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ARTICLE

Group Decision Support System (GDSS) Model on Software Engineer Selection: Integration of AHP,SAW, TOPSIS, and BORDA

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Abstrak

Salah satu persyaratan untuk keberhasilan perusahaan mana pun adalah pemanfaatan sumber daya manusia yang efisien dalam operasinya. Ada beberapa tugas berbeda yang termasuk dalam peran Manajemen Sumber Daya Manusia (SDM). Studi ini menggunakan teknik GDSS, menggabungkan TOPSIS untuk pembuat keputusan kedua dan AHP-SAW untuk pembuat keputusan pertama. Ada dua pembuat keputusan (DM), seperti halnya kasusnya. Setelah itu, peringkat setiap pembuat keputusan akan diproses menggunakan teknik BORDA. Studi ini menyimpulkan bahwa ada perbedaan dalam hasil dari DM1 dan DM2. Ini adalah hasil dari kecenderungan setiap pembuat keputusan untuk menawarkan penilaian yang unik. Sementara DM2 menggunakan teknik penilaian menggunakan persentase untuk menentukan bobot subparameter dan metode TOPSIS untuk peringkat, DM1 menggunakan metode AHP untuk bobot subparameter dan SAW untuk peringkat. Namun, para peneliti mengintegrasikan kedua pembuat keputusan dengan sistem pendukung keputusan kelompok yang memanfaatkan pendekatan BORDA, dengan memperhitungkan tingkat minat masing-masing pembuat keputusan. Temuan ini menyoroti kontribusi signifikan penelitian ini dalam menunjukkan bagaimana integrasi metode-metode ini secara efektif mengatasi perbedaan pendekatan evaluasi di antara para pengambil keputusan, khususnya dalam konteks rekayasa perangkat lunak, yang memastikan proses seleksi yang transparan dan berdasarkan data. Model GDSS diuji pada studi kasus pemilihan insinyur perangkat lunak, yang menunjukkan tingkat akurasi yang tinggi dalam mengidentifikasi kandidat yang paling sesuai untuk kebutuhan organisasi. Lebih jauh, hasil GDSS selaras dengan keputusan yang dibuat oleh perusahaan studi kasus, yang memvalidasi efektivitas model yang diusulkan. Penerapan praktis model ini dapat diadopsi oleh perusahaan untuk meningkatkan efisiensi dan kualitas proses rekrutmen.

Kata kunci: GDSS; AHP; SAW; TOPSIS; BORDA

Abstract

One of the requirements for any company's success is the efficient utilization of human resources in its operations. There are several different tasks that fall within the Human Resources Management (HRM) role. This study uses the GDSS technique, combining TOPSIS for the second decision maker and AHP-SAW for the first decision maker. There are two decision makers (DMs), as is the case. After that, each decision maker's ranking will be processed using the BORDA technique. This study concludes that there are differences in the outcomes from DM1 and DM2. This is a result of the propensity for every decision-maker to offer a unique assessment. While DM2 employs the scoring technique using percentages to determine sub-parameter weighting and the TOPSIS method for ranking, DM1 uses the AHP method for sub-parameter weighting and SAW for ranking. However, the researchers integrated the two decision makers with a group decision support system utilizing the BORDA approach, accounting for the decision makers' respective levels of interest. The findings highlight

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the significant contribution of this research in demonstrating how the integration of these methods effectively addresses differences in evaluation approaches among decision-makers, particularly in the context of software engineering, ensuring a transparent and data-driven selection process. The GDSS model was tested on a case study of software engineer selection, demonstrating a high level of accuracy in identifying the most suitable candidates for organizational needs. Furthermore, the results of the GDSS aligned with the decisions made by the case study company, validating the effectiveness of the proposed model. The practical application of this model can be adopted by companies to enhance the efficiency and quality of recruitment processes.

KeyWords: GDSS; AHP; SAW; TOPSIS; BORDA

1. Introduction

Workers are a important asset to the company. For employees to continue making a positive contribution to the organization, they must be handled as assets. One of the requirements for any company's success is the efficient utilization of human resources in its operations. The development of a corporation depends on its human resources [1]. The growth of the company depends on having high-quality human resources [2]. One of the most precious commodities is human resources, which are often lost because of the company's carelessness [3].

The Human Assets Administration (HRM) work envelops a wide run of obligations, but a few of the foremost pivotal ones are figuring out how many individuals you would like on staff and whether to fill positions with employees or free temporary workers, as well as recognizing and supporting the leading candidates and guaranteeing that they are tall entertainers, tending to execution issues, and guaranteeing that faculty and administration methods follow to legitimate necessities. Other tasks include overseeing your personnel policy, employee records, and benefits and compensation strategy [4].

The agency company understands that the best way to increase successful performance is to meet the demands of its employees. To satisfy their needs and act as a source of motivation, employees need to be rewarded or paid. According to Hazli's theory of reward and punishment in the workplace, a gift indicates acceptance of the practices and actions, but a sentence indicates rejection of the practices and activities [5]. By using reward and punishment systems, the company's primary goal should be accomplished and employee performance should be raised. One action an organization may take to enhance employee performance is to award employees [5]. According to the findings of a study [4] carried out at a financial institution, employee performance was positively impacted by rewards and penalties. However, in addition to employee performance, awards must be determined by impartial assessments. Employees may get shocks from receiving prizes that are arbitrary or misguided.

The selection of software engineers is a complex process due to the need to evaluate multiple criteria, such as technical skills, experience, and cultural fit. Traditional recruitment methods often fail to adequately balance the preferences of different decision-makers or provide a transparent evaluation process. This highlights the need for a decision-making framework that ensures fairness, accuracy, and consensus among stakeholders. Group Decision Support Systems (GDSS) have emerged as an effective solution for tackling multi-criteria decision-making challenges involving multiple stakeholders. GDSS offers structured methodologies that incorporate diverse perspectives to deliver more balanced and consensus-driven outcomes [6]. GDSS have been extensively researched and applied across various industries to address complex decision-making challenges [7][8][9][10]. By integrating methodologies such as AHP, TOPSIS, and BORDA, GDSS can address the varying evaluation approaches of decision-makers while maintaining objectivity. AHP is used to assess the relative significance of each criterion, TOPSIS evaluates and ranks alternatives by measuring their closeness to ideal solutions, and BORDA consolidates individual preferences into a collective group decision. This combination provides a comprehensive approach to managing the complexities of group decision-making in the context of software engineer selection.

This research aims to develop and evaluate a GDSS model that integrates AHP, TOPSIS, and BORDA to enhance the objectivity and efficiency of the software engineer selection process. The proposed model is tested in a dummy case study to validate its effectiveness and applicability. The study seeks to contribute to the field of decision support systems by demonstrating how the integration of these methods can address the challenges of group decision-making, particularly in handling diverse evaluation criteria and achieving consensus among decision-makers.

2. Method

In this method section, we explain several points, namely the model we propose, the GDSS theory we use, the AHP and TOPSIS theories we use, and the architecture of the GDSS we proposed.

2.1 Proposed Model

In this study, the Group Decision Support System (GDSS) model integrates the AHP-SAW method for the first decision-maker (DM1) and TOPSIS for the second decision-maker (DM2), with the final aggregation performed using the BORDA method. The choice of AHP-SAW for DM1 and TOPSIS for DM2 is based on the differing needs and evaluation approaches of each decision-maker. Figure 1 shows the proposed model.

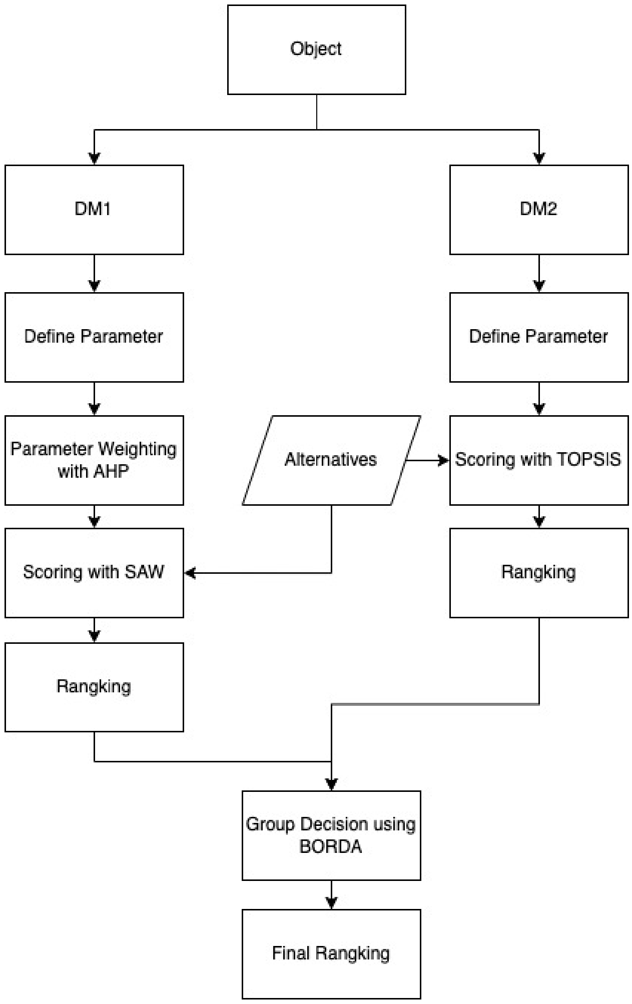

Figure 1. Model *Waterfall*

The proposed GDSS model leverages AHP to determine criteria weights, TOPSIS for individual decision-maker rankings, and BORDA for aggregating group preferences. This combination ensures a balanced consideration of all decision-makers' inputs while maintaining transparency and fairness in the selection process. This is the justification for Method Selection:

a. AHP-SAW for DM1
   AHP is employed to determine the weight of each criterion based on DM1's preferences. This method facilitates the evaluation of criteria within a hierarchical structure, assigns relative weights, and ensures consistency through the calculation of a consistency ratio. SAW is then used to compute the final scores of alternatives by summing the weighted normalized values for each criterion. The AHP-SAW

combination is selected because DM1 focuses on structured and consistent analysis of criteria and prioritizes value-based aggregation.

b. TOPSIS for DM2

TOPSIS is chosen for DM2 due to its ability to evaluate alternatives based on their proximity to the ideal solution. This method identifies the positive and negative ideal solutions and evaluates alternatives based on their relative distances to these solutions. TOPSIS is suitable for DM2, who emphasizes comparative evaluation of alternatives based on predefined criteria.

2.2 GDSS (Group Decision Support System)

A collection of devices, including hardware and software, called the GDSS makes group decision-making easier [7]. Even in situations when participants are unable to meet in person, Structure, efficient information flow, idea generation and organization, and assistance with sound decision-making are all provided by GDSS.. They appear to cover all of the requirements for conducting productive meetings [8].

Watson et al. [9] define a GDSS as a collection of technologies, such as computer, communication, and decision support tools, that help formulate and solve problems in group meetings.. Based on a variety of sources, they state that a GDSS's objective is to minimize process loss. All group interactions that impede decision-making are considered process losses. These consist of domineering individuals, haphazard activities, and peer pressure. The decision-making process can have a clear framework when a GDSS is used. It helps in idea generation, clarification, organization, reduction, and evaluation. The structuring adds value to the organization and frequently makes the decision-making process more effective and efficient.

Figure 2 shows the architecture of the GDSS IT Programmer selection.

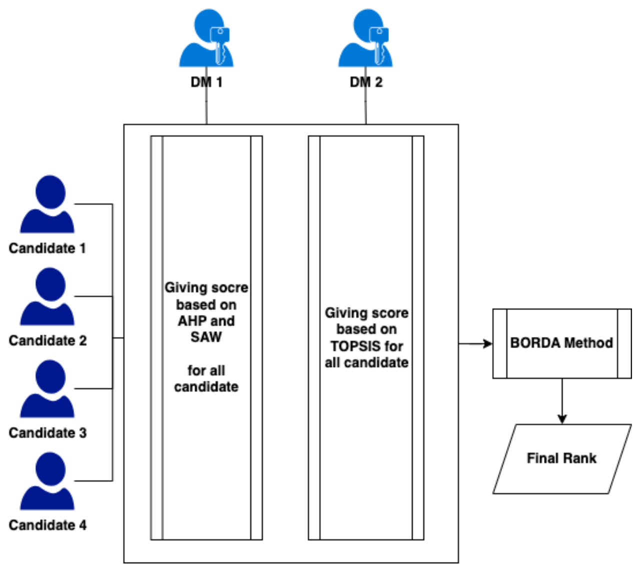

Figure 2. The GDSS architecture

Web-based technology is used in the most recent version of GDSS, which makes it affordable, available at any time and from any location, and practical as a stand-alone meeting tool [8]. The GDSS program performs calculations using a variety of voting methods, including Borda, Condorcet, Dodgson, Copeland, Coombs, Nansona, Simpson, Fishburne, and others [10].

According to Asgharpour (2003) quoted by [11], the Borda strategy includes the choice creator (DM) positioning the given problem's options agreeing to each property to begin with. Based on the profound network of bunch assention in respect to the n positions of the m gotten choices, which is taken from the arrangement of the choices positioning show, the DM at that point gets a demonstrate of zero and one programming.

2.3 Analytic Hierarchy Process (AHP)

An algorithm can be created using the AHP technique, which combines logic for experienced, intelligent, intuitive, quantitative, and qualitative data. Consequently, it enables decision-makers to determine the alternative comparison rate and the weight of each criterion.

The actions are as follows involved in solving problems with the AHP method [12]:

a. Establishing a hierarchy: One characteristic of problem-solving and solutions is the hierarchical structure.
b. By creating a square matrix $A = a_{ij} n \times n \text{covered} a_{ij} > 0, a_{ij} = \frac{1}{a_{ij}} \text{and} a_{ij} = 1$, a comparison matrix can be created. Reciprocal matrices are another name for comparative matrices. Comparative matrix utilizing the [1, 2, 3, 4, 5, 6, 13, 14, 15] comparison scores. Giving marks on a comparative scale according to suitable conditions and a quantitative scale.

$$A = \begin{bmatrix} a_{11} & K & a_{1n} \\ M & O & M \end{bmatrix} = a_{ij} \tag{1}$$

c. As indicated by equation (2), determines the multiplication result for each element on each line Mi.

$$A = \prod_{i=1}^{n} a_{ij} \tag{2}$$

d. Utilizing equation (3), determine the square root of Mi (n).

$$\overline{W} = \sqrt[n]{M_i} \tag{3}$$

e. The equation (4) illustrates the Vector number $Wi = (W1, W2, ..., Wn)t$, which is utilized in the normalization process.

$$A = \frac{\overline{W_i}}{\sum_{i=1}^{n} \overline{W_i}} \tag{4}$$

f. One of the matrix vector's features is the value $W = (W_1, W_2, W_3, \ldots, W_n)$.
g. The matrix's calculated lamdamax value is shown in equation (5).

$$\lambda_{\max} = \sum_{i=1}^{n} \sum_{i}^{n} a_{ij} W_j \tag{5}$$

h. Equation (6) shows the steps involved in determining the consistency index (CI) value.

$$CI = \frac{(\lambda_{\max} - n)}{(n - 1)} \tag{6}$$

i. The consistency ratio (CR) can be computed using equation (7). The random consistency index table can be used to determine the random consistency index (RI).

$$CR = \frac{CI}{RI} \tag{7}$$

2.4 SAW Method

According to [16], the SAW is a key multi-criteria decision-making method employed to determine the overall score of options by utilizing weighted criteria. The weighted total of each alternative's performance ratings across all categories is the basic calculation of the SAW method. The decision matrix needs to be normalized to a scale that may be compared with any available alternative rating in order to apply the SAW technique. The two types of criterion that the SAW technique recognizes are the benefit and the cost. The criterion for advantages is growing, which will raise the ranking. However, the criteria for the cost category negatively impact ranking. Put otherwise, the cost criteria has a larger value when it is ranked lower.

The steps for implementing the SAW method in this study are as follows:

a. Establishing criteria and weights: HRD interviews and discussions served as the basis for the establishment of criteria and weights in this study.
b. Alternative assessment: The purpose of this research is to evaluate employee performance and generate recommendations from those who do the best. Sample employees are thus options in this study.
c. Creating a decision matrix: A two-dimensional matrix containing the outcomes of various evaluations for every criterion is provided. After that, a different kind of value normalization is done. Equation 8 is used to normalize alternative values i for condition j. Equation 9 is used to determine the preference value (V) for each option i once the data has been normalized. The weights of the criterion are multiplied by their normalized values to get the preferred value.

$$r_{ij} = \begin{cases} \frac{x_{ij}}{\max(x_i)} & \text{if j are benefit criteria} \\ \frac{x_{ij}}{\min(x_i)} & \text{if j are cost criteria} \end{cases} \tag{8}$$

$$V_i = \sum_{i=1}^{n} W_j r_{ij} \tag{9}$$

where r_{ij} is the normalized value for alternative i and criteria j, W_j is the criteria weight, and V_i is the preference value for alternative i, n denotes the number of criteria.
d. Ranking: The preference value (V) is calculated in a method that yields the best employee suggestions.

2.5 TOPSIS Method

Yonn and Hwang first presented TOPSIS, a multi-criteria decision making technique, in 1981 in [17]. This method evaluates alternatives by calculating their relative distance from a positive ideal solution (PIS) and a negative ideal solution (NIS). The PIS represents the most desirable criteria values, while the NIS reflects the least favorable ones. In this study, TOPSIS was utilized to rate the top candidates for selection as alternative full-stack programmers.

The implementation of TOPSIS in this study involves the following steps [18]:

a. Develop a normalized matrix for decision-making
TOPSIS involves evaluating the performance of each employee alternative based on each normalized criterion. The performance rating goes through a normalization process, so that there is a uniform measurement scale for a number of indicators (the input values initiated in the matrix are on a scale of 0 to 1). To create a normalized decision matrix, each element in the matrix will be calculated using equation (10).

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{10}$$

So a normalized decision matrix will be formed as given in equation (??).

$$TM = \begin{bmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mn} \end{bmatrix} \tag{11}$$

Information for all of equation in this method:

- r_{ij} = normalized data value based on each criterion in the jth column for each employee in the it row
- x_{ij} = unnormalized data value based on each employee in the i-th row and from each criterion in the j-th column
- TM = normalized decision matrix
- i = 1,2,. . .,m is the number of employees
- j = 1,2,. . .,n is the number of criteria

b. Create a weighted normalized decision matrix
Equation (12) calculates the weighted normalized decision matrix (V) by multiplying each value in the normalized matrix (r_{ij}) by the corresponding criterion weight (W_{cj}), resulting in the weighted normalized decision matrix (V).

$$V_{ij} = W_{cj} * r_{ij} \tag{12}$$

Thus, the weighted normalized decision matrix is constructed as shown in equation (13):

$$V = \begin{bmatrix} w_{c1}r_{11} & \cdots & w_{cn}r_{1n} \\ \vdots & \ddots & \vdots \\ w_{c1}r_{m1} & \cdots & w_{cn}r_{mn} \end{bmatrix} \tag{13}$$

Added information:

- V_{ij} = value resulting from multiplying the values for each alternative in the normalized matrix (r_{ij}) with the weight of each criterion (W_{cj}).
- V = weighted normalized matrix
- W_{cj} = criteria weight in the jth column obtained from the profile matching weighting process

c. Determine the positive ideal solution and the negative ideal solution
Determining a positive ideal solution (Sj+) and a negative ideal solution (Sj-) is influenced by the nature of the criteria, whether benefit or cost. This report's calculations use the theory found in [19] research. The positive ideal solution (¬ Sj+) is determined by identifying the maximum value in the weighted normalized matrix (V) for benefit criteria. For cost criteria, the positive ideal solution (Sj+) is derived by selecting the minimum value in the weighted normalized matrix (V), as illustrated in equation (14).

$$S_j^+ = \begin{cases} \max_i V_{ij}, & \text{if } j \text{ is a benefit criterion} \\ \min_i V_{ij}, & \text{if } j \text{ is a cost criterion} \end{cases} \tag{14}$$

The negative ideal solution (Sj-) can be obtained by locating the weighted normalized matrix (V) with the lowest value if benefit is the criterion. The negative ideal solution (Sj-), which may be located by determining the weighted normalized matrix's maximum value, is the outcome of applying the cost criteria, as shown in Equation (15).

$$S_j^- = \begin{cases} \min_i V_{ij}, & \text{if } j \text{ is a benefit criterion} \\ \max_i V_{ij}, & \text{if } j \text{ is a cost criterion} \end{cases} \tag{15}$$

Added information:

- Sj+ = Positive ideal solution to the criteria in the jth column
- Sj- = Negative ideal solution to the criteria in the jth column
- Vij = Weighted normalized alternative for employees in row I and criteria in column j

d. Determine the distance between each alternative with a positive ideal solution and a negative ideal solution The distance between each employee alternative and the positive ideal solution (Sj+) is formulated in equation (16), determining the distance between each employee alternative and the positive ideal solution (Sj+) is to normalize the results of the accumulated reduction of the results of the positive ideal solution (Sj+) with the value of each weighted normalized alternative.

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \left(S_j^+ - V_{ij}\right)^2} \tag{16}$$

Equation (17) is utilized to compute the distance of each employee alternative from the negative ideal solution (Sj-). This is achieved by normalizing the cumulative difference between the values of each weighted normalized employee alternative and the negative ideal solution (Sj-), allowing the calculation of the distance for each employee alternative to the negative ideal solution (Sj-).

$$D_i^- = \sqrt{\sum_{j=1}^{n} \left(S_j^- - V_{ij}\right)^2} \quad (17)$$

Notes:

- Di+ = Distance of each alternative from the positive ideal solution (Sj+)
- Di- = Distance of each alternative from the negative ideal solution (Sj-)

e. Calculate the relative closeness value which is the preference value for each alternative
   The relative closeness value is determined by calculating the distance of each alternative from the negative ideal solution (Di-) and then dividing it by the sum of the distances between each employee alternative and both the negative ideal solution (Di-) and the positive ideal solution (Di+), as described in Equation (18). The symbol Ci represents the degree of closeness of each employee alternative to the ideal solution.

$$C_i = \frac{D_i^-}{D_i^- + D_i^+} \quad (18)$$

3. Result and Discussion

Each DMs has their own parameters in determining the best programmer. And each DMs also has their own method for determining the ranking of each alternative. The following are the results and discussion: DM1 ranking, DM2 ranking, and group ranking calculations.

3.1 Decision Maker 1

For decision maker 1, we used AHP and SAW method to select best IT Programmer. AHP is used for determining weight for each parameter and SAW is used for determining the ranking of candidates.

a. The first step is to determine the parameters used in assessing alternatives. Table 1 displays the parameter data used by DM1.

Table 1. Parameter

Parameter Code	Parameter	Sub Parameter Code	Sub Parameter
C1	Indisipliner	P1	Absence without confirmation
		P2	Number of Warning Letter (SP)
C2	Programming	P3	Web Programming
		P4	Mobile Programming
		P5	Web Services
C3	Database	P6	Query
		P7	Database Teory
		P8	Writing
C4	Design	P9	UI
		P10	UX
		P11	CSS
		P12	Graphic Design
C5	Networking	P13	Network
		P14	Security
		P15	System Engineer
		P16	Computer Teory
		P17	IT Support Experience
		P18	Subnetting

b. Stage 1, the first thing to do is evaluate all pairwise comparisons of parameters

Table 2. Pairwise Comparison of Parameter

C1	C2	C3	C4	C5	C4
C1	1	2	2	2	2
C2	0,5	1	2	2	2
C3	0,5	0,5	1	2	2
C4	0,5	0,5	0,5	1	2
C5	0,5	0,5	0,5	0,5	1

c. Next, calculations are carried out to obtain parameter weights using the following equation.

$$w_i = \frac{\sqrt[n]{\prod_{j=1}^{n} a_{ij}}}{\sum_{i=1}^{n} \sqrt[n]{\prod_{j=1}^{n} a_{ij}}} \tag{19}$$

The calculation of priority weights for each criterion can be exemplified as follows.

1) Step 1: After multiplying each element in a row by itself, take the root of the total number of elements. There are five elements (criteria) in this comparison of criteria.
2) Step 2: total all of the values derived from the step 1 root results. The following are the results of the addition:

Table 3. Value Product of Parameter

Parameters	Final Result Value
C1	1,741101127
C2	1,319507911
C3	1
C4	0,7578582833
C5	0,5743491775

3) Step 3: Each element's root result value (step 1) is divided by the total of its root result values (step 2) to determine its priority weight. Table 4 displays the outcomes of the priority weights for each criterion.

Table 4. The Priority Weights

Parameters	Final Result Value
C1	0,3228556223
C2	0,2446788077
C3	0,1854318611
C4	0,1405310719
C5	0,1065026369
Summarize	1

4) The next step is to measure consistency, and before you can do that, you must compute λ_{max} using the methods that were previously described in Research Method. The λ_{max} computation is displayed in the subsequent table.

Table 5. Addition to Measure Lamda Max

	C1	C2	C3	C4	C5
C1	1	2	2	2	2
C2	0,5	1	2	2	2
C3	0,5	0,5	1	2	2
C4	0,5	0,5	0,5	1	2
C5	0,5	0,5	0,5	0,5	1
Total per coloum	3	4,5	6	7,5	9
multiplication of Number per column and Priority Value	0,97	1,10	1,11	1,05	0,96

So λ_{max} is obtained by adding up the results of multiplying the Number of Columns with the Criteria Priority Weight, namely λ_{max} = 0.968566867 + 1.101054635 + 1.112591167 + 1.05398304 + 0.9585237323 = 5.19471944

After obtaining λ_{max}, calculations are carried out to obtain the consistency index (CI) according to equation (3).

$$CI = (5.19471944\check{}5)/(5\check{}5.19471944) = 0.04867986005$$

After the consistency index (CI) value is obtained, the consistency ratio (CR) is calculated. Based on a matrix of size 5, the random index (RI) value used is 1.12.

$$CR = 0.04867986005/1.12 = 0.03925795165$$

So the results obtained are CR = 0.03925795165, which means consistent. This result is because the CR value = 0.03925795165 is $\leq$ 0.1

5) The next step is to carry out pairwise comparisons of each sub-parameter in the same way as in stage 2 so that the absolute weights are obtained as follows:

Table 6. Weight of Parameter

Parameter Code	Weight	Sub Parameter Code	Weight
C1	0,32	P1	0,11
		P2	0,22
C2	0,24	P3	0,12
		P4	0,08
		P5	0,05
C3	0,19	P6	0,09
		P7	0,06
		P8	0,04
C4	0,14	P9	0,04
		P10	0,03
		P11	0,02
		P12	0,05
C5	0,11	P13	0,04
		P14	0,02
		P15	0,02
		P16	0,01
		P17	0,01
		P18	0,01

d. Next, ranking with SAW is as follows:

1) Assessment
Alternatives are given an assessment according to the parameters determined by DM1. The assessment results can be seen in Table 7.

Table 7. Assessment For Alternatives

	C1	C2	C3	C4	C5
P1	0	2	3	0	1
P2	0	1	0	0	1
P3	80	60	70	50	60
P4	70	80	80	80	80
P5	100	80	90	50	70
P6	70	80	90	60	70
P7	40	80	80	80	90
P8	70	80	60	60	50
P9	80	70	80	80	80
P10	90	90	80	90	90
P11	80	60	70	60	40
P12	70	80	90	90	70
P13	70	80	80	80	90
P14	70	80	60	60	50
P15	80	70	80	80	80
P16	70	60	80	90	70
P17	50	80	60	80	80
P18	80	80	60	50	60

2) Linear Interpolation

Because the score assessment results were not the same, normalization or equalization was carried out using linear interpolation. The results of linear interpolation calculations can be seen in Table 8.

Table 8. Scoring With Linear Interpolation

	C1	C2	C3	C4	C5
P1	5	2	1	5	4
P2	5	1	5	5	1
P3	5	2	4	1	2
P4	1	5	5	5	5
P5	5	3	4	1	3
P6	2	4	5	1	2
P7	1	4	4	4	5
P8	4	5	2	2	1
P9	5	1	5	5	5
P10	5	5	1	5	5
P11	5	3	4	3	1
P12	1	3	5	5	1
P13	1	3	3	3	5
P14	4	5	2	2	1
P15	5	1	5	5	5
P16	2	1	4	5	2
P17	1	5	2	5	5
P18	5	5	2	1	2

e. Multiplication of weight
   After the score is normal, the next step is to multiply the score by the weight obtained from the AHP process. The results of multiplying scores by weights can be seen in Table 9.

Table 9. Multiplication of Weight

	C1	C2	C3	C4	C5
P1	0,54	0,25	0,11	0,54	0,39
P2	1,08	0,22	1,08	1,08	0,22
P3	0,60	0,28	0,44	0,12	0,28
P4	0,08	0,38	0,38	0,38	0,38
P5	0,24	0,16	0,20	0,05	0,12
P6	0,21	0,34	0,46	0,09	0,21
P7	0,06	0,24	0,24	0,24	0,29
P8	0,13	0,18	0,08	0,08	0,04
P9	0,19	0,04	0,19	0,19	0,19
P10	0,14	0,14	0,03	0,14	0,14
P11	0,10	0,06	0,08	0,06	0,02
P12	0,05	0,16	0,27	0,27	0,05
P13	0,04	0,11	0,11	0,11	0,19
P14	0,07	0,10	0,05	0,05	0,02
P15	0,10	0,02	0,10	0,10	0,10
P16	0,03	0,01	0,04	0,06	0,03
P17	0,01	0,05	0,02	0,05	0,05
P18	0,04	0,04	0,02	0,01	0,02

f. Rank
The next step is the sum of the scores for each parameter. Table 10 below is the summation and ranking of the alternatives.

Table 10. Rank

Alternative	Total	Rank
A1	3705	2
A2	2780	4
A3	3908	1
A4	3618	3
A5	2740	5

3.2 Decision Maker 2

Numerous applications have made use of TOPSIS, such as choosing an operating system, evaluating customers, comparing business performance within an industry, making financial investment decisions, and designing robots [20]. The application of the TOPSIS method in providing assistance is a framework for making effective decisions on complex problems currently faced in decision making so that by simplifying and speeding up the decision making process, problems can be broken down into their parts so that the results obtained can help determine who those who are entitled to receive business capital assistance based on a clear ranking [18].

The method used by decision maker 2 is TOPSIS. The weighting for each existing sub-parameter is given to the decision maker based on the decision maker's preferences.

a. Create a normalized decision matrix
The first step is to determine the parameters used in assessing alternatives. Table 11 displays the parameter data used by DM2. Table 11 show the parameter from Decision Maker 2.

Table 11. Parameter

Parameter Code	Parameter	Sub Param. Code	Sub Parameter	Type	Weight
C1	Indisipliner	P1	Absence without confirmation	Cost	3.00%
		P2	Number of Warning Letter (SP)	Cost	4.00%
C2	Programming	P3	Web Programming	Benefit	15.00%
		P4	Mobile Programming	Benefit	13.00%
		P5	Web Services	Benefit	11.00%
C3	Database	P6	Query	Benefit	9.00%
		P7	Database Theory	Benefit	8.00%
C4	Design	P8	UI	Benefit	4.00%
		P9	UX	Benefit	4.00%
		P10	CSS	Benefit	5.00%
C5	Networking	P11	Network	Benefit	6.00%
		P12	Security	Benefit	6.00%
		P13	System Engineer	Benefit	7.00%
		P14	IT Support Experience	Benefit	5.00%

The employee data provided according to the sub parameters is shown by Table 12 and Table 13 show the normalized matrix using equation (10).

Table 12. Data Employee

	C1	C2	C3	C4	C5
P1	0	2	3	0	1
P2	0	1	0	0	1
P3	80	60	70	50	60
P4	70	80	80	80	80
P5	100	80	90	50	70
P6	70	80	90	90	70
P7	40	80	80	80	90
P8	80	70	80	80	80
P9	90	90	80	90	90
P10	80	60	70	60	40
P11	40	80	80	80	90
P12	70	80	60	60	50
P13	80	70	80	80	80
P14	40	80	60	80	80

Table 13. Normalized Matrix

	C1	C2	C3	C4	C5
P1	0,0000	0,5345	0,8018	0,0000	0,2673
P2	0,0000	0,7071	0,0000	0,0000	0,7071
P3	0,5521	0,4140	0,4830	0,3450	0,4140
P4	0,4008	0,4581	0,4581	0,4581	0,4581
P5	0,5599	0,4479	0,5039	0,2799	0,3919
P6	0,3889	0,4444	0,5000	0,5000	0,3889
P7	0,2353	0,4706	0,4706	0,4706	0,5294
P8	0,4581	0,4008	0,4581	0,4581	0,4581
P9	0,4569	0,4569	0,4061	0,4569	0,4569
P10	0,5643	0,4232	0,4937	0,4232	0,2821
P11	0,2353	0,4706	0,4706	0,4706	0,5294
P12	0,4830	0,5521	0,4140	0,4140	0,3450
P13	0,4581	0,4008	0,4581	0,4581	0,4581
P14	0,2561	0,5121	0,3841	0,5121	0,5121

b. Create a weighted normalized decision matrix
Table 14 show weighted normalized matrix using equation (12).

Table 14. Weighted Normalized Matrix

	C1	C2	C3	C4	C5
P1	0,0000	0,0160	0,0241	0,0000	0,0080
P2	0,0000	0,0283	0,0000	0,0000	0,0283
P3	0,0828	0,0621	0,0725	0,0518	0,0621
P4	0,0521	0,0596	0,0596	0,0596	0,0596
P5	0,0616	0,0493	0,0554	0,0308	0,0431
P6	0,0350	0,0400	0,0450	0,0450	0,0350
P7	0,0188	0,0376	0,0376	0,0376	0,0424
P8	0,0183	0,0160	0,0183	0,0183	0,0183
P9	0,0183	0,0183	0,0162	0,0183	0,0183
P10	0,0282	0,0212	0,0247	0,0212	0,0141
P11	0,0141	0,0282	0,0282	0,0282	0,0318
P12	0,0290	0,0331	0,0248	0,0248	0,0207
P13	0,0321	0,0281	0,0321	0,0321	0,0321
P14	0,0128	0,0256	0,0192	0,0256	0,0256

c. Determine the positive ideal solution and the negative ideal solution
Table 15 show the positive ideal solution using equation (14). Table 16 show the negative ideal solution using equation (15).

Table 15. Positive Ideal Solution

	S+		S+
P1	0,0000	P8	0,0183
P2	0,0000	P9	0,0183
P3	0,0828	P10	0,0282
P4	0,0596	P11	0,0318
P5	0,0616	P12	0,0331
P6	0,0450	P13	0,0321
P7	0,0424	P14	0,0256

Table 16. Negative Ideal Solution

	S-		S-
P1	0,0241	P8	0,0160
P2	0,0283	P9	0,0162
P3	0,0518	P10	0,0141
P4	0,0521	P11	0,0141
P5	0,0308	P12	0,0207
P6	0,0350	P13	0,0281
P7	0,0188	P14	0,0128

d. Determine the distance between each alternative with a positive ideal solution and a negative ideal solution
Table 17 show the distance of each alternative from the positive ideal solution using equation (16). Table 18 show the distance of each alternative from the negative ideal solution using equation (17). Table 19 show the rank of alternatives.

Table 17. D+

Alternative	Total	Rank
A1	0,0086	5
A2	0,0388	1
A3	0,0264	4
A4	0,0322	3
A5	0,0368	2

Table 18. D-

Alternative	Total	Rank
A1	0,0496	1
A2	0,0164	5
A3	0,0373	3
A4	0,0388	2
A5	0,0217	4

Table 19. Rank By Topsis

Alternative	Total	Rank
A1	0,8524	1
A2	0,2963	5
A3	3908	2
A4	3618	3
A5	2740	4

So with 14 criteria that are owned and processed using the TOPSIS method, the best fullstack programmer employee that will be selected is Alternative 1, namely Andin Cahyani Putri.

3.3 Group Decision with BORDA

After DM1 and DM2 carry out assessments according to the parameters determined by each, the next step is to calculate a joint decision using the BORDA method. The first is to determine the weight of each decision-maker. The following table shows the weights that have been determined.

Table 20. Weight of Decision Makers

DM	Weight
DM1	0,7
DM2	0,3

The scoring results of each decision maker are displayed in Table 21.

Table 21. Score from Decision Maker

DM\Alternative	A1	A2	A3	A4	A5
DM1	0,54	0,25	0,11	0,54	0,39
DM2	1,08	0,22	1,08	1,08	0,22

Next is to multiply the score from the decision makers by the predetermined weight.

Table 22. Multipliation DMs Score and Weight

DM\Alternative	A1	A2	A3	A4	A5
DM1	1,4	2,8	0,7	2,1	3,5
DM2	0,3	1,5	0,6	0,9	1,2
Total	1,7	4,3	1,3	3	4,7

The next step is to add up the weights for each alternative. So the total score and ranking are obtained which are displayed in Table 23.

Table 23. Final Rank

Alternative	Rank
A1	2
A2	4
A3	1
A4	3
A5	5

4. Conclusion

This study concludes that there are differences in the outcomes from decision makers one and two. This is a result of the propensity for every decision-maker to offer a unique assessment. While decision maker number 2 employs the scoring technique using percentages to determine sub-parameter weighting and the TOPSIS method for ranking, decision maker number 1 uses the AHP method for sub-parameter weighting and SAW for ranking. However, the researchers integrated the two decision makers with a group decision support system utilizing the BORDA approach, accounting for the decision makers' respective levels of interest. As a result, Doni Wijaya is the most skilled alternative full-stack programmer worker.

The results demonstrate that the proposed GDSS model outperforms traditional single-method approaches by effectively integrating decision-maker preferences into a unified ranking. Compared to standalone AHP or TOPSIS, the inclusion of BORDA ensures consensus while maintaining individual input fairness. The developed GDSS can be practically implemented in organizational recruitment processes to enhance the selection of candidates for critical roles, such as software engineers.

Despite its strengths, this study has certain limitations. The testing was conducted on a relatively small dataset and focused on a specific case study, which may not fully capture the complexities of larger-scale implementations. Additionally, the current model assumes predefined weights and criteria, which may not dynamically adapt to changing organizational needs. Future research can explore several potential enhancements to this model: expanding the scale of testing to include a broader range of decision-making scenarios and industries, developing a dynamic weighting mechanism that adapts to evolving organizational priorities and decision-maker preferences, integrating machine learning algorithms to improve the accuracy and adaptability of the model, and building a user-friendly application interface to facilitate the practical adoption of the GDSS in real-world settings.

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