Journal of Information System and Technology Research

journal homepage: https://journal.aira.or.id/index.php/jistr/

Robust Large-Scale Poverty Prioritization Using a-Cut Fuzzy AHP and Fuzzy WASPAS

Hauzan Hanifah Zahra[1*], Amri Muhaimin[2], Sugiarto[3]

[1,2]Departement of Data Science, Universitas Pembangunan Nasional "Veteran" Jawa Timur
[3]Departement of Business Digital, Universitas Pembangunan Nasional "Veteran" Jawa Timur

ARTICLE INFO

Article history:

Received Jan 28, 2026
Accepted May 29, 2026
Available online May 31, 2026

Keywords:

A-cut defuzzification
Fuzzy AHP
Fuzzy WASPAS
Multicriteria decision making
Social assistance targeting

How to Cite :
H. H. Zahra, A. Muhaimin, and Sugiarto, "Robust Large-Scale Poverty Prioritization Using α-Cut Fuzzy AHP and Fuzzy WASPAS," Journal of Information System and Technology Research, vol. 5, no. 2, pp. 281–294

ABSTRACT

Prioritizing poverty alleviation programs remains challenging due to multidimensional indicators and uncertainty in expert judgment. This study purposes a robust decision support framework by integrating α-cut Fuzzy Analytic Hierarchy Process (Fuzzy AHP) and Fuzzy Weighted Aggregated Sum Product Assessment (Fuzzy WASPAS) for large-scale poverty prioritization. The α-cut mechanism was incorporated into the Fuzzy AHP weighting process to improve flexibility and robustness under uncertainty, while Fuzzy WASPAS was employed to rank 20,000 household alternatives based on 14 poverty indicators derived from DTKS and BPS Data. Sensitivity analysis was conducted using several α values to evaluate ranking stability under varying confidence levels. The results demonstrate that the proposed framework produces highly stable rankings, with an average maximum rank shift of 143 positions (0.7%) and a median shift of 81 positions (0.4%) across all alternatives. Futhermore, the model achieved an average Spearman rank correlation of 0.9996, indicating strong consistency in poverty prioritization outcomes despite variations in fuzzy defuzzification parameters. The findings confirm that the integration of α-cut Fuzzy AHP and Fuzzy WASPAS provides a reliable and robust approach for evidence-based poverty targeting and social assistance allocation. The proposed framework can support policymakers in improving the accuracy, transparency, and consistency of poverty intervention strategies.

Corresponding Author:

Hauzan Hanifah Zahra,
Departement of Data Science, Universitas Pembangunan Nasional "Veteran" Jawa Timur
Rungkut Madya St., Gunung Anyar, Kec. Gunung Anyar, Surabaya.
Email: 22083010075@student.upnjatim.ac.id

1. INTRODUCTION

Poverty remains a multifaceted and strategic global challenge that necessitates organized, data-driven decision-making. [1]. Determining intervention priorities is an essential step to ensure that poverty alleviation programs are both successful and well-targeted, as local governments frequently have limited financial and administrative resources [3]. Poverty encompasses a variety of aspects, such as food security, housing conditions, access to essential services, education, and more general socioeconomic characteristics, and cannot be sufficiently captured by a single indicator [1][4]. Because of this complexity, a decision support system that can systematically and objectively integrate various indicators must be developed [5][6].

This study integrates Fuzzy Weighted Aggregated Sum Product Assessment (Fuzzy WASPAS) and Fuzzy Analytic Hierarchy Process (Fuzzy AHP) to create a robust decision support framework for poverty prioritization. The relative weights of poverty criteria and sub criteria are determined using fuzzy AHP [7][8], and alternatives are ranked using fuzzy WASPAS based on the derived weights [8][9]. Because it takes into account expert judgment uncertainty and combines additive and multiplicative aggregation mechanisms to generate comprehensive preference values, the combination of these two approaches is especially well-suited for multicriteria poverty assessment in diverse geographic contexts. [7][8][10].

In contrast to traditional fuzzy AHP methods, this study uses an α-cut based defuzzification mechanism in the weight determination process [11][12]. By adjusting the α parameter [11][12], the α-cut method allows the degree of strictness or optimism in decision-making to be adjusted [12][13], offering a scalable solution for different administrative standards. Rather than converting fuzzy weight into single, clear values, the α-cut narrows the fuzzy interval based on a predetermined confidence level, giving decision makers conceptual flexibility regarding uncertainty [12], This approach improves the interpretability of weight formation while preserving methodological rigor.

However, despite the availability of various decision making models, a fundamental research problem remain, conventional methods often fail to adequately capture the uncertainty and subjectivity inherent in expert judgments. Standard crisp AHP can be too rigid, while traditional fuzzy approaches sometimes lose information during the defuzzification process. Without addressing this uncertainty the resulting poverty rankings may be unstable or biased, leading to ineffective resource allocation.

To resolve this issue, the primary objective of this study is to develop a robust decision support framework that integrates the Fuzzy AHP and the Fuzzy WASPAS. This study updates previous research by introducing the α-cut approach into the weighing process, which offers a flexible confidence interval for decision makers a feature rarely explored in existing poverty prioritization models.

The main contributions of this research are threefold: (1) it constructs a comprehensive hierarchical model for poverty using 14 indicators from the National Integrated Social Welfare Database (DTKS); (2) it provides a novel integration of Fuzzy AHP with α-cut and Fuzzy WASPAS to enhance ranking stability; and (3) it performs a rigorous sensitivity analysis to prove that the proposed model generates consistent priority rankings even under varying levels of decision-making uncertainly. Ultimately, this framework serves as a reliable, evidence-based tool for local governments to target poverty interventions more accurately.

The efficiency and adaptability of hybrid fuzzy AHP and fuzzy WASPAS approaches in a variety of fields have been shown in numerous studies. In their study "Evaluating Environmental, Social, and Governance Criteria and Green Finance Investment Strategies Using Fuzzy AHP and Fuzzy WASPAS," Xiaokai and Ghulam (2023) demonstrated the efficacy of this method for assessing green investment strategies according to environmental, social, and governance (ESG) criteria. In "Multi-Criteria Healthcare Waste Disposal Location Selection Based on Fermatean Fuzzy WASPAS Method," Mishra and Rani (2021) created a more reliable and precise framework for healthcare waste disposal location selection.

In the education sector, Akmaludin et al. (2024) applied this method in “Integrated Selection of Permanent Teacher Appointments Recommended MCDM-AHP and WASPAS Methods” to choose permanent teachers. Similarly, Annisa et al. (2023) used “Intuitionistic Fuzzy AHP and WASPAS to Assess Service Quality in Online Transportation” to evaluate the quality of online transportation services. These different applications show that fuzzy AHP and WASPAS can effectively support complex decision-making processes with multiple criteria. Similar decision support frameworks have also been widely applied in poverty alleviation and social assistance targeting, demonstrating the relevance of multi-criteria approaches for public policy prioritization [14]. Therefore, using these methods offers a reliable solution for decision-making scenarios that involve various criteria and uncertainties.

Recent studies have increasingly applied fuzzy multicriteria decision making approaches in public policy and social evaluation contexts. Arslan and Cebi (2024) extended the WASPAS framework using decomposed fuzzy sets to improve uncertainty representation in complex decision environments. Similarly, Abbasi et al. (2025) demonstrated that Fuzzy AHP provides more flexible and reliable weighting structures for environmental and public-sector assessment compared to conventional crisp approaches. In addition, recent sensitivity-analysis studies in multi-criteria decision making emphasize that ranking robustness is essential to ensure transparency and reliability in policy-oriented decision support systems, particularly when handling large-scale social datasets.

Despite these developments, existing studies primarily focus on industrial, environmental, healthcare, or educational applications, while limited attention has been given to large-scale poverty prioritization under uncertainty. Furthermore, previous poverty-targeting studies generally rely on conventional weighting mechanisms without explicitly integrating α-cut based defuzzification to evaluate ranking robustness under varying confidence levels. Therefore, this study addresses this research gap by integrating α-cut Fuzzy AHP and Fuzzy WASPAS within a large-scale poverty prioritization framework involving 20,000 household alternatives.

By combining Fuzzy AHP with α-cut analysis and Fuzzy WASPAS, this study not only creates a prioritized list of poverty interventions but also shows that the decision model stays consistent even when parameters change. The findings have practical value for local governments. They can help in forming evidence-based policies for more focused and accountable poverty alleviation strategies.

2. RESEARCH METHOD

The research methodology employed in this study is illustrated through a systematic flowchart that describes the overall stages of the proposed decision-making framework.

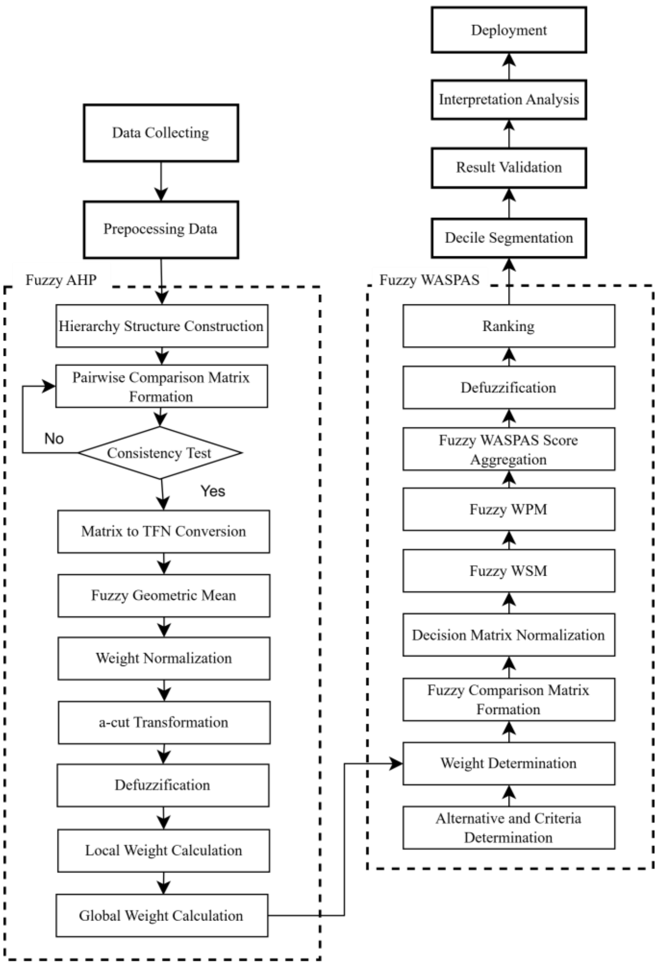

Figure 1. Flowchart
Source: Generated by the authors

Figure 1 illustrates the workflow of the proposed research framework by integrating the Fuzzy AHP and Fuzzy WASPAS methods in a structured decision-making process. The process begins with data collection and data preprocessing to ensure the quality and suitability of the dataset for further analysis. Subsequently, the Fuzzy Analytic Hierarchy Process (Fuzzy AHP) method is utilized to determine the weights of the evaluation c used to determine the weights of the evaluation criteria through the construction of a hierarchy, the formation of a pairwise comparison matrix through hierarchy construction, pairwise comparison matrix formation, consistency testing, and weight normalization. Furthermore, the Fuzzy Weighted Aggregated Sum Product Assessment (Fuzzy WASPAS) method is applied to rank the alternatives by integrating the Weighted Sum Model (WSM) and Weighted Product Model (WPM) approaches under a fuzzy environment. The final stages include result validation, interpretation analysis, and deployment to ensure that the proposed model provides accurate, reliable, and practical decision support outcomes.

2.1. Data Sources and Types

This study employs household poverty indicators from the Data Terpadu Kesejahteraan Sosial (DTKS) and the Badan Pusat Statistik (BPS), which function as benchmarks for various social protection programs in Indonesia. The data comprises 14 household-level poverty indicators that reflect various dimensions of welfare [15][16]. These indicators are the basis for deciding which poverty alleviation programs should get the most attention [17]. Decision support models can improve the objectivity and transparency of beneficiary selection in similar social welfare contexts [18]. All fourteen indicators are treated as research variables and structured into a decision hierarchy using the Fuzzy Analytic Hierarchy Process (Fuzzy AHP). The Hierarchical structure is meant to show to decision problem in a systematic way and make it easier to weight the options step by step.

This study's decision hierarchy has three levels. The first level is the main goal: to find out which poor households should get the most help by using a multidimensional poverty approach. The second level has four main criteria that come from grouping the 14 indicators: Food and Clothing Security, Socio Economic and Education Profile, Utility Access, and Housing Quality. This classification is predicated on the basic needs approach, which defines poverty as the failure of households to satisfy both food and non-food requirements [1][4]. The indicators are therefore divided into groups based on consumption adequacy, socio-economic capacity, access to basic services, and housing conditions [5][19].

There are 14 sub criteria in the third level that act as operational indicators for each main criterion. Each sub-criterion talks about certain things about a household, such as its education level, housing conditions, access to basic services, and economic and consumption conditions. It is especially important to use DTKS data because it is the official reference for targeting social assistance programs. So, putting these indicators first helps put policies into action and makes it easier for local governments to choose beneficiaries objectively. Figure 1 shows how the main criteria and sub criteria are related to each other in a hierarchy.

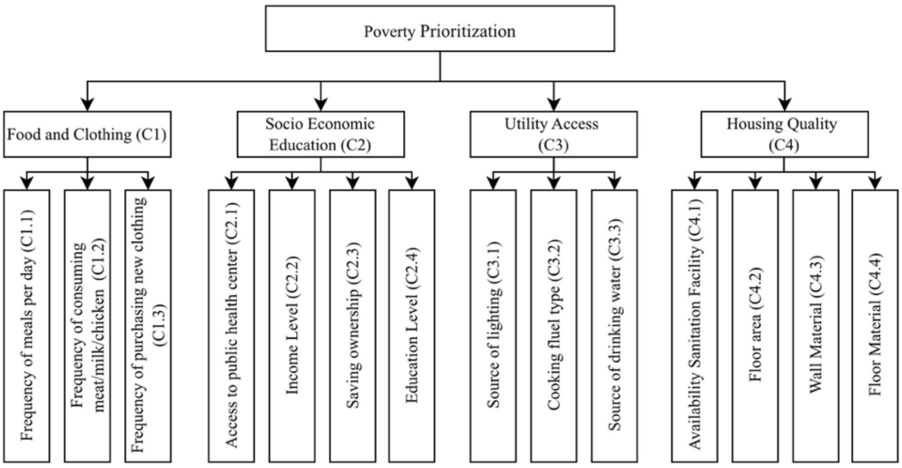

Figure 1. Structure Hierarchy
Source: Generated by the authors

Figure 1 shows that the decision-making process in this study is organized hierarchically, so that each indicator is placed in a systematic way based on its role in the evaluation framework. This hierarchical structure is the basis for the pairwise comparisons that will come next. This lets the weights show how important each criterion and sub-criterion is in relation to the others. Based on the established hierarchy, one of the 14 poverty indicators used in this study stands for each sub criteria. Table 1 gives a full list of these indicators and their definitions as variables.

Table 1. Grouping of Poverty Criteria and Sub-Criteria (Indicators)

Criteria	Sub Criteria	Description
Food and Clothing Security (C1)	Frequency of meals per day (C1.1)	Household members consume only one or two meals per day.
	Frequency of consuming meat/milk/chicken (C1.2)	Unable to purchase or consume meat, milk, or chicken at least once per week.
	Frequency of purchasing new clothing (C1.3)	Unable to purchase at least one new set of clothing per year.
Socio Economic and Education Profile (C2)	Access to public health center (C2.1)	Unable or lacking access to visit public health facilities such as community health centers.
	Income level (C2.2)	Monthly household income is below IDR 600,000.
	Savings ownership (C2.3)	Does not possess savings or valuable assets that can function as economic reserves.
	Education level (C2.4)	The head of household has a low level of educational attainment.
Utility Access (C3)	Source of lighting (C3.1)	Household lighting source is not derived from electricity.
	Cooking fuel type (C3.2)	Uses firewood, charcoal, or kerosene as the primary cooking fuel.
	Source of drinking water (C3.3)	Drinking water is obtained from unprotected water sources.
Housing Quality (C4)	Availability of sanitation facility (C4.1)	Does not have access to proper sanitation facilities.
	Floor area (C4.2)	Living space is less than 8 m² per person.
	Wall material (C4.3)	Walls are made of bamboo, thatch, low quality wood, or unplastered brick.
	Floor material (C4.4)	Floor is made of soil, bamboo, or simple wood materials.

Source: Generated by the authors

The grouping of the fourteen indicators into four main criteria was conducted to facilitate structured data representation within the decision making model. Each indicator obtained from the DTKS database was classified according to the dimension of welfare it measures, thereby forming a systematic and non overlapping variable structure. The Food and Clothing Security criterion represents the fulfilment of basic consumption needs. The Socio Economic Profile reflects household economic capacity, access to health services, and human capital quality. Utility Access describes the availability and accessibility of basic infrastructure, while Housing Quality represents the physical condition of the dwelling as a structural indicator of welfare.

The data utilized in this study are quantitative and categorical, subsequently transformed into an evaluation scale suitable for the Fuzzy AHP method. Each indicator was classified as a benefit type attribute, with elevated values indicating increased vulnerability or deprivation. Before making the pairwise comparison matrix, the data was coded and standardized to make sure the weighting process was consistent. This study organize the data into a hierarchical structure of criteria and sub criteria, making sure that each variable is based on a clear idea and fits directly with the multidimensional poverty framework used in the analysis.

2.2. Fuzzy AHP

This study uses Fuzzy Analytic Hierarchy Process (Fuzzy AHP) to figure out the priority weight of poverty criteria and sub criteria, taking into account the uncertainty that comes with making decision [7][8]. In multidimensional poverty assessment, weight determination is a crucial phase as it signifies the relative contribution of each indicator in depicting household vulnerability. Because expert opinions on public policy evaluation are always subjective and often wrong, the usual AHP method that uses crisp values may not be able to fully capture the uncertainty in pairwise comparisons [20] [21].

To address this constrains, Fuzzy AHP incorporates fuzzy set theory into the traditional AHP framework, allowing decision makes preferences to be articulate as Triangular Fuzzy Number (TFN) [8][22]. Fuzzy AHP offers adaptability in modelling uncertainty by representing judgements as intervals instead of singular point estimates, thereby diminishing the inflexibility of precise numerical comparisons [7][23]. This study employs Fuzzy AHP to ascertain local and global weight of poverty indicators before the ranking phase utilizing Fuzy WASPAS.

Moreover, this study integrates an α-cut method lets you change fuzzy weight intervals based on a certain level of confidence. This lets you control how strict the decision making process is. The α parameter narrows the fuzzy interval [13]. The α parameter narrows the fuzzy interval instead of directly turning fuzzy weights into clear values by averaging them [13]. It gives a more controlled picture of what the decision maker wants. The mechanism makes weight formation more stable while keeping the conceptual flexibility of fuzzy representation.

The addition of α-cut to Fuzzy AHP is not meant to change the main goal of prioritizing poverty, but rather to make sure that weights stay the same even when there is a lot of uncertainty about the decision. In public policy, this is especially important because consistent and reliable prioritization results are necessary for effective resource allocation [12][13]. A TFN number is shown as [7],

$$\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij}) \tag{1}$$

With its reciprocal defined as,

$$\tilde{a}_{ji} = \left(\frac{1}{u_{ij}}, \frac{1}{m_{ij}}, \frac{1}{l_{ij}}\right) \tag{2}$$

With $l_{ij} \leq m_{ij} \leq u_{ij}$,

l_{ij} : lower value (l)

m_{ij} : modal value (m)

u_{ij} : upper value (u)

The linguistic scale used refers to the development of the Saaty scale into the TFN form as presented in the following Table 2.

Table 2. Triangular Fuzzy Number [6][24]

Saaty Scale	Linguistic Variable	TFN
1	Equal importance	(1, 1, 1)
2	Intermediate value	(1, 2, 4)
3	Moderate importance	(1, 3, 5)
4	Intermediate value	(2, 4, 6)
5	Strong importance	(3, 5, 7)
6	Intermediate value	(4, 6, 8)
7	Very strong importance	(5, 7, 9)
8	Intermediate value	(6, 8, 9)
9	Extreme importance	(7, 9, 9)

Source: Generated by the authors

The steps in the Fuzzy AHP method were implemented and developed by Gogus and Boucher [7][8][13][25] as follows,

A. Hierarchical Structure Identification

The first stage is to build a decision hierarchy consisting of objectives at the top level, namely the criteria and sub criteria.

B. Fuzzy Pairwise Comparison Matrix

The second stage involves making pairwise comparisons between criteria and sub criteria using a linguistic scale converted to a TFN.

$$\tilde{A} = [\tilde{a}_{ij}]_{nxn} \tag{3}$$

C. Consistency Test

The consistency test is performed using the mean value matrix (m) to ensure the rationality of the assessment. Calculate the maximum eigenvalue with the process,

$$\lambda_{max} = \frac{1}{n}\sum\left(\frac{(A_m w)_i}{w_i}\right) \tag{4}$$

Consistency Index (CI) and Consistency Ratio (CR) are calculated by,

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{5}$$

$$CR = \frac{CI}{RI} \tag{6}$$

With Random Index,

Size Matrix	RI
1,2	0
3	0,58
4	0,90
5	1,12
6	1,24
7	1,32
8	1,41
9	1,45
10	1,49

Source: Generated by the authors

The matrix is considered consistent if $CR \leq 0,1$.

D. *Fuzzy Geometric Mean*

Next, the fuzzy geometric mean of each criterion is calculated using,

$$\widetilde{w}_i = \left(\left(\prod_{j=1}^{n} l_{ij}\right)^{\frac{1}{n}}, \left(\prod_{j=1}^{n} m_{ij}\right)^{\frac{1}{n}}, \left(\prod_{j=1}^{n} u_{ij}\right)^{\frac{1}{n}}\right) \tag{7}$$

With value $\widetilde{w}_i = (l_i, m_i, u_i)$.

E. Fuzzy Weight Normalization

The fuzzy weight of each criterion is normalized to the total number with,

$$\widetilde{w}_i = \left(\frac{l_i}{\Sigma u_k}, \frac{m_i}{\Sigma m_k}, \frac{u_i}{\Sigma l_k}\right) \tag{8}$$

F. α-Cut Defuzzification

To obtain crisp weights, an α-cut process is performed on the fuzzy weights. The a-cut interval limit is calculated as,

$$l_i^a = l_i + a(m_i - l_i) \tag{9}$$

$$u_i^a = u_i - a(u_i - m_i) \tag{10}$$

With $0 \leq \alpha \leq 1$. The crisp value is obtained through a linear combination,

$$w_i^a = \lambda u_i^a + (1 - \lambda) l_i^a \tag{11}$$

In this study, $\lambda = 0,5$ was used, resulting in an average α-cut interval. The weights were then normalized,

$$w_i^{norm} = \frac{w_i^a}{\Sigma w_i^a} \tag{12}$$

G. Sensitivity Analysis α-cut

To analyze the influence of the level of uncertainty on the weighting results, the value of α is varied at,

$$a \in \{0.1, 0.3, 0.5, 0.7, 0.9\}$$

Changes in the α value are analyzed against variations in criteria weights and changes in the priority order of alternatives. The larger the α value, the narrower the fuzzy interval so that the weights are closer to the middle (modal) value.

H. Global Weight Calculation

The global weight is obtained by multiplying the criterion weight and the sub criteria weight,

$$Global\ Weight = Criteria\ Weight \times Sub\ Criteria\ Weight \tag{13}$$

This global weight is then used as input in the Fuzzy WASPAS method for the poverty priority ranking process.

2.3. Fuzzy WASPAS

The Fuzzy WASPAS method is employed in this study to determine the priority ranking of poor households based on the criterion weights obtained from the Fuzzy AHP process with α-cut variation. Within the decision support system framework, Fuzzy WASPAS serves as the final aggregation stage, integrating weighted indicator values to produce a comprehensive preference score for each alternative [7] [9].

Fuzzy WASPAS is an extension of the classical WASPAS method, combining the Weighted Sum Model (WSM) and the Weighted Product Model (WPM) within a fuzzy environment [7][26]. The integration of these two approaches enhances ranking stability and improves decision accuracy by simultaneously considering additive and multiplicative aggregation mechanisms[26]. The additive component (WSM) allows compensatory evaluation across criteria, while the multiplicative component (WPM) reduces excessive compensatory effects, resulting in a more balanced and robust prioritizations structure [7].

In the context of poverty prioritizations, this hybrid aggregation mechanism is particularly relevant because household deprivation indicators may interact in a complex manner. By incorporating fuzzy representation, the method accommodates uncertainty in indicator assessment while maintaining computational consistency [8]. Consequently, Fuzzy WASPAS provides a structured and reliable mechanism for generating priority rankings that can support evidence based policy formulation and targeted poverty intervention strategies.

Suppose there are m alternatives and n criteria, the decision matrix is expressed as follows [7][9],

$$\mathrm{X} = \left[\mathrm{x_{ij}}\right]_{\mathrm{m \times n}} \tag{14}$$

Every x_{ij} value is converted into TFN,

$$\tilde{x}_{ij} = \left(l_{ij}, m_{ij}, u_{ij}\right) \tag{15}$$

With, $l_{ij} \leq m_{ij} \leq u_{ij}$,

l_{ij} : lower value (l)

m_{ij} : modal value (m)

u_{ij} : upper value (u)

The steps for Fuzzy WASPAS are as follows,

A. Matrix Normalization

Normalization is performed by dividing each TFN component by the maximum upper limit value for each criterion. This calculation is performed through the process,

$$\tilde{r}_{ij} = \left(\frac{\tilde{x}_{ij}}{\underset{i}{max}\tilde{x}_{ij}}\right) = \left(\frac{l_{ij}}{\max(u_j)}, \frac{m_{ij}}{\max(u_j)}, \frac{u_{ij}}{\max(u_j)}\right) \tag{16}$$

Where $\max(u_j)$ is the maximum value of the upper component in the jth criterion, in this study, all indicators are constructed in the form of benefit attributes, where large values indicate a higher level of poverty.

B. Fuzzy Weighted Sum Model

The preference value based on the weighted summation approach is calculated by,

$$\tilde{Q}_i^{(1)} = \sum_{j=1}^{n} w_j \tilde{r}_{ij} \tag{17}$$

Where w_j is the crisp weight resulting from $a - cut$ at the Fuzzy AHP.

C. Fuzzy Weighted Product Model

The preference value based on the weighted summation approach is calculated by,

$$\tilde{Q}_i^{(2)} = \prod_{j=1}^{n} \tilde{r}_{ij}^{w_j} \tag{18}$$

Where w_j is the crisp weight resulting from $a - cut$ at the Fuzzy AHP.

D. Fuzzy WASPAS Value Aggregation

The final Fuzzy WASPAS value is calculated by combining both approaches,

$$\tilde{Q}_i = \lambda \tilde{Q}_i^{(1)} + (1-\lambda)\tilde{Q}_i^{(2)} \tag{19}$$

Where value $\lambda = 0{,}5$, interpreted as the combined contribution of the WSM and WPM methods.

E. Defuzzified

The fuzzy values resulting from aggregation are then defuzzified using the centroid method to obtain crisp values,

$$Q_i = \frac{l_i + m_i + u_i}{3} \tag{20}$$

The Q_i is used as the basis for the alternative ranking process. The alternative with Q_i the highest value indicates a higher level of poverty priority.

3. RESULTS AND DISCUSSION

This section shows the result of using the integrated Fuzzy AHP and Fuzzy WASPAS framework to figure out what the 14 established indicators say about how to best deal with poverty. The analysis was done in a methodical way. It started with estimating criterion weights using the TFN based Fuzzy AHP approach, then moved on to normalizing the decision matrix by attribute type, aggregating preference values using the Fuzzy WASPAS methide, and finally defuzzifying the result to get clear scores for ranking.

The main goal of this stage is using multidimensional poverty indicators to find the most important household. The resulting ranking shows how bad deprivation is in comparison to other options and gives a structured way to plan targeted intervention strategies [27]. Stable ranking outcomes are critical for ensuring reliable and accountable policy implementation [28]. A sensitivity analysis was also done using the α-cut method at different α levels (0 < α < 1) to make sure the decision model was strong [29]. This analysis assesses the stability of criterion weights and ranking results amidst varying levels of uncertainty in fuzzy representation. So, the results show not only the best options but also how the decision support system stays the same when confidence levels change.

3.1. Fuzzy AHP Weighting Result

The first stage of the analysis involves estimating the priority weights of poverty indicators using the Fuzzy AHP method. In this study, defuzzification was performed using an α-cut approach to accommodate uncertainty in expert judgments. The α parameter was varied across several levels, namely $\alpha \in \{0.1, 0.3, 0.5, 0.7, 0.9\}$, in order to examine how different degrees of confidence in fuzzy representation affect the resulting weights. It is important to note that the variation of α influences the defuzzification interval but does not alter the hierarchical structure of criteria and sub criteria [13]. Thus, the relative conceptual relationships among indicators remain constant, while the numerical representation of their importance may slightly adjust according to the selected α level [30].

The weights used in the ranking stage are global weights rather than local criterion or sub criterion weights. Global weights are obtained by multiplying the weight of each main criterion by the corresponding sub criterion weight, thereby reflecting the overall contribution of each indicator to the primary objective of poverty prioritization. These global weights serve as the input parameters for the subsequent Fuzzy WASPAS aggregation process. Table 3 presents the global weights of each poverty indicator across the selected α values,

Table 3. Global Weight α Values

Sub Criteria	$\alpha = 0.1$	$\alpha = 0.3$	$\alpha = 0.5$	$\alpha = 0.7$	$\alpha = 0.9$
Frequency of Meals per Day	0.147927	0.148779	0.149791	0.151013	0.152518
Frequency of Consuming Meat/Milk/Chicken	0.085414	0.083477	0.081239	0.078624	0.075526
Frequency of Purchasing New Clothing	0.049424	0.047120	0.044451	0.041322	0.037598
Income Level	0.206394	0.212107	0.218918	0.227187	0.237452
Education Level of Household Head	0.138305	0.141082	0.144335	0.148205	0.152893
Savings Ownership	0.091692	0.091687	0.091543	0.091174	0.090436
Access to Public Health Center	0.064167	0.063406	0.062360	0.060898	0.058803
Source of Lighting	0.027027	0.026571	0.026047	0.025438	0.024722

Sub Criteria	$\alpha = 0.1$	$\alpha = 0.3$	$\alpha = 0.5$	$\alpha = 0.7$	$\alpha = 0.9$
Cooking Fuel Type	0.042903	0.042179	0.041347	0.040380	0.039244
Source of Drinking Water	0.068104	0.066954	0.065634	0.064100	0.062296
Availability of Sanitation Facility	0.034189	0.033700	0.033128	0.032448	0.031627
Floor Material Type	0.021583	0.021070	0.020480	0.019793	0.018983
Floor Area per Capita	0.014305	0.013682	0.012974	0.012161	0.011221
Wall Material Type	0.008568	0.008187	0.007753	0.007256	0.006681

Source: Generated by the authors

Table 3 presents the calculated global weights for each poverty criterion across varying α-cut levels. The purpose of this tabulation is to demonstrate how the importance of each criterion fluctuates depending on the decision makers confidence level. To interpret the data, the rows list the fourteen poverty indicators, while the columns display the weight values for α ranging from 0.1 high uncertainty to 0.9 low uncertainty. A higher numeric value in a cell indicates that the specific criterion holds greater influence on the final poverty score at that level of confidence. The variation of α is intended to evaluate the sensitivity of weight changes with respect to the degree of strictness in the defuzzification process. A smaller α represents a wider fuzzy interval, while a larger α narrows the interval toward the modal value.

The results indicate that several indicators exhibit gradual increases in weight as α increases, while others show consistent decreases. The most notable increases are observed in Income, whose weight rises from 0.2064 to 0.2375, followed by Education Level of Household Head, which increases from 0.1383 to 0.1529, and Frequency of Meals per Day, which increases from 0.1479 to 0.1525. These findings suggest that as uncertainty decreases (higher α values), the economic capacity and human capital dimensions become more dominant in determining poverty priorities. Income consistently holds the highest weight across all α variations, indicating that it is the most stable and influential factor within the model.

Conversely, several indicators demonstrate a consistent decrease in weight, including Meat/Milk Consumption Frequency, Frequency of Purchasing New Clothing, Access to Public Health Center, Source of Drinking Water, Floor Area per Capita, and Wall Material Type. This trend implies that as uncertainty narrows, structural housing conditions and secondary consumption indicators become relatively less dominant than core economic indicators.

The results of the weighting analysis indicate that economic related criteria hold the highest priority in determining poverty levels. This finding aligns with the study by Susanti and Supriyanto (2024), who utilized the SAW-AHP method for social assistance prioritization and similarly concluded that income and employment status are the most critical determinants. However, unlike previous studies that relied on crisp valuation, the use of Fuzzy AHP with α-cut in this study provides a more nuanced weight distribution, effectively capturing the ambiguity in defining poverty thresholds.

Importantly, although the numerical weights change across α levels, the overall priority structure remains unchanged. Income consistently ranks as the most influential indicator, followed by Frequency of Meals and Education Level. The absence of major shifts in indicator dominance suggests that the weighting model maintains structural stability across α values. Therefore, the Fuzzy AHP weighting results are relatively robust to different levels of uncertainty in the defuzzification process, providing a reliable foundation for the subsequent Fuzzy WASPAS ranking stage.

3.2. Fuzzy WASPAS Ranking Result

This subsection presents the ranking results of household alternatives obtained using the Fuzzy WASPAS method, based on the global weights derived from the Fuzzy AHP process. The computation was performed under several α-cut levels, namely $\alpha \in \{0.1, 0.3, 0.5, 0.7, 0.9\}$. The variation of α values aims to evaluate the consistency and stability of ranking outcomes under different levels of optimism in the defuzzification process. A total of 20,000 household alternatives were analyzed in this study. Each alternative's preference value was calculated using the Fuzzy WASPAS approach, which integrates both additive (WSM) and multiplicative (WPM) aggregation mechanisms under fuzzy weighting. The resulting fuzzy preference values were then defuzzified into crisp scores to enable direct comparison among alternatives.

The final ranking was generated using the dense ranking method, ensuring that alternatives with identical preference scores receive the same rank without gaps in subsequent rankings. In this context, higher preference scores indicate greater poverty vulnerability, thereby reflecting a greater priority for government intervention. Thus, the ranking results serve as a basis for decision making on targeted poverty alleviation priorities. Table 4 shows the changes in ranking of several alternatives at various values of α,

Table 4. Ranking Result Various α

Alternative	$\alpha = 0.1$	$\alpha = 0.3$	$\alpha = 0.5$	$\alpha = 0.7$	$\alpha = 0.9$	$\Delta Rank$
A1	802	799	795	791	795	802
A2	327	324	320	317	316	327
A3	1086	1066	1049	1038	1024	1086
A4	258	259	260	260	264	258
...	...	...	...	...	...	...
A19996	7627	7626	7625	7627	7627	7627
A19997	7525	7532	7533	7536	7542	7525
A19998	7461	7463	7469	7471	7472	7461
A19999	802	799	795	791	795	802
A20000	327	324	320	317	316	327

Source: Generated by the authors

This subsection presents the ranking results for the alternatives obtained using the Fuzzy WASPAS method, based on global weights derived from the Fuzzy AHP using the α-cut approach. Computations were conducted for several α values, namely $\alpha \in \{0.1, 0.3, 0.5, 0.7, 0.9\}$. The variation of α represents different levels of confidence or optimism in the defuzzification process, allowing evaluation of ranking changes under varying degrees of uncertainty in decision makers' judgments. These ranking results provide actionable insights for evidence-based prioritization of poverty-alleviation programs in the study area.

A total of 20,000 household alternatives were. For each alternative, a preference value was calculated using the Fuzzy WASPAS method, which integrates the additive Weighted Sum Model (WSM) and the multiplicative Weighted Product Model (WPM) under fuzzy weighting. The resulting preference values were then defuzzified into crisp scores to support ranking. The dense ranking technique was applied to ensure that alternatives with identical preference scores receive the same rank without gaps in the ranking sequence.

Comparison of rankings across different α levels indicates that some alternatives experience positional shifts as α varies from 0.1 to 0.9. Such shifts reflect the influence of α-cut based defuzzification on the global weights of the criteria, which, in turn, affects the preference scores and ranking positions of the alternatives. Although some positional changes occur, their magnitude is relatively small in the context of 20.000 alternatives, indicating proportional stability in priority outcomes. Overall, the observed shifts are generally gradual and do not reflect drastic structural changes in the overall ordering of alternatives. Most alternatives maintain relatively stable ranking patterns across the tested α values, despite minor adjustments. The top ranked alternatives remain largely unchanged across α levels, supporting the robustness of the identification of high-priority groups.

Conceptually, smaller α values emphasize a wider fuzzy interval (reflecting a more conservative viewpoint). In contrast, larger α values place greater emphasis on the central or modal portion of the Triangular Fuzzy Number. In fuzzy decision-making, α-cut intervals are commonly used as a defuzzification mechanism to derive crisp values from fuzzy sets at a specified confidence level, thereby accommodating uncertainty in expert judgments [23][31]. The α-cut method represents a fuzzy set as a crisp interval containing elements with membership degrees above the given threshold, providing a controlled transformation that preserves levels of uncertainty in the decision model.

Overall, while individual ranking positions may vary across α levels, the general priority pattern remains consistent. A more detailed quantitative evaluation of ranking stability is further discussed in Subsection 3.3 through sensitivity analysis.

3.3. Sensitivity Analysis

Sensitivity analysis was conducted to evaluate the stability of the Fuzzy WASPAS ranking results with respect to variations in the α-cut parameter used in the defuzzification of Fuzzy AHP weights. This analysis is essential because the α value represents the degree of confidence or optimism in interpreting fuzzy numbers; variations in α can therefore influence the global weights, and consequently the preference values and the ordering of alternatives. Sensitivity analysis is widely recognized in multicriteria decision making research as a crucial approach for testing the robustness and reliability of ranking results under variations in model inputs and parameters. It provides insights into how changes in weight distributions or parameter values influence preference structures and ranking outcomes, thus supporting transparent and dependable decision making.

To quantitatively assess the impact of α variation, two complementary metrics were computed for each alternative across the tested α levels: (1) ranking standard deviation (Std Rank), which captures the dispersion of ranking positions, and (2) maximum minimum ranking difference (Delta Rank), which represents the largest positional shift observed among the α variations. These metrics provide insight into how much an alternative's ranking changes when the defuzzification strictness is adjusted. Descriptive statistics summarizing these sensitivity measures are presented in the following Table 5. These statistics provide an overview of the ranking structure's overall stability and help identify whether significant fluctuations occur across the ranking spectrum.

Table 5. Descriptive Statistics

Statistic	Std Rank	Delta Rank
Count	20,000	20,000
Mean	55.4460	143.2534
Std Dev	56.9283	147.2267
Min	0.0000	0.0000
Q1 (25%)	9.6732	25.0000
Median (50%)	31.3566	81.0000
Q3 (75%)	92.4054	238.0000
Max	307.4147	788.0000

Source: Generated by the authors

Table 5 aims to quantify the volatility of the households position when the α parameter is shifted. In reading this table, 'Mean Delta Rank' represents the average number of positions a household moved, while 'Max Rank Shift' indicates the most extreme positional change observed among the 20,000 alternatives. These metrics collectively serve as indicators of the model's robustness against parameter uncertainty.

The descriptive statistics reveal that the ranking system demonstrates a high degree of stability. On average, the standard deviation of rankings (Std Rank) across all alternatives is 55,45, while the mean difference between the maximum and minimum rank (Delta Rank) stands at 143,25. Although a shift of 143 positions might initially appear significant, it must be contextualized within the massive dataset of 20.000 alternatives. This average shift represents a fluctuation of only 0,72% of the total ranking range. This proportionality suggests that the variations in the a parameter generally have a minimal impact on the overall hierarchy of poverty priorities.

This conclusion is further reinforced by the median Delta Rank of 81. This figure indicates that more than half of the alternatives experienced ranking changes of fewer than 81 positions equivalent to just 0,41% of the total spectrum. Similarly, the average Std Rank of approximately 55 positions roughly 0,28% of the range confirms that ranking fluctuations are mostly moderate. Taken together, these metrics show that most alternatives maintain a consistent position despite changes in the confidence level a.

While the system is globally stable, there are localized instances of higher volatility. The data records a maximum positional shift of 788 positions, which accounts for about 3,94% of the total range. However, these sharper variations are not indicative of systemic failure; rather, they predominantly occur among alternatives situated in the middle of the ranking distribution. In this zone, preference scores tend to be tightly clustered, meaning that even minor adjustments in criteria weights can cause an alternative to "leapfrog" over others. Crucially, these specific shifts do not undermine the overall reliability of the decision support structure.

Of particular importance to the objectives of this decision support system is the stability of the highest-priority alternatives, as these represent the primary targets for poverty intervention. An analysis of the Top 10% of the rankings the top 2.000 households revealed an outstanding average overlap similarity of 98,63%. This indicates that the households identified as the most critical targets remain nearly identical across various α scenarios. This high consistency ensures that the system's core recommendations are robust and reliable for policy implementation, regardless of the decision maker's confidence level.

Finally, the consistency of the overall ranking structure was quantitatively validated using Spearman's rank correlation coefficient. The analysis yielded an exceptionally high average correlation of 0,9996 between the baseline ranking $\alpha = 0{,}5$ and rankings generated at other α level. Such a near perfect correlation confirms that the relative ordering of alternatives is largely insensitive to parameter variations, demonstrating that the Fuzzy AHP and Fuzzy WASPAS model maintains high structural integrity and produces reliable decision outcomes.

Regarding the stability of the decision model, the high Spearman rank correlation coefficient obtained across different a values demonstrates the superior robustness of the proposed framework. This consistency corroborates the findings of Xiaokai and Ghulam (2023) and Akmaludin et al. (2024), who reported that integrating Fuzzy AHP with WASPAS significantly reduces rank reversal risks in complex decision environments. Furthermore, while recent approaches extending WASPAS using decomposed fuzzy sets Arslan et al. (2024) have emphasized the methods precision in handling complex uncertainty, this study extends that validity to the social welfare domain, proving that such fuzzy integration remains highly stable even when applied to a massive dataset.

Beyond numerical stability, the findings also provide important implications for practical poverty alleviation policies and social assistance targeting. From a policy perspective, the stability of ranking outcomes across different α values indicates that the proposed framework can support more consistent and transparent poverty targeting decisions. In practical implementation, minor variations in the uncertainty level do not significantly alter the identification of high-priority households, which is crucial for maintaining fairness and accountability in social assistance distribution.

The findings also suggest that economic indicators such as income level, meal frequency, and education consistently dominate the prioritization structure across all uncertainty scenarios. This implies that policymakers should continue emphasizing multidimensional economic vulnerability when designing poverty intervention programs. Furthermore, the robustness of the model under varying confidence levels demonstrates its potential applicability in real-world social protection systems, where expert judgments and household assessments are often subject to uncertainty and incomplete information.

4. CONCLUSION

This study developed an integrated α-cut Fuzzy AHP and Fuzzy WASPAS decision support framework for large-scale poverty prioritization based on multidimensional poverty indicators. Fourteen indicators derived from DTKS and BPS data were weighted using α-cut Fuzzy AHP to accommodate uncertainty in expert judgment, and subsequently applied within the Fuzzy WASPAS method to rank 20,000 household alternatives systematically and objectively. The results demonstrate that the proposed framework produces stable and reliable ranking outcomes under different α-cut scenarios. Sensitivity analysis showed that the average maximum rank shift was 143 positions (0.72%) with a median shift of 81 positions (0.41%), indicating that most alternatives experienced only minor ranking changes. The model also achieved a high average Spearman rank correlation of 0.9996 and a top-10% overlap similarity of 98.63%, confirming strong consistency in identifying high-priority households across varying uncertainty levels. These findings indicate that the integrated α-cut Fuzzy AHP and Fuzzy WASPAS framework is robust and suitable for evidence-based poverty targeting and social assistance allocation.

The primary methodological contribution of this study lies in integrating α-cut based defuzzification into the Fuzzy AHP and Fuzzy WASPAS framework to evaluate ranking robustness under uncertainty. Unlike conventional approaches that directly transform fuzzy weights into single crisp values, the proposed model introduces adjustable confidence levels that enable more flexible and reliable prioritization analysis. Despite these promising results, this study has several limitations. The analysis relies on cross-sectional household data from DTKS and BPS sources, which may not fully capture temporal poverty dynamics or sudden socioeconomic changes. In addition, the weighting process still depends on expert judgment and may contain subjective bias. Future research may incorporate longitudinal poverty data and compare the proposed framework with other fuzzy multicriteria decision-making methods, such as Fuzzy TOPSIS, Fuzzy VIKOR, or interval type-2 fuzzy approaches, to further evaluate ranking robustness and model performance.

5. ACKNOWLEDGEMENTS

The authors would like to express their sincere gratitude to the Department of Data Science and Department of Business Digital, Universitas Pembangunan Nasional "Veteran" Jawa Timur, for the academic support, facilities, and resources provided throughout this research. The authors also extend their appreciation to lecturers, colleagues, and all parties who contributed through valuable discussions, guidance, and constructive feedback during the development of this study. Their support and insights have contributed significantly to the completion and improvement of this research. This research was conducted independently and received no specific external funding.

6. REFERENCES

[1] BPS Jawa Timur, "Profil Kemiskinan Jawa Timur 2024," vol. 3, 2024.
[3] K. Tompoh, V. A. J. Masinambow, and A. L. C. P. Lapian, "Pengaruh Pengangguran, Tingkat Pendidikan Dan Jumlah Penduduk Terhadap Kemiskinan Di Provinsi Sulawesi Utara," *Jurnal Berkala Ilmiah Efisiensi*, vol. 24, no. 6, pp. 58–69, 2024.
[4] B. P. Statistika, "Memahami Perbedaan Angka Kemiskinan versi Bank Dunia dan BPS." Accessed: Sep. 18, 2025. [Online]. Available: https://www.bps.go.id/id/news/2025/05/02/702/memahami-perbedaan-angka-kemiskinan-versi-bank-dunia-dan-bps.html

[5] M. Misnawati and S. Z. Bin Tahir, "Inhibiting Factors (Internal & External) Implementation of the Family Hope Program (PKH) in Bone Regency," in *Proceedings of the 11th Annual International Conference on Industrial Engineering and Operations Management*, Universitas Iqra Buru, 2021.
[6] A. Supriyanto, J. A. Razaq, P. Purwatiningtyas, and A. Ariyanto, "Keputusan Pemberian Bantuan Sosial Program Keluarga Harapan Menggunakan Metode AHP dan SAW," *MATRIK: Jurnal Manajemen, Teknik Informatika dan Rekayasa Komputer*, vol. 21, no. 3, pp. 639–652, 2022.
[7] X. Meng and G. M. Shaikh, "Evaluating environmental, social, and governance criteria and green finance investment strategies using fuzzy AHP and fuzzy WASPAS," *Sustainability*, vol. 15, no. 8, p. 6786, 2023.
[8] A. Raj and M. Pratibha, "Multi - criteria healthcare waste disposal location selection based on Fermatean fuzzy WASPAS method," *Complex & Intelligent Systems*, vol. 7, no. 5, pp. 2469–2484, 2021, doi: 10.1007/s40747-021-00407-9.
[9] B. Kizielewicz and A. Bączkiewicz, "Comparison of Fuzzy TOPSIS, Fuzzy VIKOR, Fuzzy WASPAS and Fuzzy MMOORA methods in the housing selection problem," *Procedia Comput. Sci.*, vol. 192, pp. 4578–4591, 2021.
[10] H. T. Adikoro and F. Wurjaningrum, "Analisis Pemilihan Supplier Kain Byemi Official Store Dengan Metode Fuzzy AHP dan Fuzzy Topsis Analysis Of Supplier Selection Fabrics Of Byemi Official Store With Fuzzy AHP and Fuzzy Topsis Methods," *Jurnal Manajemen dan Perbankan (JUMPA)*, vol. 9, no. 2, pp. 38–53, 2022.
[11] A. K. Wardana and Rianto, "The Best Selection of PIP Scholarship: AHP-TOPSIS Vs Fuzzy AHP-TOPSIS," *J. Phys. Conf. Ser.*, vol. 1823, no. 1, 2021, doi: 10.1088/1742-6596/1823/1/012006.
[12] J. Močkoř, "Cut Systems with Relational Morphisms for Semiring-Valued Fuzzy Structures," *Axioms*, vol. 12, no. 2, 2023, doi: 10.3390/axioms12020153.
[13] Ö. Arslan and S. Cebi, "A novel approach for multi-criteria decision making: extending the WASPAS method using decomposed fuzzy sets," *Comput. Ind. Eng.*, vol. 196, p. 110461, 2024.
[14] A. A. Haidir and N. P. W. Setyari, "Indonesia social progress: the role of access to basic education in escaping from poverty trap," *Jurnal Ekonomi & Studi Pembangunan*, vol. 24, no. 2, pp. 428–457, 2024, doi: 10.18196/jesp.v24i2.19810.
[15] A. Fitriani Sahe, A. Faisol, and R. Primaswara Prasetya, "Penerapan Metode Fuzzy Ahp Pada Sistem Pendukung Keputusan Penerima Bantuan Pkh Di Desa Ndiwar Kabupaten Manggarai Berbasis Website," *JATI (Jurnal Mahasiswa Teknik Informatika)*, vol. 7, no. 1, pp. 928–933, 2023, doi: 10.36040/jati.v7i1.6193.
[16] M. F. Mustofa and T. Utomo, "Standar Kemiskinan Badan Pusat Statistik (BPS) Perspektif Dr. Wahbah Zuhaili," *Wasathiyyah*, vol. 5, no. 1, pp. 1–17, 2023.
[17] Trimono, Amri Muhaimin, P. C. Ekacitta, and A. E. Ardiani, "Spatial Autocorrelation Analysis of East Java Stunting Prevalence Cases in 2023," *Journal of Advances in Information and Industrial Technology*, vol. 7, no. 1, pp. 83–94, 2025, doi: 10.52435/jaiit.v7i1.689.
[18] G. Oktadiansah and F. Fitria, "Rancang Bangun Sistem Pendukung Keputusan Untuk Penerimaan Bantuan Kemiskinan Dengan Pendekatan Tsukamoto," *JATI (Jurnal Mahasiswa Teknik Informatika)*, vol. 9, no. 2, pp. 2293–2299, 2025, doi: 10.36040/jati.v9i2.12906.
[19] S. Suprapto, E. Edora, and F. A. Pasaribu, "Sistem Pendukung Keputusan Calon Penerima Program Bantuan Sosial (BANSOS) Menggunakan Metode Simple Additive Weighting (SAW): Decision Support System for Prospective Social Assistance Program Recipients (BANSOS) Using the Simple Additive Weighting (SAW) M," *MALCOM: Indonesian Journal of Machine Learning and Computer Science*, vol. 4, no. 1, pp. 188–197, 2024.
[20] R. Saatchi, "Fuzzy logic concepts, developments and implementation," *Information*, vol. 15, no. 10, 2024.
[21] A. R. Naufal, D. A. Nawangnugraeni, and M. Z. Abdillah, "Fuzzy-Analitycal Hirarchy Process (F-AHP) untuk Menentukan Keluarga Tidak Mampu Akibat Covid-19," *Techno. Com*, vol. 21, no. 1, pp. 12–25, 2022.
[22] A. Cerioli and S. Zani, "A fuzzy approach to the measurement of poverty," in *Income and Wealth Distribution, Inequality and Poverty: Proceedings of the Second International Conference on Income Distribution by Size: Generation, Distribution, Measurement and Applications, Held at the University of Pavia, Italy, September 28–30, 198*, Springer, 1990, pp. 272–284.
[23] Y. Liu, C. M. Eckert, and C. Earl, "A review of fuzzy AHP methods for decision-making with subjective judgements," *Expert Syst. Appl.*, vol. 161, p. 113738, 2020, doi: https://doi.org/10.1016/j.eswa.2020.113738.
[24] F. I. D. Susanti and A. Supriyanto, "Implementasi Metode SAW-AHP Dalam Penentuan Prioritas Penerima Bantuan Sosial Kemiskinan Berdasarkan Kriteria BPS," *Jutisi: Jurnal Ilmiah Teknik Informatika dan Sistem Informasi*, vol. 13, no. 1, pp. 234–246, 2024.
[25] S. Abbasi, V. Barzegar, S. S. Alizadeh, A. Asgari, and A. Gholampour, "The Effects of Health, Safety and Environmental Criteria on the Performance of Landfilling Process: A Comparative AHP and Fuzzy AHP Analysis," *Journal of Environmental Assessment Policy and Management*, vol. 27, no. 1, 2025, doi: 10.1142/S1464333224500170.
[26] A. Akmaludin, E. G. Sihombing, R. Rinawati, L. S. Dewi, and E. Arisawati, "Integrated selection of permanent teacher appointments recommended MCDM-AHP and WASPAS methods," *Sinkron: jurnal dan penelitian teknik informatika*, vol. 8, no. 2, pp. 661–670, 2024.

[27] N. Abughazalah and M. Khan, “A dual hesitant fuzzy entropy-TOPSIS framework for multi-criteria evaluation of medical E-learning systems,” *Sci. Rep.*, vol. 15, no. 1, pp. 1–21, 2025, doi: 10.1038/s41598-025-24563-x.
[28] F. R. Sitinjak, F. T. R. Silalahi, and F. Tupa, “Analisis Strategi Pemeliharaan Preventive Maintenance Excavator Menggunakan Pendekatan Analytical Hierarchy Process (AHP) dan Analisis Sensitivitas Analysis Of Excavator Preventive Maintenance Strategy Using Analytical Hierarchy Process (AHP) Approach,” *Journal of Integrated System (JIS)*, vol. 6, no. 2, pp. 226–242, 2023, doi: https://doi.org/10.28932/jis.v6i2.7633.
[29] V. R. B. Kurniawan, T. Yulianti, and F. H. Puspitasari, “Fuzzy AHP – DEMATEL Methods To Investigate Passengers’ Decision Factors On Using Public City Bus In An Indonesian Region,” *Jurnal OPSI*, vol. 14, no. 1, p. 10, 2021, doi: 10.31315/opsi.v14i1.4478.
[30] J. Więckowski and W. Sałabun, “Sensitivity analysis approaches in multi-criteria decision analysis: A systematic review,” *Appl. Soft Comput.*, vol. 148, p. 110915, 2023.
[31] W. C. Wibowo, I. S. Dayanti, A. N. Hidayanto, I. Eitiveni, and K. Phusavat, “Prioritizing Solutions for Overcoming Knowledge Transfer Barriers in Software Development Using the Fuzzy Analytic Hierarchy Process.,” *Knowledge Management & E-Learning*, vol. 10, no. 2, pp. 217–249, 2018.