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Determining social assistance recipients using fuzzy-TOPSIS method in Sumur Bandung district Indonesia

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ABSTRACT

This study aims to improve the selection process for social assistance recipients in the Sumur Bandung District, Indonesia, using the fuzzy-TOPSIS method. The research establishes eligibility criteria and evaluates alternatives based on data from April 2024. By combining multi-criteria decision-making with fuzzy logic, the fuzzy-TOPSIS approach enhances the accuracy and fairness of recipient selection. The methodology involves determining criteria weights, fuzzification, and ranking alternatives against ideal solutions. The results demonstrate that fuzzy-TOPSIS significantly improves decision-making, leading to more objective and reliable outcomes than traditional methods. These findings underscore the potential of fuzzy-TOPSIS in optimizing social assistance distribution, ensuring that assistance reaches the most deserving recipients efficiently.

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1. INTRODUCTION

As a nation with a large and diverse population, Indonesia faces significant challenges in addressing poverty and social inequality [1]. One of the government's primary strategies to mitigate these issues is social assistance programs to support underprivileged and vulnerable populations in meeting their basic needs [2]-[4]. The main objective of these programs is to enhance societal welfare, reduce economic disparities, and strengthen social resilience by ensuring that financial aid reaches those who need it most [5]-[7]. However, despite the structured frameworks in place, the distribution of social assistance remains a persistent challenge, with inefficiencies often arising due to limitations in accurately identifying eligible recipients [1], [8]-[10].

Various decision-support methodologies have been developed to improve social assistance recipient selection accuracy and fairness. Several studies have implemented multi-criteria decision-making (MCDM) techniques to optimize selection by ranking eligible recipients based on predefined criteria. weighted product method (WPM) and simple additive weighting (SAW) have been widely used in prior research for social assistance allocation. For instance, implementing WPM in a decision-support system demonstrated stability in ranking results, with 67.5% of rankings categorized as stable and 21.6% as highly stable, indicating a consistent ranking mechanism [11]. Similarly, SAW has been applied in multiple studies to support decision-making in selecting social assistance recipients by summing the weighted performance scores of each alternative [10], [12], [13]. However, SAW-based models heavily depend on data quality and predefined criteria, making them vulnerable to inaccuracies if critical socio-economic factors are not sufficiently captured.

Beyond SAW and WPM, other MCDM approaches, such as the Analytical Hierarchy Process (AHP), Electre, Roc, and VIKOR, have been explored to enhance the efficiency of recipient selection. A study integrating fuzzy-AHP demonstrated improvements in ranking accuracy by leveraging hierarchical weighting and fuzzy logic to handle uncertainty in decision-making [9], [14]. Meanwhile, Electre & Roc were applied to rank eligible recipients based on defined criteria, though their deterministic nature makes them less effective in handling uncertainty [15]. VIKOR has also been utilized to prioritize social assistance recipients, focusing on finding compromise solutions by considering the closeness of alternatives to an ideal solution [16]. Despite these advances, many existing MCDM models [17] still face challenges in managing uncertainty, subjectivity, and imprecise data, which are inherent in social assistance decision-making.

Fuzzy-TOPSIS has emerged as a promising method to address these limitations, offering a more robust approach to handling uncertainty and subjectivity in decision-making processes. The fuzzy-TOPSIS approach extends traditional TOPSIS [18] by incorporating fuzzy logic to represent uncertainty in criteria evaluations, making it particularly suitable for real-world applications where socio-economic factors involve imprecise and vague data. Prior studies have successfully applied fuzzy-TOPSIS in various decision-making scenarios, such as selecting suppliers [19], choosing alternative materials for industrial production [20], and evaluating top-performing students in an academic setting [21]. These studies highlight the effectiveness of fuzzy-TOPSIS in transforming subjective assessments into objective rankings, thereby improving decision transparency and reliability. However, its application in social assistance recipient selection remains underexplored, particularly in developing regions where socio-economic factors fluctuate dynamically.

In response to this research gap, this study proposes an enhanced fuzzy-TOPSIS-based decision-support model designed explicitly for selecting social assistance recipients in Sumur Bandung District, Indonesia. Unlike previous studies that rely on deterministic ranking methods such as WPM, SAW, AHP, Electre, Roc, and VIKOR, this approach leverages fuzzy logic to manage uncertainty and improve decision robustness effectively [22]. The novelty of this research lies in its ability to integrate fuzzy-TOPSIS with an optimized criteria-weighting approach, which enhances the accuracy and objectivity of recipient ranking. Furthermore, this study addresses the socio-economic complexities in recipient eligibility assessment by incorporating real-world constraints and domain expert input into the decision-making process, ensuring a more contextually relevant and adaptive framework. To validate its effectiveness, the proposed model is empirically compared with conventional methods, demonstrating its reliability in improving the precision and fairness of social assistance allocation.

The primary objective of this research is to develop and validate an optimal fuzzy-TOPSIS-based model that enhances the precision of social assistance recipient selection, thereby improving the efficiency of targeted aid distribution. Specifically, this study aims to increase decision-making accuracy by reducing uncertainty through fuzzy logic, ensure a more transparent and equitable selection process by systematically prioritizing recipients based on quantifiable socio-economic criteria, and optimize social assistance allocation to maximize its impact on poverty reduction. By addressing these challenges, the proposed model contributes to the advancement of decision-support systems in social welfare programs and provides a scalable framework that can be adapted to similar social assistance initiatives in other regions.

2. METHOD

This study employs the fuzzy-TOPSIS methodology as a structured decision-support system [22]-[24] for selecting social assistance recipients in Sumur Bandung District. The experimental setup consists of three main phases (data collection, methodological implementation, and result validation).

2.1. Data collection and preprocessing

To ensure comprehensive and reliable data, a mixed-method approach was adopted. The data were collected through:

1) Structured interviews with three social assistance officers to determine the importance of criteria and their relative weights using pairwise comparisons.
2) Official records from the local social welfare office to obtain demographic and socio-economic information of candidate recipients.

The dataset includes 26 candidate recipients (R1–R26) from April 2024 records, each evaluated based on five key criteria:

1) Occupation – categorized as unemployed, informal workers, or formal workers.
2) Housing Condition – classified based on structural integrity and ownership status.
3) Number of Dependents – measured by household size.
4) Income Level – grouped based on government-defined poverty thresholds.
5) Education Level – categorized into primary, secondary, and higher education.

The selection of these criteria was guided by a comprehensive review of policy documents and expert consultations to ensure alignment with government social assistance programs. Each criterion was further broken down into sub-criteria, as shown in Table 1, to capture nuanced differences among applicants.

Table 1. Criteria for recipients of social assistance

No	Criteria	Sub-Criteria
1	Occupation	1a. Unemployed
		1b. Private Employee/Laborer
		1c. Entrepreneur
		1d. Farmer
		1e. Civil Servant
2	Housing Condition	2a. Adequate
		2b. Moderately Adequate
		2c. Inadequate
		2d. Not Adequate
3	Dependents	3a. 1
		3b. 2
		3c. 3
		3d. >3
4	Income	4a. <500,000 IDR
		4b. ≥500,000 IDR
		4c. ≥1,000,000 IDR
		4d. ≥3,000,000 IDR
5	Education	5a. Did Not Complete Primary School
		5b. Primary School
		5c. Junior High School
		5d. Senior High School
		5e. Bachelor's Degree

Before applying the fuzzy-TOPSIS method, data preprocessing was conducted:

1) Missing values were handled using mean imputation for numerical data and mode imputation for categorical data.
2) Outliers were removed based on a standard deviation threshold of ±2.5, ensuring that extreme anomalies did not bias the ranking results.

2.2. Implementation of the fuzzy-TOPSIS methodology

The fuzzy-TOPSIS framework consists of the following structured steps:

1) Determining criteria weights
   Each criterion's relative importance was assessed using pairwise comparisons provided by social assistance officers. The Saaty scale (1–9) was used to assign weights, which were then converted into fuzzy triangular numbers to accommodate uncertainty and subjectivity. The geometric mean method was employed to compute final fuzzy weights, ensuring consistency and reliability in the weighting process.
2) Constructing the decision matrix
   A decision matrix was built, where:
   a) Each row represents a candidate recipient (alternative).
   b) Each column represents a selection criterion.
   c) The matrix entries consist of fuzzy-weighted values, assigned to each criterion per alternative.

   The geometric mean of the fuzzy numbers was used to compute a weighted score for each alternative, as shown in (1). The resulting matrix was then prepared for normalization.

$$W_i = (r_{i,1} \times r_{i,2} \times r_{i,3} \times r_{i,4} \times r_{i,5})^{\frac{1}{5}} \quad (1)$$

   The fuzzy triangular scale value, denoted by W_i, can be expressed as lW_i, mW_i, and nW_i, respectively, as determined by the corresponding $r_{i,j}$ values.
3) Data fuzzification
   To handle imprecision in assessments, fuzzification was applied, transforming crisp input values into fuzzy sets.
   a) The Saaty scale (1–9) was used as the initial weighting reference [25], [26], which were then transformed into fuzzy triangular numbers to address uncertainties in officer evaluations [27], [28].
   b) The fuzzy transformation process adhered to Table 2, ensuring consistency in logic application.

Table 2. Conversion of saaty scale to fuzzy triangular scale

Saaty scale	Definition	Fuzzy triangular scale
1	Equally important	(1,1,1)
3	Slightly important	(2,3,4)
5	Fairly important	(4,5,6)
7	Highly important	(6,7,8)
9	Absolutely important	(9,9,9)
2	Intermittent values between two adjacent scales	(1,2,3)
4		(3,4,5)
6		(5,6,7)
8		(7,8,9)

4) Normalizing the decision matrix
Normalization was conducted using the Euclidean norm, ensuring comparability across all criteria. This involved:
   a) The increasing order I is then discovered based on the sum of all criteria as three fuzzy values and the inverse of their multiplication results.
   b) At this point, W_i represents the three fuzzy values, denoted as $lW_i^{\sim}$, $mW_i^{\sim}$, and $nW_i^{\sim}$, respectively, which are derived from the corresponding W_i values.

$$W_i^{\sim} = W_i \times I \tag{2}$$

   c) Find the centroid of the area to perform defuzzification of the fuzzy numbers.

$$M_i = \frac{lW_i^{\sim} + mW_i^{\sim} + nW_i^{\sim}}{3} \tag{3}$$

   d) Next, normalize the de-fuzzified values on a scale of 0-1.

$$N_i = \frac{M_i}{\sum_{i=1}^{n} M_i} \tag{4}$$

5) Determining the ideal and anti-ideal solutions
To establish a reference for ranking, the ideal (best) and anti-ideal (worst) solutions were identified:
   a) The maximum value for each criterion was assigned as the ideal solution (S^+).
   b) The minimum value for each criterion was assigned as the anti-ideal solution (S^-).

$$R_{i,j} = \frac{X_{i,j}}{\sqrt{\sum_{j=1}^{n} X_{i,j}^2}} \tag{5}$$

In this context, $X_{i,j}$ represents the assigned value for criterion C_j for alternative A_i.
The distances between each alternative and the ideal/anti-ideal solutions were then calculated using (7) and (8).

6) Computing the distance of alternatives to the ideal solution
Using the normalized values and fuzzy weights, the distance of each alternative from the ideal solution (S^+) and anti-ideal solution (S^-) was computed.
   a) The criteria values of each alternative were multiplied by the fuzzy weights.

$$V_{i,j} = N_j \times R_{i,j} \tag{6}$$

   b) The ideal best and worst values for each criterion were determined using the criteria values of each alternative.
   c) Rank alternatives based on the Euclidean distance of each alternative to the ideal best and worst values.
   The Euclidean distance from the ideal best value:

$$S^+ = \sqrt{\sum_{j=1}^{m} (V_{i,j} - V_j^+)^2} \tag{7}$$

   The Euclidean distance from the ideal worst value:

$$S^- = \sqrt{\sum_{j=1}^{m}(V_{i,j} - V_j^-)^2} \quad (8)$$

In this context, V_j^+ denotes the ideal value and V_j^- denotes the worst value for criterion C_j.

7) Calculating the final performance score
The performance score (P_i) for each alternative was determined by calculating the relative closeness to the ideal solution, as shown in (9).

$$P_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad (9)$$

8) Sort the values of P_i for each alternative A_i
Finally, the alternatives were ranked based on their performance scores (P_i). The alternatives with the highest scores were deemed the most deserving of social assistance. This ranking provided a clear, objective method for selecting recipients.

2.3. Data validation and robustness analysis

To ensure the reliability and accuracy of the results, the following validation techniques were applied:

1) Comparison with manual expert rankings to assess the consistency of fuzzy-TOPSIS results against traditional human evaluations.
2) Cross-validation using a sensitivity analysis, where small perturbations in input data were introduced to observe their effects on final rankings. The results showed that fuzzy-TOPSIS rankings remained stable despite minor changes in input values, confirming its robustness against expert variability.
3) Benchmarking against previous methods such as SAW, WPM, and Electre [10], [11], [15], demonstrating that fuzzy-TOPSIS provides a more transparent and objective ranking system.

3. RESULTS AND DISCUSSION

This study conducted structured interviews with three social assistance officers in Sumur Bandung District in May 2024 to obtain expert-driven evaluations that support the implementation of fuzzy-TOPSIS. The collected data included pairwise comparisons of criteria, the importance of each criterion, and ranking of potential recipients based on officers' knowledge and experience. Unlike traditional selection processes that rely solely on manual evaluation, this approach integrates quantitative and qualitative factors into a structured decision-support model. The comparative rankings provided by the officers were averaged, resulting in a combined ranking for each alternative, as shown in Figure 1. These rankings were then converted into fuzzy triangular numbers, ensuring that uncertainty and subjective variations in assessments were systematically handled. The original comparison matrix of criteria weightings assigned by officers is presented in Table 3, while Table 4 shows the corresponding fuzzy numbers.

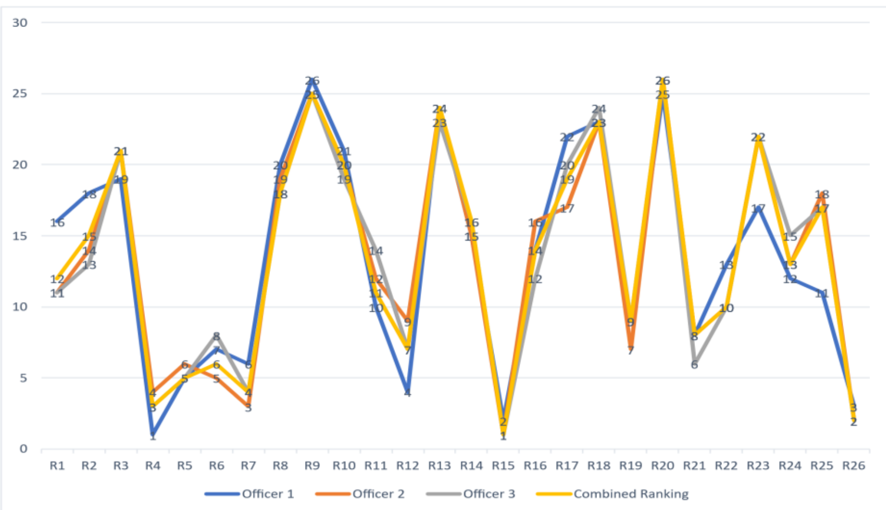

Figure 1. Alternative rankings based on officer assessments

Table 3. Pairwise comparison matrix

Criteria No.	1	2	3	4	5
1	1	3	5	7	5
2	1/3	1	3	5	3
3	1/5	1/3	1	3	3
4	1/7	1/5	1/3	1	5
5	1/5	1/3	1/3	1/5	1

Table 4. Pairwise comparison matrix in fuzzy numbers

Criteria No.	1	2	3	4	5
1	(1,1,1)	(2,3,4)	(4,5,6)	(6,7,8)	(4,5,6)
2	(1/4,1/3,1/2)	(1,1,1)	(2,3,4)	(4,5,6)	(2,3,4)
3	(1/6,1/6,1/4)	(1/4,1/3,1/2)	(1,1,1)	(2,3,4)	(2,3,4)
4	(1/8,1/7,1/6)	(1/6,1/6,1/4)	(1/4,1/3,1/2)	(1,1,1)	(4,5,6)
5	(1/6,1/6,1/4)	(1/4,1/3,1/2)	(1/4,1/3,1/2)	(1/6,1/6,1/4)	(1,1,1)

To enhance ranking stability, the geometric mean of fuzzy comparison values was computed for each criterion, ensuring a balanced and mathematically consistent weighting mechanism. These values, detailed in Table 5, 6, and 7, formed the basis for constructing the decision matrix, normalizing the data, and ultimately calculating the final rankings of social assistance recipients. The defuzzification process converted fuzzy values into crisp numbers, allowing for direct comparison and ranking, with the final normalized weights shown in Table 8.

Table 5. Geometric mean of fuzzy comparison values

Criteria	lW_i	mW_i	nW_i
Occupation	2.862	3.5	4.095
Housing Condition	1.32	1.719	2.169
Dependents	0.699	0.871	1.149
Income	0.461	0.524	0.66
Education	0.28	0.315	0.435
Total	**5.622**	**6.929**	**8.508**

Table 6. Increasing order of reverse values

Total	Reverse (power of – 1)	Increasing Order, I
5.622	0.178	**0.118**
6.929	0.144	**0.144**
8.508	0.118	**0.178**

Table 7. The average fuzzy comparison values

Criteria	$lW_i^{\sim}$	$mW_i^{\sim}$	$nW_i^{\sim}$
Occupation	0.338	0.504	0.729
Housing condition	0.156	0.248	0.386
Dependents	0.082	0.125	0.205
Income	0.054	0.075	0.117
Education	0.033	0.045	0.077

Table 8. Normalization of de-fuzzified criterion values

Criteria	M_i	N_i
Occupation	0.524	0.495
Housing Condition	0.263	0.249
Dependents	0.137	0.129
Income	0.082	0.078
Education	0.052	0.049
Total	**1.058**	**1**

The categorical data requires transformation into numerical values for normalization purposes, as Euclidean normalization typically applies to numeric data involving multidimensional space. However, categorical data must be converted to numeric meanings suitable for Euclidean measurement. Therefore, to enable this normalization, label encoding [29], [30] was employed to convert data to numerical values. The weighting of sub-criteria values, based on comprehensive interviews with social assistance officers in the Sumur Bandung District, ensures the reliability of the data. As shown in Table 9, Euclidean normalisation can be performed after converting social assistance recipient data into numerical values.

Table 9. Sum of square root values of alternatives for each criterion

	Criteria No. 1	2	3	4	5
$\sqrt{\sum_{j=1}^{n} X_{i,j}^{2}}$	17.692	9.327	13.964	13.565	11.662

Subsequently, the sum of square root criterion values for each alternative in Table 10 divides each cell $X_{i,j}$ for each criterion. The Euclidean normalization values $R_{i,j}$ required for each criterion across every alternative are obtained through this procedure, as displayed in Table 10.

Table 10. Euclidean normalization value

Alt.	Criteria No.					Alt.	Criteria No.				
	1	2	3	4	5		1	2	3	4	5
R1	0.226	0.107	0.215	0.147	0.171	**R14**	0.057	0.107	0.215	0.147	0.171
R2	0.226	0.214	0.072	0.147	0.171	**R15**	0.283	0.429	0.286	0.295	0.171
R3	0.057	0.107	0.072	0.074	0.086	**R16**	0.17	0.214	0.215	0.147	0.171
R4	0.283	0.322	0.143	0.295	0.429	**R17**	0.057	0.214	0.215	0.147	0.171
R5	0.283	0.107	0.072	0.295	0.086	**R18**	0.057	0.107	0.143	0.074	0.086
R6	0.226	0.214	0.286	0.221	0.171	**R19**	0.226	0.107	0.215	0.221	0.171
R7	0.226	0.214	0.286	0.221	0.343	**R20**	0.057	0.107	0.286	0.074	0.086
R8	0.17	0.214	0.072	0.221	0.171	**R21**	0.226	0.322	0.286	0.221	0.171
R9	0.057	0.107	0.143	0.074	0.171	**R22**	0.226	0.214	0.215	0.221	0.171
R10	0.226	0.214	0.072	0.221	0.171	**R23**	0.057	0.214	0.143	0.074	0.171
R11	0.17	0.107	0.286	0.221	0.171	**R24**	0.17	0.107	0.215	0.221	0.343
R12	0.283	0.107	0.072	0.221	0.086	**R25**	0.226	0.107	0.215	0.147	0.171
R13	0.057	0.107	0.143	0.074	0.086	**R26**	0.283	0.214	0.072	0.295	0.257

The normalized fuzzy weights N_i for each criterion, derived from Table 8, are multiplied by the Euclidean normalization values $R_{i,j}$ from Table 10. The results, represented as $V_{i,j}$ for each alternative across every criterion, are presented in Table 11.

Table 11. Criterion values multiplied by fuzzy weights

Fuzzy weight	0.495	0.249	0.129	0.078	0.049	Fuzzy weight	0.495	0.249	0.129	0.078	0.049
Alt.	Criteria No.					Alt.	Criteria No.				
	1	2	3	4	5		1	2	3	4	5
R1	0.112	0.027	0.028	0.011	0.008	**R14**	0.028	0.027	0.028	0.011	0.008
R2	0.112	0.053	0.009	0.011	0.008	**R15**	0.14	0.107	0.037	0.023	0.008
R3	0.028	0.027	0.009	0.006	0.004	**R16**	0.084	0.053	0.028	0.011	0.008
R4	0.14	0.08	0.018	0.023	0.021	**R17**	0.028	0.053	0.028	0.011	0.008
R5	0.14	0.027	0.009	0.023	0.004	**R18**	0.028	0.027	0.018	0.006	0.004
R6	0.112	0.053	0.037	0.017	0.008	**R19**	0.112	0.027	0.028	0.017	0.008
R7	0.112	0.053	0.037	0.017	0.017	**R20**	0.028	0.027	0.037	0.006	0.004
R8	0.084	0.053	0.009	0.017	0.008	**R21**	0.112	0.08	0.037	0.017	0.008
R9	0.028	0.027	0.018	0.006	0.008	**R22**	0.112	0.053	0.028	0.017	0.008
R10	0.112	0.053	0.009	0.017	0.008	**R23**	0.028	0.053	0.018	0.006	0.008
R11	0.084	0.027	0.037	0.017	0.008	**R24**	0.084	0.027	0.028	0.017	0.017
R12	0.14	0.027	0.009	0.017	0.004	**R25**	0.112	0.027	0.028	0.011	0.008
R13	0.028	0.027	0.018	0.006	0.004	**R26**	0.14	0.053	0.009	0.023	0.013

Based on the data in Table 11, a meticulous and thorough analysis has been conducted to determine the ideal best and worst values for each criterion. This analysis involves converting sub-criteria weights provided by social assistance officers using Label Encoding. The results of the calculation of the ideal best and worst values for each criterion can be found in Table 12.

Table 13 provides detailed Euclidean distance measurements for each alternative concerning the ideal best values (S^{+}) and ideal worst values (S^{-}), which are obtained from Tables 11 and 12. These distances quantify how far each alternative deviates from the optimal best and worst scenarios across the criteria considered in the evaluation process.

After calculating the Euclidean distances of each alternative from the ideal best (S^{+}) and ideal worst values (S^{-}), as shown in Table 13, the performance scores for each alternative are determined based on these distances. Table 14 provides a detailed presentation of the performance scores (P_i) assigned to each alternative, reflecting how well each alternative aligns with the earlier ideal criteria.

Table 12. Ideal best and ideal worst values for each criterion

	Criteria No.				
	1	2	3	4	5
Ideal best, V_j^{+}	0.14	0.107	0.037	0.023	0.021
Ideal worst, V_j^{-}	0.028	0.027	0.009	0.006	0.004

Table 13. Euclidean distance of each alternative

Alternative	S^{+}	S^{-}	Alternative	S^{+}	S^{-}
R1	0.084	0.084	**R14**	0.138	0
R2	0.071	0.089	**R15**	0	0.141
R3	0.141	0	**R16**	0.077	0.063
R4	0.032	0.126	**R17**	0.126	0.032
R5	0.084	0.114	**R18**	0.138	0
R6	0.063	0.095	**R19**	0.084	0.084
R7	0.063	0.095	**R20**	0.138	0.032
R8	0.084	0.063	**R21**	0.045	0.105
R9	0.138	0	**R22**	0.063	0.089
R10	0.071	0.089	**R23**	0.126	0.032
R11	0.095	0.063	**R24**	0.095	0.055
R12	0.084	0.114	**R25**	0.084	0.084
R13	0.138	0	**R26**	0.063	0.118

Table 14. Performance scores for each alternative

Alternative	$S^{+} + S^{-}$	P_i	Alternative	$S^{+} + S^{-}$	P_i
R1	0.168	0.5	**R14**	0.138	0
R2	0.16	0.556	**R15**	0.141	1
R3	0.141	0	**R16**	0.14	0.45
R4	0.158	0.797	**R17**	0.158	0.203
R5	0.198	0.576	**R18**	0.138	0
R6	0.158	0.601	**R19**	0.168	0.5
R7	0.158	0.601	**R20**	0.17	0.188
R8	0.147	0.429	**R21**	0.15	0.7
R9	0.138	0	**R22**	0.152	0.586
R10	0.16	0.556	**R23**	0.158	0.203
R11	0.158	0.399	**R24**	0.15	0.367
R12	0.198	0.576	**R25**	0.168	0.5
R13	0.138	0	**R26**	0.181	0.652

The alternatives can be ranked in ascending order based on the performance scores provided in Table 14. Figure 2 shown the comparative classification and the subsequent performance scores. The final rankings obtained using fuzzy-TOPSIS were compared to the manual rankings provided by field officers. As illustrated in Figures 3 and 4, significant ranking discrepancies emerged, particularly in cases such as R10 and R14, where officer-based evaluations placed them lower, while fuzzy-TOPSIS ranked them higher. The discrepancy indicates that manual assessments may be influenced by personal biases or non-standardized evaluation criteria, whereas fuzzy-TOPSIS consistently applies structured weightings to maintain fairness and transparency. The stability of rankings using fuzzy-TOPSIS contrasts with the greater variation observed in manual evaluations, which suggests that qualitative assessments alone may introduce inconsistencies in social assistance selection. For example, R1, R13, and R17 showed nearly identical rankings in both approaches, suggesting that objective and subjective evaluations align in certain cases, but overall, fuzzy-TOPSIS provides a more structured and reproducible decision framework. Therefore, it is recommended to use a combination of both methods in the decision-making process to achieve more comprehensive and fair results.

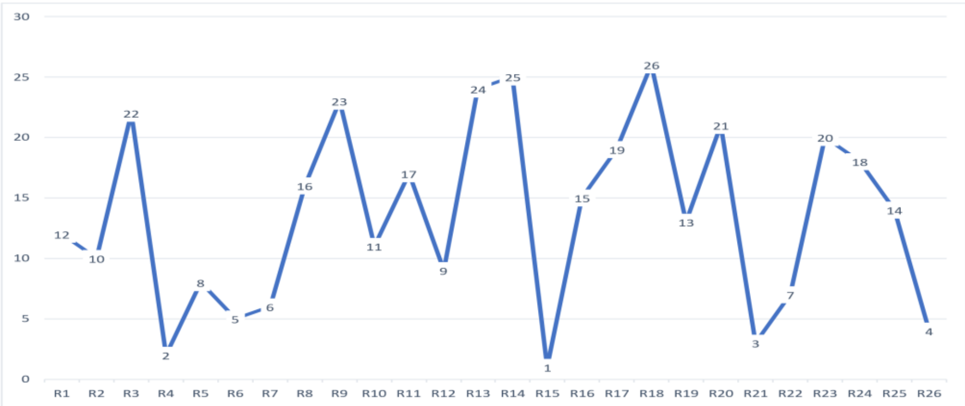

Figure 2. Order of performance scores for alternatives ranking

Figure 3. Graphical comparison of fuzzy-TOPSIS rankings and officer assessments

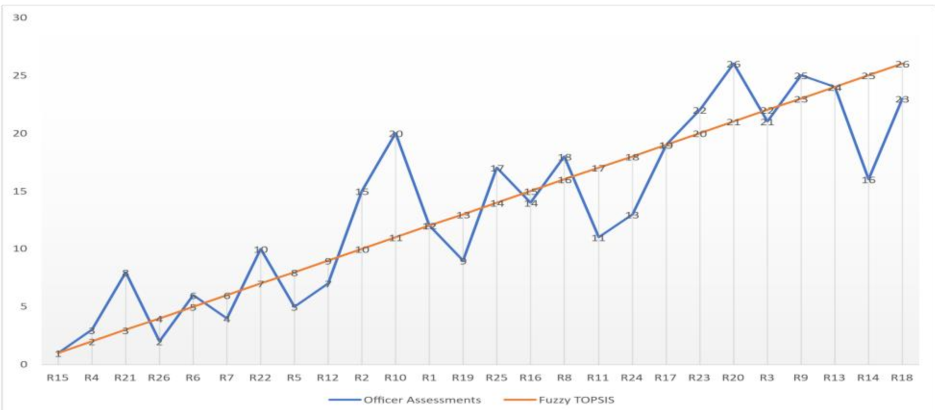

Figure 4 Graphical comparison of fuzzy-TOPSIS rankings and officer assessments sorted by fuzzy-TOPSIS ranking

To validate the effectiveness of the fuzzy-TOPSIS approach, its results are compared with existing methods applied in social assistance selection. Prior studies have primarily relied on SAW, WPM, and AHP-based approaches, which, while effective, exhibit several limitations:

a. SAW and WPM models [10]-[13] provide simple summation-based rankings, making them highly sensitive to subjective weight assignments. These methods lack mechanisms to handle uncertainty in decision-making, which may result in suboptimal recipient selection.
b. Electre & Roc-based approaches [15] offer robust prioritization but struggle with ambiguous or conflicting criteria, requiring precise numerical inputs, which are often unavailable in real-world social assistance assessments.
c. Fuzzy-AHP [9] improves hierarchical weight determination, but lacks a direct ranking mechanism, making it less suitable for cases requiring clear, ranked decisions.
d. VIKOR [16] seeks compromise solutions rather than optimal recipient selection, potentially leading to suboptimal allocations when strict eligibility criteria are required.

Unlike these methods, fuzzy-TOPSIS offers key advantages:

a. Superior ranking accuracy by incorporating triangular fuzzy numbers to reduce inconsistencies in expert evaluations.
b. Enhanced robustness against subjectivity and bias, ensuring a fairer and more equitable ranking system.
c. Better handling of qualitative socio-economic criteria, making it more adaptable to real-world policy changes.
d. More transparent selection processes, which can help reduce risks of favoritism and corruption in aid distribution.

The results of this study reinforce the need for structured and adaptive decision-support systems in social assistance allocation. Fuzzy-TOPSIS introduces a level of consistency and transparency that is often missing in manual selection methods. By using fuzzy logic to account for uncertain and ambiguous data, this model ensures fairer and more accurate decision-making than previous deterministic models. Additionally, the research demonstrates that manual assessments alone may lead to unintended biases, compromising the fairness and efficiency of social aid distribution. By integrating fuzzy-TOPSIS, this study provides a validated, scalable model that enhances accountability and decision reliability in the social assistance sector.

The findings of this study have practical implications for policymakers, social welfare administrators, and government agencies. Fuzzy-TOPSIS can be directly applied to improve social assistance distribution policies in Sumur Bandung and other regions by ensuring that aid reaches the most deserving recipients through a structured, unbiased, and data-driven process. Key real-world applications include:

a. More transparent social welfare programs by eliminating subjective biases from manual selection processes.
b. Scalable implementation in local and national government programs, allowing for data-driven decision-making across multiple administrative levels.
c. Improved efficiency in aid allocation, ensuring that funds and resources are distributed optimally.
d. Reduction of potential corruption risks, as all decisions become data-backed and verifiable, minimizing opportunities for favoritism.

4. CONCLUSION

This study applied MCDM techniques, with a particular focus on the fuzzy-TOPSIS method, to systematically assess and rank social assistance candidates in Sumur Bandung District. A rigorous research framework was established, encompassing a comprehensive review of existing literature, meticulous data collection, and comparative analysis of fuzzy-TOPSIS rankings against manual evaluations conducted by social assistance officers. The findings of this study emphasize the importance of structured and data-driven decision-making models in enhancing the fairness, transparency, and efficiency of social assistance distribution.

The key contributions of this research are as follows: a) Development of an enhanced fuzzy-TOPSIS framework specifically tailored for social assistance recipient selection, incorporating dynamic weight adjustments and uncertainty handling to improve ranking reliability. This approach addresses key limitations of previous MCDM models such as SAW, WPM, AHP, and VIKOR, which lack mechanisms for managing subjectivity and data ambiguity. Unlike SAW and WPM, which rely on fixed weight assignments, fuzzy-TOPSIS integrates fuzzy logic to accommodate uncertainty in expert evaluations, leading to more adaptive and accurate rankings; b) Empirical validation demonstrating that fuzzy-TOPSIS provides more consistent and objective rankings compared to manual officer assessments, reducing bias and inconsistencies often present in traditional selection methods. Unlike Electre & Roc, which prioritize alternatives based on deterministic criteria, fuzzy-TOPSIS refines decision-making by considering the degree of closeness to ideal solutions, making it more suitable for real-world, multi-dimensional decision environments; and c)

Significant implications for social welfare policy and decision-making, offering a replicable and scalable model that can be adopted in other districts and regions to enhance the effectiveness of targeted social assistance programs. Unlike fuzzy-AHP, which focuses on hierarchical structuring but lacks a direct ranking mechanism, fuzzy-TOPSIS offers both criteria weighting and ranking capabilities, making it a more comprehensive approach for recipient selection. This research underscores the importance of integrating computational decision-support tools into social policy frameworks, enabling more equitable distribution of aid.

While this study provides a robust framework for social assistance recipient selection, several areas can be explored in future research. One potential direction is the integration of real-time socio-economic data to dynamically adjust recipient rankings based on changing conditions, such as inflation rates, employment status, or government policy shifts. Future studies could also explore hybrid models that combine Fuzzy-TOPSIS with artificial intelligence (AI) techniques, such as machine learning or deep learning, to enhance predictive accuracy and automate decision-making. Additionally, applying the model to other social welfare programs beyond financial aid distribution, such as education scholarships, healthcare subsidies, or disaster relief assistance, could further validate its broader applicability. By advancing computational decision-support methodologies in social policy implementation, this research contributes to the development of more equitable, efficient, and transparent social assistance programs, ultimately benefiting both policymakers and underserved communities.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Rangga Sanjaya	✓	✓		✓	✓	✓			✓	✓	✓		✓	✓
Irmeila Cahaya Fatihah	✓	✓	✓		✓	✓	✓	✓	✓		✓		✓	
Titik Khawa Abdul Rahman	✓	✓		✓	✓	✓				✓		✓		

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest. They have no known competing financial interests, personal relationships, or non-financial competing interests that could have appeared to influence the work reported in this paper.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study. All participants were informed about the purpose, methods, and intended use of the data, and they voluntarily agreed to participate in accordance with ethical research standards.

ETHICAL APPROVAL

The research related to human use has complied with all the relevant national regulations and institutional policies in accordance with the tenets of the Helsinki Declaration and has been approved by the institutional review board.

DATA AVAILABILITY

The data that support the findings of this study are openly available in the institutional repository of Universitas Adhirajasa Reswara Sanjaya. Reference number and dataset access link will be provided upon request to maintain compliance with data sharing policies and participant confidentiality.

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