

An Integrated Decision Support System Using Respond to Criteria Weighting and Root Assessment Method for Content Creator Selection

Temí Ardiansah^{1*}, Iswan A. Thais², Aditia Yudhistira³, Ahmad Ari Aldino⁴, Setiawansyah⁵

^{1,3,5}Department of Informatics, Faculty Engineering and Computer Science, Universitas Teknokrat Indonesia, Bandar Lampung, Lampung, Indonesia

²Department Computer Engineering, Faculty of Engineering, Institut Teknologi Gamalama, Ternate, Maluku, Indonesia

⁴Centre for Learning Analytics, Monash University, Victoria, Australia

E-mail: ^{1*}temi@teknokrat.ac.id, ²isonearrivegita25@gmail.com, ³aditiayudhistira@teknokrat.ac.id, ⁴ahmad.alldino@monash.edu, ⁵setiawansyah@teknokrat.ac.id

(Received: 8 Apr 2026, revised: 25 Apr 2026, 5 May 2026, accepted: 7 May 2026)

Abstract

This study proposes an integrated decision support system using the RECA Weighting and RAM methods to improve the objectivity and accuracy of content creator selection in the digital marketing era. The problem addressed arises from the complexity of evaluating multiple candidates based on various criteria such as content quality, engagement, consistency, creativity, and brand alignment, which are often assessed subjectively. The RECA method is applied to determine criteria weights objectively based on data variation among alternatives, while the RAM method is used to rank candidates through normalization, weighting, and root-based transformation to ensure more stable and balanced results. The findings show that the proposed approach is capable of producing consistent and reliable rankings, where the top three alternatives are Nabila Putri as the first rank, followed by Sinta Maharani in second place, and Putri Ananda in third place, indicating their superior performance across all evaluation criteria. Furthermore, sensitivity analysis by adjusting criteria weights by ± 0.05 indicates that the ranking results remain relatively stable, demonstrating the robustness of the model. Therefore, the integration of RECA and RAM provides an effective, transparent, and accountable solution for supporting decision-making in content creator selection.

Keywords: Decision Support System, RECA Weighting, RAM Method, Content Creator Selection, Multi-Criteria Decision Making.

I. INTRODUCTION

In the increasingly competitive digital marketing era, choosing the right content creator becomes a crucial factor in determining the success of an organization's or brand's marketing strategy [1]. Content creators not only serve as message deliverers but also as representations of a brand's values, identity, and credibility in the eyes of an audience that is becoming increasingly critical and selective. Accuracy in selecting individuals who have high creativity, understanding of the target market, and effective communication skills will have a direct impact on the level of engagement and conversion generated. However, this selection process is not a simple matter as it involves many candidates with varying backgrounds, content styles, and performances. Each candidate needs to be evaluated based on various criteria such

as content quality, consistency, audience size and interaction, as well as alignment with the brand values promoted. The main challenge arises when the assessment is multidimensional and potentially contains subjectivity, especially if it is not supported by systematic and measurable evaluation methods. This complexity increases along with the development of digital platforms that present a variety of performance metrics that need to be analyzed comprehensively to produce accurate and accountable decisions.

The problem of subjectivity in criteria weighting often becomes a major obstacle in the decision-making process, especially when evaluators have different perspectives, experiences, and preferences regarding the importance level of each criterion [2], [3]. Inconsistency in assigning weights can cause evaluation results to become biased and less reflective of the actual condition of each candidate. Each candidate may

have strengths in certain criteria but weaknesses in other aspects, so an approach that can accommodate trade-offs between criteria proportionally is needed. As the number of candidates increases, the ranking process becomes more complex and prone to calculation errors as well as inconsistencies in results. This situation requires a method that can manage data objectively and provide rankings that are stable and reliable.

Decision support system (DSS) for content creator selection is a system-based approach designed to assist decision-makers in selecting the content creator who best fits the needs and goals of digital marketing. This system utilizes data processing concepts and analysis methods based on multi-criteria decision making (MCDM) to evaluate various candidates in a more structured and objective manner. In its implementation, each content creator is assessed based on several important criteria such as content quality, engagement level, publication consistency, creativity, and alignment with brand identity [4]–[6]. DSS allows the integration of various data sources, both quantitative and qualitative, making the evaluation process more comprehensive and not solely dependent on subjective assessments [7]–[9]. This approach provides a stronger basis for decision-making because it is supported by transparent and measurable analysis.

The Respond to Criteria Weighting (RECA) method is an approach to determining criteria weights that emphasizes the response or variation of values from each criterion to the evaluated alternatives [10], [11]. The main principle of RECA is that criteria with higher levels of value differences between alternatives are considered more influential and deserve to be given greater weight. This approach aims to reduce subjectivity in the weighting process by utilizing information directly contained in the data. In its implementation, RECA analyzes the distribution of values for each criterion to identify how significant its contribution is in differentiating the performance of alternatives [11]. The greater the variation or response produced by a criterion, the higher its importance in the decision-making process. This method is very suitable for problems involving many criteria and alternatives, because it can provide weights more objectively and based on data. In addition, RECA can also be combined with other ranking methods to produce more accurate and consistent decisions.

The root assessment method (RAM) is one approach in the alternative ranking process that focuses on measuring the closeness of each alternative's value to the ideal condition by utilizing root-based transformation [12]–[14]. The main concept of RAM is to reduce the extreme influence of excessively large values through the root process, thereby making the data distribution more balanced and stable for analysis [15]–[17]. In its implementation, the performance values of each alternative for each criterion are first normalized, then a root transformation is performed to obtain more proportional evaluation values. This approach helps in capturing differences between alternatives more subtly without being overly influenced by outliers. Furthermore, the values of the transformed results will be accumulated according to the criteria weights to produce the final score for each alternative. The alternative with the highest score will occupy the best rank

in the decision-making process. This method is considered effective in improving ranking accuracy because it can reduce bias due to uneven data scales and provide more stable and representative results.

The integration of the RECA method and the RAM offers significant advantages in improving the quality of multi-criteria decision-making processes. RECA plays a role in generating more objective criteria weights because it is based on the level of variation or data response among alternatives, thereby minimizing subjectivity in determining the importance level of criteria. This approach is very relevant for complex problems involving many alternatives and criteria with diverse data characteristics. The integrated use of RECA and RAM provides a final result that is more reliable because it is supported by a systematic and measurable analysis process.

This study aims to develop a DSS for the selection of content creators that is more objective, systematic, and accurate. The RECA method is used to determine data-based criteria weights to reduce subjectivity, while RAM is applied to produce stable and proportional candidate rankings. The integration of these two methods is expected to produce evaluations that are comprehensive, consistent, and accountable, while also serving as a solution to the complexity of selection in the digital marketing era and as a reference for the development of DSS in similar fields.

II. RESEARCH METHODOLOGY

Research methodology is a scientific framework used as a guideline in designing, conducting, and evaluating research in a systematic and structured manner [18]–[20]. Research methodology not only serves as a technical guide, but also as a basis for developing a systematic thought process from the beginning to the end of the research. The stages of the research method used in this study can be seen in Figure 1.

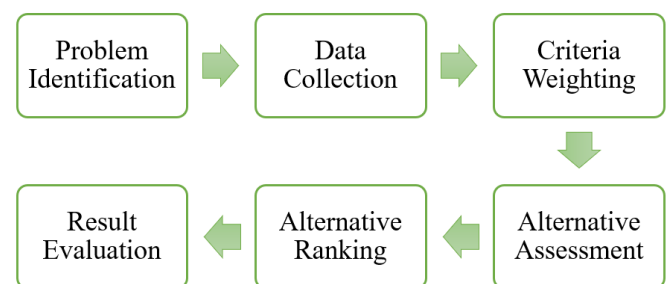


Figure 1. Research Method

The practical implication of these results indicates that the model used can serve as a reliable tool for decision-makers in selecting content creators more objectively and consistently. The stability of the rankings, even when there are changes in the weight of criteria, provides confidence that the decisions made are not easily influenced by fluctuations in preferences, thereby minimizing the risk of bias.

A. RECA Weighting Method

The RECA method is an approach to determining criteria weights based on the level of response or variation in the values of each criterion across the evaluated alternatives. The RECA method is very suitable for use in multi-criteria problems involving many alternatives with diverse data characteristics. This method can also improve the accuracy of evaluation results because it is able to represent the level of importance of criteria in a more proportional and data-based manner.

The first stage in the RECA method is the formation of a decision matrix that contains the performance values of each alternative against all the criteria used. This matrix is arranged in the form of a table with rows as alternatives and columns as criteria, making the subsequent analysis process easier. This structure becomes the main basis for calculations because the entire RECA process depends on the data arranged in the decision matrix using Equation 1.

$$X = [x_{ij}]_{m \times n} \quad (1)$$

Matrix X represents decision data consisting of m alternatives and n criteria, where each element x_{ij} indicates the value of the i^{th} alternative on the j^{th} criterion.

The second stage is determining the preference values that describe the relative importance of each value in the decision matrix. These values are obtained from the initial data that reflect the performance of alternatives on each criterion without any additional manipulation. These preference values become important inputs in the normalization process to ensure uniformity of data scale using Equation 2.

$$PV_{ij} = \frac{x_{ij}}{\sqrt[n]{\prod_{j=1}^n x_{ij}}} \quad (2)$$

The symbol PV_{ij} indicates the normalization process by dividing each value x_{ij} by the geometric mean of all the values in that criterion.

The third stage is the normalization process, which aims to equalize the value scale among criteria so that they can be compared fairly. Normalization is carried out by converting the values in the decision matrix into a proportional form according to the characteristics of the criteria, whether they are benefits or costs. The result of this normalization ensures that no criterion dominates solely due to differences in value scale using Equation 3.

$$R_{ij} = \frac{PV_{ij}}{PV_{jmax}} \quad (3)$$

The symbol R_{ij} indicates an advanced normalization process by comparing each PV value against the maximum value for the j^{th} criterion.

The fourth stage is the calculation of the average value for each criterion based on the obtained normalization results. This average value is used to represent the general condition of each criterion for all alternatives. This calculation serves as a

reference in measuring the level of value deviation in the next stage using Equation 4.

$$N_j = \frac{1}{n} \sum R_{ij} \quad (4)$$

The symbol N_j represents the average value of the normalized result R_{ij} for each criterion j^{th} across all alternatives.

The fifth stage is determining the preference variation value, which shows how large the difference is between the value of each alternative and the average of the criteria. This variation is calculated to understand the level of data dispersion for each criterion. The greater the variation produced, the greater the contribution of that criterion in differentiating the alternatives using Equation 5.

$$\emptyset_j = \sum_{i=1}^m [R_{ij} - N_j]^2 \quad (5)$$

The symbol $\emptyset_j$ represents the total squared deviation of each normalized value from the mean in the j^{th} criterion, which reflects the level of data variation.

The sixth stage is calculating the preference deviation value, which describes the level of deviation of the values from the average in more detail. This value shows how far each alternative's value deviates from the average value of each criterion. The results of this calculation become the basis for determining the relative importance level of each criterion using Equation 6.

$$\Omega_j = |1 - \emptyset_j| \quad (6)$$

The symbol Ω_j indicates the degree of closeness of the level of variation of a criterion to the ideal value, which is used to determine its level of importance.

The seventh stage is the determination of the criterion weight values obtained based on the preference deviation values that have been calculated previously. Criterion weights are calculated by considering the level of variation and deviation, resulting in more objective values. These weights are then used in the process of evaluating and ranking alternatives in the next stage using Equation 7.

$$w_j = \frac{\Omega_j}{\sum_{j=1}^n \Omega_j} \quad (7)$$

The symbol w_j represents the weight normalization process, to produce the final weight for each criterion.

The RECA method provides an approach to criterion weighting that is objective by utilizing variations in data between alternatives as the basis for assessment. With these characteristics, RECA becomes an effective method for supporting complex, data-based multi-criteria analysis.

B. RAM Ranking Method

The RAM is an approach in the process of ranking alternatives used to determine the best order based on

performance values across various criteria. This approach allows for a more sensitive analysis of value differences without neglecting the overall balance of the data.

The first stage in the RAM method is the formation of a decision matrix containing the performance values of each alternative against all predetermined criteria. This matrix is systematically arranged with alternatives as rows and criteria as columns to facilitate the analysis process. The decision matrix serves as the main basis for all calculations in the RAM method using Equation 1.

The second stage is the normalization of the decision matrix, which aims to equalize the value scales between criteria so that they can be compared proportionally. This process is carried out by considering the type of criteria, whether benefit or cost, so that the resulting values reflect a balanced condition. The normalization results ensure that there is no bias due to differences in data scales using Equation 8.

$$n_{ij} = \frac{x_{ij}}{\sum_{i=1}^n x_{ij}} \quad (8)$$

The symbol n_{ij} indicates the normalization process by dividing each value x_{ij} by the total value in the same criterion so that the relative proportion is obtained.

The third stage is the weighting multiplication, where each normalized value is multiplied by the predetermined criterion weight. This process aims to assign an appropriate level of importance to each criterion in evaluating alternatives. Thus, the contribution of each criterion to the final result can be accounted for proportionally using Equation 9.

$$k_{ij} = n_{ij} * w_j \quad (9)$$

The symbol k_{ij} represents the weighted value obtained from the multiplication of the normalization value with the criterion weight.

The fourth stage is the calculation of the total score for each alternative based on the weighting multiplication results. This total value is obtained by summing all the values of each criterion that have been multiplied by their respective weights. The total score reflects the overall performance level of each alternative using Equation 10 and 11.

$$S_{+i} = \sum_{j=1}^n k_{+ij} \quad (10)$$

$$S_{-i} = \sum_{j=1}^n k_{-ij} \quad (11)$$

The symbol S_{+i} and S_{-i} represents the total weighted value for criteria of the benefit and cost types for each alternative.

The last stage is the calculation of the final score, which is done by applying a root transformation to the total score to produce a more stable value. This transformation aims to reduce the influence of extreme values so that the evaluation results become more balanced. This final score is used as the basis for determining the ranking of the best alternative using Equation 12.

$$RI_i = \sqrt[2+S_{-i}]{2 + S_{+i}} \quad (12)$$

The symbol RI_i represents the value of the preference index of an alternative obtained from the combination of total cost and benefit criterion values to measure overall performance.

The RAM method offers a ranking approach capable of producing more stable evaluation values through root-based transformations. With these characteristics, RAM becomes an effective method for generating accurate and representative rankings in multi-criteria decision making.

III. RESULT AND DISCUSSION

An Integrated Decision Support System Using RECA and RAM for Content Creator Selection is an approach to a decision support system designed to assist the content creator selection process in a more objective, structured, and data-based manner. The combination of these two methods enables a more comprehensive evaluation as it can accommodate many criteria with different characteristics. The final result of this system is expected to be able to provide recommendations that are more consistent, transparent, and accountable.

A. Problem Identification

The identification of the problem in this study stems from the increasing need of the digital marketing industry for content creators who are able to provide a significant impact on promotion and branding strategies. In practice, the process of selecting content creators is often carried out manually based on subjective judgment, personal experience, or popularity alone without using a structured analytical approach. This condition causes the selection results to not always reflect the actual performance of the candidates because each content creator has different characteristics and strengths. In addition, the many criteria that need to be considered, such as content quality, engagement rate, posting consistency, creativity, and suitability with the brand, make the evaluation process increasingly complex. This complexity increases further when the number of candidates to be evaluated is quite large, making it difficult for decision-makers to perform an objective and comprehensive comparison.

Another identified problem is the absence of a standard method capable of combining the process of criteria weighting and alternative ranking objectively in the selection of content creators. The weighting of criteria used in many cases still depends on the decision-maker's preferences, so the level of importance between criteria does not always reflect the actual data conditions. This results in final outcomes that are less stable and difficult to replicate under different data conditions. Furthermore, the lack of an integrated decision support system causes the evaluation process to proceed separately between the weighting and ranking stages, thereby increasing the risk of inconsistent results. Therefore, an approach is needed that is capable of integrating data-based weighting and more stable ranking methods so that the process of selecting content creators can be carried out more effectively, accurately, and accountably.

B. Data Collection

Data collection in this study was conducted to obtain relevant information related to the process of selecting content creators, which will be analyzed using a decision support system approach. The data collected include alternative data in the form of a list of content creators who are candidates, as well as criteria data used as the basis for assessment. All the collected data is then selected and adjusted to fit the research needs so that only relevant data is used in the further analysis process.

The collection of criteria data in this study was carried out to determine the aspects used in evaluating content creators objectively. The criteria were established based on literature studies and observations of digital marketing practices, including content quality, engagement, consistency, creativity, and brand alignment. The structured preparation of criteria aims to make the evaluation process more systematic and objective. The results of the criteria data collection are fully presented in Table 1.

Table 1. Criteria Data

Criteria Code	Criteria Name	Criteria Type
CCT1	Endorsement Fees	Cost
CCT2	Content Creativity	Benefit
CCT3	Upload Consistency	Benefit
CCT4	Engagement	Benefit

Table 2. Assessment Data

Alternative Name	CCT1	CCT2	CCT3	CCT4	CCT5	CCT6	CCT7
CC1 – Rizky	8.5	85	80	88	84	83	86
CC2 – Maharani	12	90	85	92	88	89	91
CC3 – Dimas	6.5	78	75	80	79	77	78
CC4 – Ayu	9	88	82	86	87	85	88
CC5 – Nugroho	5.5	75	78	74	76	73	75
CC6 – Nabila	15	92	90	94	91	93	92
CC7 – Wijaya	7	80	77	82	81	79	80
CC8 – Ananda	10	87	83	89	86	88	87

C. Criteria Weighting

The determination of weights using the RECA method is carried out by utilizing the variation information of data in each criterion to produce a more objective level of importance. This approach helps reduce bias in weight determination, making the evaluation results more-fair and representative. The weights obtained are then used as the basis in the further analysis process to determine the best alternative.

The first stage in the RECA method is the formation of a decision matrix containing the performance values of each alternative against all the criteria used. This structure becomes the main basis for calculations because the entire RECA process relies on the data arranged in the decision matrix using Equation 1, the results of the decision matrix assessment data are as follows.

The second stage of determining weights using the RECA method is to determine the preference values that represent the relative importance of each value in the decision matrix using Equation 2, the calculation results of the preference values.

Criteria Code	Criteria Name	Criteria Type
CCT5	Visual & Editing Quality	Benefit
CCT6	Understanding of Target Audience	Benefit
CCT7	Storytelling Ability	Benefit

Data collection for the evaluation of alternatives in this study was conducted to obtain evaluation scores for each content creator based on predetermined criteria. Each alternative was systematically assessed based on established indicators to ensure that the evaluation process could be carried out objectively and measurably. In addition, the evaluation data were also adjusted to the same scale to facilitate the comparison process between alternatives in the subsequent analysis stage. The results of this alternative evaluation data collection are presented in full in Table 2.

The dataset in Table 2 represents performance variations of eight content creator alternatives across seven criteria (CCT1–CCT7). The values show clear differences among alternatives, reflecting heterogeneous and unbiased conditions. The mix of quantitative data (CCT1) and performance-based scores enables a balanced evaluation of productivity and quality. Overall, the dataset is suitable for testing decision-making models, as it effectively captures variation and supports objective differentiation of alternative performance.

$$X = \begin{bmatrix} 9 & 85 & 80 & 88 & 84 & 83 & 86 \\ 12 & 90 & 85 & 92 & 88 & 89 & 91 \\ 7 & 78 & 75 & 80 & 79 & 77 & 78 \\ 9 & 88 & 82 & 86 & 87 & 85 & 88 \\ 6 & 75 & 78 & 74 & 76 & 73 & 75 \\ 15 & 92 & 90 & 94 & 91 & 93 & 92 \\ 7 & 80 & 77 & 82 & 81 & 79 & 80 \\ 10 & 87 & 83 & 89 & 86 & 88 & 87 \end{bmatrix}$$

$$PV_{11} = \frac{x_{11}}{\sqrt[8]{\prod_{i=1}^8 x_{i1}}}$$

$$PV_{11} = \frac{x_{11}}{\sqrt[8]{x_{11} * x_{11} * x_{11} * x_{11} * x_{11} * x_{11} * x_{11} * x_{11}}}$$

$$PV_{11} = \frac{9}{\sqrt[8]{42865200}} = \frac{9}{8.9952} = 1.0005$$

The results of the overall preference score calculation using the RECA method are shown in Table 3.

Tabel 3. Preference Value of RECA Method

Alternative Name	CCT1	CCT2	CCT3	CCT4	CCT5	CCT6	CCT7
CC1 – Rizky	1.0005	1.0097	0.9861	1.0305	1.0016	0.9984	1.0187
CC2 – Maharani	1.3340	1.0691	1.0478	1.0774	1.0493	1.0705	1.0779
CC3 – Dimas	0.7782	0.9266	0.9245	0.9368	0.9420	0.9262	0.9239
CC4 – Ayu	1.0005	1.0454	1.0108	1.0071	1.0374	1.0224	1.0424
CC5 – Nugroho	0.6670	0.8909	0.9615	0.8666	0.9062	0.8781	0.8884
CC6 – Nabila	1.6675	1.0929	1.1094	1.1008	1.0850	1.1187	1.0898
CC7 – Wijaya	0.7782	0.9503	0.9491	0.9603	0.9658	0.9503	0.9476
CC8 – Ananda	1.1117	1.0335	1.0231	1.0422	1.0254	1.0585	1.0306

The third stage of determining weights using the RECA method is the normalization process carried out by converting the values in the decision matrix into a proportional form according to the characteristics of the criteria using Equation 3, the calculation results of the normalization values are as follows.

$$R_{11} = \frac{PV_{11}}{PV_1^{max}} = \frac{1.0005}{1.6675} = 0.6000$$

The results of the overall normalization value calculation using the RECA method are shown in Table 4.

Tabel 4. Normalization Value of RECA Method

Alternative Name	CCT1	CCT2	CCT3	CCT4	CCT5	CCT6	CCT7
CC1 – Rizky	0.6000	0.9239	0.8889	0.9362	0.9231	0.8925	0.9348
CC2 – Maharani	0.8000	0.9783	0.9444	0.9787	0.9670	0.9570	0.9891
CC3 – Dimas	0.4667	0.8478	0.8333	0.8511	0.8681	0.8280	0.8478
CC4 – Ayu	0.6000	0.9565	0.9111	0.9149	0.9560	0.9140	0.9565
CC5 – Nugroho	0.4000	0.8152	0.8667	0.7872	0.8352	0.7849	0.8152
CC6 – Nabila	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
CC7 – Wijaya	0.4667	0.8696	0.8556	0.8723	0.8901	0.8495	0.8696
CC8 – Ananda	0.6667	0.9457	0.9222	0.9468	0.9451	0.9462	0.9457

The fourth stage of determining weights using the RECA method is the calculation of the average value for each criterion based on the normalization results obtained using Equation 4, the results of the preference value calculations are as follows.

$$N_1 = \frac{1}{8} \sum_{i=1}^8 R_{i1} = \frac{1}{8} (5.0000) = 0.6250$$

The results of the overall average score calculation using the RECA method are presented in Table 5.

Tabel 5. Average Value of RECA Method

CCT1	CCT2	CCT3	CCT4	CCT5	CCT6	CCT7
0.6250	0.9171	0.9028	0.9109	0.9231	0.8965	0.9198

The fifth stage of determining weights using the RECA method is to determine the preference variation value, which indicates how much difference exists between the value of each alternative and the average of the criteria, obtained by using Equation 5. The results of the calculation of the preference variation values are as follows.

$$\begin{aligned} \phi_1 &= \sum_{i=1}^8 [R_{i1} - N_1]^2 \\ \phi_1 &= 0.0006 + 0.0306 + 0.0251 + 0.0006 + 0.0506 \\ &\quad + 0.1406 + 0.0251 + 0.0017 \\ \phi_1 &= 0.2750 \end{aligned}$$

The results of the overall preference variation value calculation using the RECA method are presented in Table 6.

Tabel 6. Preference Variation Value of RECA Method

CCT1	CCT2	CCT3	CCT4	CCT5	CCT6	CCT7
0.2750	0.0305	0.0202	0.0348	0.0213	0.0365	0.0321

The sixth stage of determining weights using the RECA method is calculating the preference deviation value, which describes the level of deviation of the value from the average more specifically calculated using Equation 6, the results of the calculation of the preference deviation value are as follows.

$$\Omega_1 = |1 - \phi_1| = |1 - 0.2750| = 0.7250$$

The results of the overall preference variation deviation calculation using the RECA method are shown in Table 7.

Tabel 7. Preference Deviation Value of RECA Method

CCT1	CCT2	CCT3	CCT4	CCT5	CCT6	CCT7
0.7250	0.9695	0.9798	0.9652	0.9787	0.9635	0.9679

The seventh stage of determining weights using the RECA method is the determination of the criteria weight values obtained based on the preference deviation values that have been calculated using Equation 7, the results of the weight value calculation are as follows.

$$w_1 = \frac{\Omega_1}{\sum_{j=1}^7 \Omega_j} = \frac{0.7250}{6.5496} = 0.1107$$

The results of the overall criteria weight calculation using the RECA method are shown in Table 8.

Tabel 8. Criteria Weight Value of RECA Method

CCT1	CCT2	CCT3	CCT4	CCT5	CCT6	CCT7
0.1107	0.1480	0.1496	0.1474	0.1494	0.1471	0.1478

The weighting results using the RECA method show a relatively balanced importance across all criteria, with only slight differences in values. Upload Consistency (CCT3) has the highest weight (0.1496), closely followed by Visual & Editing Quality (CCT5) at 0.1494, indicating these are the most influential factors in evaluating content creators. In contrast, Endorsement Fees (CCT1) has the lowest weight (0.1107), suggesting financial aspects are less dominant. Other criteria, such as creativity, engagement, audience understanding, and storytelling, have nearly equal weights (0.1471–0.1480). Overall, this distribution emphasizes quality and engagement over cost and demonstrates that RECA can generate objective, data-driven criterion weights.

D. Alternative Ranking

Ranking of alternatives using the RAM method is carried out by processing the evaluation values of each alternative, which have been adjusted according to the criteria weights,

resulting in a final preference value that reflects the overall performance of each alternative. These values are then compared among alternatives to determine their relative superiority, where alternatives with higher preference values indicate better performance. The final result of this process is a ranking order of alternatives arranged objectively based on the aggregate values obtained, which can be used as a basis for more accurate and consistent decision-making.

The first stage in the RAM method is the formation of a decision matrix containing the performance values of each alternative against all the criteria that have been determined using (1). The result of the decision matrix in the RAM method is the same as the RECA method.

The second stage in the RAM method is the normalization of the decision matrix, which aims to equalize the value scale between criteria so that they can be compared proportionally, calculated using Equation 8. The calculation of the normalization values in the RAM method is as follows.

$$n_{11} = \frac{x_{11}}{\sum_{i=1}^8 x_{i1}} = \frac{9}{75} = 0.1200$$

The results of the overall normalization value calculation in the RAM method are presented in Table 9.

Tabel 9. Normalization Value of RAM Method

Alternative Name	CCT1	CCT3	CCT3	CCT4	CCT5	CCT6	CCT7
CC1 – Rizky	0.1200	0.1259	0.1231	0.1285	0.1250	0.1244	0.1270
CC2 – Maharani	0.1600	0.1333	0.1308	0.1343	0.1310	0.1334	0.1344
CC3 – Dimas	0.0933	0.1156	0.1154	0.1168	0.1176	0.1154	0.1152
CC4 – Ayu	0.1200	0.1304	0.1262	0.1255	0.1295	0.1274	0.1300
CC5 – Nugroho	0.0800	0.1111	0.1200	0.1080	0.1131	0.1094	0.1108
CC6 – Nabila	0.2000	0.1363	0.1385	0.1372	0.1354	0.1394	0.1359
CC7 – Wijaya	0.0933	0.1185	0.1185	0.1197	0.1205	0.1184	0.1182
CC8 – Ananda	0.1333	0.1289	0.1277	0.1299	0.1280	0.1319	0.1285

The third stage in the RAM method is weight multiplication, where each normalized value is multiplied by the criterion weight that has been determined using Equation 9. The calculation of weight multiplication in the RAM method is shown as follows.

$$k_{11} = n_{11} * w_1 = 0.1200 * 0.1107 = 0.0133$$

The results of the overall weight multiplication calculation in the RAM method are displayed in Table 10.

Tabel 10. Weight Multiplication Value of RAM Method

Alternative Name	CCT1	CCT3	CCT3	CCT4	CCT5	CCT6	CCT7
CC1 – Rizky	0.0133	0.0186	0.0184	0.0189	0.0187	0.0183	0.0188
CC2 – Maharani	0.0177	0.0197	0.0196	0.0198	0.0196	0.0196	0.0199
CC3 – Dimas	0.0103	0.0171	0.0173	0.0172	0.0176	0.0170	0.0170
CC4 – Ayu	0.0133	0.0193	0.0189	0.0185	0.0193	0.0187	0.0192
CC5 – Nugroho	0.0089	0.0164	0.0180	0.0159	0.0169	0.0161	0.0164
CC6 – Nabila	0.0221	0.0202	0.0207	0.0202	0.0202	0.0205	0.0201
CC7 – Wijaya	0.0103	0.0175	0.0177	0.0176	0.0180	0.0174	0.0175
CC8 – Ananda	0.0148	0.0191	0.0191	0.0191	0.0191	0.0194	0.0190

The fourth stage in the RAM method is the calculation of the total score for each alternative based on the weighting results. The total score value reflects the overall performance

level of each alternative calculated using Equation 10 and 11; the results of the total score calculation using the RAM method are shown as follows.

$$\begin{aligned}
 S_{+1} &= k_{+12} + k_{+13} + k_{+14} + k_{+15} + k_{+16} + k_{+17} \\
 S_{+1} &= 0.0186 + 0.0184 + 0.0189 + 0.0187 + 0.0183 \\
 &\quad + 0.0188 \\
 S_{+1} &= 0.1117 \\
 S_{-1} &= k_{-11} = 0.0133
 \end{aligned}$$

The results of the overall total score calculation in the RAM method are presented in Table 11.

Tabel 11. Overall Total Value of RAM Method

Alternative Name	S_{+i}	S_{-i}
CC1 – Rizky	0.1117	0.0133
CC2 – Maharani	0.1182	0.0177
CC3 – Dimas	0.1032	0.0103
CC4 – Ayu	0.1140	0.0133
CC5 – Nugroho	0.0997	0.0089
CC6 – Nabila	0.1219	0.0221
CC7 – Wijaya	0.1058	0.0103
CC8 – Ananda	0.1149	0.0148

The final stage in the RAM method is the calculation of the final score, which is done by applying a root transformation to the total score to produce a more stable value calculated using Equation 12, the results of the final score calculation of the RAM method are shown as follows.

$$RI_1 = \sqrt[2]{S_{+1}} = \sqrt[2]{0.1117} = 0.3342$$

The results of calculating the overall weight multiplication value in the RAM method are displayed in Table 12.

Tabel 12. Final Score of RAM Method

Alternative Name	Final Score
CC1 – Rizky	4.5040
CC2 – Maharani	4.5466
CC3 – Dimas	4.4574
CC4 – Ayu	4.5135
CC5 – Nugroho	4.4378
CC6 – Nabila	4.5783
CC7 – Wijaya	4.4687
CC8 – Ananda	4.5223

The final calculation results using the RAM method show that each content creator alternative has different preference values based on the overall evaluation of the criteria. The values obtained for each alternative are within a relatively close range, namely CC1 – Rizky at 4.5040, CC2 – Maharani at 4.5466, CC3 – Dimas at 4.4574, CC4 – Ayu at 4.5135, CC5 – Nugroho at 4.4378, CC6 – Nabila at 4.5783, CC7 – Wijaya at 4.4687, and CC8 – Ananda at 4.5223. The differences in these values reflect the variations in performance among the alternatives based on the criterion weights determined in the calculation process. Overall, these results provide a quantitative overview of the relative position of each alternative within the assessment system used, thus serving as a basis for consideration in the decision-making process.

E. Alternative Ranking

The results of the alternative ranking show that each content creator occupies a different position based on the calculated preference values obtained from a comprehensive evaluation process of all the criteria used. These differences in position illustrate the variation in performance among the alternatives, which are assessed objectively through the approach applied in this study. Overall, these ranking results provide a clear picture of the performance distribution of each alternative, thus helping in understanding performance comparisons in a more systematic and measurable way.

Based on the data processing results, the ranking order of alternatives was obtained, compiled from the overall evaluation results that had been previously calculated. This final order reflects the results of a comprehensive analysis that can serve as a basis in the decision-making process. The ranking results of these alternatives are presented in Figure 2.

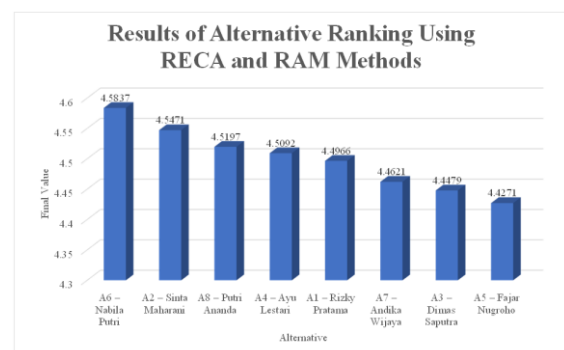


Figure 2. Alternative Ranking Results

The ranking results show that CC6 – Nabila Putri ranks first (4.5837), followed by CC2 – Sinta Maharani (4.5471) and CC8 – Putri Ananda (4.5197). Next are CC4 – Ayu Lestari (4.5092), CC1 – Rizky Pratama (4.4966), CC7 – Andika Wijaya (4.4621), CC3 – Dimas Saputra (4.4479), and CC5 – Fajar Nugroho in last place (4.4271), reflecting the overall performance comparison of all alternatives.

F. Result Evaluation

The evaluation results in this study show that the implementation of the method used is able to produce more structured and consistent assessments of all the alternatives analyzed. Each alternative is assessed based on a set of predetermined criteria, then processed through a calculation process to produce a final score that reflects the performance level comprehensively. From these results, variations in scores between alternatives can be seen, reflecting differences in contribution and quality of each in meeting the established assessment indicators. This evaluation process not only provides results in the form of quantitative scores but also offers a more objective picture of the relative position of each alternative within the assessment system.

Changes in the weight of criteria are carried out through sensitivity scenarios by increasing and decreasing each initial weight by 0.05 to test the stability of decision results. Increasing a criterion's weight by 0.05 strengthens its

influence, causing alternatives with high scores on that aspect to rise in ranking, while decreasing it by 0.05 reduces its impact and may lower the dominance of previously top-ranked alternatives. The results of these changes in Table 13 show that although there are fluctuations in weight, the ranking pattern of alternatives remains relatively stable, indicating that the

model used has a good level of resilience to weight changes. This sensitivity analysis reinforces the reliability of the method in producing consistent decisions, and also shows that key criteria such as work experience and discipline remain dominant factors even when there are variations in weights within certain limits.

Tabel 13. Criteria WeightValue of RECA Method

Test	CCT1	CCT2	CCT3	CCT4	CCT5	CCT6	CCT7
Initial Weight	0.1107	0.1480	0.1496	0.1474	0.1494	0.1471	0.1478
Weight Change Test 1	0.1530	0.1410	0.1425	0.1404	0.1423	0.1401	0.1408
Weight Change Test 2	0.1054	0.1886	0.1425	0.1404	0.1423	0.1401	0.1408
Weight Change Test 3	0.1054	0.1410	0.1901	0.1404	0.1423	0.1401	0.1408
Weight Change Test 4	0.1054	0.1410	0.1425	0.1880	0.1423	0.1401	0.1408
Weight Change Test 5	0.1054	0.1410	0.1425	0.1404	0.1899	0.1401	0.1408
Weight Change Test 6	0.1054	0.1410	0.1425	0.1404	0.1423	0.1877	0.1408
Weight Change Test 7	0.1054	0.1410	0.1425	0.1404	0.1423	0.1401	0.1884
Weight Change Test 8	0.0639	0.1558	0.1575	0.1552	0.1573	0.1548	0.1556
Weight Change Test 9	0.1165	0.1032	0.1575	0.1552	0.1573	0.1548	0.1556
Weight Change Test 10	0.1165	0.1558	0.1048	0.1552	0.1573	0.1548	0.1556
Weight Change Test 11	0.1165	0.1558	0.1575	0.1025	0.1573	0.1548	0.1556
Weight Change Test 12	0.1165	0.1558	0.1575	0.1552	0.1046	0.1548	0.1556
Weight Change Test 13	0.1165	0.1558	0.1575	0.1552	0.1573	0.1022	0.1556
Weight Change Test 14	0.1165	0.1558	0.1575	0.1552	0.1573	0.1548	0.1029

Sensitivity testing was conducted through two main scenarios, namely Test 1–7 by increasing the weight of each criterion by 0.05 alternately, and Test 8–14 by decreasing the weight by 0.05 for each criterion. In Test 1–7, the weight increase was carried out sequentially for each criterion, such as CCT1 in Test 1 up to CCT7 in Test 7, which caused the increased criterion to become more dominant compared to the other criteria due to proportional adjustments in the other weights. Conversely, in Test 8–14, the weight was decreased by 0.05 alternately for each criterion, which caused the criterion to become less influential, while the other criteria experienced a relative increase in weight. The results of these changes then impacted the shifts in ranking outcomes shown in Figure 3.

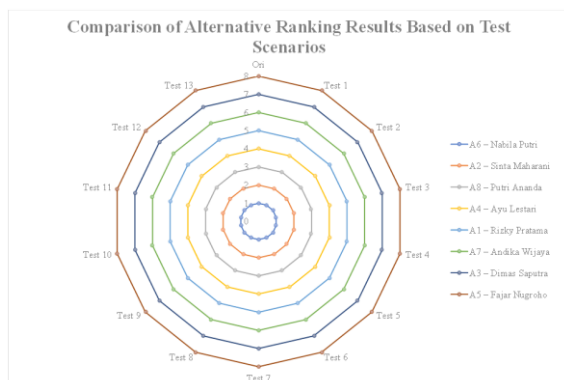


Figure 3. Comparison of Alternative Ranking Results

The results of the rank comparison across 13 scenarios show a relatively consistent pattern. Alternative A2 (Sinta

Maharani) always ranks the highest, followed by A5 (Fajar Nugroho) and A3 (Dimas Saputra) with stable performance. Other alternatives like A7, A1, A4, and A8 are in the middle positions with minor fluctuations, while A6 (Nabila Putri) consistently ranks the lowest. A weight change of ± 0.05 only causes minor shifts without significantly altering the ranking structure, indicating that the method used has high stability and robustness.

One of the main limitations of this study lies in the relatively small size of the dataset, so the variation in alternative characteristics and the distribution of criterion values do not fully represent broader conditions. This could potentially affect the level of generalization of the findings, as the ranking results and model stability might differ when applied to a larger and more diverse dataset. In addition, the limited number of samples can also reduce the model's ability to capture complex patterns or anomalies that may arise in real-world situations. Therefore, this limitation is an important concern and at the same time opens opportunities for future research to use larger, cross-context, and more representative datasets to retest the consistency and reliability of the proposed method.

IV. CONCLUSION

The results of this study demonstrate that the integration of the RECA and RAM methods in a decision support system is effective in producing a more objective, structured, and data-driven process for content creator selection. The RECA method successfully determines criteria weights based on data variation, thereby reducing subjectivity and ensuring that each

criterion reflects its true level of importance. Meanwhile, the RAM method provides a stable and consistent ranking of alternatives through a systematic calculation process, including normalization, weighting, and root-based transformation. The combination of these methods enables a comprehensive evaluation of multiple criteria with different characteristics, resulting in more accurate and reliable decision outcomes. The final ranking results show clear differentiation among alternatives, where top-performing content creators can be identified based on their overall performance across all evaluation criteria.

Furthermore, the sensitivity analysis conducted by increasing and decreasing the criteria weights by 0.05 confirms that the proposed system has a high level of stability and robustness. Although weight changes influence the contribution of each criterion and cause minor shifts in ranking positions, the overall ranking pattern remains relatively consistent across all test scenarios. This indicates that the decision-making model is not easily affected by small variations in input parameters, making it reliable for practical implementation. Therefore, the integrated RECA–RAM approach can be considered a dependable tool to support decision-makers in selecting content creators more consistently, transparently, and accountably, especially in the dynamic and competitive environment of digital marketing.

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