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Fuzzy Analytical Hierarchy Process Model for Malaria Control Strategies Prioritization in North-East, Nigeria

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Abstract

Although the Fuzzy Analytic Hierarchy Process (F-AHP) is widely used to address complex multi-criteria decision-making problems under uncertainty, its application to malaria intervention prioritization in resource-constrained settings, particularly North-East Nigeria, remains limited. This study developed and applied an F-AHP decision-support framework to prioritize malaria control interventions based on epidemiological, economic, operational, and social considerations. A mixed-methods approach involved 18 purposively selected experts, including epidemiologists, medical doctors, and health educators from the six states of North-East Nigeria. Primary data were collected through structured questionnaires, while secondary evidence was drawn from peer-reviewed literature, national malaria control guidelines, and relevant health reports. Five evaluation criteria and five intervention alternatives were assessed using fuzzy pairwise comparison matrices. Expert judgments were represented by triangular fuzzy numbers and defuzzified using the centroid method to generate normalized priority weights and global intervention rankings. All judgment matrices met the recommended consistency threshold (CR ≤ 0.10), supporting the internal consistency of the evaluations. Acceptability emerged as the most influential criterion (0.387), followed by cost-effectiveness (0.283) and health impact (0.200). Among the intervention alternatives, insecticide-treated nets/long-lasting insecticidal nets ranked first, with a global priority weight of 0.346, followed by indoor residual spraying at 0.278. These findings demonstrate that social acceptability, economic efficiency, and health impact are central determinants of malaria intervention priorities in the region. The study contributes to fuzzy multi-criteria decision-making in public health by providing a transparent and systematic framework for incorporating uncertainty into expert judgments. Practically, the framework can support policymakers, malaria control programmes, and public health stakeholders in allocating limited resources and selecting contextually appropriate interventions in North-East Nigeria. It also provides a foundation for integrating stochastic and adaptive approaches into future malaria intervention prioritization under temporal and epidemiological uncertainty.

Keywords: Fuzzy Analytic Hierarchy Process; Intervention Prioritization; Malaria Control; Multi-Criteria Decision Analysis; North-East Nigeria

Introduction

Complex decision-making has become increasingly important across healthcare, engineering, environmental management, economics, and public policy, where decision-makers are often required to select among competing alternatives under conditions of uncertainty, incomplete information, and multiple, potentially conflicting objectives. Such environments require decision-support approaches capable of integrating expert knowledge with empirical evidence while simultaneously considering several evaluation criteria (Belton & Stewart, 2021; Cinelli et al., 2020). Multi-Criteria Decision Analysis (MCDA) has consequently become an established approach for addressing complex decision problems involving multiple alternatives, criteria, and stakeholders (Thokala et al., 2021). Among the various MCDA techniques, the Analytic Hierarchy Process (AHP) is one of the most widely applied approaches because its hierarchical structure enables complex problems to be decomposed into a goal, criteria, and alternatives. Through pairwise comparisons, AHP provides a systematic mechanism for deriving priority weights from expert judgments and incorporates a consistency measure for assessing the reliability of those judgments (Ishizaka & Siraj, 2021; Kumar et al., 2023; Mandali et al., 2025). However, conventional AHP generally requires decision-makers to express preferences using precise numerical values on a fixed preference scale (Saaty, 1980). This assumption may be unrealistic in practical decision environments because expert judgments are frequently expressed through linguistic assessments such as *low*, *moderate*, *high*, or *very important*, rather than precise numerical values.

The limitations associated with precise judgments are particularly relevant to public health decision-making, where governments and health agencies must allocate financial, human, and logistical resources among competing interventions while dealing with epidemiological uncertainty, environmental changes, and diverse stakeholder preferences. Malaria represents a particularly important example of such a decision environment. The African Region accounts for approximately 94% of global malaria cases and deaths, while Nigeria contributes more than one-quarter of the global malaria burden (World Health Organization [WHO], 2024). The North-East geopolitical zone of Nigeria faces additional challenges associated with climatic variability, insecurity, population displacement, poverty, limitations in healthcare infrastructure, and inconsistent implementation of malaria control policies (National Malaria Elimination Programme [NMEP], 2023). Although malaria control interventions such as insecticide-treated nets (ITNs), indoor residual spraying (IRS), larval source management, treatment, and community health education have been implemented, their performance varies according to cost, health impact, feasibility, acceptability, and sustainability. Consequently, selecting the most appropriate malaria intervention is not a single-criterion decision but a complex multi-criteria problem in which competing objectives and uncertainty in expert judgment must be considered simultaneously.

This study therefore argues that malaria intervention prioritization requires a decision-support framework capable of accommodating both multiple evaluation criteria and the uncertainty inherent in expert judgments. While conventional AHP provides a systematic structure for comparing criteria and alternatives, its dependence on crisp numerical judgments may not adequately capture the ambiguity associated with human preferences. In practical decision environments, experts may recognize that one intervention is more feasible, acceptable, or effective than another without being able to assign an exact numerical preference. Fuzzy Set Theory provides a suitable basis for addressing this limitation by allowing imprecise concepts and linguistic judgments to be represented mathematically. The integration of fuzzy logic with AHP, commonly referred to as the Fuzzy Analytic Hierarchy Process (FAHP), enables uncertain expert assessments to be represented using fuzzy numbers before being transformed into priority values. Previous studies have demonstrated the usefulness of FAHP in healthcare technology assessment, hospital resource management, environmental planning, transportation, renewable energy, and sustainable development (Kahraman et al., 2021; Chatterjee & Stevi, 2023). Recent methodological studies have similarly emphasized the value of fuzzy extensions of MCDA for improving the representation of uncertainty and enhancing the transparency of decision-making processes (Liu et al., 2020; Taherdoost et al., 2024).

Previous research has consequently established AHP and FAHP as important tools for addressing complex decision problems across healthcare and other sectors. Conventional AHP has been applied to alternative evaluation and resource prioritization where several criteria must be considered simultaneously, whereas FAHP has increasingly been employed in situations characterized by uncertainty and linguistic judgments. Recent reviews indicate that fuzzy and hybrid MCDA approaches are gaining attention in healthcare, environmental sustainability, renewable energy, disaster management, and other complex decision contexts because of their ability to represent uncertainty more effectively than deterministic approaches (Alharairi et al., 2025; Taherdoost et al., 2024). However, important gaps remain in the application of these approaches to malaria control. Limited attention has been given to the systematic application of FAHP for prioritizing malaria control interventions within the specific socioeconomic, environmental, and epidemiological context of North-East Nigeria. In addition, several existing prioritization approaches rely on deterministic criteria weights that may inadequately represent uncertainty in expert judgments. Much of the healthcare-related application of FAHP has also focused on hospital management, healthcare technology assessment, and resource management rather than vector-borne disease intervention planning. Furthermore, many existing decision-support approaches treat intervention prioritization as relatively static and provide limited consideration of contextual differences that may influence malaria transmission and intervention performance. These limitations demonstrate the need for a context-specific decision-support framework that can incorporate uncertainty while simultaneously evaluating multiple and potentially conflicting criteria.

The novelty of this study lies in the development and application of a context-specific Fuzzy Analytic Hierarchy Process model for prioritizing malaria control interventions in North-East Nigeria. Unlike standard AHP, in which criteria and alternatives are evaluated through determinate pairwise comparisons, the proposed FAHP framework represents expert judgments using fuzzy numbers to accommodate linguistic ambiguity and imprecision. The theoretical foundation of the study integrates Multi-Criteria

Decision Analysis, Saaty's Analytic Hierarchy Process, Zadeh's Fuzzy Set Theory, and Chang's Fuzzy Extent Analysis. MCDA provides the broader framework for evaluating competing alternatives against multiple criteria; AHP provides the hierarchical structure and pairwise comparison mechanism; Fuzzy Set Theory provides a mathematical representation of uncertainty and vagueness in expert judgments; and Chang's Fuzzy Extent Analysis provides the analytical mechanism for deriving priorities from fuzzy comparisons. By integrating these complementary perspectives, the study extends the application of uncertainty-aware decision-support methods to malaria control planning and provides a structured approach for translating subjective expert assessments into transparent intervention priorities.

Against this background, the study focuses on developing and implementing a Fuzzy Analytic Hierarchy Process model for prioritizing malaria control intervention strategies in North-East Nigeria under conditions of uncertainty. Specifically, the study identifies the key criteria relevant to malaria intervention decisions, determines their relative importance, evaluates competing malaria control alternatives against the selected criteria, integrates fuzzy logic into AHP to capture vagueness and uncertainty in expert judgments, and establishes an overall priority ranking of malaria control interventions. The resulting framework is intended to provide policymakers, malaria control programmes, and public health practitioners with a transparent and evidence-based decision-support tool for improving resource allocation and selecting malaria control strategies that are appropriate to the socioeconomic and epidemiological context of North-East Nigeria.

METHODS

In order to obtain primary data and secondary data, a structured questionnaire was constructed and distributed to the three (3) relevant stakeholders (Epidemiologists, Medical Doctors and Health Educators) each from three (3) state of the north-east Nigeria using the purposive sampling method. The information sought from the respondents would be utilized to get relative weights of the criteria and of the alternatives over each other.

The relevant information for the identification of commonly used malaria control strategies as alternatives as well as the key criteria and the information on malaria in the north-east of Nigeria was sought through secondary sources. Malaria journals and medical literature search, government reports and related official documents on public health in the north east Nigeria were accessed to find relevant literature. Based on these preliminary studies the goal of the study as well as criteria for the evaluation of alternatives and the alternative malaria control intervention strategies in North East Nigeria were identified and summarized below:

Method of Analysis

This study adopted fuzzy analytical hierarchy process model. The decision was structured into a hierarchy of interrelated sub-problems that can be analyzed independently. The hierarchy includes a main goal, criteria, and alternatives, from top to bottom. The goal, criteria and the alternative were determined through literature review and collective discussion.

Linguistic judgment on each alternative and criterion with respect to the elements on the level immediately above obtained from experts through questionnaire, survey, interview, expert panels, and direct observation instead of using crisp ratio scale, nine TFNs (table1) was used to represent linguistic terms with the expectation that experts will feel more comfortable using such terms in their assessment. It should be noted that such a verbal clarification becomes impractical when too many rating scale.

Table 1: Linguistic Scale

Linguistic Term	Lower	Middle	Upper
Equally Preferred	1	1	1
Equally and weakly Preferred	1	2	3
Weakly Preferred	2	3	4
Weakly and moderately Preferred	3	4	5
Moderately Preferred	4	5	6
Moderately and strongly Preferred	5	6	7
Strongly Preferred	6	7	8
Strongly and very strongly Preferred	7	8	9
Very strongly Preferred	8	9	10

Source: Bakir, M., Atalik, O. (2021)

For the assessment of each alternative and criterion, the number of TFNs should be equal to the number of the experts. The minimum (l_{ij}), and the most(m_{ij}), and maximum (u_{ij}) values of TFNs are aggregated into three individual groups.

Fuzzy pairwise comparison matrices (FPCMs) for each hierarchy level were formed based on the fuzzy arithmetic. For example, when M alternatives (C_1............C_M) on a given level are evaluated against each other with regards to the P^{th} criterion (p = 1,2,....n) on the preceding level, an $m \times m$ FPCMs was obtained.

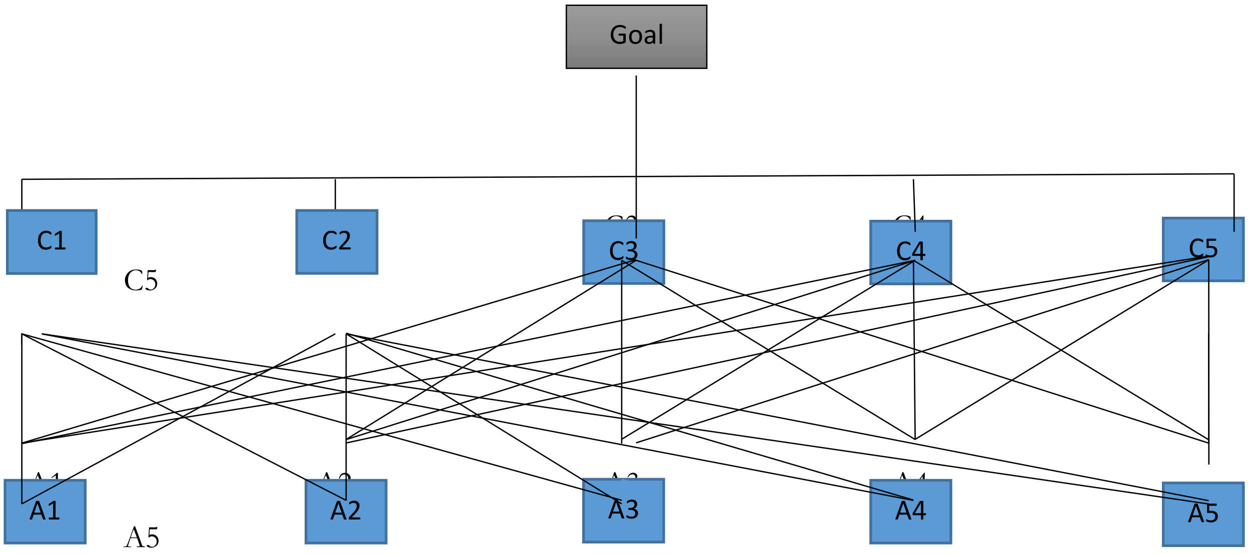

Figure 1: Hierarchical Structure of the Problem

G = GOAL*; Control malaria in North-East, Nigeria*

ALTERNATIVES*: The following were identified as major alternatives to Malaria control*

A_1 *= Insecticide treated net (ITN)/ long lasting insecticidal net (LLIN).*

A_2 *= Indoor residual spraying (IRS)*

A_3 *= Larval source management (LSM)*

A_4 *= Provide Treatment to all infected person*

A_5*= Provide health education.*

CRITERIA: *The following were the criteria identified:-*

C_1 *= Feasibility*

C_2 *= Cost-effectiveness*

C_3 *= Health impact*

C_4 *= Acceptability*

C_5 *= Sustainability*

Step 1: Construct the Pairwise Comparison Matrix

The first stage is to compare every criterion with every other criterion.

The pairwise comparison is

$$A = [a_{ij}] , \qquad i, j = 1,2,3,\dots,n \tag{2}$$

Where,

A = Pairwise comparison matrix

a_{ij} = Relative importance of criterion i over criterion j

n= number of criteria

Step 2: Fuzzification: Convert each comparison into a triangular fuzzy number

$$\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij}) \tag{3}$$

where l_{ij}= lower value (optimistic)

m_{ij} = most likely value (mean)

u_{ij} = upper value (pessimistic)

Step 3: Aggregate Expert's Opinions

Supposed there are k experts, the aggregated fuzzy judgment is

$$\bar{A}_{ij} = \left(\frac{1}{k}\sum_{k=1}^{k} l_k; \frac{1}{k}\sum_{k=1}^{k} m_k; \frac{1}{k}\sum_{k=1}^{k} u_k\right) \tag{4}$$

Where,

$\bar{A}_{ij}$= Triangular fuzzy numbers

k = number of experts

l_k, m_k, u_k = Experts' k's judgment

Step 4: Extent analysis Method for weight Calculation (Cheng's Method)

$$S_i = \left(\sum_{j=1}^{m} \bar{A}_{ij}\right) \otimes \left(\sum_{i=1}^{n} \sum_{j=1}^{m} \bar{A}_{ij}\right) \tag{5}$$

Where,

m = number of comparison

n = number of criteria

S_i = Synthetic extent

$\bar{A}_{ij}$ = Triangular fuzzy numbers

$\otimes$ = Fuzzy multiplication

Step 5: Degree of possibility

The possibility that one fuzzy number is greater than another is

$$V(\bar{A}_1 \geq \bar{A}_2) = \begin{cases} 1 & if\, m_1 \geq m_2 \\ 0 & if\, l_2 \geq u_1 \\ \frac{l_2 - u_2}{(m_1 - u_2) - (m_2 - l_2)} & otherwise \end{cases} \tag{6}$$

Where

$\bar{A}_1$ = First fuzzy number

$\bar{A}_2$ = Second fuzzy number

Step 6: Obtain Fuzzy Priority Vector

For each criterion,

$$d_i = \min V(S_i \geq S_j) \tag{7}$$

Where,

d_i = Fuzzy priority vector of criterion i.

Step 7: Normalize the Criteria Weight

The normalized weights becomes

$$W_i = \frac{d_i}{\sum_{i=1}^{n} d_i} \tag{8}$$

Where,

W_i = Normalized weight of criterion i.

Suppose,

$A_1, A_2 \ldots\ldots A_n$ are the malaria intervention for each criterion C_i, construct another pairwise comparison matrix among the alternatives. Repeat step 1-7.

This produces,

$$L_{ij} = \frac{d_{ij}}{\sum_{j=1}^{m} d_{ij}} \tag{9}$$

Where,

L_{ij} = Local priority weight of the alternative j with respect to criterion i.

d_{ij} = Fuzzy priority values of j alternative under criterion i.

M = Number of alternatives

The global priority weight for the alternative of the classical FAHP is obtained using:

$$G = \sum_{i=1}^{n} W_i L_{ij} \tag{10}$$

Where

G = Global priority ranking for the alternatives for classical FAHP

RESULTS

Data Analysis and Results

Fuzzy Pairwise Matrix for the Criteria for Evaluating Malaria Control Alternatives in North-East, Nigeria

Table2: Aggregated Fuzzy Pairwise Comparison Matrix for the criteria

Criteria	C1	C2	C3	C4	C5
C1	(1.000, 1.000, 1.000)	(0.150, 0.176, 0.214)	(0.176, 0.214, 0.273)	(0.167, 0.200, 0.250)	(4.000, 5.000, 6.000)
C2	(4.667, 5.667, 6.667)	(1.000, 1.000, 1.000)	(6.000, 7.000, 8.000)	(0.150, 0.176, 0.214)	(5.333, 6.333, 7.333)
C3	(3.667, 4.667, 5.667)	(0.125, 0.143, 0.167)	(1.000, 1.000, 1.000)	(0.176, 0.214, 0.273)	(3.333, 4.333, 5.333)
C4	(4.000, 5.000, 6.000)	(4.667, 5.667, 6.667)	(3.667, 4.667, 5.667)	(1.000, 1.000, 1.000)	(3.333, 4.333, 5.333)
C5	(0.167, 0.200, 0.250)	(0.136, 0.158, 0.188)	(0.188, 0.231, 0.300)	(0.188, 0.231, 0.300)	(1.000, 1.000, 1.000)

Table 2 above shows the aggregated fuzzy pairwise comparison matrix for the criteria obtained from the responses of the of the experts' linguistic responses from the questionnaire and was converted using the linguistic scale in table 1 above. The results shows C4 having dominance over all other criteria.

The Crisp Pairwise Comparison Matrices for the Criteria

Table 3: Crisp Pairwise Comparison Matrix for the Criteria

Criteria	C1	C2	C3	C4	C5
C1	1.000	0.180	0.221	0.206	5.000
C2	5.667	1.000	7.000	0.180	6.333
C3	4.667	0.145	1.000	0.221	4.333
C4	5.000	5.667	4.667	1.000	4.333
C5	0.206	0.161	0.239	0.239	1.000

Table 3 above show the crisp values of the fuzzy pairwise comparison matrix from table 2 using centroid method.

The Normalized Weights for the Criteria

Table 4: Defuzzified and Normalized Criteria Weights for Malaria Control Intervention Evaluation

Criterion	Description	Weight	Rank
C4	Acceptability	0.338	1
C2	Cost Effectiveness	0.283	2
C3	Health Impact	0.220	3
C1	Feasibility	0.103	4
C5	Sustainability	0.056	5

Table 4 above is the normalized weights of the criteria. The results indicated that C4 (Acceptability) was ranked the highest with 0.338 (weight).

Pairwise comparison Matrices for the Alternatives

Table 5 below shows the aggregated fuzzy pairwise comparison matrix for the alternative given criterion C1. The table shows A1 having the highest comparison compared to the others.

Table5: Aggregated Alternative Pairwise Comparison Matrix under Criterion C1 (Feasibility)

Alternatives	A1	A2	A3	A4	A5
A1	(1.000, 1.000, 1.000)	(2.722, 3.400, 4.083)	(5.000, 6.000, 7.000)	(5.000, 6.000, 7.000)	(5.667, 6.667, 7.667)
A2	(1.448, 1.806, 2.178)	(1.000, 1.000, 1.000)	(3.667, 4.667, 5.667)	(6.000, 7.000, 8.000)	(4.667, 5.667, 6.667)
A3	(0.145, 0.170, 0.222)	(0.178, 0.217, 0.278)	(1.000, 1.000, 1.000)	(0.233, 0.306, 0.444)	(0.217, 0.278, 0.389)
A4	(0.145, 0.170, 0.222)	(0.125, 0.143, 0.167)	(2.333, 3.333, 4.333)	(1.000, 1.000, 1.000)	(3.000, 3.667, 4.333)
A5	(0.131, 0.151, 0.194)	(0.151, 0.178, 0.222)	(2.667, 3.667, 4.667)	(0.444, 0.467, 0.500)	(1.000, 1.000, 1.000)

Table 6 below shows the aggregated fuzzy pairwise comparison matrix for the alternative given criterion C2. The table shows A1 having the highest comparison compared to the others alternatives

Table6: Aggregated Alternative Pairwise Comparison Matrix for under Criterion C2 (Cost Effectiveness)

Alternatives	A1	A2	A3	A4	A5
A1	(1.000, 1.000, 1.000)	(5.000, 6.000, 7.000)	(6.000, 7.000, 8.000)	(5.667, 6.667, 7.667)	(5.333, 6.333, 7.333)
A2	(0.145, 0.170, 0.222)	(1.000, 1.000, 1.000)	(4.000, 5.000, 6.000)	(4.667, 5.667, 6.667)	(5.000, 6.000, 7.000)
A3	(0.126, 0.145, 0.167)	(0.167, 0.200, 0.250)	(1.000, 1.000, 1.000)	(0.250, 0.333, 0.500)	(0.233, 0.306, 0.444)
A4	(0.131, 0.151, 0.194)	(0.156, 0.187, 0.233)	(2.000, 3.000, 4.000)	(1.000, 1.000, 1.000)	(2.333, 3.333, 4.333)
A5	(0.139, 0.162, 0.194)	(0.145, 0.170, 0.222)	(2.333, 3.333, 4.333)	(0.233, 0.306, 0.444)	(1.000, 1.000, 1.000)

Table 7 below shows the aggregated fuzzy pairwise comparison matrix for the alternative given criterionC3 (Health Impact). The table shows A1 having the highest comparison compared to A2,A3,A4 and A5.

Table7: Aggregated Alternative Pairwise Comparison Matrix for under Criterion C3 (Health Impact)

Alternatives	A1	A2	A3	A4	A5
A1	(1.000, 1.000, 1.000)	(1.722, 2.067, 2.417)	(5.667, 6.667, 7.667)	(5.000, 6.000, 7.000)	(4.667, 5.667, 6.667)
A2	(1.722, 2.067, 2.417)	(1.000, 1.000, 1.000)	(3.333, 4.333, 5.333)	(5.000, 6.000, 7.000)	(5.000, 6.000, 7.000)
A3	(0.131, 0.151, 0.194)	(0.194, 0.244, 0.333)	(1.000, 1.000, 1.000)	(0.233, 0.306, 0.444)	(0.250, 0.344, 0.583)
A4	(0.145, 0.170, 0.222)	(0.145, 0.170, 0.222)	(2.333, 3.333, 4.333)	(1.000, 1.000, 1.000)	(2.000, 3.000, 4.000)
A5	(0.151, 0.178, 0.222)	(0.145, 0.170, 0.222)	(2.333, 3.333, 4.333)	(0.250, 0.333, 0.500)	(1.000, 1.000, 1.000)

Table 8 below shows the aggregated fuzzy pairwise comparison matrix for the alternative given criterion C4 (Acceptability). The table shows A1 having the highest comparison compared to the others.

Table 8: Aggregated Alternative Pairwise Comparison Matrix for the Alternatives Given Criterion C4 (Acceptability)

Alternatives	A1	A2	A3	A4	A5
A1	(1.000, 1.000, 1.000)	(2.714, 3.389, 4.067)	(4.056, 4.733, 5.417)	(6.000, 7.000, 8.000)	(6.000, 7.000, 8.000)
A2	(1.778, 2.133, 2.500)	(1.000, 1.000, 1.000)	(4.000, 5.000, 6.000)	(5.667, 6.667, 7.667)	(5.000, 6.000, 7.000)
A3	(1.417, 1.762, 2.111)	(0.170, 0.206, 0.250)	(1.000, 1.000, 1.000)	(4.333, 5.000, 5.667)	(6.000, 7.000, 8.000)
A4	(0.126, 0.145, 0.167)	(0.131, 0.151, 0.194)	(0.417, 0.429, 0.444)	(1.000, 1.000, 1.000)	(0.194, 0.244, 0.333)
A5	(0.125, 0.143, 0.167)	(0.145, 0.170, 0.222)	(0.126, 0.145, 0.167)	(3.333, 4.333, 5.333)	(1.000, 1.000, 1.000)

Table 9 below shows the aggregated fuzzy pairwise comparison matrix for the alternative given criterion C 5(Sustainability). The table shows A1 having the dominance comparison compared to the others

Table 9: Aggregated Alternative Pairwise Comparison Matrix for the Alternatives Given Criterion C5 (Sustainability)

Alternatives	A1	A2	A3	A4	A5
A1	(1.000, 1.000, 1.000)	(0.139, 0.162, 0.194)	(0.145, 0.170, 0.222)	(6.333, 7.333, 8.333)	(6.000, 7.000, 8.000)
A2	(5.333, 6.333, 7.333)	(1.000, 1.000, 1.000)	(0.167, 0.200, 0.250)	(3.000, 3.667, 4.333)	(5.000, 6.000, 7.000)
A3	(5.000, 6.000, 7.000)	(4.000, 5.000, 6.000)	(1.000, 1.000, 1.000)	(6.000, 7.000, 8.000)	(6.000, 7.000, 8.000)
A4	(0.120, 0.137, 0.153)	(0.444, 0.467, 0.500)	(0.125, 0.143, 0.167)	(1.000, 1.000, 1.000)	(0.167, 0.200, 0.250)
A5	(0.126, 0.145, 0.167)	(0.145, 0.170, 0.222)	(0.125, 0.143, 0.167)	(4.000, 5.000, 6.000)	(1.000, 1.000, 1.000)

The Crisp Pairwise Comparison Matrices for the Alternatives Given Each Criterion

Table 10 below shows the crisp values of the fuzzy pairwise comparison matrix of the alternatives given C1. The values indicate dominance of A1 over other competing alternatives.

Table 10: Crisp Pairwise Comparison Matrix for the Alternatives Given Criterion C1 (Feasibility)

Alternatives	A1	A2	A3	A4	A5
A1	1.000	3.402	6.000	6.000	6.667
A2	1.811	1.000	4.667	7.000	5.667
A3	0.179	0.224	1.000	0.328	0.295
A4	0.179	0.145	3.333	1.000	3.667
A5	0.159	0.184	3.667	0.470	1.000

Table 11 below shows the crisp values of the fuzzy pairwise comparison matrix of the alternatives given C2. The values indicate dominance of A1 over other competing alternatives.

Table11: Crisp Pairwise Comparison Matrix for the Alternatives Given Criterion C2 (Cost Effectiveness)

Alternatives	A1	A2	A3	A4	A5
A1	1.000	6.000	7.000	6.667	6.333
A2	0.179	1.000	5.000	5.667	6.000
A3	0.146	0.206	1.000	0.361	0.328
A4	0.159	0.192	3.000	1.000	3.333
A5	0.165	0.179	3.333	0.328	1.000

Table 12 below shows the crisp values of the fuzzy pairwise comparison matrix of the alternatives given C3. The values indicate dominance of A1 over other competing alternatives.

Table12: Crisp Pairwise Comparison Matrix for the Alternatives Given Criterion C3 (Health Impact)

Alternatives	A1	A2	A3	A4	A5
A1	1.000	2.069	6.667	6.000	5.667
A2	2.069	1.000	4.333	6.000	6.000
A3	0.159	0.257	1.000	0.328	0.392
A4	0.179	0.179	3.333	1.000	3.000
A5	0.184	0.179	3.333	0.361	1.000

Table 13 below shows the crisp values of the fuzzy pairwise comparison matrix of the alternatives given C4. The values indicate dominance of A1 over other competing alternatives.

Table13: Crisp Pairwise Comparison Matrix for the Alternatives Given Criterion C4 (Acceptability)

Alternatives	A1	A2	A3	A4	A5
A1	1.000	3.390	4.735	7.000	7.000
A2	2.137	1.000	5.000	6.667	6.000
A3	1.763	0.209	1.000	5.000	7.000
A4	0.146	0.159	0.430	1.000	0.257
A5	0.145	0.179	0.146	4.333	1.000

Table 14 below shows the crisp values of the fuzzy pairwise comparison matrix of the alternatives given C5. The values indicate dominance of A3 over other competing alternatives.

Table14: Crisp Pairwise Comparison Matrix for Alternatives Given Criterion C5 (Sustainability)

Alternatives	A1	A2	A3	A4	A5
A1	1.000	0.165	0.179	7.333	7.000
A2	6.333	1.000	0.206	3.667	6.000
A3	6.000	5.000	1.000	7.000	7.000
A4	0.137	0.470	0.145	1.000	0.206
A5	0.146	0.179	0.145	5.000	1.000

The Normalized Pairwise Comparison Matrices for the Alternatives Given Each Criterion

Table 15 below shows the normalized values of the crisp values of the alternatives given criterion C1. The result shows A1 dominance over the other competing strategies.

Table15: Normalized Pairwise Comparison Matrix for the Alternatives Given Criterion C1 (Feasibility)

Alternatives	A1	A2	A3	A4	A5
A1	0.299	0.670	0.350	0.396	0.397
A2	0.540	0.197	0.240	0.326	0.397
A3	0.049	0.052	0.055	0.022	0.107
A4	0.056	0.045	0.203	0.070	0.030
A5	0.056	0.036	0.152	0.186	0.070

Table 16 shows the normalized pairwise comparison matrix for the alternatives given C2. The results show A1 having the highest comparison values compare to other alternatives.

Table16: Normalized Pairwise Comparison Matrix for Alternatives Given Criterion C2 (Cost Effectiveness)

Alternatives	A1	A2	A3	A4	A5
A1	0.636	0.440	0.323	0.396	0.326
A2	0.114	0.073	0.231	0.337	0.309
A3	0.093	0.015	0.046	0.022	0.017
A4	0.101	0.017	0.138	0.059	0.171
A5	0.056	0.455	0.262	0.186	0.177

Table 17 shows the normalized pairwise comparison matrix for the alternatives given C3. The results show A1 having the highest comparison values compare to other alternatives.

Table17: Normalized Pairwise Comparison Matrix for Alternatives Given Criterion C3 (Health Impact)

Alternatives	A1	A2	A3	A4	A5
A1	0.290	0.437	0.400	0.429	0.369
A2	0.599	0.211	0.260	0.429	0.391
A3	0.046	0.054	0.060	0.022	0.026
A4	0.052	0.038	0.200	0.072	0.195
A5	0.053	0.038	0.200	0.048	0.065

Table 18 shows the normalized pairwise comparison matrix for the alternatives given C4. The results show A1 having the highest comparison values compare to other alternatives.

Table18: Normalized Pairwise Comparison Matrix for Alternatives Given Criterion C4 (Acceptability)

Alternatives	A1	A2	A3	A4	A5
A1	0.129	0.284	0.330	0.270	0.307
A2	0.276	0.084	0.349	0.257	0.264
A3	0.229	0.014	0.070	0.193	0.307
A4	0.019	0.020	0.031	0.039	0.010
A5	0.019	0.016	0.010	0.241	0.112

Table 19 shows the normalized pairwise comparison matrix for the alternatives given C5. The results show A3 having the highest comparison values compare to other alternatives.

Table19: Normalized Pairwise Comparison Matrix for the Alternatives Given Criterion C5 (Sustainability)

Alternatives	A1	A2	A3	A4	A5
A1	0.070	0.012	0.021	0.328	0.318
A2	0.443	0.070	0.024	0.164	0.273
A3	0.420	0.349	0.117	0.313	0.318
A4	0.010	0.033	0.017	0.045	0.009
A5	0.012	0.012	0.021	0.149	0.045

The Local Priority Weights for the Alternatives Given Each Criterion

Table 20 is the local priority weights of the alternatives under each criterion. A1 ranked highest under C1, C2,C3 AND C4, while A3 was ranked highest under C5.

Table20: Local Priority Weights of Malaria Control Alternatives under Each Criterion for North-East, Nigeria

Alternative	Feasibility (C1)	Cost-Effectiveness (C2)	Health Impact (C3)	Acceptability (C4)	Sustainability (C5)
A1	.420	.424	.385	.264	.150
A2	.359	.213	.378	.246	.195
A3	.038	.039	.042	.163	.303
A4	.108	.097	.111	.024	.023
A5	.074	.227	.081	.084	.048

Final Global Ranking of the Alternatives Given the Criteria

The results in table 21 show the final global ranking of the alternatives. A1 is ranked the best malaria control strategy with the total weight of 0.346. A2 ranked second (0.287), A5 ranked third (0.200), A3 ranked fourth (0.101) and A4 ranked fifth which is the least (0.066)

Table21: Final Global Ranking of the Alternatives

Alternative	Global Weight	Rank
A1	0.346	1
A2	0.287	2
A3	0.101	4
A4	0.066	5
A5	0.200	3

Ranking: A1 > A2 > A5 > A3 > A4

DISCUSSION

This study employed the Fuzzy Analytic Hierarchy Process (F-AHP) to prioritise malaria intervention strategies under conditions characterised by uncertainty, imprecise judgments, and multiple expert opinions. The adoption of F-AHP is particularly appropriate because malaria intervention planning is inherently a multi-criteria decision-making (MCDA) problem that requires balancing epidemiological effectiveness with economic, operational, and socio-cultural considerations. By integrating fuzzy logic into the traditional Analytic Hierarchy Process, the approach effectively accommodates ambiguity in expert judgments while producing consistent and reliable priority weights.

The findings revealed that acceptability emerged as the most influential criterion (0.338) in selecting malaria intervention strategies for North-East Nigeria. This result suggests that the success of malaria interventions in conflict-affected and resource-constrained settings depends not only on their technical effectiveness but also on the willingness of communities to adopt and sustain them. The finding supports Hongoh (2011), who argued that community acceptance is fundamental to the success of malaria control programmes because interventions that are poorly accepted often experience low utilization regardless of their proven clinical effectiveness. In the context of North-East Nigeria, where insecurity, population displacement, cultural diversity, and varying perceptions of healthcare influence health-seeking behaviour, social acceptability becomes a critical determinant of intervention success. Consequently, interventions that align with local beliefs, practices, and community preferences are more likely to achieve sustained utilisation and long-term effectiveness.

Cost-effectiveness was identified as the second most important criterion (0.283), reinforcing the importance of economic efficiency in malaria control decision-making. This finding reflects the reality that malaria-endemic regions operate under severe financial constraints, requiring policymakers to maximise health outcomes with limited resources. The result corroborates previous studies (Mosha, 2022; Demissie, 2025), which demonstrated that cost-effectiveness remains a primary consideration in malaria resource allocation because it enables wider intervention coverage while ensuring efficient use of scarce public health funds. The prominence of this criterion also reflects increasing emphasis by governments and development partners on evidence-based investment decisions that optimise both health outcomes and economic sustainability.

Health impact ranked third (0.220), indicating that although reductions in malaria morbidity and mortality remain central objectives, experts considered them alongside broader implementation realities. This finding differs slightly from studies such as Firdaus (2026), which identified health impact as the dominant criterion in malaria intervention prioritisation. The difference may reflect the unique socio-economic and humanitarian context of North-East Nigeria, where interventions with high epidemiological effectiveness may fail to achieve desired outcomes if they are not socially acceptable or financially feasible. Thus, the relatively lower ranking of health impact should not be interpreted as diminishing its importance but rather as highlighting the practical necessity of balancing clinical effectiveness with contextual implementation factors.

Feasibility (0.103) and sustainability (0.056) received comparatively lower weights. Although these criteria ranked fourth and fifth, respectively, their lower priorities do not imply that they are unimportant. Instead, they suggest that experts perceived feasibility and sustainability as attributes that become meaningful only after interventions have gained community acceptance and demonstrated acceptable economic value. In practice, interventions that are technically feasible but socially unacceptable or prohibitively expensive are unlikely to achieve lasting public health impact. Therefore, these findings emphasise the interdependent nature of decision criteria in malaria intervention planning.

Regarding the intervention alternatives, Insecticide-Treated Nets (ITNs) achieved the highest overall priority (0.346), indicating that they provide the most balanced performance across acceptability, cost-effectiveness, health impact, feasibility, and sustainability. This finding aligns with previous studies (Mosha, 2022; Demissie, 2025), which consistently identified ITNs as one of the most cost-effective malaria prevention strategies due to their relatively low implementation costs, ease of distribution, and proven effectiveness in reducing malaria transmission. The continued prioritization of ITNs further demonstrates that preventive interventions remain more attractive than treatment-focused approaches because they reduce disease incidence before infection occurs, thereby lowering healthcare costs and improving population health outcomes.

Indoor Residual Spraying (IRS) ranked second (0.287), confirming its continued relevance as an effective malaria vector control strategy. This finding agrees with Zhou (2022), who reported consistently high malaria reduction rates in settings achieving adequate IRS coverage. However, the lower ranking of IRS relative to ITNs may reflect operational challenges associated with repeated spraying campaigns, higher implementation costs, logistical complexities, and the need for sustained community cooperation. These practical considerations likely reduced its overall priority despite its demonstrated epidemiological effectiveness.

Health education ranked third (0.200), suggesting that although behavioural interventions play an important supporting role in malaria control, they are insufficient as stand-alone strategies. Rather than directly preventing malaria transmission, health education primarily enhances the effectiveness of other interventions by improving community awareness, promoting proper utilization of preventive tools, and encouraging timely treatment-seeking behaviour. This interpretation is consistent with Zhou (2022), who emphasized that health education functions mainly as an enabling intervention that strengthens programme coverage, compliance, and community participation rather than producing immediate epidemiological impact independently.

Larval Source Management (LSM) was ranked fourth (0.101), reflecting its limited applicability within the study context. Although LSM has demonstrated effectiveness in reducing mosquito breeding in suitable ecological environments, its implementation requires favourable environmental conditions, continuous monitoring, strong institutional coordination, and substantial financial investment. These limitations have similarly been highlighted by Irish (2024), who noted that the effectiveness of LSM is highly context-dependent and often constrained by operational and ecological challenges, particularly in low-resource settings.

Providing treatment to all malaria patients received the lowest overall ranking (0.066). This result should not be interpreted as questioning the importance of effective case management but rather as indicating that treatment-focused strategies alone are less efficient than preventive interventions when evaluated across multiple decision criteria. Preventive measures reduce disease transmission and lessen future healthcare demand, whereas treatment strategies primarily address infections after they occur. This finding is consistent with Dengela (2018), who demonstrated that prevention-oriented interventions generally produce greater population-level health benefits and more favourable economic outcomes than treatment-only approaches, particularly where healthcare resources are limited.

Compared with previous MCDA studies on malaria intervention prioritisation, this research makes several important contributions. First, unlike most existing studies that evaluate malaria interventions at national or international levels, this study specifically focuses on North-East Nigeria, a region characterised by armed conflict, population displacement, climate variability, fragile healthcare systems, and persistent malaria transmission. These contextual factors substantially influence intervention performance and justify the need for region-specific prioritisation. Consequently, the priorities generated in this study provide more contextually relevant evidence for local decision-making than generalised national recommendations.

Second, this study demonstrates the practical value of F-AHP in addressing uncertainty associated with expert judgment during health policy decision-making. By incorporating fuzzy logic into the pairwise comparison process, the methodology produces more robust and realistic priority estimates than conventional AHP, particularly where expert opinions are inherently subjective. This methodological contribution extends the application of F-AHP within malaria intervention research and provides a replicable framework for prioritising other public health interventions under uncertainty.

The findings have several important policy implications. First, malaria control programmes in North-East Nigeria should prioritise the large-scale distribution and effective utilisation of ITNs while maintaining IRS as a complementary intervention where operationally feasible. Second, policymakers should recognise that intervention priorities are context-dependent and influenced by local socio-economic conditions, community perceptions, resource availability, and the composition of expert panels involved in the decision-making process. Consequently, malaria intervention priorities should be periodically reassessed as contextual conditions evolve.

Finally, future malaria prioritisation models should move beyond static evaluation frameworks by incorporating dynamic epidemiological data, climate variability, intervention effectiveness over time, and changing transmission patterns. Integrating stochastic modelling techniques with MCDA approaches would enable policymakers to develop adaptive malaria control strategies that remain effective under changing environmental, demographic, and health system conditions.

CONCLUSION

This study employed the Fuzzy Analytic Hierarchy Process (F-AHP) to prioritise malaria intervention strategies in North-East Nigeria under conditions of uncertainty. The findings identified Insecticide-Treated Nets (ITNs) and Indoor Residual Spraying (IRS) as the highest-priority interventions, confirming the continued importance of preventive measures in malaria control. More importantly, the study demonstrated that community acceptability is the most influential criterion for intervention selection, ranking above health impact and cost-effectiveness. This highlights that successful malaria control depends not only on the clinical effectiveness of interventions but also on their acceptance and sustained use by local communities.

The study makes a significant contribution by developing a context-specific F-AHP decision-support framework that integrates epidemiological, economic, operational, sustainability, and social factors into a single multi-criteria model. Unlike previous studies that primarily emphasised epidemiological outcomes or economic efficiency, this research explicitly incorporates uncertainty in expert judgments and reflects the unique realities of conflict-affected North-East Nigeria. The framework, therefore, provides a more comprehensive and practical basis for prioritising malaria interventions in resource-constrained settings.

From a policy perspective, the findings support continued investment in ITNs and IRS while emphasising the need to strengthen community engagement and incorporate social acceptability into malaria programme planning. Although the study relied on expert judgments and presents a static assessment of intervention priorities, it provides a transparent and robust approach for evidence-based decision-making. Future studies should integrate F-AHP with dynamic modelling techniques and include broader stakeholder participation to capture changing malaria transmission patterns and enhance decision robustness. Overall, this study advances the application of F-AHP in public health and offers a novel, context-sensitive framework that can support malaria intervention prioritisation in Nigeria and other malaria-endemic regions.

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