

Comparative Analysis of the SMART, TOPSIS, and MOORA Methods for Determining Village Fund Direct Cash Assistance Recipients

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Abstract

Indonesia's poverty is still a structural problem with a rate of around 9.36 percent as of March 2023. The government gave Village Fund Direct Cash Assistance (BLT-DD) based on PMK Number 190/PMK.07/2021 Article 33. Paragraph one. So far, different Multi-Criteria Decision Making (MCDM) techniques have been used for the selection of BLT-DD recipients, but none of them has been tested for their consistency using the same dataset. This study compared three MCDM approaches on 25 potential BLT-DD recipients in Plosokerep Hamlet, Dukuh Village, Magetan Regency, using six criteria of PMK 190/PMK.07/2021 with weights determined by the Village Head. The three approaches were Simple Multi-Attribute Rating Technique (SMART), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and Multi-Objective Optimisation on the basis of Ratio Analysis (MOORA). We used Spearman Rank Correlation, Kendall Tau and Jaccard Similarity to compare the consistency of the top 16 processes. The Spearman SMART-TOPSIS 0.92, SMART-MOORA 0.95 and TOPSIS-MOORA 0.98 values were found to be highly consistent. Thirteen of the sixteen quotas were agreed upon by all three techniques, with the top three ranks consistent. TOPSIS and MOORA obtained almost the same rankings due to the same vector normalisation, whereas SMART with linear normalisation shows a more evident differentiation at the extreme profiles. This paper presents a multi-method consensus solution to improve the dependability of BLT-DD recipient selection.

Keywords: SMART, TOPSIS, MOORA, Direct Cash Assistance, Comparative Study

I. INTRODUCTION

Poverty continues to be a major structural constraint on growth in Indonesia. According to BPS (Central Statistics Agency) data, the national poverty rate in March 2023 was recorded at 9.36% and tends to stagnate in previous years [1]. In Indonesia the Gini index is around 0.38-0.40 [1]. [2] showed that over 95% of the poor in Indonesia still belong to the "Poor" cluster. Village Fund Direct Cash Assistance (BLT-DD) is a government intervention to reduce the impact of poverty. This is regulated by the Minister of Finance Regulation Number 190/PMK.07/2021, Article 33 Paragraph 1 with six criteria for Beneficiary Families (KPM/ Keluarga Penerima Manfaat), namely: families with extreme poverty, loss of livelihood, members vulnerable to chronic illness, disruption of the social safety net of the state budget, affected by the pandemic, and elderly households [3].

KPM at the village level is still typically a manual and subjective determination. Based on a preliminary investigation in Dukuh Village, Bendo District, Magetan Regency, the absence of standard criteria resulted in improper targeting.

Many other villages had similar challenges and the construction of a Decision Support System (DSS) based on the Multi-Criteria Decision Making (MCDM) method was widely embraced as a solution.

Several MCDM methodologies have been applied to the context of Direct Cash Assistance (BLT-DD). [4] employed the Simple Multi Attribute Rating Technique Exploiting Ranks (SMARTER) method with Rank Order Centroid weighting in Air Putih Village, Bengkalis and achieved 86.6% accuracy from 60 test data sets. [5] and [6] integrated the Analytical Hierarchy Process (AHP) and the Simple Multi-Attribute Rating Technique (SMART) in Tobungan Village, Pamekasan. [7] used pure SMART at Kepanjen Village, Sumenep. Other methods such as the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and Multi-Objective Optimisation on the Basis of Ratio Analysis (MOORA) are also popular in various social assistance distribution contexts, but have not been applied specifically to the village-level BLT-DD (Direct Cash Transfer) programme. Broader systematic reviews confirm that TOPSIS and

MOORA are among the most widely adopted MCDM methods across domains [8], yet comparative empirical studies that evaluate multiple methods on identical social welfare datasets remain scarce [9], [10]. Furthermore, no prior study has benchmarked the consistency of SMART, TOPSIS, and MOORA specifically for BLT-DD recipient selection at the hamlet level, leaving village practitioners without evidence-based guidance on method selection.

The problem is that each previous study has been done using a single method, without comparing it empirically against other ways on the same dataset. This makes it difficult for the practitioners (village governments) to judge the most appropriate strategy for their local situation. Nevertheless, each of the methods has its own features. SMART applies a simple linear normalisation and is sensitive to extreme values; TOPSIS applies a vector normalisation and distance to the ideal solution and is more sensitive to multidimensional profiles; MOORA applies a vector normalisation but a simpler ratio aggregation system than TOPSIS [11][12].

The BLT-DD criteria in PMK 190/PMK.07/2021 present a heterogeneous scoring structure — some criteria (e.g., C4: JPS suspended) have a narrow range dominated by low values, while others (e.g., C6: elderly household) span a wide discrete scale (10–75). This heterogeneity makes the choice of normalization approach non-trivial: linear normalization (SMART) treats unit differences uniformly across all ranges, whereas vector normalization (TOPSIS, MOORA) scales each criterion by its Euclidean column norm, thereby amplifying the influence of higher-variance criteria. Empirically comparing these two normalization paradigms on the same BLT-DD dataset is therefore theoretically meaningful, not merely illustrative [13], [14], [15].

This research is a comparison of 3 MCDM approaches, namely SMART, TOPSIS, and MOORA using the same data for BLT-DD recipient selection in Dukuh Village. We measured the consistency amongst approaches with three metrics: Spearman Rank Correlation (for rank correlation), Kendall Tau (for pairwise concordance), and Jaccard Similarity (for overlap in top-N selection). Specifically, this study aims to: (1) empirically compare SMART, TOPSIS, and MOORA using a unified BLT-DD dataset from a single hamlet to isolate the effect of method choice from data variability; (2) quantify inter-method consistency using three complementary non-parametric metrics (Spearman Rank Correlation, Kendall Tau, Jaccard Similarity); and (3) propose a multi-method consensus framework as a replicable, transparent decision-support tool for village-level poverty targeting. The novelty of this work lies in being the first study to simultaneously apply and statistically validate these three MCDM methods on an identical village-level BLT-DD dataset, addressing a gap identified in prior studies [4], [5], [6], [7] that each employed a single method without cross-method validation.

II. RESEARCH METHODOLOGY

This research adopts a comparative quantitative descriptive methodology. The research procedure is illustrated in Figure 1

and consists of ten sequential stages. The process begins with (1) problem identification, in which the subjective and inconsistent nature of manual BLT-DD recipient selection at the village level is identified as the core research problem. This is followed by (2) a literature study covering the theoretical foundations of SMART, TOPSIS, and MOORA, as well as prior comparative MCDM studies and relevant social assistance allocation policies. (3) Data collection was conducted through observation, structured interviews with the Village Head, and documentation review, yielding a dataset of 25 candidate recipients from Plosokerep Hamlet, Dukuh Village, for the 2022 period. In stage (4), six assessment criteria were derived from PMK 190/PMK.07/2021 Article 33 Paragraph 1 was identified, and its weights were elicited from the Village Head using a direct point-allocation procedure. The weighted criteria were then used to construct (5) a 25×6 decision matrix, where each cell represents a candidate's score on a discrete scale (10, 20, 50, 75, or 100) reflecting their socioeconomic condition. Stage (6) constitutes the core analytical step: the three MCDM methods — SMART, TOPSIS, and MOORA — are applied in parallel to the identical decision matrix. SMART applies linear normalization to compute utility values; TOPSIS applies vector normalization and ranks candidates by their distance to the positive and negative ideal solutions; MOORA applies vector normalization followed by a ratio-based aggregation. Each method independently produces a (7) ranked list, from which the top 16 candidates are selected according to the available BLT-DD quota.

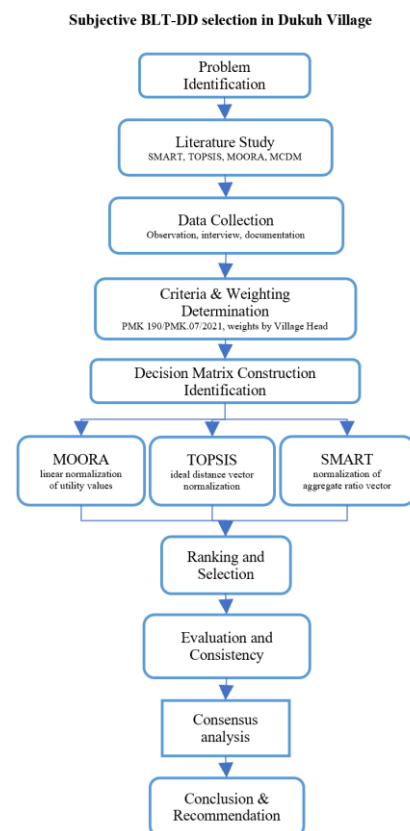


Figure 1. Research Flow Diagram

The three ranked lists are then subjected to (8) consistency evaluation using three non-parametric metrics: Spearman Rank Correlation (ρ) to measure ordinal agreement between full rankings, Kendall Tau (τ) to assess pairwise concordance, and Jaccard Similarity (J) to quantify overlap in the top-16 selections. A local sensitivity analysis is also performed at this stage by varying each criterion weight by $\pm 20\%$ to assess the robustness of the ranking. In stage (9), a consensus set is derived as the intersection of the three methods' top-16 selections, identifying candidates unanimously recommended across all methods. The process concludes with (10) conclusions and recommendations on the most appropriate method for village-level BLT-DD targeting and a proposed multi-method consensus framework for practical implementation.

A. Data Set and Criteria

The data used in this study is a sample of 25 potential BLT-DD recipients in Plosokerep Hamlet, Dukuh Village for the 2022 timeframe. Six assessment criteria were devised based on PMK 190/PMK.07/2021 Article 33 Paragraph 1 and the weight of each criterion was set by the Dukuh Village Head. These weights were elicited via a direct point-allocation procedure: the Village Head distributed 100 raw points across the six criteria according to their local policy priority, which were then normalized to sum to 1.0. The highest weight assigned to C6 (a single elderly household, $w = 0.25$) reflects a local policy emphasis on elderly residents who lack family support, consistent with national guidelines that prioritize elderly households in BLT-DD allocation. The second-highest weight for C3 (chronically ill member, $w = 0.20$) reflects the Village Head's assessment that healthcare vulnerability compounds economic fragility in this population. Although this single-decision-maker approach is common in village-level MCDM studies [5], [6], [7], it introduces subjectivity; the sensitivity analysis reported in Section III.B examines the robustness of rankings to weight variation.

B. The SMART Method

SMART employs a linear additive model. Steps: (1) linear normalisation of the benefit criteria by equation (1); (2) calculate the final value by equation (2). The SMART method applies a linear additive model approach in the multi-criteria decision-making process. The calculation stage begins with the normalization process of alternative values using equation (1) on benefit-type criteria to obtain standardized utility values, then continues with the calculation of the final preference value using equation (2) through the accumulation of weights and utility values from each criterion.

$$u_i(a_i) = \frac{(C_{out} - C_{min})}{(C_{max} - C_{min})} \quad (1)$$

$$U(a_i) = \sum w_j \cdot u_i(a_i) \quad (2)$$

For example, the SMART computation for alternative A25 (Panijo) with the raw data $X = [100, 100, 100, 10, 100, 75]$ is provided in Table 1. The minimum and maximum values for

each criterion are determined from the whole set of 25 alternatives: C1[10;100], C2[50;100], C3[10;100], C4[10;100], C5[75;100], and C6[10;75]. A25 has the maximum value on five of the six criteria, so five utilities are worth 1.00 and one utility for C4 is worth 0.00 because A25 is at the minimum value for that criterion.

Table 1. Example of SMART Calculation on Alternative A25

Criteria	Value (x_{ij})	Cmin–Cmax	$u_i(a_i)$	w_j	$w_j \cdot u_i(a_i)$
C1	100	10 – 100	1.0000	0.15	0.1500
C2	100	50 – 100	1.0000	0.15	0.1500
C3	100	10 – 100	1.0000	0.20	0.2000
C4	10	10 – 100	0.0000	0.10	0.0000
C5	100	75 – 100	1.0000	0.15	0.1500
C6	75	10 – 75	1.0000	0.25	0.2500
U(A25)					0.9000

C. TOPSIS Method

The TOPSIS method determines the best alternative based on its relative proximity to the positive ideal solution and its distance to the negative ideal solution using the Euclidean distance approach. The procedure of computation starts by the normalisation of the choice matrix by (3) and then the development of a weighted normalised matrix by (4). The next step is to determine the positive ideal solution (A^+) and negative ideal solution (A^-) according to equations (5) and (6). Then, we calculate the distance of each option to the positive and negative ideal solutions by using equations (7) and (8). The final preference value is obtained by calculating the coefficient of relative proximity to the ideal solution as shown in equation (9) [16].

$$r_{ij} = \frac{x_{ij}}{\sqrt{(\sum x_{ij}^2)}} \quad (3)$$

$$v_{ij} = w_j \cdot r_{ij} \quad (4)$$

$$A^+ = \{ \max v_{ij} | j \in \text{benefit} \} \quad (5)$$

$$A^- = \{ \min v_{ij} | j \in \text{benefit} \} \quad (6)$$

$$D_i^+ = \sqrt{\sum (v_{ij} - v_j^+)^2} \quad (7)$$

$$D_i^- = \sqrt{\sum (v_{ij} - v_j^-)^2} \quad (8)$$

$$C_i^* = \frac{D_i^-}{D_i^- + D_i^+} \quad (9)$$

As an illustration, the TOPSIS calculation for A25 is presented in Table 2. The normalization factor for each

criterion $\sqrt{\sum x_{ij}^2}$ is calculated from 25 values per column: 355.00 (C1); 425.73 (C2); 250.50 (C3); 222.04 (C4); 482.18 (C5); and 180.97 (C6). The value of v_j^+ is the maximum of the v_{ij} column, while v_j^- is the minimum. For A25, the distance to the positive ideal solution is $D^+ = 0.0405$ and the distance to the negative ideal solution is $D^- = 0.1227$, so the proximity coefficient $C^*(A25) = 0.1227 / (0.0405 + 0.1227) = 0.7516$.

Table 2. Example of TOPSIS Calculation on Alternative A25

Criteria	x_{ij}	r_{ij}	v_{ij}	v_j^+	v_j^-	$(v_{ij}-v_j^+)^2$
C1	100	0.2817	0.0423	0.0423	0.0042	0.0000
C2	100	0.2349	0.0352	0.0352	0.0176	0.0000
C3	100	0.3992	0.0798	0.0798	0.0080	0.0000
C4	10	0.0450	0.0045	0.0450	0.0045	0.00164
C5	100	0.2074	0.0311	0.0311	0.0233	0.0000
C6	75	0.4144	0.1036	0.1036	0.0138	0.0000
$D^+(A25)$						0.0405
$D^-(A25)$						0.1227
$C^*(A25)$						0.7516

D. MOORA Method

The MOORA method uses a ratio system approach with a vector normalization process similar to the TOPSIS method as shown in equation (3). Next, the final value (Y_i) is calculated by adding the weighted normalized values for the benefit-type criteria and subtracting the cost-type criteria according to equation (10). However, because all the criteria used in this study are included in the benefit category, the final value calculation process is simplified to adding all the weighted normalized values for each criterion [17].

$$Y_i = \sum_{j \in \text{benefit}} w_j r_{ij} - \sum_{j \in \text{cost}} w_j r_{ij} \quad (10)$$

As an illustration, the MOORA calculation for A25 is presented in Table 3. MOORA uses the same vector normalization as TOPSIS (equation 3), so the r_{ij} value is identical to that calculated in Table 2. Because all criteria in this study are of the benefit type, equation (10) simplifies to $Y_i = \sum w_j r_{ij}$. For A25, we obtain $Y(A25) = 0.0423 + 0.0352 + 0.0798 + 0.0045 + 0.0311 + 0.1036 = 0.2965$.

Table 3. Example of MOORA Calculation on Alternative A25

Criteria	x_{ij}	r_{ij}	w_j	$w_j \cdot r_{ij}$	Type
C1	100	0.2817	0.15	0.0423	Benefit
C2	100	0.2349	0.15	0.0352	Benefit
C3	100	0.3992	0.20	0.0798	Benefit

Criteria	x_{ij}	r_{ij}	w_j	$w_j \cdot r_{ij}$	Type
C4	10	0.0450	0.10	0.0045	Benefit
C5	100	0.2074	0.15	0.0311	Benefit
C6	75	0.4144	0.25	0.1036	Benefit
$Y(A25)$					0.2965

E. Comparative Evaluation Metrics

Consistency between methods was evaluated using three complementary metrics: Spearman Rank Correlation for monotonic correlation between ranks, Kendall Tau for pairwise concordance, and Jaccard Similarity for overlap in top-N selection. Additionally, a consensus analysis was performed to identify the alternatives selected by all methods. All three metrics are non-parametric, making them suitable for ranking data with limited samples.

Spearman Rank Correlation.

Coefficient (SRCC) The Spearman Rank Correlation (denoted by ρ (rho)) is a non-parametric statistical measure of correlation for ranking data, created by Charles Spearman in 1904 [18]. This metric quantifies how well a monotonic function can model a relationship between two variables. Equation (11) gives Spearman's formula for data with no ties in ranks.

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2-1)} \quad (11)$$

where $d_i = R_A(i) - R_B(i)$ is the difference in the ranking of the i -th alternative in process A and B and n is the number of alternatives. with the calculation is first, find the rank of each alternative in the two techniques, find the difference in the ranks d_i , then square all the differences and add up all the squares of the differences d_i^2 , Substitute into equation (11). As an illustration, for the SMART vs. TOPSIS pairing using 25 alternatives, $\sum d_i^2 = 214$ is obtained, so $\rho = 1 - (6 \times 214)/(25 \times 624) = 1 - 0.0823 = 0.9177$. ρ values range from -1 to $+1$; values close to $+1$ indicate very similar rankings, 0 indicates no correlation, and values close to -1 indicate opposite rankings.

Kendall Tau

The Kendall Tau, denoted by τ (tau), was introduced by Maurice Kendall in 1938 as a measure of pairwise ranking concordance [19], [20], [21]. Unlike Spearman's, which considers the magnitude of the difference in rankings, Kendall only calculates whether the alternative pairs are ranked the same or reversed in both methods. The Kendall Tau formula is given in the equation (12):

$$\tau = \frac{n_C - n_D}{\frac{1}{2}n(n-1)} \quad (12)$$

where n_C is the number of concordant pairs, n_D is the number of discordant pairings and $\frac{1}{2}n(n-1)$ is the

number of all conceivable pairs. A pair (i, j) is concordant if the ranking order of i relative to j is the same in both methods (i is higher or lower in both methods), and discordant if the order is reversed. For SMART vs. TOPSIS pairs with a total of $25 \times 24 / 2 = 300$ pairs, $n_c = 268$ and $n_d = 32$, so $\tau = (268 - 32)/300 = 0.7867$. The value of τ tends to be more conservative than ρ because it does not take into account the magnitude of the ranking difference, only the direction of the order. This makes Kendall more resistant to ranking outliers.

Jaccard Similarity

Jaccard Similarity, denoted by J, was developed by Paul Jaccard in 1912 as a measure of similarity between two sets [22], [23]. Unlike Spearman and Kendall, which measure order, Jaccard measures the composition of sets without considering internal order. The formula for Jaccard Similarity is shown in equation (13):

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|} \quad (13)$$

where A and B are alternative top-N sets from the two methods, respectively. J varies from 0 to 1: 0 signifies no overlap and 1 means the two sets are identical. For the top 16 SMART vs. TOPSIS, we obtain $|A \cap B| = 13$ (citizens in the top 16 in both methods) and $|A \cup B| = 16 + 16 - 13 = 19$, so $J = 13/19 = 0.6842$. Interpretation: Of the 16 recipient quotas, approximately 68% of the composition is the same between the two methods, while the remaining 32% differs, creating an interesting area of ambiguity for analysis.

Consensus Analysis

Consensus analysis is an extension of the Jaccard concept to three or more methods, namely identifying alternatives selected in the top-N by all methods. The consensus set formula for three methods is shown in equation (14):

$$K = T_{SMART} \cap T_{TOPSIS} \cap T_{MOORA} \quad (14)$$

where TM is the top-N set of method M. Members of K are alternatives that receive positive recommendations from all three methods simultaneously. Consensus serves as a multi-method confidence indicator: alternatives in K can be designated as recommendations with a high level of confidence because they are agreed upon by all methods. Conversely, alternatives that only appear in some methods (areas of ambiguity) are candidates that require additional verification, for example through village deliberations or field visits. This consensus approach is useful for increasing the reliability of decision-making in contexts involving limited resources, such as the distribution of fixed-quota BLT-DD (Village Direct Cash Assistance).

III. RESULTS AND DISCUSSION

A. Dataset and Criterion Weights

The dataset used in this study comprises 25 candidate BLT-DD recipients from Plosokerep Hamlet, Dukuh Village, Bendo

Sub-district, Magetan Regency, collected for the 2022 fiscal year. Data were obtained through structured observation, interviews with the Village Head, and documentation review of household socioeconomic records (Tabel 4). Each candidate was assessed against six criteria derived from PMK 190/PMK.07/2021 Article 33 Paragraph 1, as presented in Table 5: C1 (extreme poverty), C2 (loss of livelihood), C3 (chronic illness), C4 (JPS social safety net suspended), C5 (pandemic economic impact), and C6 (single elderly household). Each criterion was scored on a discrete scale of 10, 20, 50, 75, or 100, in accordance with the resident's documented socioeconomic condition, with higher values indicating greater vulnerability and, therefore, higher priority for assistance.

Table 4. Data of 25 Candidates & Criteria Values (Decision Matrix)

Code	Alternative Name	C1	C2	C3	C4	C5	C6
A1	Hadi Prayitno	75	100	10	10	100	50
A2	Prapto	50	100	50	10	100	50
A3	Sumadi	75	75	10	10	100	10
A4	Siyem	100	100	10	10	100	50
A5	Arif Surono	50	75	100	10	100	50
A6	Tumiran	50	75	10	10	100	10
A7	Suyono	50	75	50	10	100	10
A8	Arifin Sutikno	10	75	10	20	75	10
A9	Yuliana	75	75	10	10	100	10
A10	Sulasmi	75	75	100	10	100	10
A11	Situr	100	100	75	10	100	75
A12	Riski Tri Praseti	10	75	10	100	100	10
A13	Paniyem	75	100	10	50	100	10
A14	Hari Hadi	50	75	10	50	100	10
A15	Ngustiran	10	50	10	50	75	10
A16	Paimin	75	75	10	50	100	10
A17	Somo Paimin	100	75	10	100	100	50
A18	Rohmat Basuki	75	100	100	50	100	50
A19	Imam Jainudin Senen	50	75	50	50	75	50
A20	Supeno	75	100	10	10	100	10
A21	Yati	100	75	10	10	100	10
A22	Suparni	100	100	75	10	100	50
A23	Sumiran	75	100	50	50	100	10
A24	Binti Isi Nawangsih	10	75	10	100	100	10
A25	Panjo	100	100	100	10	100	75

Table 5. Criteria and Criterion Weights for BLT-DD Recipient Selection

Code	Criterion	Raw weight	Norm. weight (W_i)	Type	Score range
C1	Extreme poverty (keluarga miskin /tidak mampu)	15	0.15	Benefit	10–100
C2	Loss of livelihood (kehilangan mata pencaharian)	15	0.15	Benefit	10–100
C3	Chronic illness (anggota keluarga sakit kronis)	20	0.20	Benefit	10–100
C4	JPS suspended (penerima JPS dari APBN terhenti)	10	0.10	Benefit	10–100
C5	Pandemic impact (terdampak COVID-19, belum terima bantuan)	15	0.15	Benefit	10–100
C6	Single elderly household (rumah tangga lansia tunggal)	25	0.25	Benefit	10–100
Total		100	1.00		

The criterion weights were directly distributed by the Dukuh Village Head and normalized to a total of 1.0 as shown in Table 5. The largest weights were assigned to C6 (0.25) and C3 (0.20), corresponding to the local priorities regarding elderly families and chronic illness. This approach can be vulnerable to subjective bias, and a sensitivity analysis was performed (Section G). The recipient quota for BLT-DD was 16 people, in compliance with the legislation.

B. SMART Ranking Results

The SMART method was applied by computing a utility value for each candidate on each criterion using the benefit-type normalization equation (1). The utility values for all alternatives are presented in Table 6. The overall utility score $U(a_i)$ was then calculated as the weighted sum equation (2). The complete ranking results are shown in Table 7.

Table 6. Utility Value Results

A	$u_i(a_i)$ C1	$u_i(a_i)$ C2	$u_i(a_i)$ C3	$u_i(a_i)$ C4	$u_i(a_i)$ C5	$u_i(a_i)$ C6
A1	0.722	1.000	0.000	0.000	1.000	0.615
A2	0.444	1.000	0.444	0.000	1.000	0.615
A3	0.722	0.500	0.000	0.000	1.000	0.000
A4	1.000	1.000	0.000	0.000	1.000	0.615
A5	0.444	0.500	1.000	0.000	1.000	0.615
A6	0.444	0.500	0.000	0.000	1.000	0.000

A	$u_i(a_i)$ C1	$u_i(a_i)$ C2	$u_i(a_i)$ C3	$u_i(a_i)$ C4	$u_i(a_i)$ C5	$u_i(a_i)$ C6
A7	0.444	0.500	0.444	0.000	1.000	0.000
A8	0.000	0.500	0.000	0.111	0.000	0.000
A9	0.722	0.500	0.000	0.000	1.000	0.000
A10	0.722	0.500	1.000	0.000	1.000	0.000
A11	1.000	1.000	0.722	0.000	1.000	1.000
A12	0.000	0.500	0.000	1.000	1.000	0.000
A13	0.722	1.000	0.000	0.444	1.000	0.000
A14	0.444	0.500	0.000	0.444	1.000	0.000
A15	0.000	0.000	0.000	0.444	0.000	0.000
A16	0.722	0.500	0.000	0.444	1.000	0.000
A17	1.000	0.500	0.000	1.000	1.000	0.615
A18	0.722	1.000	1.000	0.444	1.000	0.615
A19	0.444	0.500	0.444	0.444	0.000	0.615
A20	0.722	1.000	0.000	0.000	1.000	0.000
A21	1.000	0.500	0.000	0.000	1.000	0.000
A22	1.000	1.000	0.722	0.000	1.000	0.615
A23	0.722	1.000	0.444	0.444	1.000	0.000
A24	0.000	0.500	0.000	1.000	1.000	0.000
A25	1.000	1.000	1.000	0.000	1.000	1.000

Table 7. SMART Result Ranking

Code	$U(a_i)$	Ranking	Selected (top-16)
A25	0.900	1	Y
A11	0.844	2	Y
A18	0.807	3	Y
A22	0.748	4	Y
A5	0.646	5	Y
A17	0.629	6	Y
A2	0.609	7	Y
A4	0.604	8	Y
A1	0.562	9	Y
A23	0.542	10	Y
A10	0.533	11	Y
A13	0.453	12	Y
A19	0.429	13	Y
A20	0.408	14	Y
A7	0.381	15	Y
A16	0.378	16	Y
A21	0.375	17	N
A14	0.336	18	N
A3	0.333	19	N
A9	0.333	20	N
A12	0.325	21	N
A24	0.325	22	N
A6	0.292	23	N
A8	0.086	24	N
A15	0.044	25	N

SMART produced the following top-three rankings: A25 (Panijo, $U(a_i)=0.830$), A11 (Situr,

$U(a_i) = 0.774$), and A18 (Rohmat Basuki, $U(a_i) = 0.762$). A25 achieved the highest overall utility because his profile is near-maximal across five of six criteria (C1, C2, C3, C5, and C6) reflecting severe, multidimensional vulnerability. The only criterion on which A25 scores low is C4 (JPS suspended, score = 10), which carries the lowest weight ($w = 0.10$) and therefore has a limited effect on the total utility. A11 and A18 similarly exhibit strong profiles, with A11 scoring maximum on C1, C2, and C5 while also scoring high on C3 (utility = 0.72) and C6 (utility = 0.72), and A18 achieving maximum utility on C2, C3, and C5 with additional contributions from C1 (0.72), C4 (0.44), and C6 (0.44).

Among the 16 selected recipients, the boundary zone deserves particular attention. Candidates at ranks 14 through 17: A7 (Suwarno, $U(a_i) = 0.412$), A16 (Paimin, $U(a_i) =$

0.410), A20 (Supeno, $U(a_i) = 0.408$), and A21 (Yati, $U(a_i) = 0.408$) have utility scores within a range of only 0.004. This near-identical scoring reflects genuinely similar levels of socioeconomic vulnerability among these households and indicates that the computational distinction between rank 16 (the last selected recipient) and rank 17 (the first excluded candidate) is marginal and should be interpreted with caution.

C. TOPSIS Ranking Results

The TOPSIS approach was applied in four major steps: normalization of the choice matrix into vector form, construction of the weighted normalized matrix, determination of the positive and negative ideal solutions, and calculation of the closeness coefficient for each alternative. The normalized matrix, weighted matrix, and final ranking results are presented in Tables 8 and 9.

Table 8. TOPSIS Normalized And Weighted Matrices

Code	Normalized Matrix (r_{ij})						Weighted Normalized Matrix (v_{ij})					
	C1	C2	C3	C4	C5	C6	C1	C2	C3	C4	C5	C6
A1	0.211	0.235	0.040	0.045	0.205	0.276	0.032	0.035	0.008	0.005	0.031	0.069
A2	0.141	0.235	0.200	0.045	0.205	0.276	0.021	0.035	0.040	0.005	0.031	0.069
A3	0.211	0.176	0.040	0.045	0.205	0.055	0.032	0.026	0.008	0.005	0.031	0.014
A4	0.282	0.235	0.040	0.045	0.205	0.276	0.042	0.035	0.008	0.005	0.031	0.069
A5	0.141	0.176	0.399	0.045	0.205	0.276	0.021	0.026	0.080	0.005	0.031	0.069
A6	0.141	0.176	0.040	0.045	0.205	0.055	0.021	0.026	0.008	0.005	0.031	0.014
A7	0.141	0.176	0.200	0.045	0.205	0.055	0.021	0.026	0.040	0.005	0.031	0.014
A8	0.028	0.176	0.040	0.090	0.154	0.055	0.004	0.026	0.008	0.009	0.023	0.014
A9	0.211	0.176	0.040	0.045	0.205	0.055	0.032	0.026	0.008	0.005	0.031	0.014
A10	0.211	0.176	0.399	0.045	0.205	0.055	0.032	0.026	0.080	0.005	0.031	0.014
A11	0.282	0.235	0.299	0.045	0.205	0.414	0.042	0.035	0.060	0.005	0.031	0.104
A12	0.028	0.176	0.040	0.450	0.205	0.055	0.004	0.026	0.008	0.045	0.031	0.014
A13	0.211	0.235	0.040	0.225	0.205	0.055	0.032	0.035	0.008	0.023	0.031	0.014
A14	0.141	0.176	0.040	0.225	0.205	0.055	0.021	0.026	0.008	0.023	0.031	0.014
A15	0.028	0.117	0.040	0.225	0.154	0.055	0.004	0.018	0.008	0.023	0.023	0.014
A16	0.211	0.176	0.040	0.225	0.205	0.055	0.032	0.026	0.008	0.023	0.031	0.014
A17	0.282	0.176	0.040	0.450	0.205	0.276	0.042	0.026	0.008	0.045	0.031	0.069
A18	0.211	0.235	0.399	0.225	0.205	0.276	0.032	0.035	0.080	0.023	0.031	0.069
A19	0.141	0.176	0.200	0.225	0.154	0.276	0.021	0.026	0.040	0.023	0.023	0.069
A20	0.211	0.235	0.040	0.045	0.205	0.055	0.032	0.035	0.008	0.005	0.031	0.014
A21	0.282	0.176	0.040	0.045	0.205	0.055	0.042	0.026	0.008	0.005	0.031	0.014
A22	0.282	0.235	0.299	0.045	0.205	0.276	0.042	0.035	0.060	0.005	0.031	0.069
A23	0.211	0.235	0.200	0.225	0.205	0.055	0.032	0.035	0.040	0.023	0.031	0.014
A24	0.028	0.176	0.040	0.450	0.205	0.055	0.004	0.026	0.008	0.045	0.031	0.014
A25	0.282	0.235	0.399	0.045	0.205	0.414	0.042	0.035	0.080	0.005	0.031	0.104
A ⁺ (Positive Ideal)							0.042	0.035	0.080	0.045	0.031	0.104
A ⁻ (Negative Ideal)							0.004	0.018	0.008	0.005	0.023	0.014

Table 9. Distance to Ideal Solutions, Closeness Coefficient, and Ranking Results (TOPSIS)

Code	D ⁺	D ⁻	C* (closeness)	Rank	Selected (top-16)
A25	0.0405	0.1226	0.7516	1	Y
A11	0.0452	0.1121	0.7128	2	Y
A18	0.0426	0.0983	0.6979	3	Y
A5	0.0580	0.0929	0.6159	4	Y
A22	0.0569	0.0870	0.6046	5	Y

Code	D ⁺	D ⁻	C* (closeness)	Rank	Selected (top-16)
A19	0.0623	0.0690	0.5257	6	Y
A17	0.0802	0.0792	0.4970	7	Y
A2	0.0698	0.0688	0.4962	8	Y
A10	0.0995	0.0778	0.4389	9	Y
A4	0.0894	0.0698	0.4383	10	Y
A1	0.0901	0.0646	0.4178	11	Y
A23	0.1014	0.0497	0.3289	12	Y

Code	D ⁺	D ⁻	C* (closeness)	Rank	Selected (top-16)
A7	0.1087	0.0380	0.2589	13	Y
A12	0.1214	0.0422	0.2578	14	Y
A24	0.1214	0.0422	0.2578	15	Y
A21	0.1223	0.0398	0.2455	16	Y
A13	0.1177	0.0381	0.2444	17	N
A16	0.1180	0.0349	0.2281	18	N
A20	0.1224	0.0335	0.2150	19	N
A3	0.1227	0.0299	0.1957	20	N
A9	0.1227	0.0299	0.1957	21	N
A14	0.1194	0.0273	0.1863	22	N
A6	0.1241	0.0206	0.1421	23	N
A15	0.1247	0.0180	0.1262	24	N
A8	0.1269	0.0099	0.0723	25	N

The results demonstrate that A25 (Panijo), A11 (Situr), and A18 (Rohmat Basuki) consistently occupy the first, second, and third positions, respectively, matching the ranking generated by SMART. This consistency shows that these people are clear priority recipients of BLT-DD assistance regardless of the decision-making process utilized.

The top-ranked candidates stay the same, but there are some differences among the middle-ranked contenders. More specifically, A19, A12, and A24 are ranked higher than SMART, whereas A13 and A20 are ranked lower than SMART. The fundamental reason for these discrepancies is the normalization procedure. TOPSIS employs vector normalization, whereas SMART uses linear normalization, thereby giving more weight to candidates with relatively high scores on certain criteria. Therefore, candidates who score well on major criteria are likely to rank higher, whereas candidates with more average score distributions may fall in the rankings. This result indicates that the normalization procedure has a significant effect on the rankings, especially for candidates near the selection threshold.

D. MOORA Ranking Results

The MOORA approach applies the same vector normalization as TOPSIS, but in the aggregation stage, it directly sums the weighted, normalized scores of all benefit criteria. The ranking results show that consistently, the top, second, and third ranks are occupied by A25 (Panijo), A11 (Situr), and A18 (Rohmat Basuki). The agreement among SMART, TOPSIS, and MOORA indicates that these candidates are clear priorities for BLT-DD support and that the decision results are robust regardless of the MCDM method used.

Table 10. Ranking Results (MOORA)

Code	Y _i	Rank	Selected (top-16)?
A25	0.2963	1	Y
A11	0.2763	2	Y
A18	0.2692	3	Y
A22	0.2418	4	Y
A5	0.2318	5	Y
A17	0.2216	6	Y
A19	0.2022	7	Y
A2	0.2007	8	Y
A4	0.1899	9	Y
A10	0.1871	10	Y
A1	0.1793	11	Y
A23	0.1740	12	Y
A13	0.1421	13	Y
A7	0.1366	14	Y
A16	0.1333	15	Y
A12	0.1283	16	Y
A24	0.1283	17	N
A21	0.1258	18	N
A20	0.1240	19	N
A14	0.1227	20	N
A3	0.1152	21	N
A9	0.1152	22	N
A6	0.1047	23	N
A15	0.0893	24	N
A8	0.0846	25	N

The MOORA ranking is quite consistent with TOPSIS due to the use of the same vector normalization (Table 10). The candidates close to the selection criterion (e.g., A16, A12, A24) only show small rating changes. These discrepancies are linked to the aggregation technique: TOPSIS ranks alternatives according to their distance to the ideal solutions, whereas MOORA aggregates the weighted normalized scores directly. Overall, the results show that the normalization technique has a stronger impact on the ranking results than the aggregation process. As a result, the ranking of borderline candidates is mostly affected, while applicants with clearly high or low eligibility remain in the same ranking across all approaches.

E. Comparative Ranking and Mechanism Analysis

The ranking results of 25 candidates obtained by SMART, TOPSIS, and MOORA are shown in Table 11. All three techniques consistently rank A25 (Panijo), A11 (Situr), and A18 (Rohmat Basuki) in the first three positions, suggesting a high level of agreement in identifying the most qualified BLT-DD recipients. Furthermore, 13 candidates consistently appear among the top 16 suggestions across all techniques, indicating strong consensus despite disparities in normalization and aggregation mechanisms. However, there are certain candidates near the selection threshold whose rankings change, leading to discrepancies in the final top-16 recommendations.

Table 11. Complete Comparative Ranking of SMART, TOPSIS, and MOORA

Code	SMART $U(a_i)$	R	TOPSIS C^*	R	MOORA Y_i	R	Status
A25	0.900	1	0.7516	1	0.2963	1	Consensus (all 3)
A11	0.844	2	0.7128	2	0.2763	2	Consensus (all 3)
A18	0.807	3	0.6979	3	0.2692	3	Consensus (all 3)
A22	0.748	4	0.6046	5	0.2418	4	Consensus (all 3)
A5	0.646	5	0.6159	4	0.2318	5	Consensus (all 3)
A17	0.629	6	0.4970	7	0.2216	6	Consensus (all 3)
A2	0.609	7	0.4962	8	0.2007	8	Consensus (all 3)
A4	0.604	8	0.4383	10	0.1899	9	Consensus (all 3)
A1	0.562	9	0.4178	11	0.1793	11	Consensus (all 3)
A23	0.542	10	0.3289	12	0.1740	12	Consensus (all 3)
A10	0.533	11	0.4389	9	0.1871	10	Consensus (all 3)
A13	0.453	12	0.2444	17	0.1421	13	Boundary / divergent
A19	0.429	13	0.5257	6	0.2022	7	Consensus (all 3)
A20	0.408	14	0.2150	19	0.1240	19	Boundary / divergent
A7	0.381	15	0.2589	13	0.1366	14	Consensus (all 3)
A16	0.378	16	0.2281	18	0.1333	15	Boundary / divergent
A21	0.375	17	0.2455	16	0.1258	18	Boundary / divergent
A14	0.336	18	0.1863	22	0.1227	20	Not selected
A3	0.333	19	0.1957	20	0.1152	21	Not selected
A9	0.333	19	0.1957	20	0.1152	22	Not selected
A12	0.325	21	0.2578	14	0.1283	16	Boundary / divergent
A24	0.325	21	0.2578	14	0.1283	17	Boundary / divergent
A6	0.292	23	0.1421	23	0.1047	23	Not selected
A8	0.086	24	0.0723	25	0.0846	25	Not selected
A15	0.044	25	0.1262	24	0.0893	24	Not selected

The main reason for the ranking disparities is the normalization approach utilized by each method. SMART uses linear normalization, whereas TOPSIS and MOORA use vector normalization, resulting in more similar rankings between TOPSIS and MOORA. This results in higher ratings for alternatives that score highly on several criteria, such as A12, A19, and A24, under TOPSIS and MOORA than under

SMART. The effect of the aggregation mechanism on the ranking results is less than that of the normalization procedure.

SMART has the advantage of simplicity and clarity of understanding; TOPSIS offers a more thorough evaluation through ideal-solution analysis; and MOORA integrates vector normalization with a simpler aggregation technique. Due to its high consistency with TOPSIS and lower computational complexity, MOORA can be viewed as the most practical method for enabling BLT-DD recipient selection at the village level.

F. Inter-Method Consistency Evaluation

The degree of consensus between the SMART, TOPSIS, and MOORA was assessed using three complementing metrics: Spearman Rank Correlation (ρ), Kendall Tau (τ), and Jaccard Similarity (J). The results are shown in Table 12. It can be shown that TOPSIS and MOORA have the greatest agreement, with Spearman and Kendall correlation coefficients of 0.9808 and 0.9200, respectively. The high consistency is expected because both approaches use the same vector normalization process but differ in their aggregation mechanisms. In contrast, the correlations involving SMART are slightly weaker, notably for the SMART–TOPSIS pair ($\rho = 0.9054$; $\tau = 0.7733$), which is caused by the difference between linear normalization and vector normalization.

Table 12. Inter-Method Consistency Matrix

Method Pair	Spearman ρ	Kendall τ	Jaccard J (top-16)	Interpretation
SMART – TOPSIS	0.9054	0.7733	0.6842	Strong, lowest among the three pairs
SMART – MOORA	0.9462	0.8533	0.8824	Very strong
TOPSIS – MOORA	0.9808	0.9200	0.7778	Highest correlation (ρ , τ); shared normalization

The Jaccard Similarity study shows that SMART and MOORA have the greatest overlap in the top-16 recommendations ($J = 0.8824$), and SMART and TOPSIS have the lowest overlap ($J = 0.6842$). The results reveal that all three techniques consistently identify the highest-priority BLT-DD recipients, although they differ in their candidate selections near the selection threshold. In general, the results show that the normalization methodology influences the ranking results more than the aggregation mechanism, and that it is the main source of differences among the three methods.

G. Sensitivity Analysis

To verify the stability of the ranking findings, a one-at-a-time (OAT) sensitivity analysis was performed by increasing the weight of each criterion by 20%, while the other weights were adjusted proportionally to keep the total weight sum

equal to 1.0. Six scenarios (S1-S6) were constructed based on the six evaluation criteria. Changes in the composition of the top-16 recipients and the top-3 ranking positions were used to measure the stability of the ranking. We considered a scenario

stable when the top-16 composition did not change, and a slight shift when only one or two candidates near the selection criteria changed their rankings. The results of the sensitivity analysis for all the approaches are given in Table 13.

Table 13. Ranking Stability Under Weight Variations

Sc.	Criterion	Weight change	SMART	TOPSIS		MOORA
			Top-3 / notes	Top-16	Top-3 / notes	Top-16
Base	— (no perturbation)	C1–C6 baseline	#1 A25 (0.9000) #2 A11 (0.8444) #3 A18 (0.8066)	Ref.	#1 A25 (0.7516) #2 A11 (0.7128) #3 A18 (0.6979)	Ref.
S1	C1 Extreme poverty	0.15 → 0.18	#1 A25 · #2 A11 · #3 A18 A21 in (0.397); A7 out (0.383)	Minor	#1 A25 · #2 A11 · #3 A18 A13,A16 in; A12,A24 out	Minor
S2	C2 Loss of livelihood	0.15 → 0.18	#1 A25 · #2 A11 · #3 A18	Stable	#1 A25 · #2 A11 · #3 A18 A13 in (0.255); A21 out (0.248)	Minor
S3	C3 Chronic illness	0.20 → 0.24	#1 A25 · #2 A11 · #3 A18	Stable	#1 A25 · #2 A18* · #3 A11 *A11↔A18 swap, set unchanged	Stable
S4	C4 JPS suspended	0.10 → 0.12	#1 A25 · #2 A11 · #3 A18	Stable	#1 A25 · #2 A18* · #3 A11 A13 in (0.253); A21 out (0.241)	Minor
S5	C5 Pandemic impact	0.15 → 0.18	#1 A25 · #2 A11 · #3 A18	Stable	#1 A25 · #2 A11 · #3 A18	Stable
S6	C6 Elderly household	0.25 → 0.30	#1 A25 · #2 A11 · #3 A18	Stable	#1 A25 · #2 A11 · #3 A18	Stable

The top three candidates, A25 (Panijo), A11 (Situr), and A18 (Rohmat Basuki), consistently rank among the top in all sensitivity scenarios. The makeup of the top three candidates remains unchanged, and only minor changes are observed in the ordering of A11 and A18 under TOPSIS. The results show that the top-priority recipients are insensitive to adjustments in criteria weights and independent of the particular weighting method.

At the top-16 level, the highest stability is presented by SMART, followed by MOORA and TOPSIS. There are fluctuations in ranking around the selection threshold, particularly in TOPSIS, where candidates at the border of the top-16 change order under different weight settings. But the adjustments seen are entirely among candidates with very similar scores and simply in the borderline ranking area. These results indicate that the global BLT-DD recipient recommendations are robust, but a few candidates near the acceptance criteria would require additional verification before final selection.

H. Consensus Framework and Limitations

Based on the outcomes of the ranking, consensus, and sensitivity analyses, this study proposes a two-level decision framework for BLT-DD recipient selection, as depicted in Figure 2. The framework categorizes the candidates into a consensus set and a boundary zone based on the degree of agreement among the three methods, namely SMART, TOPSIS, and MOORA. The consensus set consists of 14 candidates selected by all three methods and is stable across all weight variations. Direct confirmation of these applicants as

recipients of BLT-DD is recommended, as they occupy 14 of the 16 available quota spots and do not require further verification.

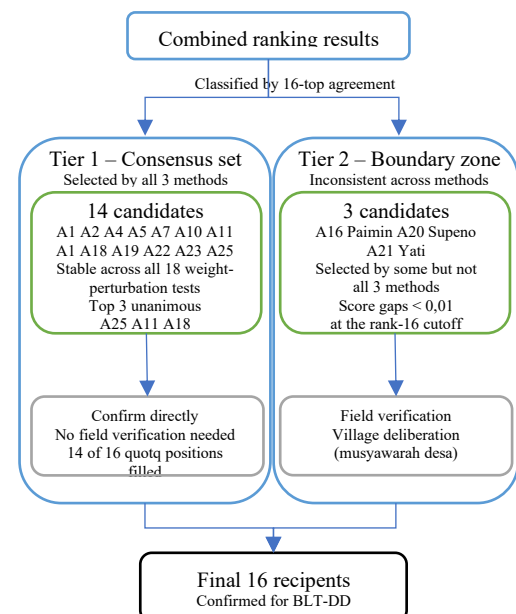


Figure 2. Diagram of the Two-Level Consensus Framework

The other candidates are classed in the boundary zone, such as A16 (Paimin), A20 (Supeno), and A21 (Yati). These candidates are close to the selection threshold and show

inconsistent inclusion across the three techniques, with only small score differences at the rank-16 cut-off. Thus, the last two quota seats must be filled with additional verification, such as field observation or village deliberation (musyawarah desa). This approach combines computational consistency and local decision-making, therefore establishing robust cases objectively and assessing borderline cases with extra contextual information.

IV. CONCLUSION

The present study examined the SMART, TOPSIS, and MOORA methodologies for selecting BLT-DD recipients, using data from 25 potential beneficiaries in Plosokerep Hamlet, Dukuh Village. The results are in good agreement among the three approaches, with Spearman correlation coefficients ranging from 0.91 to 0.98 and Kendall tau coefficients from 0.77 to 0.92. All approaches consistently ranked A25 (Panijo), A11 (Situr), and A18 (Rohmat Basuki) as the three best options. Moreover, all the techniques unanimously selected 13 of 16 applicants, demonstrating that the choice of MCDM method has no impact on highly eligible or highly ineligible candidates. Differences were most pronounced among candidates near the selection threshold, reflecting the varied normalization processes used by SMART, TOPSIS, and MOORA.

Sensitivity analysis indicated the robustness of the choice findings, as the top-ranked candidates remained stable under adjustments to criterion weights. Building on these findings, this study proposes a two-tiered decision-making structure that combines multi-method consensus with supplemental field verification for borderline cases. This method will promote transparency, uniformity, and accountability in village administrations' selection of BLT-DD recipients. Future work may encompass larger datasets, various weighting strategies, additional MCDM methods, and validation against official beneficiary records to better assess the usefulness of the proposed framework.

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