SHM PUBLISHER
SURYA HIJAU MANFAAT

Journal of Soft Computing Exploration

Homepage: htttps://shmpublisher.com/index.php/joscex

JOSCEX

p-ISSN: 2746-7686
e-ISSN: 2746-0991

.

Metaheuristic optimization in AHP–TOPSIS pairwise matrices for decision support on preventing low birth weight in adolescent pregnancies

Muhammad Annys[1], Wiharto[2], Shaifudin Zuhdi[3]
[1, 2, 3]Department of Informatics, Universitas Sebelas Maret, Indonesia

Article Info

Article history:

Received June 5, 2026
Revised June 19, 2026
Accepted June 24, 2026

Keywords:

LBW
AHP-TOPSIS
Genetic algorithm
Particle swarm optimization
Decision support system
Metaheuristic algorithm

ABSTRACT

Low Birth Weight (LBW), defined as a birth weight below 2,500 grams, remains a major public health concern in developing countries due to its association with increased neonatal morbidity and mortality. Decision-support systems based on the Analytic Hierarchy Process (AHP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) have been widely applied in healthcare prioritization; however, their reliability may be compromised by inconsistencies in expert-generated pairwise comparison matrices. Despite the growing use of metaheuristic optimization techniques, limited studies have compared the effectiveness of Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) in improving AHP–TOPSIS weighting consistency for LBW prevention. This study aims to compare the performance of GA and PSO for optimizing pairwise comparison matrices within a hybrid AHP–TOPSIS framework for adolescent-pregnancy intervention prioritization. The study utilized maternal and child health data obtained from the Indramayu District Health Office in 2025. Criterion weights were determined using AHP, while intervention alternatives were ranked using TOPSIS. GA and PSO were applied to minimize matrix inconsistency through hyperparameter-optimized search processes. Performance was evaluated using Consistency Ratio (CR), Hamming Distance, Euclidean Distance, Kendall's Tau, and computational time. The results showed that both GA and PSO successfully improved matrix consistency and generated alternative feature-weight distributions while maintaining moderate agreement with the baseline ranking structure. GA achieved higher ranking stability (Kendall's Tau = 0.7197) and lower computational time, whereas PSO produced greater weight redistribution. These findings demonstrate that metaheuristic optimization can enhance the robustness and consistency of AHP–TOPSIS-based weighting schemes, providing a more reliable ranking-based decision-support mechanism for LBW prevention and intervention prioritization.

Corresponding Author:

Wiharto
Department of Informatic,
Universitas Sebelas Maret,
Ir. Sutami Street No. 36A Kentingan, Surakarta, Central Jawa 57216, Indonesia
Email: wiharto@staff.uns.ac.id
https://doi.org/10.52465/joscex.v7i3.160

1. INTRODUCTION

Low birth weight (LBW) is any birth weight less than 2500 grams regardless of gestational age [1]. Low birth weight is a leading contributor to neonatal mortality and morbidity and continues to be a major public health concern worldwide, particularly in developing countries [2], [3]. According to the World Health Organization, low birth weight infants have an increased risk of infection, breathing difficulties, impaired growth and cognitive development, developmental disabilities, and chronic diseases later in life such as diabetes and cardiovascular disorders [1], [4]. In 2020, an estimated 19.8 million newborns worldwide (14.7% of all births) were born with low birth weight, highlighting the persistent global burden of this condition [3]. Aside from causing infant mortality, the high prevalence of LBW affects the quality of life of families and places a long-term strain on healthcare systems.

One of the major factors associated with LBW is preterm birth (delivery before 37 weeks of gestation), which significantly increases the likelihood of a baby being born with low birth weight [4], [5]. Preterm and LBW infants account for a substantial proportion of neonatal deaths and are at greater risk of adverse health outcomes throughout childhood and adulthood [4], [6]. In addition, socioeconomic conditions, access to healthcare services, maternal nutrition, and the quality of antenatal care are important determinants of LBW occurrence [1], [3], [5]. The complexity of these interacting factors requires a comprehensive assessment approach to identify pregnancies at high risk of LBW.

One of the major factors associated with LBW is preterm birth (delivery before 37 weeks of gestation) which significantly increases the likelihood of a baby being born with low birth weight. [5]. Socioeconomic factors, accessibility to health care services and quality of antenatal care also determine the risk of LBW. The complexity of these factors means that the risk identification process requires a multifaceted assessment which is far from simple.

Preventing LBW is an important strategy to reduce infant mortality rates. Prevention can be accomplished by improving the quality of prenatal care, nutrition education to pregnant women, early detection of high-risk pregnancies and management of chronic diseases in mothers. However, the process of risk stratification still largely relies on the subjective judgement of medical personnel in clinical practice. Limited numbers of experts and potential inconsistencies in the evaluation process can affect the accuracy of decision-making. Therefore, a DSS is needed to assist healthcare providers in processing various criteria systematically, objectively, and consistently.

Given the complexity of LBW risk assessment, several decision-support approaches have been developed to assist healthcare providers in prioritizing high-risk pregnancies. Previous studies have applied the Simple Multi-Attribute Rating Technique (SMART) and the Elimination et Choix Traduisant la Réalité (ELECTRE) methods to select dairy products for pregnant women. SMART has the advantage of simplicity in calculation and computational efficiency, while ELECTRE is effective in the process of selecting alternatives through an outranking approach. The results of the study showed an 80 percent level of agreement between system calculations and manual calculations. However, the study has limitations because the criteria structure cannot be dynamically updated and doesn't yet consider the consistency of relationships between parameters in the weighting process [7], [8], [9], [10].

These limitations have led to the use of the Analytic Hierarchy Process (AHP) as a more systematic approach to multi-criteria decision-making. Previous research demonstrated that AHP can structure problems into a hierarchy of objectives, criteria, and alternatives, thus making the evaluation process more structured. AHP also has a consistency test using the Consistency Ratio (CR) to reduce inconsistencies in the subjective judgments of the experts. It showed a 27 percent increase in the adherence of pregnant women to nutritional recommendations as opposed to manual education. AHP, however, has some limitations in that it does not yet provide a mechanism for ranking the alternatives with respect to their closeness to the ideal solution [11].

To address these limitations, several studies have combined the AHP with the TOPSIS. Previous studies have applied the AHP–TOPSIS combination to a system for ranking healthy toddlers, achieving an accuracy rate of 100% [12]. The method has also been used for selecting students for an accelerated program, with a 96.02% agreement with the official decision) [13]. In this approach, AHP is used to determine criterion weights consistently, while TOPSIS ranks alternatives based on their distances from the positive and negative ideal solutions. This integration has also been applied in healthcare supply chain planning [14]. TOPSIS was selected because it provides a clear concept of ideal solutions, involves relatively simple mathematical computations, and demonstrates stability in handling variations in criterion weights and alternative complexity compared with several other outranking methods [15], [16]. Additional studies have further confirmed the effectiveness of the AHP–TOPSIS approach in healthcare and educational decision-support applications [17], [18].

The integration of AHP and TOPSIS can improve the quality of decision-making, but the weighting process in AHP remains highly dependent on expert perceptions, which can potentially result in inconsistent comparison matrices. To address this issue, several studies have developed the integration of metaheuristic algorithms with AHP. Previous research applied the Genetic Algorithm (GA) to AHP and successfully reduced the Consistency Ratio to 0.0015 [19]. Meanwhile, other research integrated Particle Swarm Optimization (PSO) with Fuzzy AHP and obtained a Spearman correlation coefficient of 0.89 against expert ratings [20]. Metaheuristic approaches are considered effective in finding optimal solutions in complex, high-dimensional search spaces. However, these methods still face challenges in the form of the need for additional parameter settings that can affect convergence stability and the quality of the final solution [21], [22], [23].

Although previous studies have successfully applied AHP–TOPSIS in healthcare decision support and employed metaheuristic algorithms to improve AHP consistency, several limitations remain. First, most studies focus either on decision-support implementation or consistency optimization separately, without systematically comparing multiple metaheuristic algorithms within the same framework. Second, studies evaluating the impact of optimized pairwise matrices on ranking stability remain limited, particularly in maternal-health applications related to LBW prevention. Third, previous research rarely assesses optimization outcomes using multiple ranking-similarity metrics such as Kendall's Tau, Hamming Distance, and Euclidean Distance. Therefore, this study proposes a comparative evaluation of Genetic Algorithm and Particle Swarm Optimization for optimizing AHP pairwise matrices within an AHP–TOPSIS decision-support framework for LBW prevention.

2. METHOD

Research Framework

This study employs a computational design-and-evaluation approach to develop a Decision Support System (DSS) for prioritizing Low Birth Weight (LBW) interventions. The system employs a hybrid AHP-TOPSIS approach augmented with metaheuristic optimisation techniques such as GA and PSO for improving the consistency of AHP. The entire workflow consists of six stages: (1) dataset collection, (2) data pre-processing, (3) AHP hierarchy construction and baseline weights, (4) meta-heuristic optimisation of AHP pairwise matrices, (5) TOPSIS patient ranking and (6) comparative evaluation. Figure 1 illustrates the research workflow.

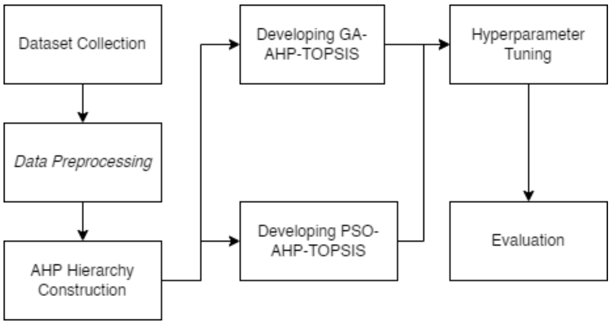

Figure 1. Research workflow

Dataset Acquisition and Preparation

Data from the Indramayu District Health Office were used in this study, containing information on infants born between January and December 2025 and corresponding maternal data. A total of 958 records were collected before preprocessing.

Table 1. Dataset features

No.	Feature	Description
1	Date of Birth	Infant date of birth
2	Birth Weight	Infant weight at birth (grams)
3	Maternal Age	Mother's age at delivery (years)
4	Parity	Total number of pregnancies
5	Inter-pregnancy Interval	Months between current and previous pregnancy
6	Last Menstrual Period	First day of the mother's last menstrual period
7	BMI	Maternal BMI category (Underweight / Normal / Overweight / Obese)
8	Immunisation Status	Tetanus Toxoid (TT) status (TT0–TT5 / not screened)
9	Hemoglobin (HB)	Maternal HB category (not examined / no anemia / mild / moderate / severe anemia)
10	Urine Protein	Urine protein result (Negative / Positive / Not examined)

11	Blood Glucose	Blood glucose category (Not examined / Normal <200 / High ≥200)
12	Antenatal Visits	Number of antenatal check-ups before delivery
13	Birth Outcome	Infant birth outcome (Live / Stillbirth / –)

Data Preprocessing and Feature Engineering

Preprocessing was performed to handle missing values, remove invalid records, derive new features, and encode categorical variables for use in numerical decision methods. The steps are as follow.

Missing and invalid data removal

Data preprocessing was performed to improve data quality and prepare the dataset for the use of numerical decision-making methods. This process included handling missing and invalid values, deleting irrelevant records, creating new features and encoding categorical variables. First, we removed records with a birth outcome value of stillbirth or "–". Then we discarded the birth outcome column. Records with "–" in the BMI (IMT) attribute were also removed. Missing values of the immunisation status attribute were replaced by "–" to indicate not screened. The LILA (mid-upper arm circumference) attribute was removed since more than 70% of its values were invalid, according to the recommendation in previous studies [24]. We also excluded records with maternal age <10 years as these were identified by domain experts as outliers that do not represent realistic maternal conditions.

Feature derivation

Subsequently, features were extracted to produce additional attributes that are relevant for the analysis. Gestational age in days was calculated by subtracting the date of last menstrual period (HPHT) from the date of birth, and then both original date attributes were removed. Also, inter-pregnancy interval values were converted from years to months by dividing the recorded values by 12, which ensured consistency in measurement units across the dataset.

Ordinal encoding

All categorical features were transformed using ordinal encoding to preserve their clinically meaningful risk hierarchy, consistent with recommendations for health decision-making datasets [25]. Body Mass Index (BMI) was encoded according to the World Health Organization (WHO) weight categories, reflecting the dose-dependent relationship between BMI and adverse pregnancy outcomes [25], [26], [27], with values assigned as Underweight = 1, Normal = 2, Overweight = 3, and Obese = 4. Immunisation status was encoded based on the cumulative level of immunological protection provided by tetanus toxoid (TT) vaccination according to WHO guidelines, where TT2 confers approximately three years of protection, TT3 five years, TT4 ten years, and TT5 lifelong protection [28], [29]. This ordering is supported by evidence of dose-proportional IgG antibody responses [30] and aligns with Permenkes No. 12/2017, which identifies TT2 as the minimum protective threshold [31]. Accordingly, immunisation status was encoded as Not screened = 0, TT0 = 1, TT1 = 2, TT2 = 3, TT3 = 4, TT4 = 5, and TT5 = 6. Haemoglobin (HB) levels were encoded according to the WHO (1989) classification of anaemia severity in pregnancy, where increasing anaemia severity is associated with a higher risk of low birth weight (LBW) [32]. The categories were defined as Not examined = 0, No anaemia (≥11 g/dL) = 1, Mild anaemia (10–10.9 g/dL) = 2, Moderate anaemia (7–9.9 g/dL) = 3, and Severe anaemia (<7 g/dL) = 4. Urine Protein was encoded following WHO and ACOG proteinuria risk guidelines, where positive findings may indicate renal dysfunction or pre-eclampsia, using the values Not examined = 0, Negative = 1, and Positive = 2. Similarly, Blood Glucose was encoded according to WHO diagnostic criteria for hyperglycaemia during pregnancy, with higher glucose levels indicating greater maternal and fatal health risks. The assigned values were Not examined = 0, Normal (<200 mg/dL) = 1, and High (≥200 mg/dL) = 2.

Handcrafted feature engineering was performed based on domain knowledge from maternal and neonatal health literature. Two derived features were generated: gestational age (calculated from the difference between the date of birth and the last menstrual period) and inter-pregnancy interval in months. These transformations were designed to provide clinically meaningful risk indicators for the subsequent AHP–TOPSIS analysis.

The final dataset comprised 904 normal-birth-weight cases and 47 low-birth-weight (LBW) cases after preprocessing. Although the dataset exhibits class imbalance, no resampling techniques were applied because the primary objective of this study was to optimize feature weighting within the AHP–TOPSIS framework and evaluate its impact on risk ranking rather than to develop a supervised classification model. Resampling techniques are primarily intended to address majority-class bias in predictive classifiers trained on imbalanced datasets [33]. Since TOPSIS operates as a multi-criteria ranking method that prioritizes alternatives based on weighted criteria rather than performing class prediction [34], the optimization process focuses on ranking quality rather than predictive accuracy. Furthermore, unlike predictive machine learning studies, this research did not employ training–testing data splitting because the entire dataset was used as a decision matrix within the AHP–TOPSIS framework, consistent with previous healthcare decision-support applications [35].

AHP Hierarchy and Baseline Weight Calculation

Based on consultation with maternal-health experts, a three-level hierarchy was developed consisting of the decision goal, main criteria, and sub criteria shown by figure 2. Pairwise comparison matrices were constructed using Saaty's nine-point scale to quantify the relative importance among criteria [36]. Criterion weights were estimated using the AHP eigenvector method, and consistency was verified using the Consistency Ratio (CR) (Equations 1–2). Matrices with CR ≤ 0.10 were accepted; those exceeding this threshold need to be reweighting.

$$CI = (\lambda_{max} - n)/n \quad (1)$$

$$CR = CI/RI \quad (2)$$

where RI is the Random Index tabulated in Saaty (1987).

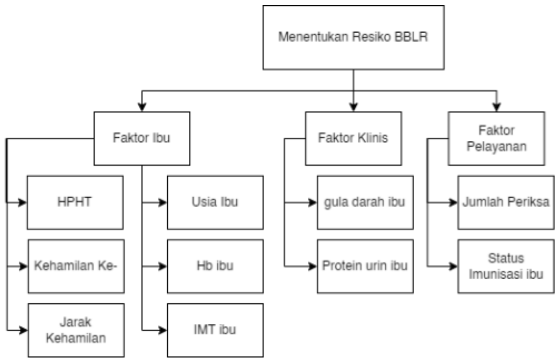

Figure 2. AHP Decision hierarchy

Baseline AHP Weight Calculation

Four pairwise matrices were constructed based on expert suggestion and are shown in tables 2–5. Each pairwise matrix is interpreted from left to right and top to bottom, where the value at the intersection of a row and a column indicates how many rows is more important than column. For example, in the main category's matrix, clinical factor is three times more important than service factor. Next, clinical factor is considered three times more important than maternal factor and five times more important than service factor. The maternal, clinical, and service pairwise matrix can be read the same way.

Table 2. Pairwise matrix – main categories

	Maternal Factor	Clinical Factor	Service Factor
Maternal Factor	1	1/3	3
Clinical Factor	3	1	5
Service Factor	1/3	1/5	1

Table 3. Pairwise Matrix – Maternal Factor Sub-criteria

	Gestational Age	Parity	Inter-preg. Interval	Maternal Age	HB	BMI
Gestational Age	1	7	5	5	1/3	3
Parity	1/7	1	1/5	1/3	1/7	1/5
Inter-preg. Interval	1/5	5	1	3	1/5	1/3
Maternal Age	1/5	3	1/3	1	1/5	1/3

.

	Gestational Age	Parity	Inter-preg. Interval	Maternal Age	HB	BMI
HB	3	7	5	5	1	3
BMI	1/3	5	3	3	1/3	1

Table 4. Pairwise matrix – clinical factor sub-criteria

	Blood Glucose	Urine Protein
Blood Glucose	1	1
Urine Protein	1	1

Table 5. Pairwise matrix – service factor sub-criteria

	Antenatal Visits	Immunisation Status
Antenatal Visits	1	3
Immunisation Status	1/3	1

All four matrices met the CR ≤ 0.10 threshold: main categories CR = 0.033; Maternal Factor CR = 0.085; Clinical Factor CR = 0.000; Service Factor CR = 0.000. The resulting global criterion weights are summarised in Table 6.

AHP Consistency Optimization via Metaheuristic Algorithms

Metaheuristic optimization was applied matrix with order higher than 2 [17] to minimize CR while preserving the expert rank order. Two algorithms were evaluated: GA, as proposed by Holland and described by Moussaoui et al. [19], and PSO, as introduced by Kennedy & Eberhart [37]. Each upper-triangular element of the pairwise matrix was treated as a decision variable bounded to Saaty's scale [1/9, 9].

Fitness function

The fitness function jointly minimizes CR and penalizes large deviations in Spearman's rank correlation, balancing consistency and similarity to the original judgement [14], [19]:

$$f(x) = \alpha . CR + \beta . (1 - \left(\frac{\rho + 1}{2}\right)); \; \alpha = 0.5; \; \beta = 0.5 \quad (3)$$

where ρ is Spearman's rank correlation between optimized and baseline rankings (Equation 4); α and β control the relative influence of each component [20].

$$\rho = 1 - \frac{6 \sum d_i^2}{N_{sc}(N_{sc}^2 - 1)} \quad (4)$$

Genetic algorithm

Genetic Algorithm (GA) employed in this study follows the standard selection–crossover–mutation framework proposed by Moussaoui et al. [19]. GA was chosen for its ability to perform global exploration effectively and generate optimized pairwise matrices for complex problems.

Particle swarm optimization

The Particle Swarm Optimization (PSO) algorithm employs the velocity and position update mechanism introduced by Kennedy and Eberhart in 1995 [37]. Inspired by the social behavior of birds and fishes. PSO is capable of exploring complex, nonlinear, and multidimensional search space without derivative calculation. This algorithm was chosen because of its simplicity, rapid convergence, and strong performance in continuous optimization tasks such as optimizing AHP pairwise comparison matrices.

Patient Ranking via AHP–TOPSIS

Criterion weights from the baseline AHP (Section 2.4) or optimized AHP (Section 2.5) were used as input to TOPSIS, following the standard procedure of Hwang & Yoon in 1981 [38][20]. The five-step procedure was applied without modification: (1) normalized decision matrix, (2) weighted normalized matrix, (3) positive and negative ideal solutions, (4) separation measures (Euclidean distances to ideal solutions), and (5) relative closeness coefficient C_i (Equation 5). Patients were ranked in descending order of C_i; a higher value indicates higher LBW intervention priority [20].

Criteria were classified as follows. Cost criteria (lower value = higher priority) such as Parity and Urine Protein. Benefit criteria (higher value = higher priority) such as Gestational Age, Inter-pregnancy Interval, Maternal Age, HB, BMI, Blood Glucose, Antenatal Visits, and Immunization Status.

$$C_i = \frac{S_i^-}{S_i^- + S_i^+} \; ; \; 0 < C < 1 \tag{5}$$

Evaluation

Evaluation compared three ranking outputs: (1) baseline AHP–TOPSIS, (2) GA-AHP–TOPSIS, and (3) PSO-AHP–TOPSIS. Rank agreement between optimized and baseline rankings was assessed using Spearman's ρ (Equation 4) and Kendall's τ (Equation 6) [20], [39], [40]. The magnitude of ranking changes was measured using Hamming Distance (Equation 7) and Euclidean Distance (Equation 8) [13].

In this study, Hamming Distance was normalized as the proportion of ranking positions that differ between the optimized and baseline results. Therefore, values approaching 1 indicate greater dissimilarity, whereas values approaching 0 indicate higher similarity. This interpretation follows the binary difference formulation adopted in Equation (7).

Hamming Distance quantifies the extent of rank reordering relative to the baseline, whereas Kendall's τ and Spearman's ρ measure the degree to which the overall ranking structure is preserved. Consequently, a ranking may exhibit substantial positional changes while still maintaining a moderate or strong ordinal relationship with the baseline. Consistency improvement was evaluated by comparing the Consistency Ratio (CR) before and after optimization. Computational efficiency was assessed using wall-clock execution time for each optimization algorithm.

$$\tau = \frac{C_{kt} - D_{kt}}{\frac{1}{2} N_{kt}(N_{kt} - 1)} \tag{6}$$

$$D_{hd}(x,y) = \frac{1}{N_{hd}} \sum_{i=1}^{i=N_{hd}} I(x_i \neq y_i) \tag{7}$$

$$I(x_i \neq y_i) = \begin{cases} 1, & if\ x_i \neq y_i \\ 0, & if\ x_i = y_i \end{cases}$$

$$D_{ed} = \sqrt{\sum_{i=1}^{N_{ed}} (p_i - q_i)^2} \tag{8}$$

3. RESULTS AND DISCUSSIONS

Experimental Dataset

This study employed a private maternal and child health dataset provided by the Department of Health of Indramayu Regency, Indonesia, covering birth records from January to December 2025. The dataset integrates maternal health characteristics and birth outcomes collected from community health centers (puskesmas) across all sub-districts in the regency. The use of real-world clinical data enables the proposed decision-support framework to be evaluated under practical healthcare conditions, thereby increasing the relevance of the findings for maternal and child health risk assessment.

Hyperparameter Tuning

Hyperparameter tuning was conducted to ensure that both the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) operated under configurations capable of achieving stable convergence and effective exploration of the search space. Since feature-weight optimization involves a complex, multidimensional search problem, inappropriate parameter settings may lead to premature convergence or insufficient exploration, ultimately affecting the quality of the generated feature weights.

For the GA, the selected configuration balanced exploration and exploitation through a moderate crossover probability (0.7) and a relatively low mutation probability (0.05). The use of tournament selection and elitism helped preserve high-quality solutions while maintaining population diversity throughout the optimization process. A population size of 20 and 500 generations were found to provide sufficient search capability without introducing excessive computational cost. This configuration allowed the algorithm to gradually refine feature weights while avoiding rapid convergence toward local optima.

Similarly, the PSO parameters were chosen to promote stable particle movement and convergence behavior. The inertia weight of 0.4 encouraged exploitation of promising regions in the search space, whereas the cognitive coefficient (1.5) and social coefficient (2.0) maintained a balance between individual learning and collective swarm intelligence. The relatively large swarm size of 80 particles enhanced search diversity, enabling broader exploration of potential weight combinations. The velocity limit further prevented excessive particle movement that could destabilize convergence.

Overall, the selected configurations demonstrated consistent optimization performance across repeated runs and were therefore adopted for subsequent experiments. The tuning results suggest that both metaheuristic algorithms were capable of effectively searching for discriminative feature-weight distributions, although they relied on different search mechanisms: GA through evolutionary operators and PSO through collective swarm behavior. These differences are further examined in the comparative evaluation presented in the following sections.

Quality Evaluation

Metaheuristic optimization was performed only on pairwise comparison matrices with an order greater than 2; therefore, GA and PSO were applied exclusively to the main-category and maternal-factor matrices. The optimized main-category matrix achieved CR values of 0.0047 with GA and 0.0000 with PSO, while the maternal-factor matrix achieved CR values of 0.0030 and 0.0640, respectively. All optimized matrices satisfied the AHP consistency requirement ($CR < 0.10$), indicating that both algorithms were effective in improving matrix consistency. Compared with the baseline matrices, which yielded CR values of 0.033 for the main-category matrix and 0.085 for the maternal-factor matrix, the optimized solutions demonstrated a notable reduction in inconsistency.

Quality evaluation was performed by comparing the weight distributions produced by the baseline, GA, and PSO methods across all features. The results are summarized in Table 6. Under GA, Blood Glucose and Urine Protein each received the highest weight at 0.3454, whereas under PSO, both features remained the most influential at 0.3 each. This demonstrates that the optimization process successfully identified new weight distributions that are more balanced across features. Several features with previously low weights experienced notable increases in contribution after optimization.

Table 6. Feature weight comparison: Baseline, GA, and PSO

Feature	Baseline	GA	PSO
Blood Glucose	0.3185	0.3454	0.3000
Urine Protein	0.3185	0.3454	0.3000
HB	0.1037	0.0179	0.0306
Antenatal Visits	0.0785	0.1116	0.0750
Gestational Age	0.0711	0.0565	0.1365
BMI	0.0381	0.0171	0.0295
Immunisation Status	0.0262	0.0372	0.0250
Inter-preg. Interval	0.0234	0.0094	0.0295
Maternal Age	0.0143	0.0049	0.0163
Parity	0.0076	0.0057	0.0575

The magnitude of change from the baseline was quantitatively measured using Hamming Distance, Euclidean Distance, and Kendall's Tau. As shown in Table 7, the Hamming Distance values obtained by both optimization algorithms were very close to 1.0 (GA: 0.9895; PSO: 0.9916), indicating that the optimized weight vectors differ substantially from the baseline configuration according to the adopted Hamming Distance formulation. This result suggests that the optimization process generated alternative weight distributions rather than making only minor adjustments to the original AHP-derived weights.

The Euclidean Distance results provide additional insight into the magnitude of numerical changes between weight values. GA produced a total Euclidean Distance of 0.4480 (average: 0.0230), while PSO produced a total Euclidean Distance of 0.4853 (average: 0.0145). Although the Hamming Distance indicates substantial structural differences in the weight patterns, the relatively moderate Euclidean Distance values suggest that the numerical deviations of individual feature weights remain limited.

Table 7 also presents the Kendall's Tau values, which measure the degree of rank-order agreement between the optimized and baseline feature rankings. GA achieved a higher Tau value (0.7197) compared to PSO (0.6897), suggesting that the feature priority ordering produced by GA is more consistent with the baseline. Despite the substantial Hamming Distance values, the positive Kendall's Tau coefficients indicate that the optimized rankings still maintain a relatively strong correspondence with the original ordering. In contrast, PSO produced a more pronounced reordering of feature priorities, reflecting broader exploration behavior during optimization.

Table 7. Hamming distance, euclidean distance and kendalls's tau comparation relative to baseline

Algorithm	Hamming Distance vs. Baseline	Euclidean Distance vs. Baseline (Normalized)	Kendall's Tau vs. Baseline
GA	0.9895	0.4480 (0.0230)	0.7197
PSO	0.9916	0.4853 (0.0145)	0.6897

The findings of this study are generally consistent with previous research that applied metaheuristic optimization techniques to improve decision-making models. Study [15] demonstrated that Genetic Algorithm (GA) can effectively optimize parameter weights by exploring alternative solutions while maintaining acceptable consistency within the decision model. Similarly, the present study shows that GA successfully generated a highly consistent pairwise comparison matrix (CR = 0.0030–0.0047) and produced a modified feature-weight distribution while preserving a relatively high rank-order agreement with the baseline (Kendall's Tau = 0.7197). These results suggest that GA is capable of refining feature importance without substantially disrupting the original decision structure.

Likewise, the results obtained using Particle Swarm Optimization (PSO) support the findings reported in [18], where PSO demonstrated strong exploration capabilities and was able to discover alternative optimal weighting schemes. In the current study, PSO achieved the lowest consistency ratio for the main criteria matrix (CR = 0.0000) and produced the largest deviation from the baseline weights according to Euclidean Distance and Hamming Distance measurements. This indicates that PSO explored a broader search space than GA, resulting in a more substantial redistribution of feature importance across maternal health factors.

Furthermore, the observed differences between GA and PSO align with the comparative analysis reported in [19], which found that GA tends to preserve existing ranking structures, whereas PSO often generates more diverse solutions due to its population-based search dynamics. This tendency is reflected in the present study, where GA achieved a higher Kendall's Tau value (0.7197) than PSO (0.6897), indicating stronger agreement with the baseline ranking. Conversely, PSO produced a greater degree of ranking reorganization, suggesting a more exploratory optimization behavior.

Unlike previous studies that primarily evaluated optimization performance using objective-function values or classification accuracy, this research additionally assessed optimization quality through Hamming Distance, Euclidean Distance, and Kendall's Tau metrics. These complementary measures provide a more comprehensive understanding of how optimization affects both numerical weight distributions and feature-priority rankings. Therefore, the present study contributes additional evidence regarding the interpretability of metaheuristic-based weight optimization within AHP–TOPSIS decision-support systems for LBW risk assessment.

Table 8 shows that GA was slightly faster at 15 seconds compared to PSO at 22.75 seconds. The difference of about 7.75 seconds is due to the different mechanisms of operation of both algorithms. GA includes the selection, crossover and mutation operations per generation whereas PSO continuously updates the particle positions and velocities until convergence. Despite the slightly higher computation time, PSO exhibited a competitive stability of feature ranking in terms of its Kendall's Tau score.

Although PSO required approximately 52% more computation time than GA, both execution times remained below 30 seconds, indicating that either method is computationally feasible for decision-support applications in clinical settings. Therefore, the choice between GA and PSO may depend more on the desired balance between ranking stability and exploration capability than on computational cost.

Table 8. Computation time comparison

Algorithm	Computation Time

.

GA	15 seconds
PSO	22.75 seconds

The evaluation yielded several important findings. Both Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) successfully improved the consistency of the pairwise comparison matrices while generating feature-weight distributions that differed substantially from the baseline configuration, as indicated by the high Hamming Distance values. Among the two approaches, GA produced a more conservative redistribution of weights, reflected by its higher Kendall's Tau value (0.7197), indicating stronger rank-order agreement with the baseline weighting scheme. In terms of computational efficiency, GA and PSO exhibited comparable execution times, although GA was slightly faster. The results also showed that Blood Glucose and Urine Protein remained the most influential features across all weighting methods, with weights of 0.3454 under GA and 0.3000 under PSO, highlighting their importance in maternal and child health decision-making. Overall, the findings demonstrate that metaheuristic optimization can improve pairwise-comparison matrix consistency and generate alternative weighting schemes while maintaining a meaningful degree of ranking consistency with the baseline model. These results suggest that the proposed framework has potential as a ranking-based decision support system for maternal and child health applications.

4. CONCLUSION

This study investigated the application of Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) for optimizing pairwise comparison matrices within an AHP–TOPSIS decision-support framework for low birth weight (LBW) prevention in adolescent pregnancies. The results demonstrated that both algorithms successfully improved matrix consistency while generating alternative feature-weight distributions compared with the conventional AHP–TOPSIS approach. GA achieved higher ranking stability, as indicated by a Kendall's Tau value of 0.7197, and required less computational time, whereas PSO exhibited stronger exploratory behaviour and produced greater redistribution of feature importance. Across all weighting schemes, Blood Glucose and Urine Protein consistently emerged as the most influential criteria, highlighting their potential importance in maternal-health intervention prioritization.

The difference in optimized Consistency Ratio (CR) values between matrices is primarily influenced by matrix order and optimization search-space complexity. The main-category matrix contains fewer pairwise comparison elements, resulting in a smaller search space and enabling PSO to converge to a near-perfect consistency level (CR = 0.0000). In contrast, the maternal-factor matrix involves a larger number of criteria and pairwise comparisons, increasing optimization complexity and yielding a slightly higher but still acceptable consistency level (CR = 0.0640).

The primary contribution of this study is the comparative evaluation of GA and PSO for optimizing AHP pairwise comparison matrices and the assessment of their effects on consistency, weight distribution, ranking behaviour, and auxiliary predictive validity. The findings indicate that metaheuristic optimization can enhance the robustness of AHP–TOPSIS weighting while producing alternative weighting patterns with preserved ranking consistency, as indicated by correlation-based ranking metrics. Overall, the proposed framework demonstrates potential as a ranking-based decision-support tool for maternal and child health programs by providing more consistent and balanced weighting schemes while preserving clinically relevant feature priorities.

Several limitations should be acknowledged. The study utilized data from a single district, evaluated only two metaheuristic optimization algorithms, and relied on a limited number of expert judgments. Furthermore, the dataset exhibited substantial class imbalance, and the framework was not specifically designed or optimized for predictive classification tasks. Future research should validate the framework using larger and more diverse multi-regional datasets, investigate additional optimization techniques such as Differential Evolution (DE), Ant Colony Optimization (ACO), and Simulated Annealing (SA), and perform more comprehensive validation using both ranking-based and prediction-based evaluation metrics to further assess the practical applicability and generalizability of the proposed approach.

ACKNOWLEGEMENTS

This research was supported by the Penelitian Fundamental B (PFB-UNS) grant managed by the Institute for Research and Community Service (LPPM), Sebelas Maret University (UNS), Surakarta, Indonesia, under grant number 460/UN27.22/PT.01.03/2026, funded through Non-Tax State Revenue (PNBP).

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Author1: Conceptualization, Methodology, Software, Project administration. **Author2**: review & editing. **Author3**: review & editing.

DECLARATION OF COMPETING INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

Data is not available publicly.

REFERENCES

[1] WHO, "Low birth weight."
[2] and L. S. of H. & T. M. UNICEF, WHO, "Low Birthweight Estimates: Levels and Trends 2000–2020."
[3] WHO, "Global nutrition targets 2030: low birth weight brief."
[4] WHO, "Preterm and low birth weight infants."
[5] M. K. Al-Muqhni and R. Kurniawan, "Determinan Kejadian Berat Badan Lahir Rendah (BBLR) Pada Bayi di Provinsi Sulawesi Selatan: Analisis Data SKI 2023," *J. Ners*, vol. 9, no. 4, pp. 6535–6543, 2025, doi: 10.31004/jn.v9i4.48761.
[6] WHO, "WHO recommendations for care of the preterm or low-birth-weight infant."
[7] K. Yusnitha, T. Tursina, and M. A. Irwansyah, "Sistem Pendukung Keputusan Pemilihan Wilayah Prioritas Intervensi Kegiatan Keluarga Berencana dengan Metode AHP-SMART," *J. Edukasi dan Penelit. Inform.*, vol. 5, no. 1, p. 99, 2019, doi: 10.26418/jp.v5i1.31338.
[8] Y. Brianorman, "Sistem Pendukung Keputusan Wilayah Promosi Menggunakan Metode AHP-SMART pada Universitas Muhammadiyah Pontianak," *J. Teknol. Inf. dan Ilmu Komput.*, vol. 8, no. 3, p. 439, 2021, doi: 10.25126/jtiik.2021832997.
[9] A. Akmaludin, A. D. Suriyanto, N. Iriadi, T. Sukendar, and B. Santoso, "AHP-SMART Method as Evaluation Decision Support for Employee Promotion," *SinkrOn*, vol. 7, no. 2, pp. 341–350, 2022, doi: 10.33395/sinkron.v7i1.11228.
[10] Salnadila, M. Arhami, M. Rizka, and M. Davi, "Spk Pemilihan Makanan Bergizi Untuk Ibu Hamil Menggunakan Metode Electre," *eProceedingofTIK*, vol. 2, no. 2, pp. 40–50, 2022.
[11] S. Yusnita, D. P. Wijaya, A. S. Yazid, and A. Pramuntadi, "Sistem Pendukung Keputusan Penentuan Nutrisi Masa Kehamilan Menggunakan Metode Analitycal Hierarcy Process (AHP)," *J. JTIK (Jurnal Teknol. Inf. dan Komunikasi)*, vol. 9, no. September, pp. 1035–1047, 2025.
[12] A. Aqilah and R. Vania, "SISTEM PENDUKUNG KEPUTUSAN MENENTUKAN PERINGKAT BALITA SEHAT MENGGUNAKAN METODE AHP DAN TOPSIS," *J. Manaj. Inform.*, vol. 14, no. 1, pp. 1–9, 2025.
[13] E. N. Sejati Purnomo, S. Widya Sihwi, and R. Anggrainingsih, "Analisis Perbandingan Menggunakan Metode AHP, TOPSIS, dan AHP-TOPSIS dalam Studi Kasus Sistem Pendukung Keputusan Penerimaan Siswa Program Akselerasi," *J. Teknol. Inf. ITSmart*, vol. 2, no. 1, p. 16, 2013, doi: 10.20961/its.v2i1.612.
[14] Y. Ommane, M. Lachgar, M. Hanine, M. D. Laanaoui, and S. Kaouri, "Optimizing healthcare supply chain capacity planning during disasters using fuzzy AHP and TOPSIS methods," *Sci. Rep.*, vol. 15, no. 1, pp. 1–22, 2025, doi: 10.1038/s41598-025-19338-3.
[15] F. Ciardiello and A. Genovese, "A comparison between TOPSIS and SAW methods," *Ann. Oper. Res.*, pp. 967–994, 2023.
[16] H. Taherdoost and M. Madanchian, "A Comprehensive Survey and Literature Review on TOPSIS," *Int. J. Serv. Sci. Manag. Eng. Technol.*, vol. 15, no. 1, pp. 1–65, 2024, doi: 10.4018/IJSSMET.347947.
[17] Muhamad Wahyu Tirta, Muhammad Khumaidi Nursyarif, Hamada Zein, Rita Yulfani, Melisa Nur Aini, and Farhan Akbar, "Analisis Perbandingan Penerapan Metode AHP-SAW dan AHP-TOPSES Dalam Pemilihan Mahasiswa Terbaik Prodi Ilmu Keperawatan," *J. Tek. Mesin, Elektro dan Ilmu Komput.*, vol. 4, no. 1, pp. 40–52, 2024, doi: 10.55606/teknik.v4i1.2672.
[18] S. F. Dita, N. Safrudin, F. Sianturi, M. Hasbiallah, and A. H. Anshor, "Sistem Pendukung Keputusan Kebijakan Fasilitas Kampus Universitas pelita bangsa Menggunakan Metode AHP-TOPSIS," *J. Media Inform.*, vol. 6, no. 2, pp. 1066–1071, 2025.
[19] F. Moussaoui, M. Cherrared, M. A. Kacimi, and R. Belarbi, "A genetic algorithm to optimize consistency ratio in AHP method for energy performance assessment of residential buildings—Application of top-down and bottom-up approaches in Algerian case study," *Sustain. Cities Soc.*, vol. 42, no. August 2017, pp. 622–636, 2018, doi: 10.1016/j.scs.2017.08.008.
[20] D. Al Ghozali *et al.*, "Application of Fuzzy-AHP Combined with Particle Swarm Optimization (PSO) for Determining Prioritization and Strategies in Debt Collection," *J. Artif. Intell. Eng. Appl.*, vol. 5, no. 1, 2025.
[21] H. Rahman *et al.*, "Optimizing SVC placement for enhanced voltage stability using a novel index and hybrid ABC-PSO algorithm," *Franklin Open*, vol. 11, no. September 2024, 2025, doi: 10.1016/j.fraope.2025.100299.
[22] Z. Tajani, C. Tajani, I. Khattabi, and M. Sabbane, "A metaheuristic approach to improve consistency of the pairwise matrix in AHP," *Math. Model. Comput.*, vol. 10, no. 4, pp. 1164–1173, 2023, doi: 10.23939/mmc2023.04.1164.
[23] R. Zhang, C. Gao, X. Chen, F. Li, D. Yi, and Y. Wu, "Genetic algorithm optimised Hadamard product method for inconsistency judgement matrix adjustment in AHP and automatic analysis system development," *Expert Syst. Appl.*, vol. 211, no. January 2022, p. 118689, 2023, doi: 10.1016/j.eswa.2022.118689.
[24] S. Zhang, C. Zhang, and Q. Yang, "Dara Prepartion for Data Mining," *Appl. Artif. Intel.*, vol. 17(5–6), pp. 375–381, 2003, doi: 10.1080/08839510390219264.
[25] A. Seveso, A. Campagner, D. Ciucci, and F. Cabitza, "Ordinal labels in machine learning: A user-centered approach to improve data validity in medical settings," *BMC Med. Inform. Decis. Mak.*, vol. 20, no. Suppl 5, pp. 1–15, 2020, doi: 10.1186/s12911-020-01152-8.
[26] K. Zaballa, A. Liu, M. J. Peek, M. Mongelli, and R. Nanan, "Association between World Health Organization categories of body mass index and relative risks for weight-related pregnancy outcomes: a retrospective cohort study," *Obstet. Med.*, vol. 5, no. 3, pp. 112–118, 2012, doi: 10.1258/om.2012.110091.
[27] X. Zong *et al.*, "Maternal Pre-pregnancy Body Mass Index Categories and Infant Birth Outcomes: A Population-Based Study of 9 Million Mother–Infant Pairs," *Front. Nutr.*, vol. 9, no. February, pp. 1–10, 2022, doi: 10.3389/fnut.2022.789833.
[28] F. J. I. Fowkes, R. McGready, S. Johnstone-Robertson, F. Nosten, and J. G. Beeson, "Antibody boosting and longevity following tetanus immunization during pregnancy," *Clin. Infect. Dis.*, vol. 56, no. 5, pp. 749–750, 2013, doi: 10.1093/cid/cis979.
[29] WHO, "Tetanus protection for neonates, neonates protected at birth against neonatal tetanus (PAB) (%)."

[30] H. Blencowe, J. Lawn, J. Vandelaer, M. Roper, and S. Cousens, "Tetanus toxoid immunization to reduce mortality from neonatal tetanus," *Int. J. Epidemiol.*, vol. 39, no. SUPPL. 1, pp. 102–109, 2010, doi: 10.1093/ije/dyq027.

[31] N. E. Johns *et al.*, "Inequalities in Immunization against Maternal and Neonatal Tetanus: A Cross-Sectional Analysis of Protection at Birth Coverage Using Household Health Survey Data from 76 Countries," *Vaccines*, vol. 11, no. 4, 2023, doi: 10.3390/vaccines11040752.

[32] E. Slack, K. E. Best, J. Rankin, and N. Heslehurst, "Maternal obesity classes, preterm and post-term birth: A retrospective analysis of 479,864 births in England," *BMC Pregnancy Childbirth*, vol. 19, no. 1, pp. 1–9, 2019, doi: 10.1186/s12884-019-2585-z.

[33] V. Kashtriya and P. Singh, "Enhancing Machine Learning for Imbalanced Medical Data: A Quantum-Inspired Approach to Synthetic Oversampling (QI-SMOTE)," *arXiv Prepr. arXiv2509.02863*, 2025.

[34] J. M. Conejero, J. C. Preciado, A. E. Prieto, M. C. Bas, and V. J. Bolós, "Applying data driven decision making to rank vocational and educational training programs with TOPSIS," *Decis. Support Syst.*, vol. 142, no. December 2020, pp. 1–10, 2021, doi: 10.1016/j.dss.2020.113470.

[35] A. Alharbi *et al.*, "Selection of data analytic techniques by using fuzzy AHP TOPSIS from a healthcare perspective," *BMC Med. Inform. Decis. Mak.*, vol. 24, no. 1, 2024, doi: 10.1186/s12911-024-02651-8.

[36] R. W. Saaty, "The analytic hierarchy process-what it is and how it is used," *Math. Model.*, vol. 9, no. 3–5, pp. 161–176, 1987, doi: 10.1016/0270-0255(87)90473-8.

[37] J. Kennedy and R. Eberhart, "Particle Swarm Optimisation," in *IEEE International Conference on Neural Networks (ICNN), Perth, Australia*, 1995, pp. 1942–1948. doi: 10.1109/ICNN.1995.488968.

[38] N. Pohan, H. K. AR, A. A. Salsabilla, D. K. Abrianisyah, and D. Tanjung, "Decision support system for prioritizing tourism development using TOPSIS-Borda method," *Sist. Pendukung Keputusan dengan Apl.*, vol. 4, no. 1, pp. 17–28, 2025.

[39] B. Monjardet, "On the comparison of the Spearman and Kendall metrics between linear orders," *Discrete Math.*, vol. 192, no. 1–3, pp. 281–292, 1998, doi: 10.1016/S0012-365X(98)00076-4.

[40] E. F. El-Hashash and R. H. A. Shiekh, "A Comparison of the Pearson, Spearman Rank and Kendall Tau Correlation Coefficients Using Quantitative Variables," *Asian J. Probab. Stat.*, vol. 20, no. 3, pp. 36–48, 2022, doi: 10.9734/ajpas/2022/v20i3425.