Volume 1 Number 2 November 2026, Available online November 24, 2026. Page 109-129

Journal of Computer and Data Science
E-ISSN 3164-5194

journal homepage: https://e-journal.pilar.or.id/index.php/jcoda/index

Integration of the MEREC Objective Weighting Method and PIV Ranking Method for Multi-Criteria Vendor Selection

A. Ferico Octaviansyah Pasaribu[1]*, Ajeng Savitri Puspaningrum[1], Sanriomi Sintaro[2]

[1]Faculty Engineering and Computer Science, Universitas Teknokrat Indonesia, Bandar Lampung, Indonesia
[2]Faculty of Mathematics and Natural Sciences, Universitas Sam Ratulangi, Manado, Indonesia

Keywords:
Vendor Selection; Multi-Criteria Decision Making; MEREC Weighting; PIV Method; Decision Support System;

ABSTRACT

Vendor selection is a critical decision in supply chain management because it directly influences procurement costs, product quality, delivery performance, and operational continuity. The presence of multiple evaluation criteria with different characteristics makes vendor selection a complex multi-criteria decision-making problem. This study proposes an integrated MEREC-PIV method to provide an objective and systematic approach to vendor selection. MEREC is applied to determine the objective weights of the evaluation criteria based on the effect of criterion removal on overall alternative performance, while PIV is used to rank vendor alternatives according to their proximity to reference values. The proposed approach was implemented using a dataset consisting of 25 vendor alternatives and six criteria, namely price, delivery time, quality, service, reputation, and flexibility. The MEREC results indicate that delivery time (KT2) and price (KT1) are the most influential criteria, with weights of 0.3620 and 0.3618, respectively. The PIV ranking results show that V07 achieved the highest priority with a final value of 0.2665, followed by V18 (0.2762), V13 (0.2796), V03 (0.2962), and V23 (0.3287). These findings demonstrate that the MEREC-PIV integration can objectively determine criterion importance and generate a systematic ranking of vendor alternatives. The proposed approach can support decision-makers in identifying the most suitable vendor based on quantitative and data-driven evaluation.

I. Introduction

Vendor selection is an important strategic aspect of supply chain management because vendor choices can directly affect operational efficiency, procurement costs, supply continuity, on-time fulfillment of needs, and the quality of products or services an organization

*Corresponding Author: fericopasaribu@teknokrat.ac.id (A. Ferico Octaviansyah Pasaribu)
DOI: https://doi.org/10.67449/jcoda.v1i2.6

Volume 1 Number 2 November 2026, Available online November 24, 2026. Page 109-129

Journal of Computer and Data Science
E-ISSN 3164-5194

journal homepage: https://e-journal.pilar.or.id/index.php/jcoda/index

receives[1], [2]. Choosing the right vendor isn't just about their ability to provide goods or services at competitive prices; it also involves considering various other aspects related to performance and the sustainability of supply chain relationships. In practice, vendors are evaluated based on many criteria that have different characteristics, measurement scales, and levels of importance, such as price, quality, delivery timeliness, capacity, flexibility, service, reputation, and reliability. This situation makes the vendor evaluation process quite complex because each option may have strengths in certain criteria but also weaknesses in others, so decisions can't be made by just looking at a single indicator[2], [3]. The complexity increases even more when the number of vendors and criteria being evaluated goes up, so an approach is needed that can systematically integrate various information to produce decisions that are objective and accountable. In this context, multi-criteria decision-making (MCDM) can handle the complexity of evaluating vendors by considering various criteria at the same time, determining the importance weights, and systematically ranking the alternatives. Its application supports a more objective, consistent vendor selection and can improve supply chain efficiency and performance[4]–[6].

Although MCDM can help handle the complexity of vendor evaluation, the decision-making process still faces several challenges, especially in determining the weighting of criteria objectively[7], [8]. Assessments that rely too much on the decision-maker's subjectivity can lead to inconsistencies in setting the importance level of each criterion. Moreover, vendor criteria generally have different measurement scales and characteristics, so a proper normalization process is needed to ensure all values can be compared fairly. After that, a ranking method that can accurately integrate evaluation results from various criteria is needed to produce a reliable vendor order. Therefore, choosing the right MCDM method is important to achieve a vendor evaluation that is more objective, consistent, and representative.

Method based on the Removal Effects of Criteria (MEREC) is one of the objective weighting methods that determines the importance level of criteria based on their impact on evaluation results[9], [10]. This method uses the concept of removing criteria to identify how much each criterion contributes to the aggregation result. Each criterion is evaluated by comparing the aggregation result before and after the criterion is removed. Criteria that cause a bigger change when removed show a stronger influence on the evaluation outcome. Therefore, these criteria will get a higher weight compared to criteria that cause smaller changes. This approach allows the importance level of criteria to be determined based on the information contained in the evaluation data[11]–[13]. The MEREC method is relevant to use in decision-making because it can produce weights objectively without relying on subjective judgments or preferences from experts.

The Proximity Indexed Value (PIV) method is a ranking method used to determine the priority of alternatives based on how close their values

*Corresponding Author: fericopasaribu@teknokrat.ac.id (A. Ferico Octaviansyah Pasaribu)
DOI: https://doi.org/10.67449/jcoda.v1i2.6

Volume 1 Number 2 November 2026, Available online November 24, 2026. Page 109-129

Journal of Computer and Data Science
E-ISSN 3164-5194

journal homepage: https://e-journal.pilar.or.id/index.php/jcoda/index

are to a reference condition[13], [14]. This method evaluates the performance of each alternative across various criteria to get a proximity index value that represents the alternative's position relative to the desired condition. The better the alternative's position compared to the reference condition, the higher the priority it gets in the decision-making process. In the context of selecting vendors, PIV can be used to rank vendors after the weight of each criterion is obtained through an objective weighting method[15], [16]. Using these weights allows the contribution of each criterion to be considered in determining the overall performance of the vendor. The integration of MEREC and PIV allows the weighting and ranking process to be done systematically by combining data-based objective weights with the evaluation of how close alternatives are to reference conditions.

Some research on vendor selection still applies weighting and ranking methods separately or uses a combination of different methods. This situation shows that there is still room for development in integrating MEREC and PIV specifically to support the vendor selection process. MEREC has the ability to determine criteria weights based on the impact of removing a criterion on the evaluation results, while PIV provides a ranking mechanism based on the proximity of alternatives to reference conditions. Integrating these two methods can link the objective weighting process with a proximity-based ranking mechanism. This approach allows criteria weights to be determined based on data characteristics without relying on subjective judgment. Therefore, an integrated MEREC-PIV approach is needed to create a more systematic, objective, and consistent vendor evaluation and ranking process.

Previous studies have demonstrated the potential of integrating objective weighting and ranking methods to address multi-criteria selection problems. Keshavarz-Ghorabaee et al. introduced MEREC (Method based on the Removal Effects of Criteria) as an objective weighting approach that determines criterion importance based on the impact of removing each criterion from the decision process, providing a different perspective from conventional variation-based weighting methods[17]. Subsequent studies have applied MEREC in various selection problems, including distribution center location assessment and supplier selection, confirming its applicability for deriving data-driven criterion weights[18]. In particular, the integration of MEREC and PIV (Preference Index of Ideal Solution/Preference Index Vector) has been applied to renewable energy source selection, where MEREC was used to determine objective weights and PIV to rank alternatives, with sensitivity analysis employed to examine the robustness of the results[19]. However, existing applications of MEREC-PIV remain relatively limited across different vendor-selection contexts, particularly in comprehensive evaluation involving heterogeneous criteria such as cost, delivery performance, quality, service, reputation, and flexibility. This indicates a research gap in further examining the integration of MEREC and PIV specifically for multi-criteria vendor selection, including whether the combination can provide stable and interpretable rankings when criteria have different

*Corresponding Author: fericopasaribu@teknokrat.ac.id (A. Ferico Octaviansyah Pasaribu)
DOI: https://doi.org/10.67449/jcoda.v1i2.6

Volume 1 Number 2 November 2026, Available online November 24, 2026. Page 109-129

Journal of Computer and Data Science
E-ISSN 3164-5194

journal homepage: https://e-journal.pilar.or.id/index.php/jcoda/index

characteristics and levels of importance. Therefore, this study proposes the integration of the MEREC objective weighting method and PIV ranking method for multi-criteria vendor selection to address this gap and provide a data-driven framework for evaluating competing vendors.

This study aims to develop the MEREC-PIV framework to support a systematic and objective vendor selection process. The MEREC method is used to determine the weight of each criterion based on its impact on the evaluation results. Then, the PIV method is applied to rank vendors according to how close their performance is to the reference conditions. Integrating these two methods is expected to create a structured and consistent weighting and ranking process. In addition, this study evaluates the stability and consistency of the results through sensitivity analysis and/or comparison with other MCDM methods. The evaluation results are used to assess the reliability of the MEREC-PIV framework in supporting vendor selection decision-making.

II. Methodology

2.1. Research Stage

The research stages are a series of systematic processes carried out to achieve the research objectives, starting from identifying the problems, determining criteria and alternatives, collecting data, forming a decision matrix, weighting using MEREC, ranking using PIV, to evaluating the stability and consistency of the results. Each stage is carried out sequentially to ensure the vendor selection process is objective and structured. Overall, the research stages used in developing the MEREC-PIV framework are shown in Figure 1.

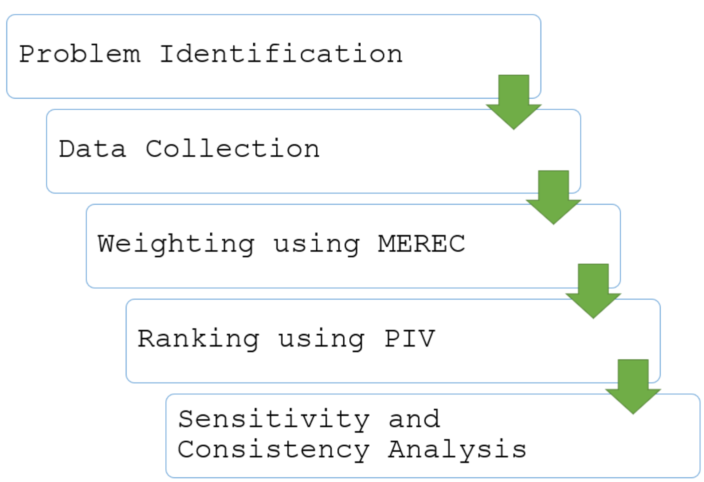

Figure 1. Research Stages

The research process begins with problem identification, which focuses on defining the vendor selection problem and determining the criteria required to evaluate vendor performance. The next stage is data

*Corresponding Author: fericopasaribu@teknokrat.ac.id (A. Ferico Octaviansyah Pasaribu)
DOI: https://doi.org/10.67449/jcoda.v1i2.6

Volume 1 Number 2 November 2026, Available online November 24, 2026. Page 109-129
Journal of Computer and Data Science
E-ISSN 3164-5194
journal homepage: https://e-journal.pilar.or.id/index.php/jcoda/index

collection, where relevant data are obtained for each vendor based on the selected criteria. The collected data are then processed through weighting using MEREC to determine the objective importance of each criterion based on its removal effect. Subsequently, ranking using PIV is performed to evaluate and prioritize vendors according to their proximity-based performance. Finally, sensitivity and consistency analysis is conducted to assess the stability, robustness, and reliability of the resulting vendor rankings.

2.2. MEREC Method

MEREC method is an objective weighting method in MCDM that determines the importance level of each criterion based on its impact on the evaluation results when the criterion is removed. The main principle of MEREC is that the greater the change in the evaluation results due to removing a criterion, the higher the importance level of that criterion. By using information from the decision matrix, MEREC can determine criteria weights objectively without requiring subjective judgment from decision-makers or experts.

The MEREC stages start with creating a decision matrix that includes alternatives and criteria as the main input in the data processing using (1). Next, the values in the decision matrix are normalized by considering the characteristics of each criterion, both benefit and cost, as shown in (2). Based on the normalization results, the aggregate performance value for each alternative is then calculated using (3). Afterwards, a recalculation of the alternatives' performance is done by removing each criterion one by one to identify the impact of each criterion on the evaluation results using (4). The difference between the initial performance and the performance after removal is used to determine the size of the removal effect for each criterion through (5). These values then serve as the basis for determining the importance level of each criterion, resulting in objective weights through (6).

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

$$n_{ij} = \begin{cases} \dfrac{x_{ij}}{\max\limits_{j} x_{ij}}; j \epsilon B \\ \dfrac{\min\limits_{j} x_{ij}}{x_{ij}}; j \epsilon C \end{cases} \tag{2}$$

$$S_i = \ln\left(1 + \left(\frac{1}{m}\sum_{j=1}^{n}\left|\ln(n_{ij})\right|\right)\right) \tag{3}$$

$$S_{ij}' = \ln\left(1 + \left(\frac{1}{m}\sum_{k,k\neq j}^{n}\left|\ln(n_{ij})\right|\right)\right) \tag{4}$$

$$E_j = \sum_{j=1}^{n}\left|S_{ij}' - S_i\right| \tag{5}$$

$$w_j = \frac{E_j}{\sum_{j=1}^{n} E_j} \tag{6}$$

MEREC can be used as an objective weighting method that determines the importance level of criteria based on their contribution to evaluation results. The main advantage of this method lies in its ability to utilize data characteristics and the impact of removing criteria

*Corresponding Author: fericopasaribu@teknokrat.ac.id (A. Ferico Octaviansyah Pasaribu)
DOI: https://doi.org/10.67449/jcoda.v1i2.6

Volume 1 Number 2 November 2026, Available online November 24, 2026. Page 109-129

Journal of Computer and Data Science
E-ISSN 3164-5194

journal homepage: https://e-journal.pilar.or.id/index.php/jcoda/index

without needing subjective assessments from experts. MEREC also allows each criterion to receive a weight according to its level of influence, so criteria that contribute more to changes in evaluation results will get a higher weight. This approach makes MEREC suitable for use in MCDM problems, especially in vendor selection processes that involve many criteria with varying levels of importance.

2.3. PIV Method

PIV is an MCDM method used to determine priorities based on how close performance values are to reference values for each criterion. This method considers the weight of each criterion when calculating the overall closeness. The calculation results for each criterion are then aggregated to get the final value, which serves as the basis for ranking. The main feature of PIV is its use of the proximity concept to compare performance against reference values in a systematic and measurable way.

The PIV method steps start by determining a reference value as a basis for measuring how close each alternative's performance is to the desired condition. Next, the closeness value of each alternative to the reference value for each criterion is calculated by considering the benefit and cost characteristics of the criteria using (7). These closeness results are then combined with the criteria weights obtained from MEREC to get weighted values using (8). After that, the weighted values from all criteria are aggregated to obtain the PIV index value for each alternative using (9). The final step is to determine the final value and rank the alternatives based on the PIV calculation results using (10), giving the ranking of the alternatives.

$$r_{ij} = \begin{cases} \dfrac{x_{ij} - \min_j x_{ij}}{\max_j x_{ij} - \min_j x_{ij}}; j \epsilon B \\ \dfrac{\max_j x_{ij} - x_{ij}}{\max_j x_{ij} - \min_j x_{ij}}; j \epsilon C \end{cases} \tag{7}$$

$$n_{ij} = w_j * r_{ij} \tag{8}$$

$$\delta_{ij} = \begin{cases} \max_j n_{ij} - n_{ij}; j \epsilon B \\ n_{ij} - \min_j n_{ij}; j \epsilon C \end{cases} \tag{9}$$

$$\varphi_i = \sum_{j=1}^{n} \delta_{ij} \tag{10}$$

PIV is a ranking method that can provide priority results based on how close performance is to reference values in a systematic way. One of PIV's advantages is its ability to integrate criteria weights into the evaluation process, so the importance level of each criterion is taken into account. Additionally, PIV can handle criteria with both benefit and cost characteristics, and it produces final scores that are easy to use for determining priority order. These features make PIV suitable to be combined with objective weighting methods in building a more structured and data-driven decision-making process.

*Corresponding Author: fericopasaribu@teknokrat.ac.id (A. Ferico Octaviansyah Pasaribu)
DOI: https://doi.org/10.67449/jcoda.v1i2.6

Volume 1 Number 2 November 2026, Available online November 24, 2026. Page 109-129

Journal of Computer and Data Science
E-ISSN 3164-5194

journal homepage: https://e-journal.pilar.or.id/index.php/jcoda/index

III. Result and Discussion

Choosing a vendor is an important part of supply chain management because the decisions made can affect procurement costs, product or service quality, timeliness, and operational continuity. The process generally involves various criteria that have different characteristics, scales, and levels of importance, making selecting the best vendor a complex issue. MCDM can be used to handle these conditions by considering several criteria at the same time. However, the effectiveness of the MCDM process is greatly influenced by the method's ability to determine criteria weights objectively and produce consistent rankings. Relying on subjective weights can impact decision outcomes, while differences in characteristics between criteria require proper evaluation and ranking mechanisms.

The integration of MEREC and PIV offers an approach that links objective weighting with a closeness-based ranking process. MEREC determines the weights of criteria based on how much a criterion influences the evaluation results when it is removed, so weights can be obtained from the data characteristics without relying on expert judgment. Then, PIV is used to determine priorities based on how close performance is to reference values, taking into account the weights already obtained. Integrating these two methods allows the evaluation process to be carried out systematically, from determining the importance level of criteria to forming rankings. The MEREC-PIV approach is expected to result in a vendor selection process that is more objective, consistent, and capable of providing a more reliable basis for decision-making.

3.1. Problem Identification

Choosing a vendor is an important issue in supply chain management because the decisions made can affect operational efficiency, procurement costs, product or service quality, and supply continuity. In practice, organizations have to pick a vendor from several alternatives while considering various criteria that differ from one another. These criteria can include price, quality, on-time delivery, service, capacity, flexibility, and reputation. The varying characteristics and importance of each criterion mean that evaluation can't be done based on just one indicator. That's why a decision-making approach that can consider multiple criteria at the same time and in a structured way is needed.

Another problem arises in determining the importance level of each criterion. Using weights based on subjective judgment can lead to differences in decisions because it heavily depends on the decision-maker's perception or preference. This situation can reduce consistency and objectivity in the evaluation process. Moreover, each criterion may have different measurement scales and characteristics, so proper data processing is needed before ranking. This complexity highlights the

*Corresponding Author: fericopasaribu@teknokrat.ac.id (A. Ferico Octaviansyah Pasaribu)
DOI: https://doi.org/10.67449/jcoda.v1i2.6

Volume 1 Number 2 November 2026, Available online November 24, 2026. Page 109-129

Journal of Computer and Data Science
E-ISSN 3164-5194

journal homepage: https://e-journal.pilar.or.id/index.php/jcoda/index

importance of using a weighting method that can utilize the information contained in the data to determine criteria weights objectively.

Based on these issues, an approach is needed that can integrate the weighting and ranking process systematically. MEREC can be used to determine the weights of criteria based on the influence of each criterion on changes in evaluation results when a criterion is removed. Then, PIV can be used to generate priorities based on how close performance is to reference values while considering the weights that have been obtained. Integrating MEREC and PIV is expected to reduce reliance on subjective judgments while providing a more structured evaluation mechanism. The MEREC-PIV approach becomes relevant to support decision-making in multi-criteria problems that require objective and consistent evaluation results.

3.2. Data Collection

Data collection was carried out to obtain the information needed in the vendor selection process based on the criteria that had been set. The data used includes several vendor alternatives along with their performance scores on each evaluation criterion. Each criterion was chosen to represent relevant aspects in assessing the capability and performance of vendors, so the data obtained can be used as a basis for weighting and ranking. The vendor selection data used in this study is presented in Table 1.

Table 1.Dataset Vendor Selection

Alternative	KT1	KT2	KT3	KT4	KT5	KT6
V01	3	8	88	7	86	4
V02	2	6	92	8	90	5
V03	5	12	85	6	84	2
V04	1	5	94	9	93	5
V05	4	10	87	7	88	3
V06	2	7	91	8	92	4
…	…	…	…	…	…	…
V24	1	5	94	9	93	5
V25	4	8	89	7	88	4

Table 1 presents the Vendor Selection Dataset, consisting of 25 alternatives (V01–V25) evaluated using six criteria (KT1–KT6). The criteria include Price (KT1), Delivery Time (KT2), Quality (KT3), Service (KT4), Reputation (KT5), and Flexibility (KT6), with different measurement ranges and characteristics. KT1 (Price) ranges from 1 to 5 and is categorized as a cost criterion, while KT2 (Delivery Time) ranges from 3 to 15 and is also classified as cost. In contrast, KT3 (Quality) with values of 80–95, KT4 (Service) with values of 5–9, KT5 (Reputation) with values of 80–95, and KT6 (Flexibility) with values of 1–5 are classified as benefit criteria, where higher values indicate better performance. The variation in the values and criterion types provides a diverse decision matrix for evaluating vendor performance. The dataset is subsequently used as the input for the MEREC weighting process and PIV ranking process.

*Corresponding Author: fericopasaribu@teknokrat.ac.id (A. Ferico Octaviansyah Pasaribu)
DOI: https://doi.org/10.67449/jcoda.v1i2.6

Volume 1 Number 2 November 2026, Available online November 24, 2026. Page 109-129

Journal of Computer and Data Science
E-ISSN 3164-5194

journal homepage: https://e-journal.pilar.or.id/index.php/jcoda/index

3.3. Criterion Weight Calculation using MEREC

Calculating criteria weights using the MEREC method is done to determine the level of importance of each criterion objectively, based on its impact on the evaluation results of alternatives. MEREC measures criteria weights by looking at the changes in the aggregate value of alternatives when a criterion is removed from the calculation process. The bigger the change caused by removing a criterion, the more important that criterion is. This approach lets criteria weights be set based on each criterion's actual contribution to the overall decision, which helps reduce reliance on subjective judgment in the weighting process.

The MEREC weighting procedure is conducted through a sequence of calculations designed to objectively determine the relative importance of each criterion. First, the decision matrix is established by arranging all alternatives according to the selected criteria using Equation (1), and the decision matrix results are the same as those in Table 1. The matrix is subsequently transformed through criterion-based normalization, where the calculation is adjusted to distinguish between benefit and cost criteria according to Equation (2), with the normalized results presented in Table 2.

Table 2. Normalization Results of the MEREC Method

Alternative	KT1	KT2	KT3	KT4	KT5	KT6
V01	0.3333	0.3750	0.9263	0.7778	0.9053	0.8000
V02	0.5000	0.5000	0.9684	0.8889	0.9474	1.0000
V03	0.2000	0.2500	0.8947	0.6667	0.8842	0.4000
V04	1.0000	0.6000	0.9895	1.0000	0.9789	1.0000
V05	0.2500	0.3000	0.9158	0.7778	0.9263	0.6000
V06	0.5000	0.4286	0.9579	0.8889	0.9684	0.8000
…	…	…	…	…	…	…
V24	1.0000	0.6000	0.9895	1.0000	0.9789	1.0000
V25	0.2500	0.3750	0.9368	0.7778	0.9263	0.8000

The normalized data are then used to obtain the overall performance measure of each alternative through Equation (3), and the calculated values are summarized in Table 3.

Table 3. Overall Alternative Performance Score of the MEREC Method

Alternative	Alternative Performance Value
V01	0.3750
V02	0.2351
V03	0.5645
V04	0.0866
V05	0.4613
V06	0.2822
…	…
V24	0.0866
V25	0.4036

To assess the contribution of individual criteria, the performance values are recalculated repeatedly after excluding one criterion at a time using Equation (4), with the results provided in Table 4.

*Corresponding Author: fericopasaribu@teknokrat.ac.id (A. Ferico Octaviansyah Pasaribu)
DOI: https://doi.org/10.67449/jcoda.v1i2.6

Volume 1 Number 2 November 2026, Available online November 24, 2026. Page 109-129

Journal of Computer and Data Science
E-ISSN 3164-5194

journal homepage: https://e-journal.pilar.or.id/index.php/jcoda/index

Table 4. Alternative Performance Scores After Elimination of the MEREC Method

Alternative	KT1	KT2	KT3	KT4	KT5	KT6
V01	0.2405	0.2558	0.3662	0.3458	0.3635	0.3491
V02	0.1393	0.1393	0.2309	0.2195	0.2280	0.2351
V03	0.3990	0.4237	0.5539	0.5254	0.5528	0.4737
V04	0.0866	0.0053	0.0850	0.0866	0.0833	0.0866
V05	0.3039	0.3261	0.4520	0.4345	0.4532	0.4061
V06	0.1911	0.1696	0.2768	0.2673	0.2782	0.2538
…	…	…	…	…	…	…
V24	0.0866	0.0053	0.0850	0.0866	0.0833	0.0866
V25	0.2360	0.2880	0.3963	0.3752	0.3951	0.3785

The resulting changes are compared with the original performance values to obtain the removal effect associated with each criterion through Equation (5), which is presented in Table 5.

Table 5. Performance Scores for each Criteria of the MEREC Method

KT1	KT2	KT3	KT4	KT5	KT6
2.7207	2.7222	0.1968	0.6295	0.2243	1.0266

Finally, these removal effects are converted into criterion importance values and objective weights using Equation (6), and the final weights are reported in Table 6.

Table 6. Criteria Weight Value of the MEREC Method

KT1	KT2	KT3	KT4	KT5	KT6
0.3618	0.3620	0.0262	0.0837	0.0298	0.1365

The weighting results using the MEREC method show that KT2 has the highest weight at 0.3620, followed by KT1 with a weight of 0.3618, making these two criteria the most dominant factors in the evaluation process. Next, KT6 got a weight of 0.1365, while KT4 has a weight of 0.0837. Meanwhile, KT5 and KT3 have relatively low weights, at 0.0298 and 0.0262 respectively. These results show that MEREC assigns different levels of importance to each criterion based on their impact on changes in alternative performance when a criterion is removed.

3.4. Calculation of Alternative Values Using the PIV Method

The calculation of alternative values using the PIV method is done to determine how close each alternative is to the ideal condition based on all the criteria that have been weighted. This process uses the weight values from the MEREC method as a basis to measure each criterion's contribution to the final alternative score. Each alternative is evaluated based on normalized criterion values, then combined with the criterion weights to produce the PIV value. This final value is used as a basis to determine the ranking of alternatives, where the alternative with the best closeness value gets a higher rank according to the PIV calculation characteristics. All calculation steps are done systematically until the final values are obtained, which can be used to compare the performance of all alternatives.

*Corresponding Author: fericopasaribu@teknokrat.ac.id (A. Ferico Octaviansyah Pasaribu)
DOI: https://doi.org/10.67449/jcoda.v1i2.6

Volume 1 Number 2 November 2026, Available online November 24, 2026. Page 109-129

Journal of Computer and Data Science
E-ISSN 3164-5194

journal homepage: https://e-journal.pilar.or.id/index.php/jcoda/index

The calculation of alternative values using the PIV method is performed through several sequential stages to determine the relative performance of each alternative. First, a reference value is established for each criterion as a benchmark for assessing the proximity of the alternatives to the desired performance level. The reference values are determined according to the characteristics of the criteria and presented in Table 7.

Table 7. Preference Value of the PIV Method

Alternative	KT1	KT2	KT3	KT4	KT5	KT6
V01	0.5000	0.5833	0.5000	0.5000	0.4000	0.7500
V02	0.7500	0.7500	0.7857	0.7500	0.6667	1.0000
V03	0.0000	0.2500	0.2857	0.2500	0.2667	0.2500
V04	1.0000	0.8333	0.9286	1.0000	0.8667	1.0000
V05	0.2500	0.4167	0.4286	0.5000	0.5333	0.5000
V06	0.7500	0.6667	0.7143	0.7500	0.8000	0.7500
…	…	…	…	…	…	…
V24	1.0000	0.8333	0.9286	1.0000	0.8667	1.0000
V25	0.2500	0.5833	0.5714	0.5000	0.5333	0.7500

Subsequently, the proximity value of each alternative to the corresponding reference value is calculated by considering whether each criterion is classified as benefit or cost using Equation (7), and the results are presented in Table 8.

Table 8. Proximity Value of the PIV Method

Alternative	KT1	KT2	KT3	KT4	KT5	KT6
V01	0.1809	0.2112	0.0131	0.0419	0.0119	0.1024
V02	0.2713	0.2715	0.0206	0.0628	0.0199	0.1365
V03	0.0000	0.0905	0.0075	0.0209	0.0080	0.0341
V04	0.3618	0.3017	0.0243	0.0837	0.0259	0.1365
V05	0.0904	0.1508	0.0112	0.0419	0.0159	0.0683
V06	0.2713	0.2413	0.0187	0.0628	0.0239	0.1024
…	…	…	…	…	…	…
V24	0.3618	0.3017	0.0243	0.0837	0.0259	0.1365
V25	0.0904	0.2112	0.0150	0.0419	0.0159	0.1024

The obtained proximity values are then combined with the criterion weights generated by the MEREC method to calculate the weighted proximity values using Equation (8), with the resulting values presented in Table X. Next, the weighted values across all criteria are aggregated to obtain the PIV index for each alternative using Equation (9), and the calculated index values are presented in Table X.

Table 9. PIV Index of the PIV Method

Alternative	KT1	KT2	KT3	KT4	KT5	KT6
V01	0.1809	0.2112	0.0131	0.0419	0.0179	0.0341
V02	0.2713	0.2715	0.0056	0.0209	0.0099	0.0000
V03	0.0000	0.0905	0.0187	0.0628	0.0219	0.1024
V04	0.3618	0.3017	0.0019	0.0000	0.0040	0.0000
V05	0.0904	0.1508	0.0150	0.0419	0.0139	0.0683
V06	0.2713	0.2413	0.0075	0.0209	0.0060	0.0341
…	…	…	…	…	…	…

*Corresponding Author: fericopasaribu@teknokrat.ac.id (A. Ferico Octaviansyah Pasaribu)
DOI: https://doi.org/10.67449/jcoda.v1i2.6

Volume 1 Number 2 November 2026, Available online November 24, 2026. Page 109-129

Journal of Computer and Data Science
E-ISSN 3164-5194

journal homepage: https://e-journal.pilar.or.id/index.php/jcoda/index

V24	0.3618	0.3017	0.0019	0.0000	0.0040	0.0000
V25	0.0904	0.2112	0.0112	0.0419	0.0139	0.0341

Finally, the PIV results are processed to obtain the final alternative values and rankings using Equation (10), with the resulting ranking presented in Table 10. This final ranking represents the relative performance of the alternatives based on their proximity to the reference conditions.

Table 10. PIV Index of the PIV Method

Alternative	Final Value
V01	0.4990
V02	0.5793
V03	0.2962
V04	0.6693
V05	0.3803
V06	0.5812
…	…
V24	0.6693
V25	0.4027

The final values obtained from the PIV method are subsequently used to determine the ranking of the alternatives based on their overall performance across all criteria. Each alternative is ordered according to its final PIV value, allowing the relative position of each alternative to be clearly identified. The resulting ranking provides an objective comparison of the alternatives based on their proximity to the reference conditions, where the alternative with the most favorable PIV result occupies the highest position. The complete ranking of the alternatives based on the final PIV values is presented visually in Figure 2.

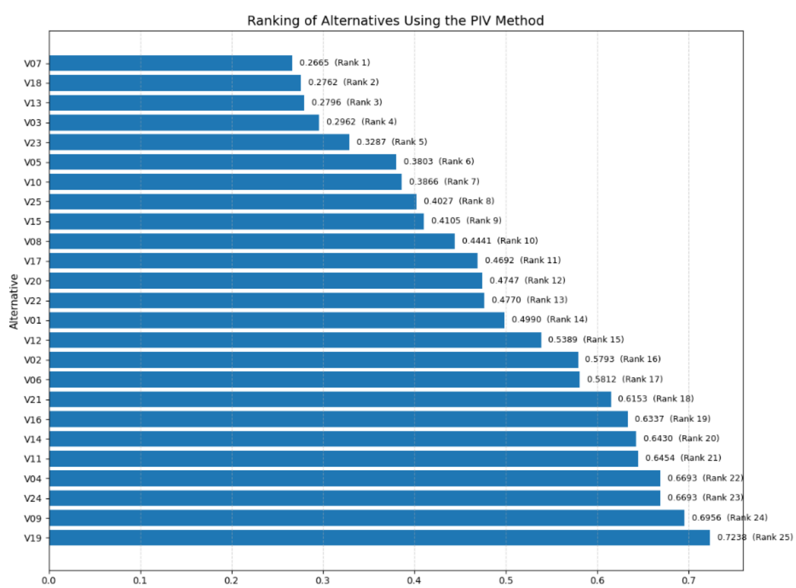

Figure 2. Research Stages

*Corresponding Author: fericopasaribu@teknokrat.ac.id (A. Ferico Octaviansyah Pasaribu)
DOI: https://doi.org/10.67449/jcoda.v1i2.6

Volume 1 Number 2 November 2026, Available online November 24, 2026. Page 109-129

Journal of Computer and Data Science
E-ISSN 3164-5194

journal homepage: https://e-journal.pilar.or.id/index.php/jcoda/index

The results of the calculations using the PIV method show that Alternative V07 ranked first with a final score of 0.2665, followed by V18 in second place with a score of 0.2762, and V13 in third place with a score of 0.2796. Next, V03 ranked fourth with a score of 0.2962, while V23 took fifth place with a score of 0.3287. Positions six to ten were occupied sequentially by V05 with a score of 0.3803, V10 with 0.3866, V25 with 0.4027, V15 with 0.4105, and V08 with 0.4441. These results indicate that the smaller the final score obtained, the higher the priority of the alternative. Therefore, V07 is the alternative with the highest priority based on the PIV method.

3.5. Sensitivity and Consistency Analysis

Sensitivity and consistency analysis is conducted to provide a comprehensive evaluation of the robustness, stability, and reliability of the proposed decision-making model. Sensitivity analysis examines the extent to which changes in criteria weights, decision parameters, or other relevant input values affect the final ranking of alternatives. This analysis is important because a reliable decision-making method should not produce substantially different results as a consequence of minor changes in the initial conditions. By observing variations in the ranking results under different scenarios, the sensitivity analysis can demonstrate the stability of the proposed model and identify the extent to which its performance is influenced by changes in the decision environment. In addition, consistency analysis is performed to evaluate the level of agreement between the ranking results generated by the proposed method and those obtained using other established methods. Statistical correlation measures or ranking comparison techniques may be employed to assess the consistency of the results. A high level of consistency indicates that the proposed method produces results that are reliable and aligned with broader decision patterns. Therefore, the combination of sensitivity and consistency analysis provides important evidence to support the robustness, credibility, and practical applicability of the proposed method in solving multi-criteria decision-making problems.

The sensitivity analysis was conducted by examining the effect of changes in the criteria weights on the final ranking results. The analysis was performed using two modification scenarios for each criterion: an increase and a decrease of 0.05 from its original weight. In the first scenario, the weight of each criterion was individually increased by 0.05, while the weights of the remaining criteria were proportionally adjusted to ensure that the total weight remained equal to one. In the second scenario, the weight of each criterion was individually decreased by 0.05, followed by a proportional adjustment of the remaining criteria to maintain the normalization requirement. This procedure was repeated for all criteria to generate a series of alternative weighting conditions. The resulting rankings from each scenario were then compared with the original ranking to evaluate the stability and robustness of the proposed method. A decision model is

*Corresponding Author: fericopasaribu@teknokrat.ac.id (A. Ferico Octaviansyah Pasaribu)
DOI: https://doi.org/10.67449/jcoda.v1i2.6

Volume 1 Number 2 November 2026, Available online November 24, 2026. Page 109-129

Journal of Computer and Data Science
E-ISSN 3164-5194

journal homepage: https://e-journal.pilar.or.id/index.php/jcoda/index

considered less sensitive when the changes in criteria weights produce only minor variations in the ranking positions, particularly for the highest-ranked alternatives. Conversely, substantial changes in the ranking results indicate a higher sensitivity of the model to variations in the weighting structure. Through these two scenarios, the sensitivity analysis provides an assessment of the extent to which the proposed method can maintain consistent decision results under moderate changes in criteria importance. The results of the sensitivity analysis under all weight modification scenarios are presented in Table 11.

Table 11. Scenario of Changing Criteria Weights

Scenario	KT1	KT2	KT3	KT4	KT5	KT6
Initial Weight	0.3618	0.3620	0.0262	0.0837	0.0298	0.1365
Test Scenario 1	0.3922	0.3448	0.0250	0.0797	0.0284	0.1300
Test Scenario 2	0.3446	0.3924	0.0250	0.0797	0.0284	0.1300
Test Scenario 3	0.3446	0.3448	0.0726	0.0797	0.0284	0.1300
Test Scenario 4	0.3446	0.3448	0.0250	0.1273	0.0284	0.1300
Test Scenario 5	0.3446	0.3448	0.0250	0.0797	0.0760	0.1300
Test Scenario 6	0.3446	0.3448	0.0250	0.0797	0.0284	0.1776
Test Scenario 7	0.3282	0.3811	0.0276	0.0881	0.0314	0.1437
Test Scenario 8	0.3808	0.3284	0.0276	0.0881	0.0314	0.1437
Test Scenario 9	0.3808	0.3811	0.0000	0.0881	0.0314	0.1437
Test Scenario 10	0.3808	0.3811	0.0276	0.0355	0.0314	0.1437
Test Scenario 11	0.3808	0.3811	0.0276	0.0881	0.0000	0.1437
Test Scenario 12	0.3808	0.3811	0.0276	0.0881	0.0314	0.0911

The sensitivity analysis was performed using twelve test scenarios based on systematic modifications to the initial criterion weights. The initial weight values were obtained as KT1 = 0.3618, KT2 = 0.3620, KT3 = 0.0262, KT4 = 0.0837, KT5 = 0.0298, and KT6 = 0.1365. In Test Scenarios 1 to 6, the weight of one criterion was increased by 0.05 in each scenario. Specifically, Test Scenario 1 increased the weight of KT1, Test Scenario 2 increased KT2, Test Scenario 3 increased KT3, Test Scenario 4 increased KT4, Test Scenario 5 increased KT5, and Test Scenario 6 increased KT6. After increasing the selected criterion, the remaining criteria were proportionally adjusted to maintain the total weight equal to one. Conversely, Test Scenarios 7 to 12 examined the effect of decreasing the weight of each criterion by 0.05. Test Scenario 7 reduced the weight of KT1, Test Scenario 8 reduced KT2, Test Scenario 9 reduced KT3, Test Scenario 10 reduced KT4, Test Scenario 11 reduced KT5, and Test Scenario 12 reduced KT6. Because the initial weights of KT3 and KT5 were lower than 0.05, their weights were set to 0.0000 when the reduction was applied, while the remaining criteria were proportionally adjusted to preserve the total weight of one. Therefore, the twelve scenarios represent systematic increases and decreases in the relative importance of each criterion. The ranking results obtained under these modified weighting conditions were compared with the initial ranking to evaluate the sensitivity, stability, and robustness of the proposed decision-making method.

*Corresponding Author: fericopasaribu@teknokrat.ac.id (A. Ferico Octaviansyah Pasaribu)
DOI: https://doi.org/10.67449/jcoda.v1i2.6

Volume 1 Number 2 November 2026, Available online November 24, 2026. Page 109-129

Journal of Computer and Data Science
E-ISSN 3164-5194

journal homepage: https://e-journal.pilar.or.id/index.php/jcoda/index

Based on the twelve sensitivity analysis scenarios, the ranking process was subsequently performed for each modified weighting condition to examine the effect of changes in criterion importance on the ranking of alternatives. Each scenario was calculated using the corresponding modified weights, covering both an increase and a decrease of 0.05 for each criterion. The ranking results obtained from Test Scenarios 1 to 12 were then compared with the ranking generated using the initial weights to identify changes in the position and relative preference of each alternative. This comparison allows the stability of the ranking results to be assessed under different weighting conditions and provides an indication of the robustness of the proposed method against changes in the relative importance of the criteria. If the ranking positions remain relatively stable across the scenarios, the proposed method can be considered less sensitive to changes in criterion weights. Conversely, substantial changes in ranking positions indicate a higher degree of sensitivity. The complete ranking results for the initial condition and all twelve sensitivity analysis scenarios are presented in Figure 3.

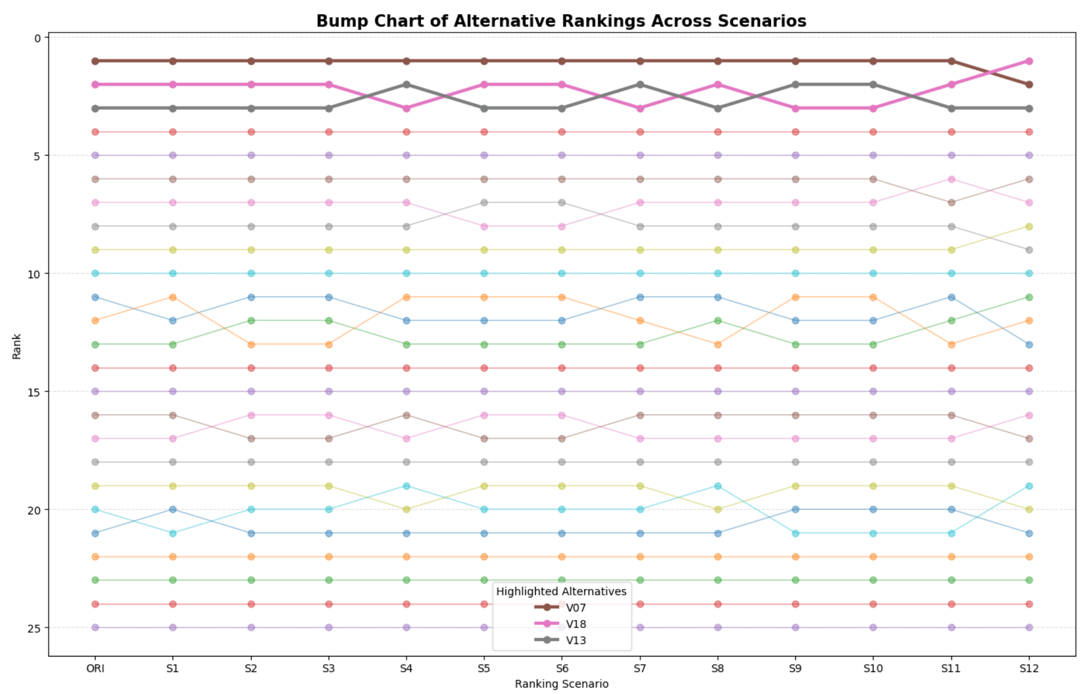

Figure 3. Alternative Ranking Stability Across Sensitivity Scenarios

The bump chart illustrates the ranking stability of 25 alternatives under the original ranking (ORI) and 12 sensitivity scenarios (S1–S12). Overall, most alternatives maintain highly consistent ranking positions across all scenarios, as indicated by the predominantly horizontal lines. The most noticeable changes occur among the top-ranked alternatives, particularly V07, V18, and V13, which exchange positions under several scenarios. V07 remains the leading alternative in most scenarios but shifts from rank 1 to rank 2 in S12,

*Corresponding Author: fericopasaribu@teknokrat.ac.id (A. Ferico Octaviansyah Pasaribu)
DOI: https://doi.org/10.67449/jcoda.v1i2.6

Volume 1 Number 2 November 2026, Available online November 24, 2026. Page 109-129
Journal of Computer and Data Science
E-ISSN 3164-5194
journal homepage: https://e-journal.pilar.or.id/index.php/jcoda/index
while V18 moves from rank 2 to rank 1 in S12. V13 also fluctuates slightly between ranks 2 and 3. Minor ranking changes are additionally observed among groups such as V17, V20, and V22, as well as V02 and V06, but these changes remain limited in magnitude. Overall, the bump chart indicates that the ranking results are relatively robust and stable across the sensitivity scenarios, with most alternatives experiencing only minor positional changes and the leading alternatives consistently remaining within the top-ranked group.

To evaluate the changes in ranking results resulting from variations in criterion weights, a correlation analysis was conducted using the Spearman Rank Correlation method. This analysis aims to measure the consistency and stability of the ranking order between the initial condition and each scenario involving changes in criterion weights. The correlation values obtained for each scenario were then compared to assess the extent to which weight variations affected the ranking positions of the alternatives. The results of the Spearman correlation analysis for all scenarios are presented in Figure 4.

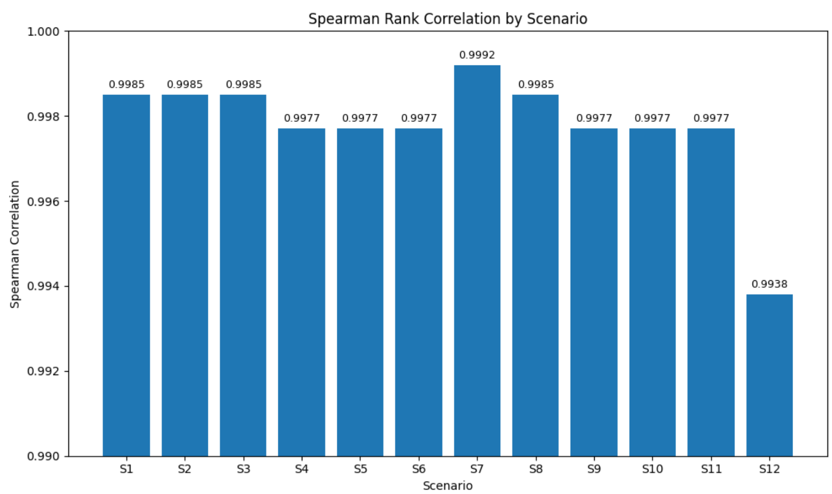

Figure 4. Comparison of Spearman Correlation Values

The Spearman correlation results indicate a very high level of consistency between the original ranking and the rankings generated under all weight variation scenarios. The correlation coefficients range from 0.9938 to 0.9992, demonstrating that changes in criterion weights have only a minimal effect on the ranking order of the alternatives. The highest correlation is observed in S7 (0.9992), while the lowest is found in S12 (0.9938). Nevertheless, all scenarios remain within the very strong correlation range, indicating that the ranking results are highly stable and robust against variations in criterion weights. Overall, these findings confirm that the proposed ranking model maintains a consistent ordering of alternatives despite changes in the weighting configuration.

*Corresponding Author: fericopasaribu@teknokrat.ac.id (A. Ferico Octaviansyah Pasaribu)
DOI: https://doi.org/10.67449/jcoda.v1i2.6

Volume 1 Number 2 November 2026, Available online November 24, 2026. Page 109-129

Journal of Computer and Data Science
E-ISSN 3164-5194

journal homepage: https://e-journal.pilar.or.id/index.php/jcoda/index

3.6. Discussion

The findings demonstrate that the MEREC-PIV approach provides a systematic mechanism for addressing the complexity of vendor selection involving multiple criteria with different characteristics. The MEREC weighting results indicate that Delivery Time (KT2) and Price (KT1) are the two most influential criteria, with weights of 0.3620 and 0.3618, respectively. This indicates that cost and delivery performance constitute the dominant factors in the evaluation of the 25 vendor alternatives. Meanwhile, Flexibility (KT6) obtained a weight of 0.1365, followed by Service (KT4) at 0.0837. Reputation (KT5) and Quality (KT3) received relatively lower weights of 0.0298 and 0.0262. These differences indicate that the importance of criteria is not determined merely by their conceptual relevance but by the extent to which each criterion affects changes in the overall performance of alternatives. The relatively high weights assigned to KT1 and KT2 suggest that variations in price and delivery time provide greater discriminatory information among the evaluated vendors, making them more influential in the decision-making process.

The application of PIV using the MEREC-derived weights further demonstrates how objective criterion importance can be incorporated into the ranking process. The final PIV results show that V07 achieved the highest priority with a score of 0.2665, followed by V18 with 0.2762 and V13 with 0.2796. V03, V23, V05, V10, V25, V15, and V08 subsequently occupied the fourth to tenth positions. The ranking indicates that vendor performance cannot be determined from a single criterion because the final position reflects the combined contribution of price, delivery time, quality, service, reputation, and flexibility. In particular, the high weights of KT1 and KT2 cause performance differences in these criteria to have a substantial influence on the final results. At the same time, the contribution of the remaining criteria ensures that the ranking still reflects a broader assessment of vendor capability. Therefore, the integration of MEREC and PIV provides a structured transition from objective weighting to preference-based ranking and reduces the possibility that the final decision is dominated by arbitrary subjective preferences.

The sensitivity analysis provides further evidence regarding the robustness of the proposed MEREC-PIV approach. Twelve scenarios were generated by increasing and decreasing each criterion weight by 0.05 while maintaining the total weight at one. The bump chart shows that most alternatives maintain relatively stable positions across the original condition and the twelve modified scenarios. The most visible changes occur among the highest-ranked alternatives, particularly V07, V18, and V13. V07 remains the leading alternative in most scenarios and changes only to second place in S12, while V18 moves to first place in that scenario. These changes are relatively limited and do not substantially alter the overall structure of the ranking. The stability of the results is also supported by the Spearman correlation coefficients, which range from 0.9938 to 0.9992 across all scenarios.

*Corresponding Author: fericopasaribu@teknokrat.ac.id (A. Ferico Octaviansyah Pasaribu)
DOI: https://doi.org/10.67449/jcoda.v1i2.6

Volume 1 Number 2 November 2026, Available online November 24, 2026. Page 109-129

Journal of Computer and Data Science
E-ISSN 3164-5194

journal homepage: https://e-journal.pilar.or.id/index.php/jcoda/index

Such high correlation values indicate that modifications in criterion weights have only a minor influence on the ranking order. Consequently, the proposed model demonstrates a high degree of stability even when the relative importance of the criteria is moderately changed.

Overall, the findings indicate that the MEREC-PIV approach is capable of producing objective and robust vendor rankings in a multi-criteria decision-making environment. MEREC contributes by deriving criterion weights from the removal effect of each criterion rather than depending directly on subjective assessments, while PIV translates these weights into an integrated ranking based on the proximity of alternatives to reference conditions. The dominance of Price and Delivery Time in the weighting results provides useful managerial information because these criteria should receive particular attention when evaluating vendor performance. At the same time, the sensitivity and Spearman correlation analyses demonstrate that the resulting ranking remains highly consistent under different weighting scenarios. The combination of objective weighting, systematic ranking, and robustness testing therefore strengthens the reliability of the decision-making process and provides a practical basis for selecting vendors. These findings suggest that the MEREC-PIV integration can be considered a suitable approach for vendor selection problems where multiple heterogeneous criteria must be evaluated while maintaining objectivity, consistency, and ranking stability.

IV. Conclusion

This study applied an integrated MEREC-PIV method to support objective vendor selection based on multiple evaluation criteria. The MEREC method successfully determined the objective importance of the six criteria based on their removal effects on alternative performance. The results showed that KT2 (Delivery Time) had the highest weight of 0.3620, followed closely by KT1 (Price) with a weight of 0.3618. Meanwhile, KT6, KT4, KT5, and KT3 obtained weights of 0.1365, 0.0837, 0.0298, and 0.0262, respectively. These results indicate that delivery time and price were the most influential criteria in the vendor evaluation process. The criterion weights generated by MEREC were subsequently incorporated into the PIV method to determine the priority of 25 vendor alternatives. The PIV results showed that V07 achieved the best performance with a final value of 0.2665, followed by V18 (0.2762) and V13 (0.2796). The next highest-ranked alternatives were V03 (0.2962), V23 (0.3287), V05 (0.3803), V10 (0.3866), V25 (0.4027), V15 (0.4105), and V08 (0.4441). Because a lower final PIV value indicates a better position, V07 was identified as the most prioritized vendor alternative.

Overall, the integration of MEREC and PIV provides a structured decision-making framework that combines objective criterion weighting with alternative ranking based on proximity to reference values. The approach enables vendor alternatives to be evaluated consistently across criteria with different characteristics while reducing dependence on

*Corresponding Author: fericopasaribu@teknokrat.ac.id (A. Ferico Octaviansyah Pasaribu)
DOI: https://doi.org/10.67449/jcoda.v1i2.6

Volume 1 Number 2 November 2026, Available online November 24, 2026. Page 109-129

Journal of Computer and Data Science
E-ISSN 3164-5194

journal homepage: https://e-journal.pilar.or.id/index.php/jcoda/index

subjective weighting. The main contribution of this study lies in integrating MEREC, which determines criterion weights objectively based on the influence of criteria on the overall evaluation, with PIV, which ranks alternatives according to their proximity to ideal reference values. This integration provides a transparent and reproducible framework for vendor selection and demonstrates its applicability in handling multi-criteria evaluation with varying criterion characteristics. The resulting ranking can therefore serve as a quantitative basis for selecting the most appropriate vendor, with V07 identified as the leading alternative in the evaluated dataset. However, this study has several limitations. The evaluation was conducted on a specific dataset with a limited number of vendor alternatives and criteria, so the generalizability of the findings to other decision-making contexts may be limited. In addition, the robustness of the proposed MEREC-PIV integration may depend on the characteristics and quality of the input data. Future research should therefore validate the approach using larger and more diverse datasets, compare it with other objective weighting and ranking methods, and conduct more extensive sensitivity and robustness analyses to further assess the stability of the resulting rankings.

CRediT Authorship Contribution Statement

A.F.O. Pasaribu: Writing – original draft, Validation, Methodology, Conceptualization. **A.S. Puspaningrum:** Writing – review draft, Formal analysis, Data curation, Conceptualization. **S. Sintaro:** Writing – final draft, Software, Investigation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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.

*Corresponding Author: fericopasaribu@teknokrat.ac.id (A. Ferico Octaviansyah Pasaribu)
DOI: https://doi.org/10.67449/jcoda.v1i2.6

Volume 1 Number 2 November 2026, Available online November 24, 2026. Page 109-129

Journal of Computer and Data Science
E-ISSN 3164-5194

journal homepage: https://e-journal.pilar.or.id/index.php/jcoda/index

References

[1] S. Dhruva, R. Krishankumar, E. K. Zavadskas, K. S. Ravichandran, and A. H. Gandomi, "Selection of Suitable Cloud Vendors for Health Centre: A Personalized Decision Framework with Fermatean Fuzzy Set, LOPCOW, and CoCoSo," *Informatica*, vol. 35, no. 1, pp. 65–98, Nov. 2024, doi: 10.15388/23-INFOR537.

[2] Z. K. D. Indriyanti and S. Sumanto, "Decision support for trucking vendor selection at PT. Ricakusuma Lestari Abadi Based on the SAW method," *J. Mandiri IT*, vol. 14, no. 1 SE-Articles, pp. 67–75, Jul. 2025, doi: 10.35335/mandiri.v14i1.420.

[3] A. M. Yiğit, "Supplier Selection with AHP, TOPSIS and WASPAS as Multi-criteria Decision-making Techniques: An Application in Office Chairs Industry," *Uluslararası İşletme Bilim. ve Uygulamaları Derg.*, vol. 5, no. 2, pp. 116–130, 2025.

[4] M. A. M. Al-Gerafi *et al.*, "Promoting inclusivity in education amid the post-COVID-19 challenges: An interval-valued fuzzy model for pedagogy method selection," *Int. J. Manag. Educ.*, vol. 22, no. 3, p. 101018, 2024, doi: 10.1016/j.ijme.2024.101018.

[5] H. Onuoha *et al.*, "Integrating GIS and AHP for Photovoltaic Farm Site Selection: A Case Study of Ikorodu, Nigeria," *Processes*, vol. 13, no. 1. 2025. doi: 10.3390/pr13010164.

[6] H. A. Dağıstanlı and K. G. Kurtay, "Facility Location Selection for Ammunition Depots based on GIS and Pythagorean Fuzzy WASPAS," *J. Oper. Intell.*, vol. 2, no. 1, pp. 36–49, Jan. 2024, doi: 10.31181/jopi2120247.

[7] J. Wang, Setiawansyah, and A. R. Isnain, "Decision Support System for Performance Assessment of the Best Salesperson with the Integration of Entropy and WASPAS," *Int. J. Informatics Data Sci.*, vol. 2, no. 2 SE-, pp. 63–71, Jun. 2025, doi: 10.64366/ijids.v2i2.88.

[8] Junhai Wang and Setiawansyah, "Integration of LOPCOW and ARAS Methods for Selecting the Best Employees in the Finance Division," *J. Decis. Support Syst. Res.*, vol. 2, no. 3, pp. 125–134, May 2025, doi: 10.64366/dss.v2i3.102.

[9] P. Liu, T. Zhang, F. Tian, Y. Teng, and M. Yang, "Optimized Grid Partitioning and Scheduling in Multi-Energy Systems Using a Hybrid Decision-Making Approach," *Energies*, vol. 17, no. 13. 2024. doi: 10.3390/en17133253.

[10] B. S. Mahapatra, D. Ghosh, D. Pamucar, and G. S. Mahapatra, "Dynamic group decision-making for enterprise resource planning selection using two-tuples Pythagorean fuzzy MOORA approach," *Expert Syst. Appl.*, vol. 263, p. 125675, 2025, doi: 10.1016/j.eswa.2024.125675.

[11] M. Seidi, S. Yaghoubi, and F. Rabiei, "Multi-objective optimization of wire electrical discharge machining process using multi-attribute decision making techniques and regression analysis," *Sci. Rep.*, vol. 14, no. 1, p. 10234, 2024, doi: 10.1038/s41598-024-60825-w.

[12] M. S. Saidin, L. S. Lee, S. M. Marjugi, M. Z. Ahmad, and H.-V. Seow, "Fuzzy Method Based on the Removal Effects of Criteria (MEREC) for Determining Objective Weights in Multi-Criteria Decision-Making Problems," *Mathematics*, vol. 11, no. 6, p. 1544, Mar. 2023, doi: 10.3390/math11061544.

[13] T. Van Dua, D. Van Duc, N. C. Bao, and D. D. Trung, "Integration of objective weighting methods for criteria and MCDM methods: application in material selection," *EUREKA Phys. Eng.*, no. 2, pp. 131–148, Mar. 2024, doi: 10.21303/2461-4262.2024.003171.

*Corresponding Author: fericopasaribu@teknokrat.ac.id (A. Ferico Octaviansyah Pasaribu)
DOI: https://doi.org/10.67449/jcoda.v1i2.6

Volume 1 Number 2 November 2026, Available online November 24, 2026. Page 109-129

Journal of Computer and Data Science
E-ISSN 3164-5194

journal homepage: https://e-journal.pilar.or.id/index.php/jcoda/index

[14] D. D. Trung, N. T. P. Giang, D. Van Duc, T. Van Dua, and H. X. Thinh, "The Use of SAW, RAM and PIV Decision Methods in Determining the Optimal Choice of Materials for the Manufacture of Screw Gearbox Acceleration Boxes," *Int. J. Mech. Eng. Robot. Res.*, vol. 13, no. 3, pp. 338–347, 2024, doi: 10.18178/ijmerr.13.3.338-347.

[15] K. Shunmugesh *et al.*, "Enhancing drilling performance in 3D printed PLA implants application of PIV and ML models," *Sci. Rep.*, vol. 15, no. 1, p. 13314, 2025, doi: 10.1038/s41598-025-96126-z.

[16] D. T. Do, "Assessing the Impact of Criterion Weights on the Ranking of the Top Ten Universities in Vietnam," *Eng. Technol. Appl. Sci. Res.*, vol. 14, no. 4, pp. 14899–14903, Aug. 2024, doi: 10.48084/etasr.7607.

[17] M. Keshavarz-Ghorabaee, M. Amiri, E. K. Zavadskas, Z. Turskis, and J. Antucheviciene, "Determination of Objective Weights Using a New Method Based on the Removal Effects of Criteria (MEREC)," *Symmetry (Basel).*, vol. 13, no. 4, p. 525, Mar. 2021, doi: 10.3390/sym13040525.

[18] M. Keshavarz-Ghorabaee, "Assessment of distribution center locations using a multi-expert subjective–objective decision-making approach," *Sci. Rep.*, vol. 11, no. 1, p. 19461, Sep. 2021, doi: 10.1038/s41598-021-98698-y.

[19] S. S. Goswami, S. K. Mohanty, and D. K. Behera, "Selection of a green renewable energy source in India with the help of MEREC integrated PIV MCDM tool," *Mater. Today Proc.*, vol. 52, no. 1, pp. 1153–1160, 2022, doi: 10.1016/j.matpr.2021.11.019.

*Corresponding Author: fericopasaribu@teknokrat.ac.id (A. Ferico Octaviansyah Pasaribu)
DOI: https://doi.org/10.67449/jcoda.v1i2.6