0.05 using the PIV method



The criterion weights were subsequently varied by ± 0.10 and the alternatives were re-ranked using the PIV method. This sensitivity analysis examines how larger weight adjustments affect the ranking order and identifies potential rank shifts among alternatives. Comparing these results with the original ranking provides an indication of PIV stability as the magnitude of weight variation increases. The ranking results for the ± 0.10 scenarios are presented in Figure 5.

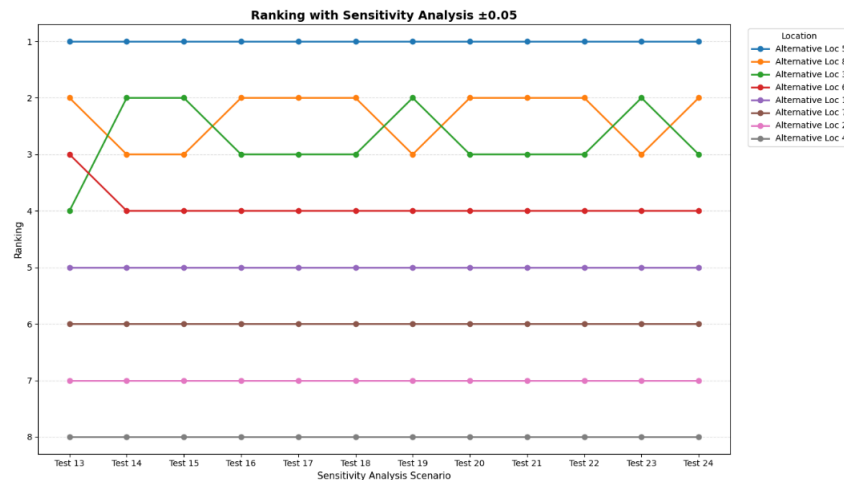


Figure 5. Sensitivity Analysis Ranking of 0.1 using the PIV method

The criterion weights were subsequently varied by ± 0.15 , followed by recalculation of the alternative rankings using the PIV method. This scenario examines the effect of larger weight adjustments on ranking changes and potential rank reversals. The results were compared with the original ranking to assess the stability of PIV under greater weight variation. The ranking results for the ± 0.15 scenarios are presented in Figure 6.

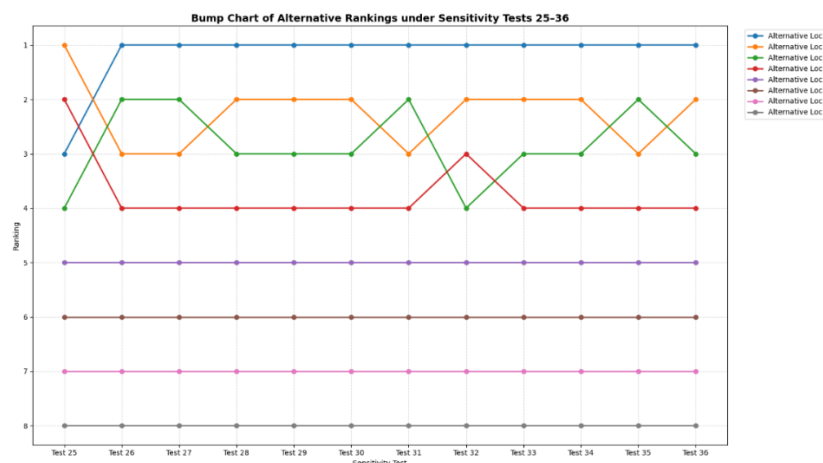


Figure 6. Sensitivity Analysis Ranking of 0.15 using the PIV method

Sensitivity analysis of the PIV baseline method, conducted across 36 criteria-weight testing scenarios, reveals that the majority of alternatives consistently maintain their ranking positions, particularly



Alternative Loc 1 and Alternative Loc 4, which stably occupy the fifth and eighth ranks, respectively, across all testing scenarios without any observed deviation. Nevertheless, a number of scenarios exhibit rank reversal, particularly within the upper-middle-ranked group of alternatives, namely Loc 5, Loc 3, Loc 8, and Loc 6. In Test 13, Test 15, Test 25, Test 27, Test 29, Test 32, Test 33, and Test 36, positional exchanges occur among Loc 3, Loc 8, and Loc 6, with the changes in Test 25 and Test 27 being sufficiently substantial to affect the position of Loc 5, which had previously occupied the first rank in every other scenario. In addition, positional exchange is also observed between the pair Loc 7 and Loc 2 in Test 18 and Test 31, although this change is localized and does not affect the other alternatives. Overall, this pattern indicates that the PIV baseline method exhibits a relatively high degree of sensitivity to variations in criteria weights among alternatives with closely spaced proximity values, rendering it susceptible to ranking instability even under moderate weight perturbations.

Based on the specified criterion-weight changes, the alternative rankings were recalculated using the D-PIV method under ± 0.05 variations for each criterion. This sensitivity analysis examines the extent to which these weight adjustments affect the ranking order and identifies potential rank shifts among alternatives. The resulting rankings were then compared with the initial ranking obtained using the original weights to evaluate the consistency and stability of D-PIV when the criterion weights are subject to moderate variation. This comparison also provides an indication of how individual alternatives respond to changes in criterion importance within the decision-making process. The ranking results for the ± 0.05 weight variation scenarios under the D-PIV method are presented in Figure 7.

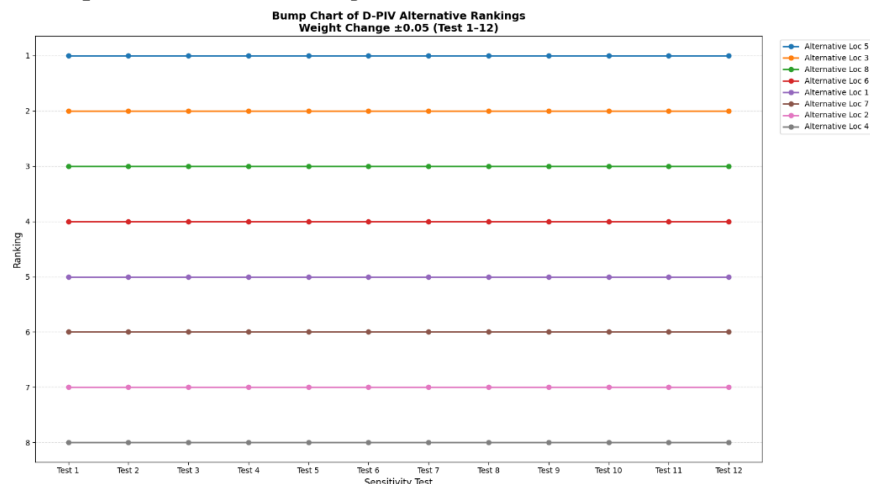
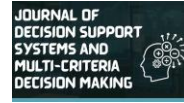


Figure 7. Sensitivity Analysis Ranking of 0.05 using the D-PIV method

The criterion weights were subsequently varied by ± 0.10 , and the alternative rankings were recalculated using the D-PIV method. This scenario examines the effect of larger weight adjustments on the ranking



order and identifies potential rank shifts among alternatives. The results were compared with the initial ranking based on the original weights to assess the consistency and stability of D-PIV as the magnitude of weight variation increases. This analysis also shows how alternatives respond to greater changes in criterion importance. The resulting rankings for the ± 0.10 scenarios are presented in Figure 8.

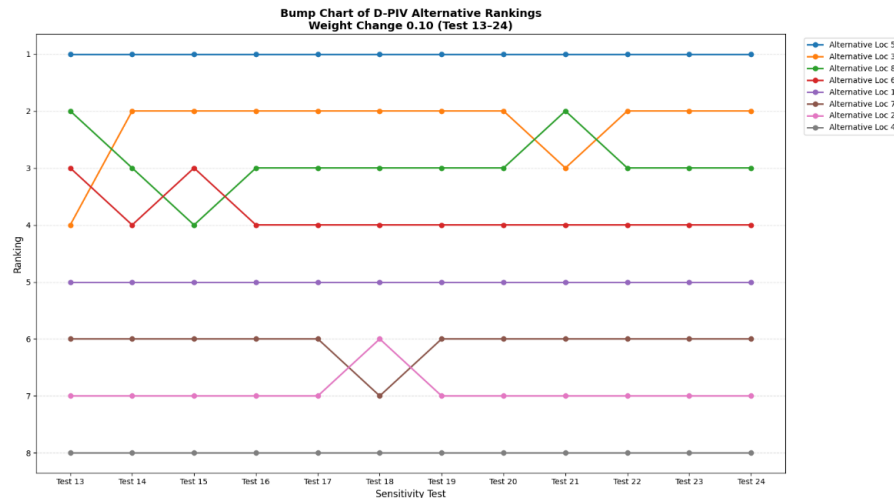


Figure 8. Sensitivity Analysis Ranking of 0.1 using the D-PIV method

To further examine the robustness of the D-PIV method, the criterion weights were varied by ± 0.15 , followed by recalculation of the alternative rankings. This larger perturbation examines whether greater weight changes lead to increased ranking shifts or rank reversals. The resulting rankings were compared with the initial ranking based on the original weights to assess the consistency of D-PIV under more substantial weight variation. Figure 9 presents the alternative rankings for the ± 0.15 scenarios under the D-PIV method.

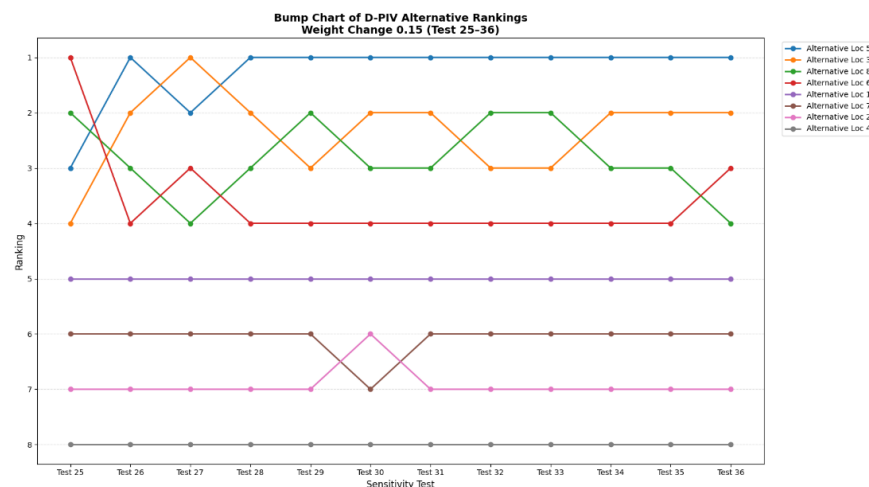


Figure 9. Sensitivity Analysis Ranking of 0.15 using the D-PIV method

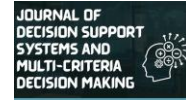


Sensitivity analysis of the D-PIV method, conducted across the same 36 criteria-weight testing scenarios, reveals that the majority of alternatives consistently maintain their ranking positions, particularly Alternative Loc 1 and Alternative Loc 4, which stably occupy the fifth and eighth ranks, respectively, across all testing scenarios without any observed deviation. Nevertheless, a number of scenarios still exhibit rank reversal, particularly within the upper-middle-ranked group of alternatives, namely Loc 5, Loc 3, Loc 8, and Loc 6. In Test 13, Test 15, Test 25, Test 27, Test 29, Test 32, Test 33, and Test 36, positional exchanges occur among Loc 3, Loc 8, and Loc 6, with the changes in Test 25 and Test 27 being sufficiently substantial to affect the position of Loc 5, which had previously occupied the first rank in every other scenario. In addition, positional exchange is also observed between the pair Loc 7 and Loc 2 in Test 18 and Test 31, although this change is localized and does not affect the other alternatives. Overall, this pattern indicates that, under the present set of test scenarios, the D-PIV method exhibits a comparable degree of sensitivity to variations in criteria weights among alternatives with closely spaced proximity values, suggesting that the distance-based normalization modification does not, by itself, fully eliminate ranking instability under this particular perturbation structure and that its effect should be interpreted alongside the ranking-correlation results discussed elsewhere in the analysis.

The ranking stability analysis was performed to evaluate the consistency of the alternative rankings generated by the original Proximity Indexed Value (PIV) and the proposed Distance-Based Proximity Indexed Value (D-PIV) under different sensitivity scenarios. This analysis is important because changes in criterion weights may influence the relative positions of alternatives, particularly when several alternatives have relatively close performance values. Therefore, evaluating only the initial ranking is insufficient to determine whether the resulting decision is consistent under changes in the weighting configuration. The sensitivity analysis was conducted through 36 test scenarios in which the criterion weights were systematically varied, while the resulting rankings were recorded for each alternative. The RSI comparison results obtained from PIV and D-PIV are presented in Table 15 as a basis for examining the stability of both methods.

Table 15. Ranking Stability Analysis of PIV and D-PIV

Alternatives	PIV: Rank Changes	D-PIV: Rank Changes	PIV Stability (%)	D-PIV Stability (%)
Alternative Loc 1	0	0	100	100
Alternative Loc 2	0	2	100	94.44
Alternative Loc 3	13	14	63.89	61.11
Alternative Loc 4	0	0	100	100
Alternative Loc 5	1	2	97.22	94.44
Alternative Loc 6	2	4	94.44	88.89
Alternative Loc 7	0	2	100	94.44
Alternative Loc 8	11	10	69.44	72.22



The ranking stability analysis was conducted to examine the response of PIV and D-PIV to changes in criterion weights across 36 sensitivity tests. The ranking obtained in Test 1 was used as the baseline for identifying changes in the position of each alternative. The results indicate that the degree of ranking variation differs among alternatives and between the two methods. In general, Loc 1, Loc 2, and Loc 4 maintain relatively stable positions under PIV, whereas greater variations are observed for Loc 3, Loc 5, Loc 6, and Loc 8. For D-PIV, the same general pattern is observed, although several alternatives exhibit different frequencies of rank changes.

Under PIV, Loc 1, Loc 2, Loc 4, and Loc 7 retain their baseline positions throughout the sensitivity tests, resulting in a stability value of 100%. Loc 5 changes position in only one test, giving a stability of 97.22%, while Loc 6 changes in two tests, corresponding to 94.44%. More substantial variations are observed for Loc 3 and Loc 8, whose positions differ from their baseline ranks in 13 and 11 tests, respectively. Their corresponding stability values are 63.89% and 69.44%. This pattern indicates that the sensitivity of the ranking is not distributed uniformly across all alternatives.

The D-PIV results show a similar ranking structure but with some differences in the frequency of rank changes. Loc 1 and Loc 4 remain unchanged throughout the 36 tests, while Loc 2, Loc 5, and Loc 7 exhibit only limited changes. Loc 8 shows a stability value of 72.22%, which is higher than its corresponding value under PIV. In contrast, Loc 3 and Loc 6 show lower stability values under D-PIV, with values of 61.11% and 88.89%, respectively. These differences demonstrate that the distance-based modification affects the sensitivity of individual alternatives to changes in criterion weights.

Overall, the results show that both methods preserve the general structure of the ranking across the sensitivity scenarios, while variations occur primarily among alternatives with relatively close positions. The stability analysis therefore provides additional information beyond the initial ranking by identifying which alternatives are more responsive to changes in criterion weights. The comparison between PIV and D-PIV also demonstrates that the distance-based normalization can alter the distribution of ranking changes without necessarily producing uniform effects across all alternatives. Consequently, the stability assessment is useful for evaluating whether the ranking produced by the proposed D-PIV method remains consistent when the weighting configuration is subjected to systematic perturbation.

3.5. Discussion

The comparative results demonstrate that the proposed D-PIV method modifies the way alternative performance is represented without changing the original decision matrix, vector normalization, or criterion weighting structure. The most important difference arises from the introduction of distance-based normalization, which explicitly measures the deviation of each normalized criterion value from its corresponding

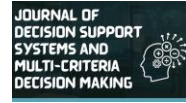


ideal condition. In the conventional PIV approach, the weighted proximity values are derived directly from normalized performance values, whereas D-PIV first transforms the deviations into proximity scores relative to the ideal reference. This additional transformation produces a more explicit representation of how close each alternative is to the desired condition for every criterion. The results show that this modification does not substantially alter the overall ranking structure, as Loc 5, Loc 6, Loc 1, Loc 7, Loc 2, and Loc 4 maintain the same positions between PIV and D-PIV. This indicates that the proposed modification preserves the dominant preference relationships while modifying the treatment of alternatives whose criterion-level performances are relatively close.

The ranking comparison provides more specific evidence of the effect of the distance-based mechanism. Under the original PIV method, Loc 5 remains the first-ranked alternative, while Loc 6, Loc 1, Loc 7, Loc 2, and Loc 4 also retain their respective positions. The only discrepancy occurs between Loc 3 and Loc 8, where PIV places Loc 8 second and Loc 3 third, despite the opposite order in the original ranking. After incorporating distance-based normalization, D-PIV places Loc 3 second and Loc 8 third, thereby restoring the original ordering. Consequently, the D-PIV ranking matches all eight positions of the reference ranking, whereas PIV differs at two positions. This result is further supported by the Spearman correlation analysis, where PIV obtains a coefficient of 0.9762 against the reference ranking, while D-PIV obtains 1.0000. The difference suggests that the distance-based transformation can be particularly relevant when alternatives have similar relative performance and small differences in their proximity values can determine their ordinal positions. Rather than producing a fundamentally different ranking structure, D-PIV primarily influences the ordering of alternatives located near each other in the preference hierarchy.

The sensitivity analysis provides a different perspective on the behavior of the two methods under systematic changes in criterion weights. Across the 36 testing scenarios, both PIV and D-PIV preserve the positions of several alternatives, particularly Loc 1 and Loc 4, which remain unchanged throughout the tested perturbations. Under PIV, Loc 5 and Loc 6 exhibit only one and two ranking changes, respectively, whereas Loc 3 and Loc 8 experience substantially more variation, with 13 and 11 changes. A similar pattern is observed for D-PIV, although the frequency of changes differs for individual alternatives. Loc 8 improves its stability from 69.44% under PIV to 72.22% under D-PIV, while Loc 3 decreases from 63.89% to 61.11%. Loc 6 also shows a decrease from 94.44% to 88.89%. These results indicate that the distance-based normalization does not uniformly reduce sensitivity to weight perturbations. Instead, its influence depends on the relative position of each alternative with respect to the ideal values and on the interaction between criterion weights and alternative-level deviations.

The contrasting results between the initial ranking comparison and the sensitivity analysis are particularly important for interpreting the contribution of D-PIV. At the original weighting configuration, D-

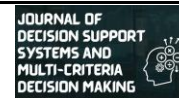


PIV achieves a perfect correspondence with the reference ranking and corrects the two-position reversal observed in PIV. However, under the 36 weight perturbation scenarios, D-PIV does not consistently outperform PIV for every alternative. The stability values show improvements for Loc 8 but reductions for Loc 2, Loc 3, Loc 5, Loc 6, and Loc 7, while Loc 1 and Loc 4 remain equally stable under both methods. This finding suggests that ranking agreement at the original weighting configuration and robustness under weight variation represent two related but distinct properties. The distance-based mechanism is effective in modifying the ranking structure toward the reference configuration in the baseline case, but this modification does not guarantee lower sensitivity under all weight perturbations. Therefore, the performance of D-PIV should be interpreted not simply in terms of whether it produces fewer rank changes, but also in terms of how the distance transformation redistributes sensitivity among alternatives.

Overall, the findings indicate that D-PIV provides a meaningful modification of the PIV framework by introducing an explicit distance-to-ideal perspective while retaining the same underlying decision matrix and criterion weights. Its strongest effect is observed in the baseline ranking, where the modification resolves the rank reversal between Loc 3 and Loc 8 and increases the Spearman correlation with the reference ranking from 0.9762 to 1.0000. At the same time, the sensitivity results demonstrate that ranking stability remains dependent on the characteristics of the alternatives and the magnitude and direction of weight perturbations. Alternatives with relatively close preference positions remain more susceptible to positional changes, even after distance-based normalization is introduced. Thus, the empirical evidence supports D-PIV as a modification that improves ranking consistency in the evaluated baseline configuration, while its robustness under broader weighting uncertainty should be considered as an alternative-specific property rather than as a universal improvement over conventional PIV.

IV. Conclusion

The main contribution of this study is the development of D-PIV as a distance-based modification of the conventional PIV method. Rather than introducing a completely new ranking framework, D-PIV extends the PIV mechanism by incorporating the distance of each normalized performance value from an ideal reference before the aggregation process. This modification provides a clearer representation of alternative proximity to ideal conditions and addresses the rank reversal observed between Loc 3 and Loc 8 in the baseline PIV results. Empirically, D-PIV achieves a Spearman correlation of 1.0000 with the reference ranking, compared with 0.9762 for PIV, demonstrating improved ranking agreement in the evaluated case. The study also contributes a systematic robustness assessment through 36 weight-variation scenarios, showing that the effect of the proposed modification on ranking stability varies across alternatives rather than assuming uniform improvement. Thus, the contribution of D-PIV lies in enhancing the representation of distance



to ideal conditions and improving ranking consistency while retaining the fundamental structure of the PIV method. The methodological contribution of this study is the development of D-PIV through the integration of distance-based normalization into the conventional PIV framework. This modification introduces an explicit measurement of the distance between normalized criterion values and their ideal conditions while retaining the fundamental weighting and aggregation structure of PIV. These findings distinguish the methodological contribution of the proposed distance-based mechanism from its empirical performance in improving ranking consistency within the evaluated decision problem.

Future research may extend the D-PIV method by testing its performance on larger and more diverse datasets from different MCDM application domains. Further studies can also examine the interaction of D-PIV with alternative objective and subjective weighting methods to determine whether the distance-based mechanism remains consistent under different weighting configurations. Comparative evaluations with other distance- and proximity-based MCDM methods would also help establish the applicability and generalizability of D-PIV across different decision-making conditions.

CRediT Authorship Contribution Statement

Desyanti: Conceptualization, Visualization, Writing - Original Draft Preparation, Writing - Review & Editing. **Gellysa Urva:** Investigation, Methodology, Writing - Original Draft Preparation. **Sunggito Oyama:** Data Curation, Formal Analysis, Writing - Original Draft Preparation. **Kristina Febriani:** Conceptualization, Methodology, Validation, Writing - Original Draft Preparation.

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.

Funding Statements

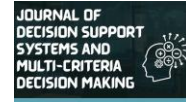
The author(s) received no financial support for the research, authorship, and/or publication of this article.

Data Availability

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

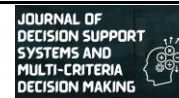
Declaration of Generative AI and AI-assisted Technologies in The Writing Process

The authors used Generative 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.

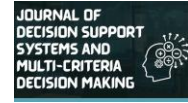


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