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Modification of the Weighted Product Model: Towards a Fairer and More Rational Ranking

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***Abstract*—The weighted product (WP) method is one of the popular methods in decision support systems (DSSs) due to its simplicity, calculation efficiency, and ability to handle various types of criteria with different weights. This research proposes a modification to the WP model designed to enhance fairness and rationality in the ranking process of alternatives. Therefore, a modified approach, Weighted Product with Averaging and Mean-Normalized Evaluation (WP-A), is adopted by integrating objective weighting methods and more adaptive normalization, so that each criterion can be evaluated proportionally. The supplier selection case study is used to test the effectiveness of the proposed model by comparing it with other MCDM methods. The results of the study show that the WP-A method produces more consistent results and has a stronger correlation with other methods, as indicated by Spearman's correlation test, with a value of 0.9828, indicating a very strong level of consistency with the reference rankings. The main contribution of this research is to provide a new framework for the development of the WP method so that it can be relied upon to support a more transparent and objective decision-making system.**

Keywords*—*decision support system; multi-criteria decision-making; Spearman's correlation; supplier selection; weighted product with averaging and mean-normalized evaluation

1 INTRODUCTION

Decision support systems (DSS) play a crucial role in multi-criteria decision-making by helping decision-makers evaluate various alternatives based on multiple complex and conflicting criteria [1], [2], [3]. In situations where intuition or experience alone is not sufficient, DSS provides a systematic, objective, and measurable approach to filtering information, establishing criterion weights, and generating rational recommendations. By utilizing analytical methods such as AHP, TOPSIS, or MOORA, DSS not only enhances accuracy and consistency in decision-making but also simplifies the evaluation process, which is often time-consuming and prone to subjectivity. DSS provides flexibility for simulating various decision scenarios, enabling decision-makers to better understand the impacts of each choice. This is particularly important in dynamic and uncertain environments, where the decisions made have long-term consequences. With the existence of DSS, the decision-making process becomes more transparent and accountable because every step in the analysis can be tracked and explained [4], [5], [6], [7]. The implementation of DSS in a multi-criteria context not only enhances decision quality but also strengthens the strategic foundation for planning and managing organizations.

The weighted product (WP) method is one of the popular methods in DSS due to its simplicity, calculation efficiency, and ability to handle various types of criteria with different weights [8], [9], [10]. The popularity of WP is mainly driven by its effectiveness in handling ratio and proportional data through a multiplication process that combines alternative values with the weighted criteria raised to a power [11], [12], [13], [14]. Unlike additive methods such as simple additive weighting (SAW), WP takes into account the multiplicative relationships among criteria, giving it an advantage in situations where small changes in criterion values can significantly impact the final results [11], [15], [13]. This method is also widely used in various applications, ranging from product selection, performance evaluation, to employee candidate selection, because its outcomes are easy to understand and can quickly provide rankings of the optimal alternatives.

Although the WP method is popular in DSS, it also faces several challenges that can affect its reliability. One of the main challenges is sensitivity to extreme weights, where excessively high or low weights on a criterion can disproportionately dominate the final results, thereby neglecting the contributions of other criteria. Furthermore, WP does not account for criterion correlations, so when criteria are interrelated or redundant, their effects can accumulate unreasonably and compromise assessment accuracy. Another challenge is the potential unfairness in the weighting process, especially when weights are determined subjectively without an objective or participatory approach, which can lead to biased, less representative decisions. Therefore, it is important to combine or modify the WP method with appropriate weight validation techniques or hybrid approaches to enhance fairness and accuracy in multi-criteria decision-making [16], [17], [18].

To develop a modification of the WP method that is fairer and more rational, one approach that can be applied is to use the average value of each criterion as the basis for weight determination. In this approach, the weights of the criteria are calculated objectively based on the relative contribution of each criterion's average value to the entire dataset, so that criteria with more significant values generally have larger weights [19]. This method reduces subjectivity in weighting and reflects the actual conditions of the data. It makes the decision-making process more transparent and representative. The generated weights are then used in the typical WP exponentiation mechanism, but to avoid the dominance of extreme weights, the exponent can be adjusted using a square root or logarithmic transformation [11], [13], [15]. This modification not only maintains WP's the efficiency in processing alternatives but also introduces fairness and rationality in assessment through data-driven weighting.

To demonstrate the effectiveness of the modified WP model, this approach is applied to a real case study involving the selection of the best alternative based on several evaluation criteria. The weights of the criteria are calculated using the average values of each criterion to ensure objective and proportional weighting. Subsequently, the values of the alternatives are processed using the refined WP formula with square root-based weight transformation to maintain balance and avoid the dominance of extreme values. The ranking results from this model are then compared with those from the classical WP method and other methods, such as SAW or TOPSIS. The results show that the modified model produces decisions that are more stable, fair, and consistent with intuition and real-world conditions. This proves that the new approach is not only theoretically viable but also effective in the real practice of multi-criteria decision-making.

In DSS and MCDM, several important issues remain primary concerns in the development of methods and their implementation, particularly regarding the objectivity, stability, and validity of decision results. One crucial issue is the dependence on data quality and characteristics, as an uneven distribution of values or outliers can affect the weighting process and bias the evaluation of criteria. In addition, the sensitivity of methods to changes in weights poses a challenge as small variations in criterion weights can lead to significant changes in alternatives rankings, raising doubts about decision consistency. Another issue is the lack of integration between theoretical approaches and empirical evaluation, as many methods are developed without adequate testing across diverse real-world scenarios, limiting the generalizability of results. In addition, the computational complexity of some MCDM methods can also hinder practical implementation in DSS, especially in systems that require high computational efficiency. Therefore, an approach is needed that not only can objectively generate criterion weights but also has adaptive capabilities, is robust to data variations, and is supported by comprehensive validation to ensure reliability in various

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decision-making contexts.

The main contributions of this development lie in two important aspects. First, introduce a new weighting approach that uses the average value of each criterion to determine weights, providing an objective, data-driven alternative to reduce subjectivity in the decision-making process. This approach ensures that the criterion weights reflect the data's actual contributions, making them fairer and more representative of the conditions. Second, refinements have been made to the basic formula of the WP method by adjusting the weighting exponentiation mechanism using softening functions, such as square roots or logarithms, to maintain stability and prevent the dominance of extreme weights. These improvements enhance the method's resilience to value distortions and ensure more balanced, fair, and rational outcomes in multi-criteria decision-making. This research aims to modify the WP by integrating averaging and mean-normalized evaluation to calculate the solutions, reduce the extreme values in criterion values, and provide more objective and consistent ranking results. This modification is expected to make the WP method more adaptable to various data conditions without sacrificing its advantages of simplicity and efficient computation. The novelty of this research lies in integrating averaging and mean-normalized evaluation into the WP calculation process, an approach that has not been widely explored [11], [13], [15]. This approach not only modifies the normalization stage but also introduces a data-balancing mechanism that can reduce distortion caused by scale differences across criteria. Therefore, this research offers a more robust, flexible WP method that provides more accurate results than both classical WP methods and other existing variations.

2 METHOD

This research method uses a quantitative approach with model development within the framework of multiple criteria decision-making (MCDM). The main focus of the research is to modify the WP method to produce fairer and more rational rankings. The research stages begin with identifying issues and analyzing weaknesses in the classical WP, particularly regarding the sensitivity of weights and the dominance of certain criteria. Subsequently, a modification to WP is formulated by introducing a weight adjustment mechanism based on objective normalization and integrating scale control factors to ensure that the calculation results are not biased towards extreme values. The proposed model is then tested using both simulation data and real case study data to assess the consistency and validity of the rankings. The evaluation is conducted by comparing ranking results between classical WP and modified WP using rank correlation measures (Spearman's correlation) and by performing a sensitivity analysis to assess decision stability. With this approach, the research is expected to demonstrate that modifying WP not only improves ranking accuracy but also establishes a more transparent, fair, and accountable decision-making system.

2.1 Research Stage

The research stages undertaken in this study are presented in Fig. 1. Research stages refer to a sequence of systematic steps arranged and implemented by the researcher to achieve the research objectives in a directed and measurable manner. These stages serve as a guideline to ensure that the research process is conducted in an orderly, logical manner that can be scientifically accounted for. Each stage usually includes problem identification, objective formulation, theoretical review, model or research framework development, data collection, method implementation, analysis of results, and, finally, drawing conclusions and recommendations. With clear research stages, researchers can maintain workflow consistency, reduce the potential for errors, and ensure research results are highly valid and reliable.

As shown in Fig. 1, the research stages begin with problem identification and literature studies, namely examining the weaknesses of the classic Weighted Product (WP) method, which often results in unfair rankings due to the dominance of certain criteria [20], [21], [22]. Next, a modification model is formulated by creating a new formula based on objective weight normalization and adjusting the scaling control factor to reduce bias from extreme values. After the model is developed, the research proceeds to the design and data collection stage, using both simulated data and real case studies that align with the decision-making context. The data obtained were then analyzed using two approaches: classical WP as a comparison and modified WP as the proposed model during the implementation stage. The calculation results from both methods are evaluated using rank correlation and sensitivity analyses to assess the stability and rationality of the decision results. Finally, the research concludes with conclusions and recommendations, emphasizing the advantages of modified WP in producing fairer, more transparent, and more rational rankings, while also providing direction for future methodological development.

2.2 Modified Weighted Product Framework

The modified WP framework is designed to address the weaknesses of classical models that often produce unfair rankings due to the dominance of certain criteria. The process begins with problem identification and the determination of relevant criteria, followed by the assignment of weights using an objective approach to achieve more rational results. Next, the WP formula is modified by adding a normalization mechanism and a scale control factor to prevent extreme values from distorting decision-making outcomes. After that, calculations are carried out by comparing the results of the classical WP and the modified WP on the same data. The evaluation stage involves using rank correlation analysis and sensitivity testing to assess the consistency, stability, and fairness of the proposed model.

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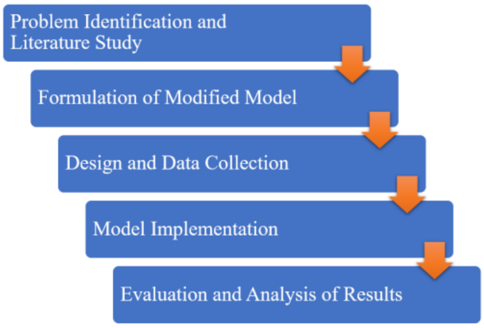

Figure 1. Research stage

The weighted product method with averaging and mean-normalized evaluation (WP-A) is a development of the WP model designed to produce a fairer and more rational ranking of alternatives [11], [13], [15]. In this method, the process begins by forming a decision matrix that contains the values of each alternative against the established criteria. Next, normalization is performed using the mean-normalized evaluation approach, where each criterion value is adjusted by the average, thereby balancing the data distribution and reducing the influence of extreme values. The normalized average value is then used as a basis to determining the objective weight of the criteria through averaging, ensuring that each criterion receives a proportion of importance that corresponds to the distribution of its data. With these weights, calculations are performed using a weighted-multiplication model as in classical WP, but with more stable results. The final stage is to calculate the relative value of each alternative to determine the ranking, and the WP-A method provides more transparent, objective, and consistent results compared to the traditional WP approach.

The initial stage begins by creating a decision matrix that lists alternatives and theirerformance values for each criterion [23]. This matrix serves as the foundation to illustrate the actual conditions of the decision-making problem. Each column represents a criterion, while the rows represent the alternatives to be chosen. With the decision matrix, comparisons between alternatives can be conducted systematically and structured as shown in (1).

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

The symbol X is a decision matrix of size m×n, where m is the number of alternatives and n is the number of criteria. Each element x_{ij} represents the performance value of the i[th] alternative with respect to the j[th] criterion.

The second stage begins by calculating the normalization value to ensure that the values for each criterion are comparable [24]. This is important because criteria often use different units or value ranges, so they need to be standardized. The normalization value is calculated as shown in (2).

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

The symbol r_{ij} is the normalized value of x_{ij}, which is the performance value of the i[th] alternative on the j[th] criterion. The denominator is the square root of the sum of the squares of all values on the j[th] criterion for all alternatives (m), which functions to standardize the data scale so that each value becomes proportional and can be fairly compared among alternatives.

The third stage involves calculating the average value for each criterion from the normalization results. The goal is to obtain a general representation of [25]. This average value is used as a basis for determining the weights objectively, without being influenced by the decision maker's subjective preferences. The average value of each criterion is calculated as shown in (3).

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

The symbol AV_j represents the calculation of the average value for each j[th] criterion, where r_{ij} is the normalized value of the i[th] alternative. The symbol m denotes the number of alternatives, so this value represents the average contribution of all alternatives to that criterion as a basis in the weighting process.

The fourth stage involves calculating the criterion weights by normalizing the average values so that the total weight sums to one [26]. This process ensures that the relative importance of the criteria remains consistent across the model. The resulting weights reflect each criterion's relative contribution to the decision-making process. The criterion weight is calculated as shown in (4).

$$w_j = \frac{AV_j}{\sum_{j=1}^{n} AV_j} \quad (4)$$

The symbol w_j is the final weight for the j-th criterion, obtained from the average value of AV_j. The denominator is the sum of all average values across all criteria (n), so the resulting weight is proportional and sums to 1.

The fifth stage is to calculate the vector value for each alternative. The Weighted Product formula is used by multiplying the normalized criterion values according to their weights [27]. The result of this calculation shows an aggregate score that represents the overall performance of the alternatives. The vector value of each alternative is calculated as shown in (5).

$$V_{ij} = r_{ij} * w_j \quad (5)$$

The symbol V_{ij} is the weighted value of the i[th] alternative for the j[th] criterion, obtained from the multiplication of the normalization value r_{ij} and the criterion weight w_j. This process aims to integrate the criterion's importance level into

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the alternative's evaluation value.

The sixth stage calculates the relative value of alternatives using this multiplication mechanism, emphasizing that each criterion has a significant contribution that cannot be ignored, because poor performance on one criterion will have a significant impact on the final result even if the alternative performs well on other criteria [28], [29]. Thus, the multiplicative nature of this calculation provides higher sensitivity to variations among criteria compared to the additive approach, so the results obtained can be considered more proportional and reflect a comprehensive balance among the assessment dimensions, as shown in (6).

$$RV_i = \prod_{i=1}^{m} V_{ij} \tag{6}$$

The symbol RV_i is the preference value for the i^th alternative obtained from multiplying all the weighted values V_{ij} for each criterion. This process combines the contribution of all criteria multiplicatively to produce the final value used in ranking the alternatives.

The seventh stage calculates the final value of each alternative by comparing its relative value withhe total sum of all alternatives [30]. This calculation aims to normalize the scores so they can be compared fairly. The resulting relative values are then used as the basis for ranking to determine the best alternative. The final value of each alternative is calculated as shown in (7).

$$S_i = \frac{RV_i}{\sum_{i=1}^{m} RV_i} \tag{7}$$

The symbol S_i is the final value of the i-th alternative obtained by dividing the value of RV_i by the total of all RV values. This result yields a proportional value used to determine the ranking of alternatives.

The WP-A method has several advantages that make it superior to the classic WP. First, WP-A can reduce the dominance of certain criteria by using a mean-normalized evaluation approach, thereby preventing extreme values from distorting the calculation results. Second, weighting is done more objectively through the averaging of normalized values, so the criterion weights do not depend solely on the decision-maker's subjectivity. In addition, WP-A produces a more stable ranking because the data distribution is balanced through average normalization. Another advantage is the fairness in evaluating alternatives, where each criterion receives proportional treatment according to its data distribution. The entire calculation process in WP-A is also more transparent and systematic, as it follows clear stages: from the decision matrix and average normalization to weight calculation and the final ranking.

The methodological use of average-based weighting in the modification of WP-A is based on its ability to represent the central tendency of data objectively and stably in the context of multi-criteria decision-making. This approach utilizes the average value as an aggregate indicator that reflects each criterion's the relative contribution based on the distribution of alternative values, thereby reducing reliance on subjective judgment in determining weights. In addition, average-based weighting has simple, transparent, and easily reproducible properties, which align with the principle of accountability in decision support systems. In WP-A, the integration of this mechanism also enables more adaptive weight adjustments to data variations, thereby improving the consistency of ranking results across different distribution conditions.

3 RESULT AND DISCUSSION

The WP method is one of the popular techniques in MCDM due to its simplicity in combining criterion values with specific weights. However, a fundamental weakness of the classic WP is its high sensitivity to weights and its tendency for certain criteria to dominate, leading to rankings that are less fair and irrational. Therefore, modifications are needed to address these shortcomings through a more objective weighting approach, more balanced normalization, and control over the influence of extreme values. This research modifies the WP method by focusing on the development of a new formula that maintains its basic principles while providing a more stable, transparent, and representative ranking to support multi-criteria decision-making.

3.1 Data Collection

Data collection in supplier selection was carried out by involving ten alternative suppliers, evaluated based on six main criteria: price (CS-1), product quality (CS-2), delivery accuracy (CS-3), service (CS-4), availability (CS-5), and communication (CS-6). Of these six criteria, one criterion, namely price and discount, is categorized as a cost criterion because the lower the score, the better it is, while the other five criteria are benefit criteria. Assessment data is obtained through a combination of interview results with the procurement team and documentation of supplier performance over a specified period, thereby providing an objective picture of each alternative's performance. With this data, the analysis can be carried out in a structured manner to determine the best supplier, not only competitive on price but also able to meet quality standards and maintain service accuracy.

Data was collected through a combination of internal transaction summaries (price, delivery accuracy, delivery timeliness), warehouse observations (availability), and quality and service assessment surveys by the QC and procurement teams. Each supplier was assigned a code from SUP01 to SUP09. Validation was performed using source triangulation (price from PO vs. invoice), outlier checks (extreme values), and handling missing data using listwise deletion or median imputation as per criteria. One criterion was set as cost (price), while five others were benefit criteria. The final release data was approved by the procurement manager before it was analyzed and presented in Table 1.

Objective performance measurement can be understood as the utilization of assessment data for each alternative as the basis a quantitative subjectivity-free evaluation. In this

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case, each alternative is evaluated based on numerical values that reflect actual performance for each relevant and directly measurable criterion. This data represents real empirical conditions, so it can serve as a benchmark to assess the alignment between the ranking results produced by the WP-A method and actual field performance. With this approach, performance measurement no longer relies on assumptions or subjective preferences, but is based on quantitative evidence that depicts the factual conditions of each alternative.

3.2 *Model Implementation*

Model Implementation is a crucial stage in research that focuses on the application of designed methods to solve real-world problems. At this stage, the modified or developed model, such as Weighted Product with a specific approach, is applied to the obtained data to evaluate the performance of the alternatives more objectively and rationally. The implementation follows a systematic process from data normalization and weight calculation to ranking to produce accurate recommendations. Thus, Model Implementation serves as a bridge between theory and practice, demonstrating the model's effectiveness in delivering more accurate and fair decision-making solutions. In addition, the Model Implementation serves as validation of the developed framework, to determine whether the method provides consistent results that align with the research objectives. This implementation process involves testing various alternatives against predetermined criteria, both in terms of benefits and costs, thereby providing a comprehensive picture of each alternative's strengths and weaknesses. The results of the model implementation not only play a role in determining the best alternative but can also serve as a basis for decision-makers in formulating more effective long-term strategies. In other words, this stage ensures that the methods used are not merely theoretical concepts but can be applied to produce relevant, targeted decisions that support the improvement of organizational performance.

The WP-A model is implemented in the research by first creating a decision matrix that contains alternatives and performance values for each criterion, based on the data in Table 1, as formulated in (1).

Table 1. Supplier Assessment Data

Supplier ID	Criteria Code					
	CS-1	*CS-2*	*CS-3*	*CS-4*	*CS-5*	*CS-6*
SUP01	3	9	7	8	9	8
SUP02	2	8	8	7	8	7
SUP03	4	7	9	9	8	9
SUP04	3	6	8	8	7	7
SUP05	2	8	7	6	9	8
SUP06	4	9	8	7	9	9
SUP07	3	7	7	8	8	7
SUP08	1	6	8	7	6	6
SUP09	2	8	9	6	7	8

$$X = \begin{bmatrix} x_{11} & x_{21} & x_{31} & x_{41} & x_{51} & x_{61} \\ x_{12} & x_{22} & x_{32} & x_{42} & x_{52} & x_{62} \\ x_{13} & x_{23} & x_{33} & x_{43} & x_{53} & x_{63} \\ x_{14} & x_{24} & x_{34} & x_{44} & x_{54} & x_{64} \\ x_{15} & x_{25} & x_{35} & x_{45} & x_{55} & x_{65} \\ x_{16} & x_{26} & x_{36} & x_{46} & x_{56} & x_{66} \\ x_{17} & x_{27} & x_{37} & x_{47} & x_{57} & x_{67} \\ x_{18} & x_{28} & x_{38} & x_{48} & x_{58} & x_{68} \\ x_{19} & x_{29} & x_{39} & x_{49} & x_{59} & x_{69} \end{bmatrix}$$

The general form of the decision matrix for assessment data is as follows.

$$X = \begin{bmatrix} 3 & 9 & 7 & 8 & 9 & 8 \\ 2 & 8 & 8 & 7 & 8 & 7 \\ 4 & 7 & 9 & 9 & 8 & 9 \\ 3 & 6 & 8 & 8 & 7 & 7 \\ 2 & 8 & 7 & 6 & 9 & 8 \\ 4 & 9 & 8 & 7 & 9 & 9 \\ 3 & 7 & 7 & 8 & 8 & 7 \\ 1 & 6 & 8 & 7 & 6 & 6 \\ 2 & 8 & 9 & 6 & 7 & 8 \end{bmatrix}$$

The second stage is to calculate normalization values to ensure that each criterion's values are on a comparable scale. This process yields a normalization matrix ready for use in the weighting stage by using the formula in (2).

$$r_{11} = \frac{x_{11}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$

$$r_{11} = \frac{x_{11}}{\sqrt{\begin{matrix} x_{11}^2 + x_{12}^2 + x_{13}^2 + x_{14}^2 + x_{15}^2 \\ + x_{16}^2 + x_{17}^2 + x_{18}^2 + x_{19}^2 \end{matrix}}}$$

$$r_{11} = \frac{3}{\sqrt{3^2 + 2^2 + 4^2 + 3^2 + 2^2 + 4^2 + 3^2 + 1^2 + 2^2}}$$

$$r_{11} = \frac{3}{8.48528} = 0.3536$$

The results of the normalization matrix calculations for each alternative based on each criterion are presented in Table 2.

Table 2. Results of the Normalized Matrix Calculations

Supplier ID	Criteria Code					
	CS-1	*CS-2*	*CS-3*	*CS-4*	*CS-5*	*CS-6*
SUP01	0.3536	0.3932	0.2945	0.3607	0.3773	0.3452
SUP02	0.2357	0.3495	0.3366	0.3156	0.3354	0.3021
SUP03	0.4714	0.3058	0.3786	0.4058	0.3354	0.3884

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SUP04	0.3536	0.2621	0.3366	0.3607	0.2935	0.3021
SUP05	0.2357	0.3495	0.2945	0.2705	0.3773	0.3452
SUP06	0.4714	0.3932	0.3366	0.3156	0.3773	0.3884
SUP07	0.3536	0.3058	0.2945	0.3607	0.3354	0.3021
SUP08	0.1179	0.2621	0.3366	0.3156	0.2515	0.2589
SUP09	0.2357	0.3495	0.3786	0.2705	0.2935	0.3452

The third stage is to calculate the average value for each criterion from the normalization results. Each criterion is treated fairly according to its data distribution by using the Formula in (3).

$$AV_1 = \frac{1}{9}\sum_{i=1}^{m} r_{1j} = \frac{1}{9}(r_{11} + r_{12} + r_{13} + r_{14} + r_{15} + r_{16} + r_{17} + r_{18} + r_{19})$$

$$AV_1 = \frac{1}{9}(0.35355 + 0.23570 + 0.47140 + 0.35355 + 0.23570 + 0.47140 + 0.35355 + 0.11785 + 0.23570)$$

$$AV_1 = \frac{1}{9}(2.82843) = 0.31427$$

The average values for each criterion are displayed in Table 3.

The fourth stage involves calculating the weighted values of the criteria by normalizing the average values so that the total weight equals 1 by using the Formula in (4).

$$w_1 = \frac{AV_1}{\sum_{j=1}^{6} AV_j}$$

$$w_1 = \frac{AV_1}{AV_1 + AV_2 + AV_3 + AV_4 + AV_5 + AV_6}$$

$$w_1 = \frac{0.31427}{0.31427 + 0.33007 + 0.33189 + 0.33061 + 0.33072 + 0.33084}$$

$$w_1 = \frac{0.31427}{1.96840} = 0.1597$$

The results of the weight calculation for each criterion are displayed in Table 4.

Table 3. Results of the Average Value Criteria Calculations

Criteria Code					
CS-1	***CS-2***	***CS-3***	***CS-4***	***CS-5***	***CS-6***
0.3143	0.3301	0.3319	0.3306	0.3307	0.3308

Table 4. The Result of the Weighted Criteria Calculation

Criteria Code					
CS-1	***CS-2***	***CS-3***	***CS-4***	***CS-5***	***CS-6***
0.1597	0.1677	0.1686	0.168	0.168	0.1681

The fifth stage is to calculate the vector value for each alternative. The higher the vector value, the better the position of that alternative compared to other alternatives by using the Formula in (5).

$$V_{11} = r_{11} * w_1 = 0.35355 * 0.1597 = 0.84705$$

The results of the calculation of the vector values for each alternative for each criterion are shown in Table 5.

The sixth stage is calculating the relative value of alternatives using a multiplication mechanism. The multiplicative nature of this calculation provides higher sensitivity to variations among criteria compared to the additive approach; thus, the results obtained can be considered more proportional and reflect a comprehensive balance among the assessment dimensions by using the Formula in (6).

$$RV_1 = \prod_{i=1}^{m} V_{i1} = V_{11} * V_{21} * V_{31} * V_{41} * V_{51} * V_{61}$$

$$RV_1 = 0.847047 * 0.855101 * 0.813732 * 0.842581 * 0.848940 * 0.836307 = 0.35258$$

The results of the relative value calculations for each alternative are displayed in Table 6.

The final value calculation results for each alternative, which were calculated using the Formula in (7), are displayed in Table 7. The final WP-A result represents each supplier's preference value based on normalized criterion values and predetermined criterion weights. In this process, each alternative's performance value is weighted and combined to obtain the final preference score. A higher preference score indicates a better alternative, while a lower score indicates a less competitive supplier. Therefore, the WP-A results provide a supplier ranking from the most feasible to the least feasible alternative. The ranking results obtained from the WP-A method are shown in Fig. 2.

$$S_1 = \frac{RV_1}{\sum_{i=1}^{m} RV_i}$$

$$S_1 = \frac{RV_1}{RV_1 + RV_2 + RV_3 + RV_4 + RV_5 + RV_6 + RV_7 + RV_8 + RV_9}$$

$$S_1 = \frac{0.35258}{0.35258 + 0.31065 + 0.37662 + 0.31581 + 0.30873 + 0.37657 + 0.32405 + 0.24604 + 0.30878}$$

$$S_1 = \frac{0.35258}{2.91984} = 0.12075$$

Table 5. The Result of Calculating the Vector Values for Each Alternative

Supplier ID	**Criteria Code**					
	CS-1	***CS-2***	***CS-3***	***CS-4***	***CS-5***	***CS-6***
SUP01	0.8470	0.8551	0.8137	0.8426	0.8489	0.8363
SUP02	0.7940	0.8384	0.8323	0.8239	0.8323	0.8177

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SUP03	0.8869	0.8198	0.8490	0.8594	0.8323	0.8530
SUP04	0.8470	0.7989	0.8323	0.8426	0.8138	0.8177
SUP05	0.7940	0.8384	0.8137	0.8028	0.8489	0.8363
SUP06	0.8869	0.8551	0.8323	0.8239	0.8489	0.8530
SUP07	0.8470	0.8198	0.8137	0.8426	0.8323	0.8177
SUP08	0.7108	0.7989	0.8323	0.8239	0.7930	0.7968
SUP09	0.7940	0.8384	0.8490	0.8028	0.8138	0.8363

Table 6. The Results of the Calculation of the Relative Value of Each Alternative

Supplier ID	Relative Value
SUP01	0.3526
SUP02	0.3107
SUP03	0.3766
SUP04	0.3158
SUP05	0.3087
SUP06	0.3766
SUP07	0.3241
SUP08	0.2460
SUP09	0.3088

The graph in Fig. 2 shows that SUP03 achieved the highest score of 0.12899, followed by SUP06 with 0.12897 and SUP01 with 0.12075. This indicates that these three alternatives occupy the top positions in the ranking. Next, SUP07 (0.11098), SUP04 (0.10816), and SUP02 (0.10639) occupy the middle positions in the comparison. Meanwhile, SUP09 (0.10575) and SUP05 (0.10574) are ranked lower, with nearly identical scores that differ only slightly. SUP08 obtained the lowest score of 0.08427, making it the alternative with the poorest performance among all evaluated alternatives. Overall, this graph shows a distribution of relatively close ranking scores, with only slight differences among the alternatives, yet enough to determine a clear order of priority.

3.3 *Evaluation and Analysis of Results*

Evaluation and analysis of results are important stages in research and in the implementation of decision support systems because they show how well the proposed method produces accurate and relevant results in line with the research objectives. The evaluation process compares calculation results with predetermined needs, criteria, and decision-making objectives. This analysis assesses the strengths, weaknesses, consistency, and reliability of the method in providing appropriate recommendations. In addition, it helps determine whether the resulting alternative rankings align with real conditions and whether the method can improve the effectiveness of the decision-making process. Therefore, this stage provides a basis for interpretation, validation, and further recommendations for both users and future researchers.

Table 7. Final Value Calculation Results for Each Alternative

Supplier ID	Final Value
SUP01	0.12075
SUP02	0.10639
SUP03	0.12899
SUP04	0.10816
SUP05	0.10574
SUP06	0.12897
SUP07	0.11098
SUP08	0.08427
SUP09	0.10575

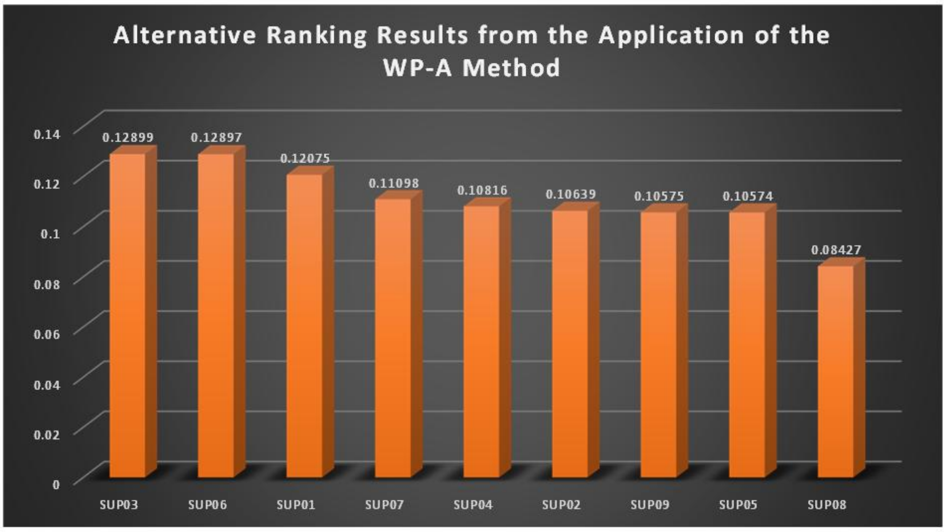

Figure 2. Alternative ranking results using the WP-A method

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The performance of the Weighted Product method with averaging and mean-normalized evaluation (WP-A) in supplier selection is evaluated by comparing its rankings with those of several widely used multi-criteria decision-making methods, including SAW, MAUT, GRA, MOORA, and TOPSIS. This comparison aims to assess the consistency, validity, and reliability of the rankings produced by WP-A against conventional methods. Since each method applies a different mathematical approach, the ranking comparison serves as a benchmark for evaluating the objectivity and stability of the proposed model. Therefore, this analysis not only examines the performance of WP-A but also highlights its contribution to fairer, more rational decision-making. The comparison of rankings is displayed in Table 8.

Spearman's correlation is a statistical technique used to measure the degree of association between two different rankings. In the context of decision support system research, this method is highly relevant for assessing the extent to which the consistency of ranking results from various methods can be maintained. By calculating the Spearman correlation coefficient, it can be determined whether the ranking results obtained with the WP-A method match those from comparative methods such as SAW, MAUT, GRA, MOORA, and TOPSIS. A correlation value close to 1 indicates a high degree of similarity in rankings, while a value close to 0 indicates low congruence among rankings. The application of Spearman's correlation analysis in this study aims to provide additional validation of the WP-A method's reliability in producing the best supplier rankings. By comparing the rankings generated by WP-A with other methods, an objective picture of the consistency and accuracy of the rankings can be obtained. The results of this analysis are expected to demonstrate that WP-A is not only superior in the calculation process but also capable of generating rankings that align with those of other popular methods in multi-criteria decision-making. The Spearman correlation results are presented in Fig. 3.

Table 8. Results of Alternative Ranking Comparison

Supplier ID	Ori	WP-A	SAW	MAUT	GRA	MOORA
SUP03	1	2	2	2	2	2
SUP06	2	1	1	1	1	1
SUP01	3	3	3	3	3	3
SUP07	4	4	5	7	7	4
SUP04	5	5	7	8	6	7
SUP02	6	6	6	6	5	6
SUP09	7	8	8	5	8	7
SUP05	8	7	4	4	4	5
SUP08	9	9	9	9	9	9

The graph in Fig. 3 shows the Spearman correlation values for several MCDM methods, with the WP-A method achieving the highest correlation of 0.9828, indicating very strong consistency with the reference ranking. Other methods that also show high correlation are TOPSIS (0.9656) and MOORA (0.9342), indicating that both have quite good reliability in producing ranking results similar to WP-A. On the other hand, the SAW method achieved a correlation value of 0.8968, followed by GRA with 0.871, which is still in the fairly high category but lower than the previous three methods. Meanwhile, the MAUT method has the lowest correlation value at 0.828, although it still shows a significant positive relationship. Overall, this chart shows that WP-A is the most consistent and reliable method in the context of alternative ranking evaluation, while MAUT tends to yield results that are less aligned with the benchmarks compared to other methods. The analysis results using Spearman's correlation indicate that a high correlation value essentially reflects the level of agreement or consistency of rankings between methods rather than indicating the inherent superiority of a method. Thus, when two or more methods produce similar rankings of alternatives, this cannot be directly interpreted as evidence that the method is more accurate or superior. Conversely, this condition suggests that the methods tend toward a consistent evaluation pattern across the same data, so the interpretation needs to be supplemented with additional analysis to provide a more comprehensive understanding.

The next evaluation emphasizes the importance of the evaluation process in determining the criteria weights produced through objective weighting methods, which serve as the main foundation for ensuring the quality of the decisions made. Objective weighting, which is entirely based on data characteristics such as variation, distribution, and the level of information in each criterion, reduces the subjectivity that often arises in conventional approaches. Therefore, the analysis in this section focuses on comparing the weight results obtained from several objective weighting methods to assess consistency, sensitivity, and each method's ability to accurately represent the relative importance of the criteria. Additionally, the evaluation considers the impact of weight differences on alternative rankings, enabling determination of the extent to which variations in weighting affect decision stability. Table 9 shows the results of comparing the criterion weights obtained from each objective weighting method, which are then analyzed to examine differences in the weight distribution among criteria and their implications for each criterion's contribution to the decision-making process.

The comparison results of the criteria weights generated by several objective weighting methods, namely WP-A, Entropy, MEREC, RECA, and LOPCOW, show significant differences in the weight distribution patterns between methods. The WP-A method produces a relatively balanced weight distribution across all criteria (CS-1 to CS-6), with values that are almost uniform, ranging from 0.1597 to 0.1686, indicating that this method tends to treat each

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criterion evenly without strong dominance. In contrast, the Entropy method shows a very striking imbalance, with the CS-1 criterion having a highly dominant weight of 0.6336 compared to the other much smaller criteria, reflecting that the data variation in CS-1 is much higher, making it considered more informative [11], [13], [15]. A similar pattern is also seen in the MEREC method, although not as extreme as Entropy, with CS-1 remaining the most dominant criterion (0.5310), while the other criteria have lower and varied contributions. On the other hand, the RECA method produces a more proportional weight distribution with a tendency to increase from criteria CS-3 to CS-6, indicating greater sensitivity to the relative contributions among criteria than Entropy and MEREC. The LOPCOW method lies between the two approaches, with CS-1 still having the highest weight (0.3886). However, the differences with other criteria are not too extreme, thus still maintaining a certain level of balance. This comparison shows that each method has distinct characteristics in evaluating the importance of criteria, which can ultimately affect the final ranking of alternatives, especially in terms of sensitivity to the dominance of certain criteria and the overall stability of the weight distribution.

3.4 Discussion

The research results show that the integration of averaging and mean-normalized evaluation into the Weighted Product method successfully reduces the sensitivity of calculations to differences in criterion scales. In the application of the classical WP, a significant difference in values between criteria often leads to the domination of one attribute in the ranking determination. However, through the modified approach, previously extreme criterion values can be balanced, making the contributions of each attribute more proportional. This results in a more consistent ranking and reduces potential bias in decision-making.

The comparison results show that the modified WP method with averaging and mean-normalized evaluation yields a higher Spearman correlation than SAW, MAUT, GRA, MOORA, and TOPSIS. This indicates that the modified WP is capable of producing ranking results that are more consistent with objective preferences, as well as more stable against changes in weights and variations in data scale. This advantage demonstrates that the WP modification not only enhances the fairness of distribution among criteria but also improves the method's reliability in supporting multi-criteria decision-making compared to other MCDM methods.

This modification enriches the literature on the development of MCDM methods by offering solutions to the limitations of WP, which have long been debated. The averaging approach and mean-normalized evaluation can serve as references for developing other multiplicative-based methods, the benefits of this research are not limited to WP. The practical implications of this research's results are highly relevant to decision-makers across business, industry, and management, as they can provide a fairer, more flexible, and more reliable evaluation system to support the multi-criteria decision-making process.

Table 9. Comparison results of the criteria weights

Method	Criteria Code					
	CS-1	***CS-2***	***CS-3***	***CS-4***	***CS-5***	***CS-6***
WP-A	0.1597	0.1677	0.1686	0.168	0.168	0.1681
Entropy	0.6336	0.0960	0.0414	0.0788	0.0775	0.0727
MEREC	0.5310	0.1022	0.0754	0.1202	0.0779	0.0934
RECA	0.0999	0.1745	0.1877	0.1800	0.1778	0.1800
LOPCOW	0.3886	0.1259	0.1154	0.1289	0.1189	0.1223

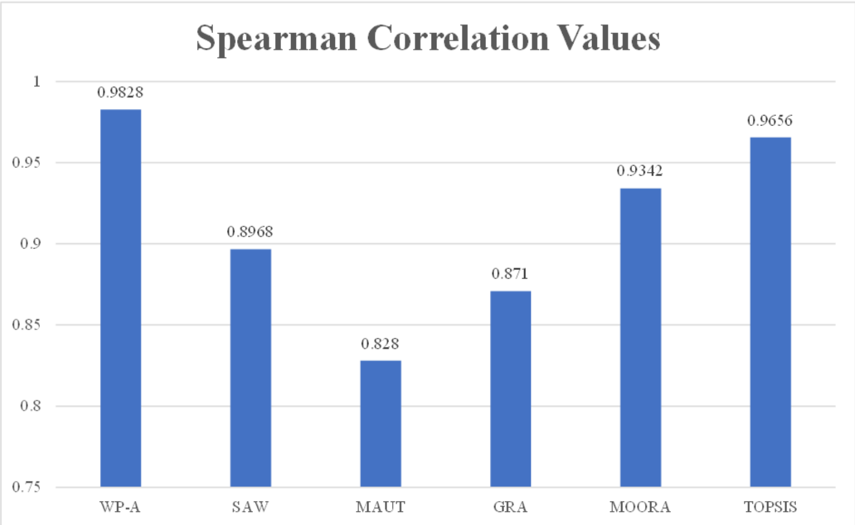

Figure 3. Spearman correlation comparison results

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4 CONCLUSION

The development of the WP method through the proposed modifications shows potential in improving ranking characteristics, particularly in terms of consistency and the management of criterion weight distribution. Nevertheless, the findings from this study are still comparative across methods, so interpretations of performance improvement need to be communicated proportionally. The analysis results indicate that the WP-A method produces relatively stable rankings and shows high conformity with the references, as evidenced by a Spearman correlation of 0.9828. However, this value is more appropriately interpreted as an indication of result consistency rather than as direct evidence of increased decision-making accuracy. In addition, WP-A demonstrates strong capability to handle variations in data distributions and criterion weights, thereby providing greater flexibility in applying MCDM methods without losing the computational simplicity that is the advantage of the WP method. Therefore, the main contribution of this study lies in enriching the methodological approach and providing an alternative formulation that is better adapted to data characteristics. Moving forward, further evaluation involving empirical data or real-world scenarios, as well as more in-depth sensitivity analysis, is needed to gain a more comprehensive understanding of WP-A behavior in various complex decision-making conditions.

CREDIT AUTHOR STATEMENT

Adhie Thyo Priandika: Writing – original draft, Methodology, Conceptualization. **Sumanto**: Writing – review & editing, Methodology, Conceptualization. **Permata**: Writing – review & editing, Purposed Method, Conceptualization. **Setiawansyah**: Software, Methodology, Writing – original draft.

COMPETING INTERESTS

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

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 took full responsibility for the final publication.

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