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Combination of Logarithmic Least Square Weighting and MAUT Method for Best Employee Selection in Retail Companies

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ABSTRACT

Selecting the best employees plays a crucial role in enhancing the performance of retail companies. Given that each employee has unique roles, responsibilities, and working conditions, creating a truly fair and consistent assessment standard can be challenging. Additionally, subjective factors such as personal bias or preferences of the assessor can influence the evaluation outcome. The integration of LLSW and the MAUT method in employee selection offers a systematic approach that combines precise weighting with multi-criteria utility analysis. This combination aims to improve the accuracy, objectivity, and transparency of the decision-making process. By utilizing both methods, retail companies can establish a more effective, transparent, and data-driven selection system, ensuring that the best employees are chosen based on rational and fair evaluations. The results of the employee selection process using LLSW and MAUT showed that Employee RS ranked first with the highest score of 0.7485, indicating the strongest qualifications compared to the other candidates. Employee LK and Employee ML ranked second and third with scores of 0.6035 and 0.572, respectively, demonstrating solid performance. These selection outcomes can assist companies in recruiting the most suitable workforce for their operational needs and vision, ultimately leading to improved productivity and service quality in the long run. The main contribution of this research is capable of improving accuracy and fairness in employee performance evaluation. This approach reduces the subjectivity that often occurs in conventional assessment processes in the retail sector, as well as providing a basis for transparent and measurable decision-making.

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INTRODUCTION

The selection of the best employees has a very important role in improving the performance of retail companies. In this competitive industry, qualified employees not only contribute to increased productivity, but also help create a better customer experience. The right selection process allows companies to get individuals with skills, knowledge, and work attitudes that are in accordance with the company's operational needs and culture(Saputra & Setiawansyah, 2024; Wang, Setiawansyah, et al., 2024; Yudhistira et al., 2024). In addition, competent employees are able to carry out their duties efficiently, provide the best service to customers, and adapt to dynamic market changes. Thus, good employee selection not only has an impact on increasing sales, but also strengthens customer loyalty and the company's reputation(Pratama & Hardianto, 2024). Therefore, retail companies need to implement an objective and systematic selection process to ensure

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that they recruit the best workforce that can support sustainable business growth.

Assessing and comparing employee performance objectively is a challenge for many companies, especially due to the various subjective factors and complexity of the work that must be considered(Karim, 2024). Each employee has different roles, responsibilities, and working conditions, making it difficult to establish a truly fair and equitable standard of assessment. In addition, subjective factors from the assessor, such as personal bias or certain preferences, can affect the outcome of the evaluation. Companies also have to face challenges in measuring qualitative aspects of performance, such as creativity, leadership, and teamwork, which are often difficult to convert into quantitative data. Additionally, employees may feel dissatisfied or disagree with the results of the assessment if they find the process not transparent or do not accurately reflect their contributions. Therefore, it is important for companies to develop clear, data-based, and objectively measurable evaluation methods so that the performance appraisal process becomes fairer and more accurate.

Decision Support Systems (DSS) play a crucial role in supporting data-driven decision-making by offering objective and structured analysis(Chen, 2024; Purba et al., 2023; Sulistiani et al., 2023). In the world of business and management, decision-making often involves a variety of complex factors that are difficult to evaluate manually. DSS allows processing large amounts of data, identifying patterns, and presenting recommendations based on analytical methods and artificial intelligence(Mishra et al., 2023; Siciliani et al., 2023). With this approach, decision-makers can avoid subjective bias and make more accurate and efficient decisions. In addition, DSS can help in various aspects, such as selecting the best employees, performance assessment, strategic planning, and risk management. By leveraging this technology, companies can improve operational effectiveness, optimize resources, and respond more quickly to market changes. Therefore, the implementation of DSS is a very valuable solution in supporting data-based and objectively weighted decision-making(Megawaty et al., 2025; Wang, Darwis, et al., 2024).

Research related to the application of the MAUT method in employee selection was conducted by (Putra et al., 2022), the MAUT method provides recommendations for decision-makers to determine which daily employees are eligible to be appointed as permanent employees based on the highest calculation results. Research from (Nuroji, 2022), the application of the MAUT method as a consideration in decision-making to produce recommendations for the best employees. Research from (BENADIA LATIFAH & PUTRI AISYIYAH RAKHMA DEVI, 2022), the application of MAUT and Rank Order Centroid weighting in determining the selection of outsourcing employees according to the specified field.

In multi-criteria decision-making, an objective weighting method is essential to optimally determine the weight of the criteria and avoid subjective bias(Ezell et al., 2021; Magableh, 2024). One widely used method is Logarithmic Least Squares Weighting (LLSW), which offers a mathematical approach to calculating weights based on paired comparisons(Csató, 2024; Mahendra & Setiawansyah, 2024). The main advantage of LLSW is its ability to optimize the consistency of assessments, so that the weights obtained are more stable and reliable. This method works by processing data from paired comparison matrices using a logarithmic approach and the least squared error reduction technique. Thus, LLSW is able to provide more accurate results than purely subjective methods, such as direct weighting based on the intuition of decision-makers(Aydi & Alatiyyah, 2024). In addition, LLSW can be used in a variety of situations where the comparison between criteria is multi-application, such as in employee performance evaluation, supplier selection, or business strategy determination. The application of objective weighting methods, such as LLSW, not only increases fairness and transparency in decision-making, but also ensures that each criterion has a weight that mathematically reflects its level of importance(SARSAR & ECHAOUI, 2024; Wang et al., 2025). With optimally calculated weights, the results of the evaluation become more credible, consistent, and accountable, thus supporting more rational and data-driven decisions.

The Multi-Attribute Utility Theory (MAUT) method offers several advantages in multi-criteria evaluations, particularly in assisting decision-makers in assessing multiple alternatives across a range of diverse criteria(Akpan & Morimoto, 2022; AlFaraidy et al., 2023). One of MAUT key strengths is its ability to quantitatively measure preferences, allowing decision-makers to assess each alternative by weight and scalable utility. This method also provides a systematic and transparent approach, where decisions are made based on clear and explainable mathematical calculations. In addition, MAUT is able to handle scale differences between criteria, so that different types of data can be effectively integrated in a single evaluation model (AlFaraidy et al., 2023; Arshad & Setiawansyah, 2024). The flexibility of this method also allows users to accommodate subjective preferences, which can be tailored to the specific needs of the decision-maker. Another advantage is its ability to analyze trade-off scenarios, where decision-makers can evaluate how changes in the weight or value of certain criteria affect the final outcome. With these advantages, MAUT is one of the methods that is widely used in various fields, such as employee selection, supplier selection, investment, and risk management. This method provides more objective and data-driven results, thereby improving the quality of decision-making in situations that are complex and involve many factors.

The integration of LLSW and MAUT in selecting the top employees in retail companies seeks to enhance the accuracy, objectivity, and transparency of the decision-making process. The combining these two methods, retail companies can obtain a more effective, transparent, and data-driven selection system, thus ensuring that the best employees are selected based on rational and fair calculations. This combination also helps companies in better managing human resources, increasing productivity, and supporting sustainable business growth.

RESEARCH METHOD

The research stages generally include several systematic steps starting with the formulation of the problem, where the researcher identifies the issue or question to be investigated(Hadad et al., 2025; Setiawansyah & Rahmanto, 2025). Furthermore, a literature study is carried out to understand previous theories and research that are relevant to the topic being studied(Lubis et al., 2024). After that, the researcher designs a research method, including the selection of approaches, data collection techniques, and analysis methods to be used. The next stage is data collection which is then analyzed using statistical techniques or other appropriate methods. The results of this analysis are interpreted to answer the research question, followed by conclusions and recommendations based on the findings obtained.

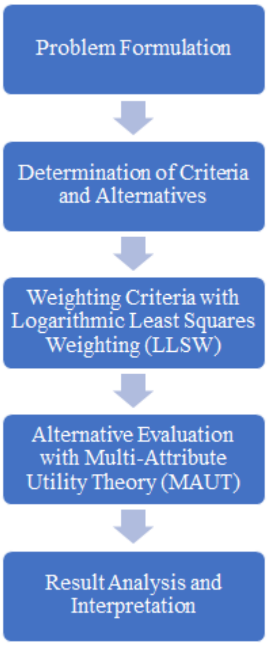

Figure 1. Research Stages

The stage of Figure 1 starts from identifying problems in the selection process of the best employees in retail companies, including subjectivity constraints in weighting criteria and the need for more objective and accurate methods. Determine employee assessment criteria, such as communication skills, work experience, loyalty, productivity, and teamwork ability. In addition, establish a list of employee candidates to be evaluated. Using LLSM to objectively determine the weighting of criteria based on the paired comparisons provided by the decision makers. Using the MAUT method to calculate the utility value of each candidate based on the weights obtained from the LLSM, resulting in the final ranking of the best employees. Evaluate the results of the selection by comparing the final rankings of candidates, analyzing sensitivity to weight changes, and assessing the effectiveness of the combination of methods in improving the quality of decisions.

1. Logarithmic Least Squares Weighting (LLSW) Method

   Logarithmic Least Squares Weighting (LLSW) is a weighting technique used in multi-criteria decision-making to objectively derive criterion weights through pairwise comparisons. This method operates on the principle of minimizing squared errors on a logarithmic scale, which enables it to produce more precise weights compared to other subjective approaches.

   Decision matrices play a crucial role in the overall decision-making process as they represent actual conditions assessed in a structured manner and allow employee evaluations to be conducted rationally and transparently, created using the following equation.

$$X = \begin{bmatrix} a_{11} & \cdots & a_{1j} \\ \vdots & \ddots & \vdots \\ a_{i1} & \cdots & a_{ij} \end{bmatrix} \quad (1)$$

   The weights of the criteria using LLSW are calculated using the following formula.

$$w_i = \frac{\sqrt[n]{\prod_{j=1}^{n} a_{ij}}}{\sum_{i=1}^{n}\left(\sqrt[n]{\prod_{j=1}^{n} a_{ij}}\right)} \quad (2)$$

2. Multi-Attribute Utility Theory (MAUT) Method

   MAUT Method is a decision-making method involving multiple criteria, used to evaluate and determine the most suitable alternative by calculating the overall utility derived from each attribute or criterion. This method is grounded in utility theory, where each option is assessed based on the degree of satisfaction or benefit it provides for each criterion.

   Decision matrices play a crucial role in the overall decision-making process as they represent actual conditions assessed in a structured manner and allow employee evaluations to be conducted rationally and transparently, created using the following equation.

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1j} \\ \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} \end{bmatrix} \quad (3)$$

   The normalization matrix is the benchmark of all criteria in standardizing the values in the same range, the value of the normalization matrix with a range of 0 to 1 is calculated by the following formula.

$$r_{ij}^{*} = 1 + \frac{\min x_{ij} - x_{ij}}{\max x_{ij} - \min x_{ij}} \quad (4)$$

$$r_{ij}^{*} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}} \quad (5)$$

Utility values are values that show how well the alternatives meet each criterion from the calculation of each alternative value of each criterion and are calculated using the following equation.

$$u_{ij} = \frac{e\left(\left(r_{ij}^{*}\right)^{2}\right) - 1}{1.71} \quad (6)$$

The final value of the utility of the alternative is the process of calculating the value of the utility with each weight of a predetermined criterion calculated using the following equation.

$$u_{(x)} = \sum_{j=1}^{n} u_{ij} * w_j \quad (7)$$

RESULTS AND DISCUSSION

The integration of LLSW with the MAUT method in selecting top-performing employees in retail companies offers a structured and effective approach that merges precise weighting with multi-criteria utility evaluation. LLSW objectively assigns weights to the criteria through pairwise comparisons, minimizing subjectivity in the evaluation process. The results of the criteria weights in the LLSW will be used in the MAUT method to calculate the final utility value of the existing candidate from the candidate's performance or value based on the predetermined criteria. Through this combination approach, each employee can be evaluated quantitatively, resulting in a final rating based on the highest utility value. This method provides more transparent, accurate, and accountable decisions, thus helping retail companies in selecting the best employees objectively and efficiently. In addition, the LLSW-MAUT combination allows companies to accommodate different levels of importance of criteria more fairly and consistently, as the logarithmic weights avoid subjective bias in decision-making. The normalization process in MAUT also ensures that scale differences between criteria do not distort the final result, so that each employee is judged against a balanced standard. By implementing this approach, retail companies can improve the effectiveness of employee selection, not only based on subjective assessments from managers, but also with the support of more rational data-driven analysis. The selection results obtained can help companies in recruiting the workforce that best suits the company's operational needs and vision, as well as improve productivity and service quality in the long term.

1. Determination of Criteria and Alternatives

   In the selection of the best employees in a retail company, determining criteria and alternatives is a crucial first step to ensure an objective decision that is relevant to the company's needs. The criteria used in the selection process should reflect important aspects that contribute to employee performance in the retail work environment. Some of the criteria used are communication skills (S-1), Work Ethics and Discipline (S-2), Productivity (S-3), Innovation and Problem Solving (S-4), Flexibility and Adaptation (S-5), and Loyalty and Dedication (S-6).

   Employee appraisal data is a crucial element to ensure objective and performance-based decisions. This data is obtained from various sources, such as supervisor evaluations, productivity reports, attendance records, and feedback from customers and colleagues. Each employee is assessed based on a number of key criteria in the retail environment. The assessment data of each employee is shown in table 1.

Table 1. Assessment Data

Employee Name	Criteria					
	S-1	S-2	S-3	S-4	S-5	S-6
Employee AN	8	9	7	8	7	9
Employee SR	9	8	8	7	9	8
Employee BS	7	9	9	6	7	9
Employee RA	8	7	6	9	8	7
Employee DW	9	8	9	7	6	8
Employee LK	8	9	7	8	9	9
Employee FN	7	7	8	6	8	8
Employee RS	9	9	9	8	7	9
Employee HS	8	8	7	7	9	8
Employee ML	7	9	8	9	7	9
Employee AH	9	7	7	8	8	7
Employee DP	8	8	9	6	9	8
Employee RP	7	9	8	7	6	9

The best employee appraisal data is sourced from retail companies that are derived from various appraisal methods that reflect employee performance, ethics, and contributions in the work environment. This data comes from the evaluation of supervisors who assess aspects of communication skills, work ethics, discipline, and productivity based on direct observation in store or office operations. Each candidate is assessed by three respondents consisting of a direct supervisor, team colleagues, and division supervisor. Each respondent provides an independent evaluation based on five predetermined criteria. In addition, quantitative data on employee productivity is collected through sales reports, the number of completed transactions, and the speed of customer service recorded in the company's management system. Peer surveys are also used to measure aspects of flexibility, adaptability, and teamwork, while customer feedback provides insights into communication skills and innovation in problem-solving. In addition, employee attendance history and loyalty data is collected from HRD records that include the level of attendance, tardiness, and participation in the company's development program.

2. Determination of Criteria with LLSW

The LLSW method is applied in determining the weights of criteria based on data objectively in the selection process of the best employees based on paired comparisons between criteria. This approach aims to eliminate subjectivity in weighting by using a logarithmic approach that optimizes consistency in assessment. The stage in determining weights with LLSW begins with building a paired comparison matrix, where each matrix element represents the level of importance of a criterion compared to other criteria. Next, the calculation of the logarithmic average value of each row of the comparison matrix is carried out. This value is then used to determine the relative weight of each criterion by normalizing the calculation results so that the total number of weights is equal to 1. The decision matrix is created using equation (1) based on the assessment data in table 1, the general form of the decision matrix is as follows.

$$X = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} & a_{15} & a_{16} \\ a_{21} & a_{22} & a_{23} & a_{24} & a_{25} & a_{26} \\ a_{31} & a_{32} & a_{33} & a_{34} & a_{35} & a_{36} \\ a_{41} & a_{42} & a_{43} & a_{44} & a_{45} & a_{46} \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} & a_{56} \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} \\ a_{71} & a_{72} & a_{73} & a_{74} & a_{75} & a_{76} \\ a_{81} & a_{82} & a_{83} & a_{84} & a_{85} & a_{86} \\ a_{91} & a_{92} & a_{93} & a_{94} & a_{95} & a_{96} \\ a_{101} & a_{102} & a_{103} & a_{104} & a_{105} & a_{106} \\ a_{111} & a_{112} & a_{113} & a_{114} & a_{115} & a_{116} \\ a_{121} & a_{122} & a_{123} & a_{124} & a_{125} & a_{126} \\ a_{131} & a_{132} & a_{133} & a_{134} & a_{135} & a_{136} \end{bmatrix}$$

The results of the decision matrix in its general form are as follows.

$$X = \begin{bmatrix} 8 & 9 & 7 & 8 & 7 & 9 \\ 9 & 8 & 8 & 7 & 9 & 8 \\ 7 & 9 & 9 & 6 & 7 & 9 \\ 8 & 7 & 6 & 9 & 8 & 7 \\ 9 & 8 & 9 & 7 & 6 & 8 \\ 8 & 9 & 7 & 8 & 9 & 9 \\ 7 & 7 & 8 & 6 & 8 & 8 \\ 9 & 9 & 9 & 8 & 7 & 9 \\ 8 & 8 & 7 & 7 & 9 & 8 \\ 7 & 9 & 8 & 9 & 7 & 9 \\ 9 & 7 & 7 & 8 & 8 & 7 \\ 8 & 8 & 9 & 6 & 9 & 8 \\ 7 & 9 & 8 & 7 & 6 & 9 \end{bmatrix}$$

The LLSW method in determining the weight of criteria by using (2), the calculation results for the communication skills criteria are as follows.

$$w_1 = \frac{\sqrt[13]{a_{11} * a_{12} * a_{13} * a_{14} * a_{15} * a_{16} * a_{17} * a_{18} * a_{19} * a_{110} * a_{11} * a_{112} * a_{113}}}{\begin{gathered}\left(\sqrt[13]{a_{11} * a_{12} * a_{13} * a_{14} * a_{15} * a_{16} * a_{17} * a_{18} * a_{19} * a_{110} * a_{11} * a_{112} * a_{113}}\right) + \\ \left(\sqrt[13]{a_{21} * a_{22} * a_{23} * a_{24} * a_{25} * a_{26} * a_{27} * a_{28} * a_{29} * a_{210} * a_{211} * a_{212} * a_{213}}\right) + \\ \left(\sqrt[13]{a_{31} * a_{32} * a_{33} * a_{34} * a_{35} * a_{36} * a_{37} * a_{38} * a_{39} * a_{310} * a_{311} * a_{312} * a_{313}}\right) + \\ \left(\sqrt[6]{a_{41} * a_{42} * a_{43} * a_{44} * a_{45} * a_{46} * a_{47} * a_{48} * a_{49} * a_{410} * a_{411} * a_{412} * a_{413}}\right) + \\ \left(\sqrt[6]{a_{51} * a_{52} * a_{53} * a_{54} * a_{55} * a_{56} * a_{57} * a_{58} * a_{59} * a_{510} * a_{511} * a_{512} * a_{513}}\right) + \\ \left(\sqrt[6]{a_{61} * a_{62} * a_{63} * a_{64} * a_{65} * a_{66} * a_{67} * a_{68} * a_{69} * a_{610} * a_{611} * a_{612} * a_{613}}\right)\end{gathered}}$$

$$w_1 = \frac{\sqrt[13]{8 * 9 * 7 * 8 * 9 * 8 * 7 * 9 * 8 * 7 * 9 * 8 * 7}}{\begin{gathered}\left(\sqrt[13]{8 * 9 * 7 * 8 * 9 * 8 * 7 * 9 * 8 * 7 * 9 * 8 * 7}\right) + \\ \left(\sqrt[13]{9 * 8 * 9 * 7 * 8 * 9 * 7 * 9 * 8 * 9 * 7 * 8 * 9}\right) + \\ \left(\sqrt[13]{7 * 8 * 9 * 6 * 9 * 7 * 8 * 9 * 7 * 8 * 7 * 9 * 8}\right) + \\ \left(\sqrt[13]{8 * 7 * 6 * 9 * 7 * 8 * 6 * 8 * 7 * 9 * 8 * 6 * 7}\right) + \\ \left(\sqrt[13]{7 * 9 * 7 * 8 * 6 * 9 * 8 * 7 * 9 * 7 * 8 * 9 * 6}\right) + \\ \left(\sqrt[13]{9 * 8 * 9 * 7 * 8 * 9 * 8 * 9 * 8 * 9 * 7 * 8 * 9}\right)\end{gathered}}$$

$$w_1 = \frac{7.9613}{7.9613 + 8.1906 + 7.7871 + 7.3162 + 7.6167 + 8.2752} = 0.1689$$

Figure 2 shows the overall result of the criterion weight value from the calculation of the LLSW method.

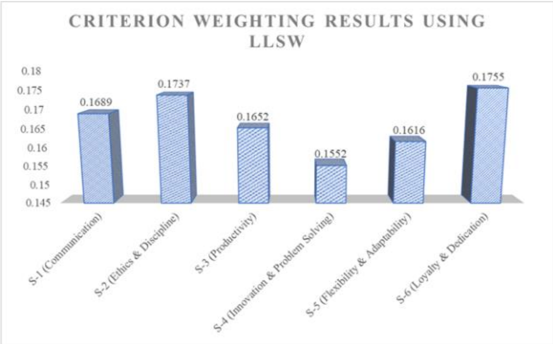

Figure 2. Criterion Weight Results

The criterion weighting graph Figure 2 displays the results of the criterion weighting using the Logarithmic Least Squares Weighting (LLSW) method. There are six main criteria evaluated, each with a specific weight. The criterion with the highest weight is Loyalty & Dedication (S6) with a score of 0.1755, followed by Ethics & Discipline (S2) with 0.1737. The Communication (S1) criterion received a weight of 0.1689, while Productivity (S3) had a weight of 0.1652. Furthermore, Flexibility & Adaptability (S5) has a weight value of 0.1616, and the lowest criterion weight is Innovation & Problem Solving (S4) with 0.1552. These results show that Loyalty & Dedication is the most important aspect of this evaluation, while Innovation & Problem Solving has the least role compared to other criteria.

3. Multi-Attribute Utility Theory (MAUT) Method for Best Employee Selection

The MAUT is a method within the MCDM framework that is used to evaluate and identify the most appropriate employees from a set of criteria. Decision-makers can measure utility value by applying the MAUT of each alternative by considering the relative importance of each attribute, so that the selection results are more objective and structured. In the context of employee selection, this method can systematically integrate factors to produce optimal recommendations for the company. With a clear and rationality-based calculation structure, MAUT helps companies reduce subjectivity in decision-making and increase accuracy in selecting the most potential employees. Therefore, the selection of the best employees in the recruitment process by implementing MAUT contributes to the development of better from quality human resources in the organization.

The decision matrix is created using equation (3) based on the assessment data in table 1, the general form of the decision matrix is as follows.

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{13} & x_{14} & x_{15} & x_{16} \\ x_{21} & x_{22} & x_{23} & x_{24} & x_{25} & x_{26} \\ x_{31} & x_{32} & x_{33} & x_{34} & x_{35} & x_{36} \\ x_{41} & x_{42} & x_{43} & x_{44} & x_{45} & x_{46} \\ x_{51} & x_{52} & x_{53} & x_{54} & x_{55} & x_{56} \\ x_{61} & x_{62} & x_{63} & x_{64} & x_{65} & x_{66} \\ x_{71} & x_{72} & x_{73} & x_{74} & x_{75} & x_{76} \\ x_{81} & x_{82} & x_{83} & x_{84} & x_{85} & x_{86} \\ x_{91} & x_{92} & x_{93} & x_{94} & x_{95} & x_{96} \\ x_{101} & x_{102} & x_{103} & x_{104} & x_{105} & x_{106} \\ x_{111} & x_{112} & x_{113} & x_{114} & x_{115} & x_{116} \\ x_{121} & x_{122} & x_{123} & x_{124} & x_{125} & x_{126} \\ x_{131} & x_{132} & x_{133} & x_{134} & x_{135} & x_{136} \end{bmatrix}$$

The results of the decision matrix in its general form are as follows.

$$X = \begin{bmatrix} 8 & 9 & 7 & 8 & 7 & 9 \\ 9 & 8 & 8 & 7 & 9 & 8 \\ 7 & 9 & 9 & 6 & 7 & 9 \\ 8 & 7 & 6 & 9 & 8 & 7 \\ 9 & 8 & 9 & 7 & 6 & 8 \\ 8 & 9 & 7 & 8 & 9 & 9 \\ 7 & 7 & 8 & 6 & 8 & 8 \\ 9 & 9 & 9 & 8 & 7 & 9 \\ 8 & 8 & 7 & 7 & 9 & 8 \\ 7 & 9 & 8 & 9 & 7 & 9 \\ 9 & 7 & 7 & 8 & 8 & 7 \\ 8 & 8 & 9 & 6 & 9 & 8 \\ 7 & 9 & 8 & 7 & 6 & 9 \end{bmatrix}$$

The normalization matrix contains the values obtained from the initial decision matrix, adjusted to all criteria on a uniform scale. Since all criteria are of the beneficial type, the normalization values are calculated using formula (5).

$$r_{11}^{*} = \frac{x_{11} - \min x_{11,113}}{\max x_{11,113} - \min x_{11,113}} = \frac{8-7}{9-7} = \frac{1}{2} = 0.5$$

Table 2 is the overall result of the calculation of the matrix normalization value for each employee.

Table 2. Matrix Normalization Value

Employee Name	Criteria					
	S-1	S-2	S-3	S-4	S-5	S-6
Employee AN	0.5	1	0.333	0.667	0.333	1
Employee SR	1	0.5	0.667	0.333	1	0.5
Employee BS	0	1	1	0	0.333	1
Employee RA	0.5	0	0	1	0.667	0
Employee DW	1	0.5	1	0.333	0	0.5
Employee LK	0.5	1	0.333	0.667	1	1
Employee FN	0	0	0.667	0	0.667	0.5
Employee RS	1	1	1	0.667	0.333	1
Employee HS	0.5	0.5	0.333	0.333	1	0.5
Employee ML	0	1	0.667	1	0.333	1
Employee AH	1	0	0.333	0.667	0.333	0

Employee DP	0.5	0.5	1	0	1	0.5
Employee RP	0	1	0.667	0.333	0	1

The utility value is calculated using a specific equation of each alternative criterion. This utility describes the extent to which the alternative meets the criteria and is determined using formula (6).

$$u_{11} = \frac{e((r_{11}^*)^2) - 1}{1.71} = \frac{e((0.5)^2) - 1}{1.71} = \frac{0.2840}{1.71} = 0.1661$$

Table 3 is the overall result of the calculation of the utility value for each employee's assessment.

Table 3. Utility Value

Employee Name	Criteria					
	S-1	S-2	S-3	S-4	S-5	S-6
Employee AN	0.1661	1.0048	0.0687	0.3273	0.0687	1.0048
Employee SR	1.0048	0.1661	0.3273	0.0687	1.0048	0.1661
Employee BS	0.0000	1.0048	1.0048	0.0000	0.0687	1.0048
Employee RA	0.1661	0.0000	0.0000	1.0048	0.3273	0.0000
Employee DW	1.0048	0.1661	1.0048	0.0687	0.0000	0.1661
Employee LK	0.1661	1.0048	0.0687	0.3273	1.0048	1.0048
Employee FN	0.0000	0.0000	0.3273	0.0000	0.3273	0.1661
Employee RS	1.0048	1.0048	1.0048	0.3273	0.0687	1.0048
Employee HS	0.1661	0.1661	0.0687	0.0687	1.0048	0.1661
Employee ML	0.0000	1.0048	0.3273	1.0048	0.0687	1.0048
Employee AH	1.0048	0.0000	0.0687	0.3273	0.3273	0.0000
Employee DP	0.1661	0.1661	1.0048	0.0000	1.0048	0.1661
Employee RP	0.0000	1.0048	0.3273	0.0687	0.0000	1.0048

The utility's final value is calculated based on the alternative value taking into account the weighted value of the criteria. The final result of the utility value of the existing alternative is used to determine the rank calculated by the formula (7).

$$u_{(1)} = \sum_{j=1}^{n} u_{11,61} * w_{1,6}$$

$$u_{(1)} = (u_{11} * w_1) + (u_{21} * w_2) + (u_{31} * w_3) + (u_{41} * w_4) + (u_{51} * w_5) + (u_{61} * w_6)$$

$$u_{(1)} = (0.1661 * 0.1689) + (1.0048 * 0.1737) + (0.0687 * 0.1652) + (0.3273 * 0.1552) + (0.0687 * 0.1616) + (1.0048 * 0.1755)$$

$$u_{(1)} = 0.4522$$

The overall results of the calculation of the final value of the utility for each employee's assessment are shown in table 4.

Table 4. Utility Final Value

Employee Name	Final Value
Employee AN	0.4522
Employee SR	0.4547
Employee BS	0.5280
Employee RA	0.2368
Employee DW	0.4043
Employee LK	0.6035
Employee FN	0.1361
Employee RS	0.7485
Employee HS	0.2704
Employee ML	0.5720
Employee AH	0.2847
Employee DP	0.4144
Employee RP	0.4157
Employee AN	0.4522

The final value of the utility in the Multi-Attribute Utility Theory (MAUT) method reflects the level of preference of each alternative based on the total utility value obtained. Each alternative is evaluated by combining the normalized values of each criterion that has been weighted according to its importance. The higher the utility value of an alternative, the greater the level of satisfaction or importance in decision-making. Thus, the alternative with the highest utility value is considered the best option because it has the most optimal combination of attributes according to the decision-making objectives.

4. Analysis of Results and Interpretation of Best Employee Selection

   The analysis of the results and interpretation of the selection of the best employees using a combination of LLSW and MAUT weighting was carried out by assessing each candidate based on the objective weight obtained from the LLSW as well as the total utility calculated through DEATH. LLSM gives more proportional weight to each criterion based on its level of importance, while MAUT is used to measure the extent to which each candidate meets predetermined criteria. The end result in the form of a utility score shows the employee's ranking, where the candidate with the highest score is considered the most qualified. The interpretation of these results not only helps in the objective selection of the best employees, but also provides insight into the key factors that contribute to the decision, allowing the company to devise a more effective employee development strategy. The ranking results in the selection of the best employees are shown in figure 3.

Figure 3. Alternative Ranking Results

Based on the results of the best employee selection shown in the chart, Employee RS ranked first with the highest score of 0.7485, indicating that he has the most superior qualifications compared to other candidates. In second and third place were Employee LK and Employee ML with scores of 0.6035 and 0.572, respectively, which also showed good performance. Employee BS followed in fourth place with a score of 0.528, while Employee SR and Employee AP were next with scores of 0.4547 and 0.4522. Other candidates, such as Employee RP, Employee DP, and Employee DW, have relatively lower scores in the range of 0.4157 to 0.4043. Meanwhile, the three candidates with the lowest scores were Employee HS(0.2847), Employee RA (0.2704), and Employee FN (0.1361). These results show significant differences in employee performance and competence, which can be the basis for decision-making for further promotions, training, or evaluations.

5. Discussion

Sensitivity analysis of alternative rankings is conducted to examine the extent to which the stability of the selection results for the best employees is affected by changes in the weights of the criteria. In the context of this study, sensitivity is analyzed by proportionally modifying the weights of one or several criteria, then observing whether significant changes occur in the ranking order of alternatives. The results of the analysis show that the final ranking tends to be stable even with moderate variations in weighting, which indicates that the combination of the LLSW and MAUT methods produces an assessment system that is quite robust against fluctuations in weight values. This stability suggests that the methods used are capable of consistently capturing the performance dominance of candidates, making the decisions taken not easily influenced by subjective changes in the determination of criteria weights.

Sensitivity analysis in this study was carried out by simulating changes in the weight of one criterion, specifically by increasing the weight by 0.05 on a certain criterion while simultaneously decreasing the weight by 0.05 on other criteria, so that the total weight remained constant. This approach was used to observe its impact on the ranking of alternatives or employees being evaluated. The results of the weight changes with the addition of weights in scenario S-1 increased by 0.05 (Test 1), S-2 increased by 0.05 (Test 2), S-3 increased by 0.05 (Test 3), S-4 increased by 0.05 (Test 4), S-5 increased by 0.05 (Test 5), S-6 increased by 0.05 (Test 6). Next, the scenario of changes with weight reduction in scenario S-1 decreased by 0.05 (Test 7), S-2 decreased by 0.05 (Test 8), S-3 decreased by 0.05 (Test 9), S-4 decreased by 0.05 (Test 10), S-5 decreased by 0.05 (Test 11), S-6 decreased by 0.05 (Test 12). The results of the sensitivity analysis of weight changes on the ranking of alternatives are displayed in table 5.

Table 5. Sensitivity Analysis Results of Alternative Ranking

Employee Name	Ori	Test 1	Test 2	Test 3	Test 4	Test 5	Test 6	Test 7	Test 8	Test 9	Test 10	Test 11	Test 12
Employee AN	1	1	1	1	1	1	1	1	1	1	1	1	1
Employee SR	2	2	2	2	3	2	2	2	2	2	2	3	2
Employee BS	3	3	3	3	2	3	3	3	3	3	4	2	3
Employee RA	4	4	4	4	4	4	4	4	4	4	3	4	4
Employee DW	5	5	7	5	6	5	5	8	5	6	5	7	7
Employee LK	6	6	5	7	5	7	7	5	7	5	6	5	5
Employee FN	7	9	6	9	7	8	9	6	9	7	8	6	6
Employee RS	8	8	8	6	8	6	6	7	6	8	7	9	8
Employee HS	9	7	9	8	9	9	8	8	8	9	9	8	9
Employee ML	10	10	10	10	10	10	10	10	10	10	10	10	10
Employee AH	11	11	11	11	11	11	11	9	11	11	11	11	11
Employee DP	12	12	12	12	12	12	12	12	12	12	12	12	12
Employee RP	13	13	13	13	13	13	13	13	13	13	13	13	13

The results of the sensitivity testing on alternative rankings show the overall the candidate rankings are quite stable despite changes in the weight of criteria in both directions, namely an increase and a decrease of 0.05. Employee RS consistently ranks first in all 12 testing scenarios, indicating that this candidate has very superior performance and is unaffected by changes in weighting. Employees LK and ML also show relative stability, with occasional rank exchanges between the second and third positions, indicating that both have competitive performance and are closely matched. Meanwhile, Employee BS maintained the fourth position in almost all scenarios, except in one test where it rose to third place. In contrast, candidates such as Employee SR, AN, RP, DP, and DW showed greater ranking fluctuations, indicating that their positions were more sensitive to changes in weights. Candidates with the lowest performance such as Employee AH, HS, RA, and FN showed stability in the bottom rankings without experiencing position changes, indicating low performance consistency across all weighting scenarios. Overall, these results confirm that the combination method of LLSW and MAUT has a high level of ranking stability against changes in weights, particularly for candidates with extreme performance (best and worst), while candidates with medium performance are more vulnerable to position shifts.

CONCLUSION

The combination of LLSW and the MAUT method in selecting the best employees in retail companies is a systematic approach that combines the accuracy of weighting with multi-criteria utility analysis. The combination of LLSW and MAUT in the selection of the best employees at retail companies aims to improve accuracy, objectivity, and transparency in the decision-making process. By combining these two methods, retail companies can obtain a more effective, transparent, and data-driven selection system, thus ensuring that the best employees are selected based on rational and fair calculations. This combination also helps companies in better managing human resources, increasing productivity, and supporting sustainable business growth. The results of the best employee selection using a combination of LLSW and MAUT resulted in Employee RS ranking first with the highest score of 0.7485, showing that he has the most superior qualifications compared to other candidates. In second and third place were Employee LK and Employee ML with scores of 0.6035 and 0.572, respectively, which also showed good performance. The selection results obtained can help companies in recruiting the workforce that best suits the company's operational needs and vision, as well as improve productivity and service quality in the long term. The results of the sensitivity testing on alternative rankings show that overall, the rankings of candidates are quite stable despite changes in the criteria weights in both directions, namely increases and decreases of 0.05. Employee RS consistently ranks first in all 12 testing scenarios, indicating that this candidate has an exceptional performance and is not affected by changes in weighting. These results confirm that the combination method of LLSW and MAUT has a high level of ranking stability against changes in weights, particularly for candidates with extreme performances (highest and lowest), while candidates with intermediate performances are more vulnerable to positional shifts.

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