International Journal of Management Science and Information Technology
IJMSIT

E-ISSN: 2774-5694 P-ISSN: 2776-7388

Volume 6 (1), January-June 2026, 10-22
DOI: https://doi.org/10.35870/ijmsit.v6i1.6511

# Comparative Analysis of SAW and WP Methods for Employee Selection in MSMEs

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Article history:
Received February 3, 2026
Revised February 9, 2026
Accepted February 10, 2026

## Abstract
The process of selecting new employees in Micro, Small, and Medium Enterprises (MSMEs) is often still carried out subjectively, which can lead to less optimal decision-making. This study aims to apply and compare the Simple Additive Weighting (SAW) and Weighted Product (WP) methods as decision support systems for new employee selection in MSMEs. The evaluation is conducted based on four criteria: education level, work experience, skill competency, and interview results. The dataset consists of ten job candidates that are processed through weight normalization, preference value calculation, and ranking stages. The results show that both methods are capable of providing objective and measurable recommendations for selecting the best employees, although differences appear in the final ranking of candidates because the SAW method calculates scores by summing weighted normalized values for each criterion, while the WP method multiplies each criterion value raised to its weight, making the influence of high or low scores more pronounced. The SAW method is simpler and easier to understand, while the WP method is more sensitive to criterion weights and better distinguishes candidates with varied performance levels. The best alternative tends to consistently rank at the top in both methods. Therefore, the implementation of the SAW and WP methods can assist MSMEs in making systematic and accurate employee selection decisions based on a dataset of ten candidates evaluated across four assessment criteria.

**Keywords**:
Decision support system; SAW; WP; MSMEs.

## 1. INTRODUCTION

Micro, Small, and Medium Enterprises (MSMEs) are an economic sector that plays an important role in national economic growth (Habibie, 2023). Various studies indicate that MSMEs are able to absorb a large number of workers, drive local economic growth, and serve as a foundation for equitable development (Bungkuran et al., 2022). The flexible characteristics of MSMEs and their ability to adapt to changing market conditions make them more resilient to economic crises compared to large-scale enterprises. In addition, MSMEs often serve as a platform for community creativity in utilizing local resource potential, thereby increasing regional value added (Fatmariani et al., 2024).

MSMEs face various challenges, such as limited access to financing, relatively low managerial capabilities, and the low adoption of digital technology. In the era of global competition, innovation and digital transformation have become key factors in improving the efficiency and competitiveness of MSMEs (Wijaya et al., 2024). Mentoring programs, training initiatives, and collaboration with the government, educational institutions, and the private sector are essential to strengthening the MSME ecosystem. With appropriate support, MSMEs can grow more sustainably and make a more significant contribution to the economy (Ikhlas, 2022).

The ability of MSMEs to grow is strongly influenced by the quality of their human resources; therefore, the selection of new employees becomes a crucial stage in maintaining business sustainability (Saputri et al., 2021). However, in practice, the employee selection process in MSMEs is still largely carried out manually based on the subjective judgment of business owners without standardized criteria. This condition often results in suboptimal selection outcomes and has the potential to cause decision-making errors in workforce placement (Alaina et al., 2023).

Employee selection is a systematic process used by organizations to choose the best candidates from a pool of available applicants (Khotimah et al., 2023). The selection process aims to ensure alignment between applicants' abilities, personalities, and experiences with job requirements. It typically involves several stages such as administrative screening, competency tests, interviews, and final evaluation. Previous studies have shown that the application of structured selection methods can improve the quality of recruited employees and reduce the risk of errors in job placement (Putra et al., 2025).

Employee selection is influenced by the use of valid and reliable selection instruments, such as psychological tests, technical ability tests, or technology-based methods such as decision support systems (Etikawati & Udjang, 2016). Along with technological advancements, many organizations have begun to utilize evaluation algorithms, machine learning, and data-driven systems to support decision-making processes in employee selection so that they become more objective and efficient. A well-designed selection process not only improves organizational performance but also creates a more productive work environment that aligns with the competencies of the recruited individuals (Pahira & Rinaldy, 2023).

Decision Support Systems (DSS) serve as an alternative solution to assist MSME owners in conducting employee selection in a more objective and structured manner. DSS are capable of processing data based on predefined criteria, thereby supporting a more effective decision-making process (Hadiana, 2022). By utilizing technology, the employee evaluation process can be carried out using clear calculation methods and can generate recommendations for the best candidates quickly and accurately. This is important given that MSMEs are required to remain competitive and continuously improve the quality of their services and production (Novita et al., 2022).

In research related to Decision Support Systems, there are several multicriteria evaluation methods that are commonly used, including the Simple Additive Weighting (SAW) and Weighted Product (WP) methods. These two methods have different characteristics and calculation mechanisms, yet both can be used to determine the best alternative based on a set of given criteria (Adibrata & Mustafidah, 2021). The SAW method works by normalizing the data and summing the normalized values that have been weighted (Supriadi, 2021). Meanwhile, the WP method uses the multiplication of each criterion value raised to the power of its weight, making the influence of each criterion more significant in the final result (Mardian et al., 2023).

The differences in the calculation processes between the SAW and WP methods make both approaches interesting to compare in the context of new employee selection for MSMEs. A comparative analysis is necessary to determine which method is more effective, more sensitive to criterion weights, and capable of producing consistent results (Suartini et al., 2023). The evaluation will be conducted using several common recruitment criteria, such as work experience, education level, interview results, and skill competency. Therefore, this study not only assesses algorithm performance but also examines its relevance for real-world implementation in MSMEs.

In addition, the comparison of these two methods is expected to provide a clearer understanding of the effectiveness of each approach in supporting the decision-making process (Supriyanti, 2023). The analysis results will demonstrate differences in final scores and rankings of job candidates according to the method used. Through this discussion, MSME owners will have a better reference for selecting an appropriate method to support the employee selection process in a more objective manner with more measurable evaluation standards.

Overall, this study aims to develop a decision support system for new employee selection in MSMEs by comparing the SAW and WP methods through candidate data processing and ranking analysis. It is expected that this research will identify the most suitable method to assist MSMEs in selecting the most competent employees according to business needs. This study can also serve as a reference for the development of information technology–based selection systems in the field of human resource management, thereby improving the efficiency and quality of workforce recruitment.

## 2. RESEARCH METHOD

This study employs a quantitative descriptive approach supported by qualitative data to develop and analyze a decision support system for the selection of new employees in Micro, Small, and Medium Enterprises (MSMEs). The quantitative method is applied through numerical processing of candidate assessment data using predefined criteria weights, normalization, and preference value calculations with the SAW and WP methods to produce objective rankings. Data collection techniques combine primary and secondary data to ensure the information obtained is comprehensive and reflects real conditions in the field. Primary data were collected through direct interviews with MSME owners or managers to explore system requirements, evaluation criteria, and the employee selection mechanisms that have been implemented. In addition, direct observation of the recruitment process was conducted to understand the selection workflow, assessment indicators, and challenges faced by MSMEs in selecting new employees.

Meanwhile, secondary data were gathered from MSME administrative documents, such as job application forms, standard operating procedures (SOPs) for employee selection, and summaries of previous candidate evaluations. The researcher also conducted a literature review of reference books and scientific journals to establish a theoretical foundation regarding decision support systems and the Simple Additive Weighting (SAW) and Weighted Product (WP) methods. All collected data were then processed into a dataset consisting of alternative candidates and evaluation criteria used in the calculation and comparison of methods.

The types of data used in this study include both qualitative and quantitative data. Qualitative data consist of information regarding employee profiles, descriptions of evaluation criteria, and the employee selection process in MSMEs. Quantitative data consist of numerical values for each evaluation criterion, the number of alternative candidates, and the scores obtained from the SAW and WP methods used in the ranking process. Primary data sources in this study come from several MSMEs located in Jembrana Regency, while secondary data sources were obtained from reference books, scientific articles, and official journal publication websites in relevant PDF formats.

This study is designed to provide a systematic understanding of the issues addressed, from issue identification to solution implementation. With this systematic approach, it is expected to present a clear and measurable study. The following provides an overview of the research flow.

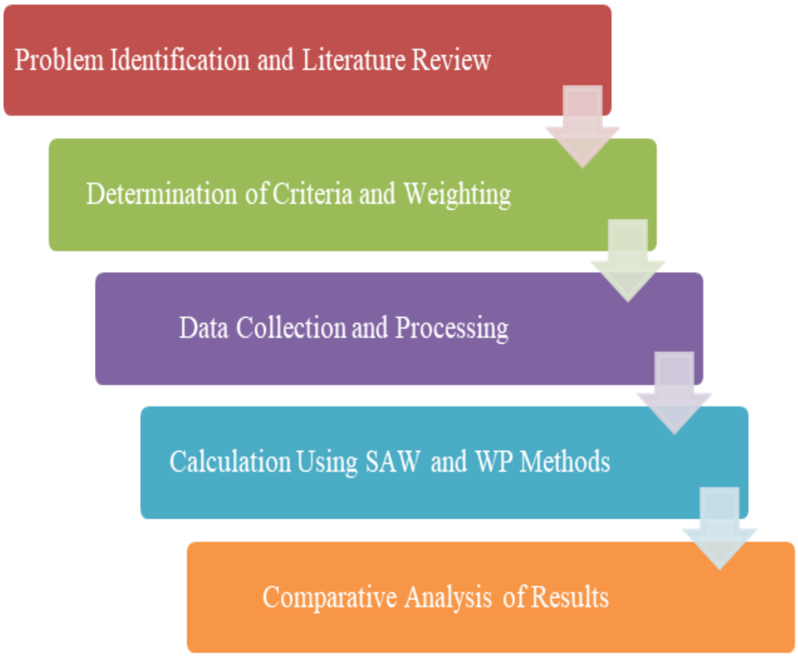


Figure 1. Research Procedure

The research begins by identifying the problems in employee performance assessment in SMEs, which are still conducted subjectively and have not yet employed a decision support system approach. Next, a literature review is conducted using books, scientific journals, and previous studies related to Decision Support Systems (DSS), employee performance assessment, as well as the Simple Additive Weighting (SAW) and Weighted Product (WP) methods. This stage aims to obtain relevant theoretical foundations and methods to serve as the basis for research design.

The next stage is the determination of evaluation criteria and weights. At this stage, performance assessment criteria suitable for the needs and characteristics of SMEs are established, such as attendance, discipline, responsibility, productivity, and teamwork. Each criterion is assigned a weight according to its importance in supporting employee performance. The determination of weights is based on managerial considerations or discussions with SME stakeholders to ensure the weights reflect real conditions in the field.

In the data collection and processing stage, employee performance data is collected through observation, interviews, and documentation. The obtained data is then processed and arranged in a decision matrix containing employee alternatives and performance scores for each criterion. This stage aims to prepare valid and structured data that can be used in the calculation processes of the SAW and WP methods.

The calculation process using the SAW and WP methods involves assessing employee performance with both methods. The SAW method is conducted by normalizing the decision matrix based on benefit and cost attributes, followed by calculating preference values through summing the products of normalized values and criterion weights. Meanwhile, the WP method multiplies the value of each criterion raised to the power of its respective weight to obtain preference vector values. The results of both methods yield preference values and employee rankings.

The final stage of the research is the comparative analysis of employee performance assessment results obtained from the SAW and WP methods. The analysis compares rankings, preference values, and decision consistency generated by both methods. This comparison is used to determine the method that is more suitable and effective for implementation in a decision support system for employee performance assessment in SMEs, and serves as the basis for drawing research conclusions.

## 3. RESULTS AND DISCUSSION

### 3.1. General Overview of the Comparative Analysis of SAW and WP Methods

This section discusses a general overview of the comparative analysis process between the Simple Additive Weighting (SAW) and Weighted Product (WP) methods in the context of employee performance assessment in SMEs. The comparative analysis is conducted to understand the advantages and limitations of each method and to determine which method is more appropriate and effective for implementation in a decision support system. The process involves several stages, starting from the identification of evaluation criteria and assignment of weights, the collection and processing of employee performance data, to the calculation of preference values and ranking using both methods. The calculation results are then compared to evaluate decision consistency, ranking differences, and the relevance of the methods to the practical needs of SMEs. This general overview serves as the foundation for a more detailed discussion of the analysis stages, which will be explained further in the following sub-section. The following is a general illustration of the comparative analysis process of the SAW and WP methods.

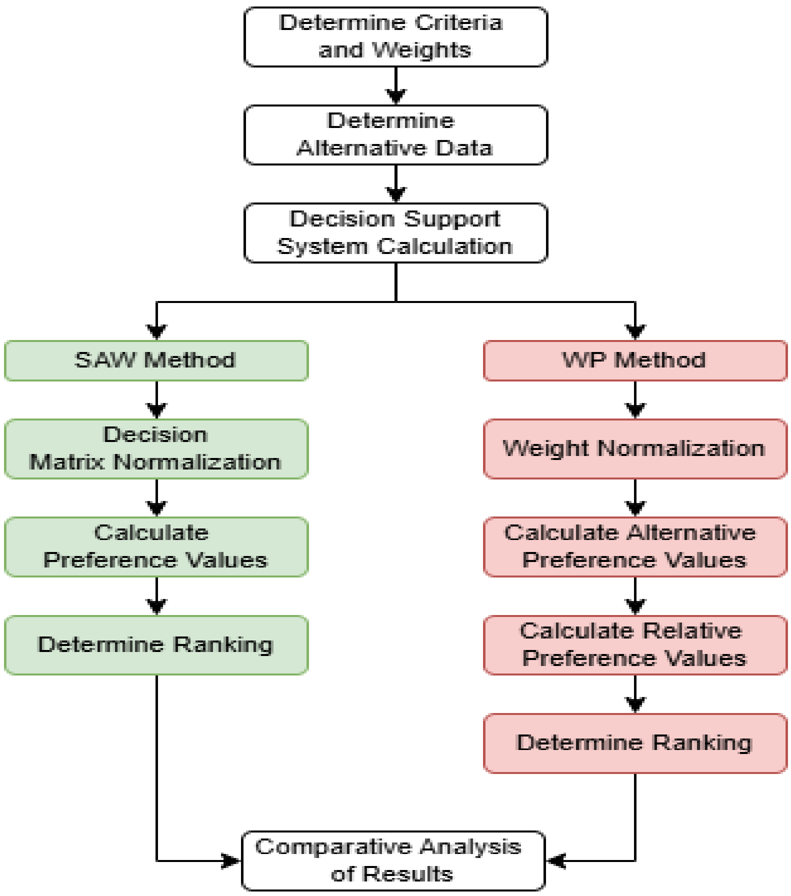


Figure 2. General Overview of the Comparative Analysis of SAW and WP Methods

The figure presents an overview of the comparative analysis process between the Simple Additive Weighting (SAW) and Weighted Product (WP) methods in a decision support system. The process starts with determining the evaluation criteria and assigning appropriate weights to each criterion, which serve as the basis for assessing alternatives. These criteria reflect the aspects used to measure performance or suitability in the decision-making process.

The next stage involves determining the alternative data to be evaluated. This data represents the set of alternatives, such as employees or options, whose performance values are collected according to the predefined criteria. Once the alternative data are defined, the system proceeds to the decision support system calculation stage, where both methods are prepared to be applied simultaneously.

In the SAW method, the calculation begins with normalizing the decision matrix to ensure that the values of different criteria are comparable. After normalization, preference values for each alternative are calculated by summing the weighted normalized scores. These preference values are then used to determine the ranking of alternatives, with higher values indicating better performance.

In contrast, the WP method starts with weight normalization to ensure proportional contribution of each criterion. The method then calculates alternative preference values by multiplying the criterion values according to their respective weights. This process continues with the calculation of relative preference values, which are used to reflect the comparative strength of each alternative. Based on these values, the final ranking of alternatives is determined.

The final stage of the process is the comparative analysis of results, where the rankings obtained from the SAW and WP methods are compared. This comparison aims to evaluate the consistency of decisions, identify differences in ranking outcomes, and assess the suitability and effectiveness of each method in supporting decision-making. The results of this analysis provide insights into which method is more appropriate for the given decision context.

### 3.2. Comparative Analysis of Decision Support System Methods

This subsection presents a comparative analysis of decision support system methods applied in the context of new employee selection in Micro, Small, and Medium Enterprises (MSMEs). The analysis focuses on evaluating the performance of the Simple Additive Weighting (SAW) and Weighted Product (WP) methods by examining their calculation processes, preference values, and ranking results. Through this comparison, the strengths and limitations of each method are identified, providing insights into their effectiveness, consistency, and suitability for supporting decision-making. The results of this analysis are expected to assist MSMEs in selecting the most appropriate decision support method based on their practical needs and data characteristics.

#### 3.2.1. Determination of Criteria and Weights

This subsection explains the determination of evaluation criteria and the assignment of weights used in the decision support system for new employee selection in MSMEs. The criteria are defined to represent the key factors considered important by decision-makers, while the weights indicate the relative importance of each criterion. This step is crucial because the accuracy of the final decision is highly dependent on the relevance and proportional weighting of the selected criteria.

Table 1. Criteria and Weights

| Code | Criteria | Type | Weight |
|---|---|---|---|
| C1 | Education Level | Benefit | 0.30 |
| C2 | Work Experience | Benefit | 0.25 |
| C3 | Skill Competency | Benefit | 0.25 |
| C4 | Interview Result | Benefit | 0.20 |

The table presents the evaluation criteria used in the Decision Support System (DSS) for the employee selection process along with their attribute types and importance weights. Each criterion is assigned a code (C1–C4) to simplify calculations in the SAW and WP methods. All criteria are categorized as benefit attributes, meaning that higher values indicate better candidate performance. The Education Level (C1) criterion has the highest weight of 0.30 because it is considered the most influential factor in determining a candidate's fundamental capability to understand job tasks. Next, Work Experience (C2) and Skill Competency (C3) each have a weight of 0.25, indicating that experience and skills are equally important in assessing job readiness. Meanwhile, the Interview Result (C4) has a weight of 0.20, which remains important for evaluating attitude, communication, and cultural fit, but is slightly lower due to its more subjective nature. Overall, these weights reflect the decision priority where education is the main factor, followed by experience and competency, and finally the interview assessment.

#### 3.2.2. Determination of Alternative Data

This subsection describes the identification and preparation of alternative data used in the selection process. The alternatives represent the candidates being evaluated based on the predetermined criteria. Accurate and consistent data collection at this stage ensures that each candidate is assessed fairly and objectively, providing a reliable foundation for subsequent calculations using the SAW and WP methods.

Table 2. Alternative Data

| Candidate | C1 | C2 | C3 | C4 |
|---|---|---|---|---|
| A1 | 80 | 75 | 85 | 70 |
| A2 | 85 | 70 | 80 | 75 |
| A3 | 75 | 85 | 75 | 80 |
| A4 | 90 | 80 | 85 | 85 |
| A5 | 70 | 65 | 70 | 75 |
| A6 | 88 | 78 | 82 | 80 |
| A7 | 82 | 72 | 78 | 70 |
| A8 | 78 | 80 | 80 | 85 |
| A9 | 85 | 88 | 90 | 88 |
| A10 | 76 | 70 | 75 | 72 |

The table shows the decision matrix of candidates based on the previously defined evaluation criteria (C1–C4). Each row represents a candidate (A1–A10), while each column represents the score obtained for a specific criterion: Education Level (C1), Work Experience (C2), Skill Competency (C3), and Interview Result (C4). The values indicate the performance level of each candidate on a scale from 0 to 100, where higher scores represent better qualifications.

From the data, candidate A9 demonstrates the strongest overall performance with consistently high scores across all criteria, particularly in work experience and skill competency. Candidate A4 also shows strong performance, especially in education and interview results. On the other hand, candidates such as A5 and A10 have relatively lower scores across multiple criteria, indicating comparatively weaker qualifications. This matrix serves as the initial input for the SAW and WP calculation processes, where the values will be normalized and weighted to produce the final ranking of candidates objectively.

### 3.2.3. Simple Additive Weighting (SAW) Method Calculation

This subsection discusses the application of the Simple Additive Weighting (SAW) method in evaluating new employee candidates. The SAW method involves normalizing the decision matrix and calculating preference values by summing the weighted scores of each criterion. Due to its simplicity and ease of interpretation, the SAW method is widely used in decision support systems, particularly in environments such as MSMEs that require transparent and straightforward decision-making processes.

#### 3.2.3.1. Normalization of Decision Matrix

Normalization of the decision matrix is a crucial step in the decision support system process, particularly in the Simple Additive Weighting (SAW) method. This process aims to transform the original decision matrix, which may consist of values with different scales and units, into a comparable form. By normalizing the data, each criterion can be evaluated fairly without being influenced by differences in measurement ranges (Wahyuni et al., 2023).

In this study, normalization is performed by dividing each criterion value by the maximum value of the corresponding criterion for benefit-type criteria. This approach ensures that all normalized values fall within a range between 0 and 1, where higher values indicate better performance. The normalization formula used is expressed as (Nathaniel et al., 2024).

$$r_{ij} = \frac{x_{ij}}{\max(x_j)}$$

where $r_{ij}$ represents the normalized value, $x_{ij}$ is the original value of alternative i on criterion j, and $\max(x_j)$ is the maximum value of criterion j among all alternatives.

The normalized decision matrix serves as the basis for calculating preference values in the next stage. By standardizing the data through normalization, the SAW method can accurately reflect the relative performance of each alternative, leading to more reliable and objective ranking results.

Table 3. Normalization of Decision Matrix

| Candidate | C1 | C2 | C3 | C4 |
|---|---|---|---|---|
| A1 | 0.89 | 0.85 | 0.94 | 0.80 |
| A2 | 0.94 | 0.80 | 0.89 | 0.85 |
| A3 | 0.83 | 0.97 | 0.83 | 0.91 |
| A4 | 1.00 | 0.91 | 0.94 | 0.97 |

| Candidate | C1 | C2 | C3 | C4 |
|---|---|---|---|---|
| A5 | 0.78 | 0.74 | 0.78 | 0.85 |
| A6 | 0.98 | 0.89 | 0.91 | 0.91 |
| A7 | 0.91 | 0.82 | 0.87 | 0.80 |
| A8 | 0.87 | 0.91 | 0.89 | 0.97 |
| A9 | 0.94 | 1.00 | 1.00 | 1.00 |
| A10 | 0.84 | 0.80 | 0.83 | 0.82 |

The table represents the normalized decision matrix obtained after converting the original candidate scores into comparable values between 0 and 1. The normalization process is required in decision support methods such as SAW and WP so that different criteria scales can be evaluated fairly. Because all criteria are categorized as benefit attributes, each value is divided by the maximum value in its respective column. As a result, a value closer to 1 indicates better performance relative to other candidates for that criterion.

From the normalized data, candidate A9 achieves the highest performance across all criteria, reaching the maximum value (1.00) in work experience, skill competency, and interview results, showing superior qualifications compared to others. Candidate A4 and A6 also demonstrate strong and balanced performance across criteria, while candidates such as A5 and A10 have lower normalized values, indicating comparatively weaker performance. This normalized matrix becomes the basis for calculating preference values by multiplying each criterion with its corresponding weight in order to produce the final ranking of candidates objectively.

#### 3.2.3.2. Preference Value Calculation

This subsection presents the calculation of preference values using the Simple Additive Weighting (SAW) method as a fundamental step in determining the ranking of candidates for new employee selection in MSMEs. After obtaining the normalized decision matrix, each normalized value is multiplied by its corresponding criterion weight to reflect the relative importance of each criterion in the decision-making process (Aldisa et al., 2022). The weighted normalized values are then summed to produce a single preference value for each alternative. The preference value for each candidate is calculated using the following formula (Mulyani & Hutahaean, 2021).

$$V_i = \sum_{j=1}^{n} (w_j \times r_{ij})$$

Where V_i represents the preference value of alternative i, w_j denotes the weight of criterion j, and r_ij is the normalized value of alternative i on criterion j. In this study, the weights used are 0.30 for education level (C1), 0.25 for work experience (C2), 0.25 for skill competency (C3), and 0.20 for interview results (C4), with the total weight equal to one. The results of the preference value calculation are presented below.

Table 4. Preference Value Calculation

| Candidate | C1 ($0.30 \times r_{ij}$) | C2 ($0.25 \times r_{ij}$) | C3 ($0.25 \times r_{ij}$) | C4 ($0.20 \times r_{ij}$) | $V_i$ |
|---|---|---|---|---|---|
| A1 | 0.267 | 0.213 | 0.235 | 0.160 | 0.875 |
| A2 | 0.282 | 0.200 | 0.223 | 0.170 | 0.875 |
| A3 | 0.249 | 0.243 | 0.208 | 0.182 | 0.882 |
| A4 | 0.300 | 0.228 | 0.235 | 0.194 | 0.957 |
| A5 | 0.234 | 0.185 | 0.195 | 0.170 | 0.784 |
| A6 | 0.294 | 0.223 | 0.228 | 0.182 | 0.927 |
| A7 | 0.273 | 0.205 | 0.218 | 0.160 | 0.856 |
| A8 | 0.261 | 0.228 | 0.223 | 0.194 | 0.906 |
| A9 | 0.282 | 0.250 | 0.250 | 0.200 | 0.982 |
| A10 | 0.252 | 0.200 | 0.208 | 0.164 | 0.824 |

The table shows the preference value calculation using the SAW (Simple Additive Weighting) method. Each normalized value rijr_{ij}rij from the previous matrix is multiplied by its corresponding criterion weight: C1 (0.30), C2 (0.25), C3 (0.25), and C4 (0.20). The results of these multiplications represent the weighted contribution of each criterion to the candidate's overall evaluation. The final preference value $V_i$ is obtained by summing all weighted scores in each row.

The results indicate that candidate A9 achieves the highest preference value (0.982), meaning this candidate is the most recommended according to the SAW method because they consistently perform well across all criteria. Candidate A4 (0.957) and A6 (0.927) also rank highly, showing strong overall qualifications. Meanwhile, candidates such as A5 (0.784) and A10 (0.824) have lower preference values, indicating weaker suitability compared to others. Therefore, this table represents the final ranking stage in the SAW method, where candidates with higher $V_i$ values are considered more eligible for selection.

### 3.2.3.3. SAW Ranking Result

The preference value calculation shows that Candidate A9 achieves the highest score, indicating the best overall performance based on the weighted criteria. This result demonstrates the effectiveness of the SAW method in aggregating normalized values into a single preference score that supports objective ranking.

Table 5. SAW Ranking Result

| Rank | Candidate | Vi |
|---|---|---|
| 1 | A9 | 0.982 |
| 2 | A4 | 0.957 |
| 3 | A6 | 0.927 |
| 4 | A8 | 0.906 |
| 5 | A3 | 0.882 |
| 6 | A2 | 0.875 |
| 7 | A1 | 0.875 |
| 8 | A7 | 0.856 |
| 9 | A10 | 0.824 |
| 10 | A5 | 0.784 |

The table shows the final ranking of candidates based on the calculated preference values (Vi) obtained from the decision-making process. Candidates are ordered from the highest score to the lowest, where a higher Vi indicates a better overall evaluation after considering all criteria and their respective weights. Candidate A9 occupies the first position with a score of 0.982, indicating the best overall qualification among all applicants. This is followed by A4 (0.957) and A6 (0.927), which also demonstrate strong performance across the evaluated criteria. Candidates A2 and A1 have identical scores (0.875), meaning their overall qualifications are considered equivalent in the assessment. Meanwhile, A10 (0.824) and A5 (0.784) rank at the bottom, suggesting lower suitability compared to other candidates. In conclusion, this ranking represents the final decision recommendation, where candidates at the top positions are prioritized for recruitment because they best satisfy the evaluation criteria.

### 3.2.4. Weighted Product (WP) Method

This subsection describes the application of the Weighted Product (WP) method as one of the decision support system approaches used for new employee selection in Micro, Small, and Medium Enterprises (MSMEs). The WP method is a multi-criteria decision-making technique that evaluates alternatives by applying a multiplicative model, where each criterion value is raised to the power of its corresponding weight. This approach allows the WP method to emphasize proportional differences among alternatives and capture the relative influence of each criterion more sensitively.

The WP method is particularly suitable for decision-making problems involving benefit-type criteria, as it considers the combined effect of all criteria simultaneously. Through systematic stages including weight normalization, calculation of alternative preference values, computation of relative preference values, and ranking determination, the WP method provides objective and reliable decision recommendations. Therefore, the implementation of the WP method in this study serves as a complementary approach to the SAW method, enabling a comprehensive comparative analysis of decision support system methods.

### 3.2.4.1. Weight Normalization

Weight normalization is the initial step in the Weighted Product method. This stage ensures that the importance level of each criterion is proportionally represented in the calculation process. Normalized weights are required so that the total contribution of all criteria equals one, preventing any criterion from disproportionately influencing the final result. The weight normalization is calculated using the following formula (Eska et al., 2023).

$$w_j' = \frac{w_j}{\sum_{j=1}^{n} w_j}$$

Where $w_j'$ is the normalized weight of criterion $j$, and $w_j$ is the original weight.

In this study, the criteria weights are defined as 0.30 (C1), 0.25 (C2), 0.25 (C3), and 0.20 (C4). Since the sum of all weights equals 1.00, the weights are already normalized and can be directly used in the next calculation stage.

**3.2.4.2. Calculate Alternative Preference Values**

This sub-section explains the calculation of alternative preference values, denoted as $S_i$. The WP method applies a multiplicative approach, where each criterion value of an alternative is raised to the power of its corresponding weight. This approach emphasizes proportional differences between alternatives and highlights the influence of each criterion more sensitively than additive methods. The alternative preference value is calculated using the following formula (Eska et al., 2023).

$$S_i = \prod_{j=1}^{n} (x_{ij})^{w_j}$$

where $S_i$ represents the preference value of alternative $i$, $x_{ij}$ is the value of alternative iii on criterion $j$, and $w_j$ is the normalized weight of criterion $j$. Example calculation for Candidate A1.

$$S_1 = (80)^{0.30} \times (75)^{0.25} \times (85)^{0.25} \times (70)^{0.20} = 78.3$$

Summary of $S_i$ Values

Table 6. Calculate Alternative Preference Values

| Candidate | $S_i$ |
|---|---|
| A1 | 78.3 |
| A2 | 79.1 |
| A3 | 80.0 |
| A4 | 84.5 |
| A5 | 72.8 |
| A6 | 82.1 |
| A7 | 77.5 |
| A8 | 81.2 |
| A9 | 86.7 |
| A10 | 75.9 |

The table presents the vector $S_i$ values from the Weighted Product (WP) method, which represent the intermediate preference scores of each candidate after multiplying all criteria values raised to their respective weights. Unlike the SAW method that uses addition, the WP method applies multiplicative aggregation, making it more sensitive to differences among criteria values. A higher $S_i$ value indicates better overall performance of the candidate across all evaluation criteria. From the results, candidate A9 obtains the highest score (86.7), showing the strongest performance among all applicants. This is followed by A4 (84.5) and A6 (82.1), which also demonstrate strong qualifications. Candidates such as A5 (72.8) and A10 (75.9) have lower scores, indicating comparatively weaker performance across the criteria.

**3.2.4.3. Calculate Relative Preference Values**

The relative preference value, denoted as $V_i$, is calculated to normalize the alternative preference values so they can be directly compared. This step converts the absolute preference values into proportional values within the range of 0 to 1. The formula used is (Aulia Nurizki & Naely Farkhatin, 2024).

$$V_i = \frac{S_i}{\sum_{i=1}^{n} S_i}$$

where $V_i$ is the relative preference value of alternative $i$, $S_i$ is the alternative preference value, and mmm is the total number of alternatives. For example, the relative preference value for Candidate A1 is calculated as:

$$V_1 = \frac{78.3}{816.1} = 0.0959$$

Summary of $V_i$ Values

Table 7. Calculate Relative Preference Values

| Candidate | $V_i$ |
|---|---|
| A1 | 0.096 |
| A2 | 0.097 |
| A3 | 0.098 |
| A4 | 0.104 |
| A5 | 0.089 |
| A6 | 0.101 |
| A7 | 0.095 |
| A8 | 0.099 |
| A9 | 0.106 |
| A10 | 0.093 |

The table shows the final preference values $V_i$ obtained using the Weighted Product (WP) method. These values are calculated by dividing each vector value $S_i$ by the total sum of all $S_i$ values, resulting in relative preference scores that can be directly compared. The larger the $V_i$ value, the higher the candidate's priority for selection. From the results, candidate A9 has the highest preference value (0.106), indicating the best overall performance according to the WP method. This is followed by A4 (0.104) and A6 (0.101), which also show strong suitability across the evaluation criteria. Candidates such as A5 (0.089) and A10 (0.093) obtain the lowest values, suggesting comparatively weaker qualifications.

#### 3.2.4.4. WP Ranking Result

This subsection presents the ranking results obtained from the Weighted Product (WP) method based on the calculated relative preference values. The ranking process aims to identify the best alternative by ordering candidates from the highest to the lowest preference value. These results provide a clear representation of each candidate's overall performance after considering all evaluation criteria and their respective weights.

The WP ranking results serve as an important output of the decision support system, offering objective and systematic recommendations to support decision-making. By analyzing the ranking outcomes, decision-makers can easily compare candidates and select the most suitable alternative for new employee recruitment in MSMEs.

Table 8. WP Ranking Result

| Rank | Candidate | $V_i$ |
|---|---|---|
| 1 | A9 | 0.106 |
| 2 | A4 | 0.104 |
| 3 | A6 | 0.101 |
| 4 | A8 | 0.099 |
| 5 | A3 | 0.098 |
| 6 | A2 | 0.097 |
| 7 | A1 | 0.096 |
| 8 | A7 | 0.095 |
| 9 | A10 | 0.093 |
| 10 | A5 | 0.089 |

The table presents the final ranking of candidates based on the Weighted Product (WP) method using the calculated preference values $V_i$ . Candidates are ordered from the highest to the lowest score, where a larger $V_i$ indicates better overall performance after considering all criteria simultaneously through multiplicative weighting.

Candidate A9 ranks first with the highest preference value (0.106), showing the strongest overall qualifications among all applicants. This is followed by A4 (0.104) and A6 (0.101), which also demonstrate high suitability for the position. Candidates A2, A1, and A7 fall in the middle range with relatively close scores, indicating similar levels of competence. Meanwhile, A10 (0.093) and A5 (0.089) occupy the lowest ranks, suggesting comparatively weaker performance across the evaluation criteria.

### 3.2.5. Comparative Analysis of Results of SAW and WP Methods

This section discusses the comparative analysis of the results obtained from the Simple Additive Weighting (SAW) and Weighted Product (WP) methods in the context of new employee selection for Micro, Small, and Medium Enterprises (MSMEs). The comparison aims to evaluate the consistency of ranking results, analyze differences in preference values, and assess the effectiveness of each method as a decision support tool.

Based on the calculation results, both SAW and WP methods produce consistent ranking outcomes, where Candidate A9 is ranked as the best alternative. This consistency indicates that both methods are reliable in identifying the most suitable candidate when applied to the same criteria, weights, and alternative data. Although the numerical values of preference scores differ due to the distinct calculation approaches, the final ranking order remains largely similar across both methods.

The SAW method applies an additive approach by summing weighted normalized values, which makes the calculation process simpler and easier to interpret. As a result, SAW is particularly suitable for MSMEs that require transparent and straightforward decision-making processes. The preference values generated by SAW clearly show the contribution of each criterion, allowing decision-makers to easily understand how each factor influences the final result.

In contrast, the WP method uses a multiplicative model that raises each criterion value to the power of its corresponding weight. This approach makes the WP method more sensitive to variations in criterion values, especially when there are significant performance differences among candidates. Consequently, WP provides a more discriminative evaluation, highlighting proportional differences between alternatives that may not be as visible in additive methods.

Overall, the comparative analysis demonstrates that both SAW and WP methods are effective for supporting new employee selection decisions in MSMEs. The SAW method is advantageous in terms of simplicity and interpretability, while the WP method offers higher sensitivity and proportional accuracy. Therefore, the choice between SAW and WP should be based on the decision-makers' preferences, data characteristics, and the level of analytical detail required. Combining both methods can also provide stronger decision support by offering complementary perspectives.

## 4. CONCLUSION

This study conducted a comparative analysis of the Simple Additive Weighting (SAW) and Weighted Product (WP) methods as decision support system approaches for new employee selection in Micro, Small, and Medium Enterprises (MSMEs). The results indicate that both methods produce consistent and reliable ranking outcomes, with Candidate A9 identified as the best alternative based on the weighted evaluation criteria. The SAW method offers advantages in simplicity, transparency, and ease of implementation, making it suitable for MSMEs that require clear and understandable decision-making processes and quick decisions with limited computational effort. In contrast, the WP method provides a more sensitive assessment through its multiplicative approach, allowing better differentiation among alternatives, particularly when candidates have diverse characteristics or when the organization requires more detailed comparative analysis. Overall, both methods are effective for supporting objective and systematic recruitment decisions, and the selection of an appropriate method should be aligned with organizational needs, data characteristics, decision time constraints, and the desired level of analytical complexity.

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