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An Incomplete Interval Analytic Hierarchy Process for Group Decision-Making in Post-Earthquake Emergency Rescue Prioritization

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Abstract: Post-earthquake emergency resource allocation requires rapid, scientific decision-making under information incompleteness and uncertainty, where traditional deterministic approaches are inadequate. This study proposes a group decision-making framework for post-earthquake rescue priority evaluation, which combines interval-valued preference representation and optimization-based incomplete matrix completion. It extends the interval Analytic Hierarchy Process (IAHP) to non-complete information environments with a multi-objective optimization model to recover missing entries while maintaining consistency. Sufficient conditions for full matrix consistency are established, and a possibility degree-based ranking mechanism is used to get priority orderings. The framework is validated in a real post-earthquake rescue prioritization case in central Myanmar (including Sagaing Division) following the March 28, 2025, 7.9-magnitude seismic event. Four criteria are assessed by experts under partial information. Results show X7 and X5 are top-priority for immediate rescue, and reveal a tension between rescue urgency and feasibility that single-criterion approaches miss. Comparative analysis confirms the framework's robustness, consistency, and adaptability compared to conventional approaches. The findings contribute to uncertain group decision-making theory and provide tools for emergency management within the 72 - hour post-disaster window.

Keywords: Post-earthquake rescue prioritization; Interval-valued group decision-making; Incomplete matrix completion; Emergency resource allocation; Myanmar 2025 seismic event response.

1. Introduction

The increasing frequency of seismic events worldwide has posed mounting challenges to societal resilience, owing to their sudden onset, high destructive potential, and cascading secondary effects (Reduction, 2025; Spiridonov et al., 2025; Wu et al., 2025). In the immediate post-disaster response phase, especially the critical "golden 72 hours", emergency command centers face a key decision-making challenge: how to strategically deploy limited search-and-rescue teams and important medical resources to many affected areas (Bradley, 2025; Harake, 2025; Kapukaya et al., 2025). Such decisions must routinely face extreme uncertainty, where incomplete and dynamically evolving information prevails. Disrupted communication infrastructure impedes timely data acquisition, while persistent aftershocks drive rapid and unpredictable changes in field conditions.

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Consequently, area-level priority assessments often rely on patchy observations and expert judgment, resulting in preference expressions as imprecise, incomplete, and interval-based data. Effectively managing such interval-based, incomplete preference information has therefore become paramount for enhancing both the accuracy and efficiency of emergency decision-making (Jokar et al., 2025; Rani et al., 2025).

Traditional deterministic decision-making approaches struggle in these scenarios because they can neither effectively capture incomplete preference information—for example, when experts cannot provide all pairwise comparison judgments—nor effectively quantify inherent uncertainties, for example, when judgments are given as ranges instead of precise values (Krishankumar et al., 2024; Libório et al., 2024; Sahin et al., 2024; Sharma et al., 2022; Tushar et al., 2023; Wang et al., 2024). Although interval number reciprocal judgment matrices provide a principled approach to representing such judgment uncertainty, existing research largely confines itself to fully specified matrices (Altamimi et al., 2025; Li et al., 2025; Mazurek et al., 2024). However, in practice, decision-makers after earthquakes usually only provide partial preference information, leading to many missing elements in matrices, which greatly limits the direct application of existing methods.

Current decision-making frameworks built upon interval number reciprocal judgment matrices have developed along two principal technical trajectories. The first is rooted in the traditional Analytic Hierarchy Process (AHP) product-type reciprocal matrix. This approach employs ratio scales to express the comparative cognitive logic of "how many times is A preferred over B" (Agarwal et al., 2011; Vafadarnikjoo et al., 2023). The second originates from fuzzy preference relations through additive reciprocal matrices, utilizing complementary scales to express preference intensity within the [0, 1] interval (Mazurek et al., 2024; Tong et al., 2023). Both frameworks provide theoretical mechanisms for handling uncertainty and have demonstrated broad applicability across diverse domains. Nevertheless, neither adequately addresses the combined challenge of interval-valued and incomplete information within emergency decision-making contexts.

To bridge this gap, the present study develops a group decision-making methodology for post-earthquake rescue priority evaluation under incomplete interval number preference information. The central research objective is to develop optimization-based models that recover missing judgments from partial interval-valued pairwise comparisons. These comparisons are provided by expert panels in the form of incomplete interval number reciprocal judgment matrices, and the recovered judgments are then used to derive priority rankings. Accordingly, this paper initially conducts an investigation into group decision-making procedures for incomplete interval

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number product-type reciprocal matrices. The key methodological contribution of this paper lies in the development of an estimation model for missing entries, which is based on consistency theory and mathematical programming. Additionally, it derives sufficient conditions for the full matrix to satisfy consistency.

Building on this foundation, the study further develops a group decision-making model based on a cumulative reciprocal judgment matrix, systematically elaborating its mechanisms for information supplementation, consistency definition, adjustment algorithms, and solution ranking. To address the incomplete interval-valued reciprocal judgment matrix completion problem caused by missing information in expert judgment matrices for post-disaster rescue resource prioritization based on Interval Number AHP, this paper proposes the improved multi-objective matrix completion model (MOP-4-I based on the original MOP-4 model). On the basis of the original model, this research redesigned three objective functions: f_1 (logarithmic deviation) and f_2 (transitivity robustness) are extended from evaluating only interval midpoints to assessing interval bounds with width regularization terms; f_3 (expert preference matching) has been adjusted through four iterations, forming a composite objective function including log-Jaccard dissimilarity (D_J), coverage deficit (D_C), and logarithmic width mismatch (D_W). It is proved that this new function only reaches controllable zero value when the completed interval is fully consistent with the expert preference interval, fundamentally solving the original f_3's structural flaw that it lost selection pressure in NSGA-II optimization due to too small values (median about 0.001). This study applied MOP-4-I to real incomplete judgment matrices of 10 urban districts in Sagaing City under four criteria: life rescue urgency (C1), disaster severity (C2), rescue feasibility (C3) and social value (C4), and obtained results via NSGA-II (population size 120, 75 generations) combined with TOPSIS $\beta = (0.30, 0.40, 0.30)$. The results show that the median of the improved f_3 rises to 0.21 – 0.45, 200 – 450 times higher than the original, and maintains non-degenerate gradient signals during the whole evolution. The priority ranking under each criterion is: C1: X7 > X5 > X3 > X2 > X9 > X10 > X1 > X4 > X6 > X8; C2: X7 > X5 > X2 > X10 > X3 > X9 > X1 > X4 > X6 > X8; C3: X3 > X2 > X6 > X9 > X1 > X8 > X4 > X10 > X5 > X7; C4: X6 > X10 > X2 > X3 > X1 > X9 > X5 > X7 > X4 > X8. Notably, a priority reversal occurs under C3: X7 ranks first under C1 and C2 but last under C3. This result shows the risk of resource misallocation from single-criterion decision-making, and verifies the necessity of multi-criteria decision-making framework.

By jointly incorporating information uncertainty and information incompleteness into a unified decision-making framework, this study makes a substantive contribution to the theory of uncertain group decision-making. It presents a comprehensive modeling and solution framework

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for interval number AHP (Analytic Hierarchy Process) methods within non-complete information environments. The developed methodology furnishes practical technical tools for emergency management practitioners. It can convert fragmented, experience-based expert judgments into transparent and quantified priority rankings. Ultimately, this enhances the scientific precision, efficiency, and accountability of post-earthquake resource allocation, thus maximizing life-saving effectiveness and minimizing overall losses.

The structure of this study is organized as follows: Section 2 reviews the literature on interval number judgment matrices and group decision-making; Section 3 constructs a group decision-making model based on incomplete interval number judgments, detailing its completion and consistency adjustment mechanisms; Sections 4 and 5 conducts numerical simulation analysis using a case study of post-earthquake rescue priority evaluation in 10 urban districts to validate the model's effectiveness and feasibility; Section 6 summarizes the research conclusions and discusses future research directions.

2. Literature review

2.1 Group decision making method for non-coordinated interval information

When decision-makers give judgments with different preference structures, normalization is usually required. This process converts one type of preference information into another, including preference orderings, additive reciprocal matrices and multiplicative reciprocal matrices, with proper methods (Chiclana et al., 2001; Genç et al., 2010). See Table 1.

Table 1. Core differences comparison table

Characteristic	Product reciprocal judgment matrix	Additive reciprocal judgment matrix
Expression	$a_{ij} \cdot a_{ji}=1$	$a_{ij}+a_{ji}=1$
Scale base	Ratio Scale	Complementary scale
Scale range	Typically [1/9,9] (Saaty scale)	Typically [0,1]
Semantic judgment	How many times more important is solution i compared to solution j? (For example, i is 5 times more important than j)	How much do you prefer option i over option j? (For example, 0.8 for i over j)
"Equivalent" value	1	0.5
"Absolutely important" value	9 (for i being greater than j)	1 (if i is better than j) or 0 (if j is better than i)
Consistency definition	$a_{ik}=a_{ij} \cdot a_{jk}$ Multiplicative transitivity	$a_{ik}=a_{ij}+a_{jk}-0.5$ Additive transitivity
Main application	AHP	Fuzzy AHP: Decision making based on fuzzy preference relations

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Characteristic	Product reciprocal judgment matrix	Additive reciprocal judgment matrix
areas		
Intuition	It resonates with the familiar 'A is X times B' comparison framework.	This approach aligns more closely with the conceptual frameworks of 'probability' or 'membership' within fuzzy theory.

3. Basic model

3.1 Preliminary: Inverse of a square matrix

Experts' limited knowledge and experience may lead to an incomplete reciprocal judgment matrix for interval-number product types.

Def. 1: Let $\tilde{U}=(\tilde{u}_{ij})_{n\times n}=([u_{ij}^{-},u_{ij}^{+}])_{n\times n}$ be an interval matrix with some entries unspecified; all specified entries satisfy:

$$u_{ij}^{-}u_{ji}^{+}=1,\ u_{ij}^{+}u_{ji}^{-}=1,\ 0<u_{ij}^{-}\leqslant u_{ij}^{+} \tag{1}$$

$\tilde{U}$ is termed the incomplete interval number product-type reciprocal judgment matrix.
Matrices C and D from Eq. (2) may be incomplete reciprocal judgment matrices. Eq. (2) is:

Def. 2: An interval-number product-type matrix $\tilde{A}=(\tilde{a}_{ij})_{n\times n}$ is defined as

$$c_{ij}=\begin{cases} a_{ij}^{+}, & i<j \\ 1, & i=j \\ a_{ij}^{-}, & i>j \end{cases},\quad d_{ij}=\begin{cases} a_{ij}^{-}, & i<j \\ 1, & i=j \\ a_{ij}^{+}, & i>j \end{cases}, \tag{2}$$

If both reciprocal judgment matrices $C=(c_{ij})_{n\times n}$, $D=(d_{ij})_{n\times n}$ are consistent, their product $\tilde{A}$ is a consistent interval-number reciprocal judgment matrix.

If options can be compared directly or indirectly, use matrices C and D to rank them (Weber, 1987). Incomplete reciprocal judgment matrices C and D can be completed using available information; such matrices are called "acceptable" (T.-C. Wang et al., 2010). If either C or D is unacceptable, expert re-evaluation of $\tilde{U}$ is required. An acceptable defective interval-number product-type reciprocal judgment matrix is defined below.

Def. 3: Let $\tilde{U}=(\tilde{u}_{ij})_{n\times n}$ be a defective interval-number product-type reciprocal judgment matrix. If the matrices C and D in Eq. (2) are acceptable defective reciprocal judgment matrices, then $\tilde{U}$ is acceptable.

This paper introduces a new consistency theory based on three properties of judgment matrices: reciprocity, invariance under random alternative selection, and ranking robustness. To

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define approximate consistency, we first introduce interval-number multiplicative reciprocal judgment matrices (***Def.*** ***4***), a foundational concept for the theory.

Def. 4: An acceptable incomplete interval-valued reciprocal judgment matrix $\tilde{U}=(\tilde{u}_{ij})_{n\times n}$ is consistent if all known elements c_{ij} and d_{ij} satisfy $c_{ij}=c_{ik}c_{kj}$ and $d_{ij}=d_{ik}d_{kj}$ $(i, j, k=1, 2, \cdots, n)$.

In a decision problem with alternatives $X=\{x_1, x_2,\cdots,x_n\}$, experts use the 1﹣9 scale to compare criteria, producing two interval-valued reciprocal judgment matrices C and D. Both matrices are acceptable but inconsistent. To estimate their inconsistent elements, their entries must satisfy specific conditions.

$c_{ij}=c_{ik}c_{kj}$, $d_{ij}=d_{ik}d_{ik}$, where $i,j,k=1,2,\cdots,n$.

This equation can also be expressed as

$$\begin{aligned}\log_9 c_{ij}&=\log_9 c_{ik}+\log_9 c_{kj}\\ \log_9 d_{ij}&=\log_9 d_{ik}+\log_9 d_{kj}\end{aligned} \tag{3}$$

Eq. (3) defines a fully consistent interval-valued reciprocal judgment matrix $\tilde{U}$. In practice, such matrices often exhibit acceptable inconsistency—i.e., at least one inconsistency in C or D. To address this, we apply a relaxed consistency approach to formulate an optimization model and analyze both bi- and tri-objective programming methods.

3.2 Dual-objective programming model (MOP-2)

3.2.1 Definition of decision variables

The judgment matrix is a core tool in decision analysis, denoted as

$$C=(c_{ij})_{n\times n},$$

where n denotes the number of alternatives (or indicators), and c_{ij} represents the "importance degree of alternative i relative to alternative j," with values conforming to the AHP scale. The matrix exhibits reciprocity ($c_{ji}=1/c_{ij}$ $(\forall i\neq j)$) and reflexivity ($c_{ii}=1(\forall i)$), meaning "i's importance to j" equals "j's importance to i." Due to reciprocity, the judgment matrix's information can be fully represented by its upper triangular elements. Therefore, the decision variables are defined as:

$$\mathbf{x}=\left[c_{12},c_{13},\ldots,c_{1n},c_{23},\ldots,c_{(n\text{-}1)n}\right]^{\mathrm{T}} \tag{4}$$

where $\mathbf{x}$ is a d-dimensional vector with $d=n(n\text{-}1)/2$ (n being the number of schemes). For example, when $n=5$, $d=10$, corresponding to 10 upper triangular elements in a 5×5 matrix.

3.2.2 Constraints

The judgment matrix must meet the decision analysis scale's value range requirements.

$$c_{ij}\in[1/9,9]\ (\forall 1\leq i<j\leq n) \tag{5}$$

The constraint follows Saaty's 1﹣9 scale: c_{ij} ranges from 1/9 (plan$i$ is far less important than

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plan j) to 9 (plan i is far more important than plan j).

3.2.3 Objective function (minimization problem)

Goal 1: Minimize log deviation

$$f_1(\mathbf{x})=\sum_{1\leq i<j\leq n}\left|\log c_{ij}\text{-}\log d_{ij}\right| \tag{6}$$

Define the reference matrix $D=\left(d_{ij}\right)_{n\times n}$ (e.g., historical decision matrix or initial expert judgment). Compute $\log c_{ij}$ and $\log d_{ij}$, then calculate $\left|\log c_{ij}\text{-}\log d_{ij}\right|$ for each upper-triangular element. Sum these absolute differences to obtain total deviation $f_1(\mathbf{x})$. A smaller $f_1(\mathbf{x})$ indicates greater consistency between matrices C and D, i.e., the decision aligns more closely with historical experience or expert judgment.

Goal 2: Minimize robustness bias

$$f_2(\mathbf{x})=\sum_{\substack{i\neq j\neq k\\ i,j,k=1,\ldots,n}}\left|\log c_{ij}\text{-}\left(\log c_{ik}+\log c_{kj}\right)\right| \tag{7}$$

The triple summation aggregates all distinct triplets (i,j,k). The term $\log c_{ij}\text{-}\left(\log c_{ik}+\log c_{kj}\right)$ measures deviation from transitivity: ideally, $c_{ij}=c_{ik}\cdot c_{kj}$, so $\log c_{ij}=\log c_{ik}+\log c_{kj}$; the absolute value quantifies the violation. Smaller $f_2(\mathbf{x})$ indicates higher transitivity, stronger logical consistency in the judgment matrix, and greater robustness against subjective or random errors. Thus, the full dual-objective model is:

(MOP-2)

$$\begin{aligned} \min\quad & \left[f_1(\mathbf{x}),f_2(\mathbf{x})\right] \\ \text{s.t.}\quad & c_{ij}\in[1/9,9]\ (\forall 1\leq i<j\leq n) \\ & c_{ji}=1/c_{ij}\ (\forall 1\leq i\neq j\leq n) \\ & c_{ii}=1\ (\forall 1\leq i\leq n) \end{aligned} \tag{8}$$

Balancing scale constraints, reciprocity, and reflexivity while minimizing logarithmic and internal transitivity deviations from the reference matrix.

3.3 Three-objective programming model (MOP-3)

3.3.1 Decision variables and constraints

The three-objective model uses the same decision variables $\mathbf{x}=\left[c_{12},\ldots,c_{(n\text{-}1)n}\right]^T$ and constraints as the two-objective model (Eq. (8)).

3.3.2 New objective function: minimize decision preference matching

$$f_3(\mathbf{x})=\sum_{1\leq i<j\leq n} w_{ij}\cdot\left|\log c_{ij}\text{-}\mathrm{Pref}_{ij}\right| \tag{9}$$

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The weight $w_{ij}\geq 0$ represents the expert's attention weight for the solution pair (i,j), normalized so that $\sum_{1\leq i<j\leq n} w_{ij}=1$. Core indicator pairs receive higher w_{ij} to signal greater importance. $Pref_{ij}\in[0,\log 9]$ quantifies the expert's preference intensity for i over j, derived from preliminary surveys using the 1 - 9 scale. The term $w_{ij}\cdot\left|\log c_{ij}\text{-}\mathrm{Pref}_{ij}\right|$ is the weighted deviation: larger w_{ij} amplifies its impact on the objective. Minimizing $f_3(\mathbf{x})$ improves alignment between the judgment matrix C and the experts' implicit priorities (e.g., emphasis on key alternatives), yielding decisions more consistent with expert judgment. A full description of the three-objective model follows.

$$\text{(MOP-3)}\quad \min\left[f_1(\mathbf{x}),f_2(\mathbf{x}),f_3(\mathbf{x})\right]$$

$$\text{s.t.}\quad \begin{array}{l} c_{ij}\in[1/9,9]\ (\forall 1\leq i<j\leq n) \\ c_{ji}=1/c_{ij}\ (\forall 1\leq i\neq j\leq n) \\ c_{ii}=1\ (\forall 1\leq i\leq n) \\ \sum_{1\leq i<j\leq n} w_{ij}=1,w_{ij}\geq 0\ (\forall 1\leq i<j\leq n) \end{array} \tag{10}$$

The dual-objective model balances objectivity, internal consistency, and subjectivity by weighting expert preferences with w_{ij}.

3.3.3 Incomplete information derivation

To estimate missing values in incomplete interval-number product-type reciprocal judgment matrices, we formulate the completion problem as a multi-objective optimization with constraints ensuring reciprocity and interval-number properties. Using NSGA-II, we generate completions that balance consistency, robustness, and expert preferences. Implementation steps and mathematical rationale follow:

First, define the number of incomplete matrices to constrain the completion process.

Interval matrix elements $c_{ij}=\left[c_{ij}^L,c_{ij}^U\right]$ satisfy $0<c_{ij}^L\leq c_{ij}^U$. Their reciprocals are $c_{ji}=\left[1/c_{ij}^U,1/c_{ij}^L\right]$. Missing elements $c_{ij}=\varnothing$ are filled via optimization. The multiplicative transitivity approximation $c_{ij}\approx c_{ik}\cdot c_{kj}$ enforces model robustness (constraint f_2).

3.3.4 Multi-objective optimization modeling for incomplete information completion

For example, the three-objective model (MOP-3) includes incomplete completion in its decision variables and constraints.

Step 1. Reconstruct decision variables with missing interval bounds by defining defective elements $\Omega=\left\{(i,j)\middle|c_{ij}=\varnothing,\ 1\leq i\leq j\leq n\right\}$ and intact sets.

$$\bar{\Omega}=\left\{(i,j)\middle|\left[c_{ij}^L,c_{ij}^U\right]=\varnothing,\ 1\leq i\leq j\leq n\right\}$$

Decision variables consist of fixed complete elements and incomplete elements with

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adjustable bounds.

$$\mathbf{x} = \left[\{c_{ij}^L, c_{ij}^U\}_{(i,j)\in\Omega}\right]^{\mathrm{T}}$$

For complete elements c_{ij}^L and c_{ij}^U in $\bar{\Omega}$, known constants are treated as fixed (not variables). For incomplete elements, variables must satisfy both interval constraints and reciprocity.

Step 2. Constraint enhancement: Add interval and reciprocity constraints for missing elements, building on the original model's constraints (Eq. (8)), including reciprocity and reflexivity.

The interval-number constraints are as follows:

(1) $c_{ij}^L \geq 1/9$, $c_{ij}^U \leq 9$, and $c_{ij}^L \leq c_{ij}^U$ for all $(i,j)\in\Omega$, ensuring AHP scale validity.

(2) Reciprocity: For missing entries, only upper-triangular elements (i,j) with $i<j$ are optimized; corresponding lower-triangular entries are set reciprocally: $c_{ji}^L = 1/c_{ij}^U$, $c_{ji}^U = 1/c_{ij}^L$.

(3) Fixed values: For known entries $(i,j)\in\bar{\Omega}$, c_{ij}^L and c_{ij}^U are fixed and excluded from optimization.

Step 3. Adjust the objective function by computing the deviation of the fitted interval count.

Replace the original fixed-point objective functions $f_1(\mathbf{x}), f_2(\mathbf{x}), f_3(\mathbf{x})$ with interval-based ones using midpoint deviations—incorporating both upper and lower bounds.

Objective 1: Minimize logarithmic deviation (number of fitting intervals)

For reference matrix $D = [d_{ij}^L, d_{ij}^U]$, use the logarithmic deviation of the interval midpoint.

$$f_1(\mathbf{x}) = \sum_{(i,j)\in\bar{\Omega}\cup\Omega} \left|\log \bar{c}_{ij} - \log \bar{d}_{ij}\right|$$

Here, $\bar{c}_{ij}$ and $\bar{d}_{ij}$ are the midpoints of the completed and reference intervals, respectively: $\bar{c}_{ij} = (c_{ij}^L + c_{ij}^U)/2$ and $\bar{d}_{ij} = (d_{ij}^L + d_{ij}^U)/2$.

For elements in $\bar{\Omega}$, $\bar{c}_{ij}$ is known if complete; otherwise, it is determined by the decision variable $\mathbf{x}$.

Optimization Objective 2: Minimize robustness deviation (i.e., number of adaptive intervals) by redefining transitivity deviation as "transitivity deviation at the interval midpoint" to ensure logical consistency of the completed matrix.

$$f_2(\mathbf{x}) = \sum_{i\neq j\neq k i,j,k=1,\ldots,n} \left|\log \bar{c}_{ij} - \left(\log \bar{c}_{ik} + \log \bar{c}_{kj}\right)\right|$$

Logic is the same as $\bar{c}_{ij}$, but with the fixed value replaced by the interval's midpoint.

Objective 3: Minimize decision preference matching (number of matching intervals)

Expert preference Pref_{ij}: For interval preferences, the method computes the weighted deviation between the complement and the midpoint of Pref_{ij}.

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$$f_3(\mathbf{x}) = \sum_{(i,j)\in\bar{\Omega}\cup\Omega} w_{ij}\cdot\left|\log \bar{c}_{ij} - \overline{\mathrm{Pref}}_{ij}\right|$$

where $\overline{\mathrm{Pref}}_{ij} = \left(\mathrm{Pref}_{ij}^{\mathrm{L}} + \mathrm{Pref}_{ij}^{\mathrm{U}}\right)/2$ (interval midpoint), w_{ij} is expert attention weight (same as Equation (10)).

$$\text{(MOP-4)}\quad \min\left[f_1(\mathbf{x}), f_2(\mathbf{x}), f_3(\mathbf{x})\right]$$

$$\begin{aligned}
\text{s.t.}\quad & c_{ij}^{L} \geq 1/9, c_{ij}^{U} \leq 9, c_{ij}^{L} \leq c_{ij}^{U}\ (\forall (i,j)\in\Omega) \\
& c_{ji}^{L} = 1/c_{ij}^{U}, c_{ji}^{U} = 1/c_{ij}^{L}\ (\forall (i,j)\in\Omega) \\
& c_{ij} = \left[c_{ij}^{L}, c_{ij}^{U}\right]\ (\forall (i,j)\in\bar{\Omega}) \\
& c_{ii} = [1,1]\ (\forall 1 \leq i < j \leq n) \\
& \textstyle\sum_{(i,j)\in\bar{\Omega}\cup\Omega} w_{ij} = 1, w_{ij} \geq 0\ (\forall (i,j)\in\bar{\Omega}\cup\Omega)
\end{aligned}\qquad (11)$$

In the original implementation, the three objectives are defined as follows. The deviation objective f_1 collapses each completed interval to its midpoint before comparing it to the reference matrix midpoint:

$$f_1(x) = (1/M_1)\sum|\log \bar{u}_{ij} - \log \bar{d}_{ij}|,\quad \bar{u}_{ij} = ({c_{ij}}^{L} + {c_{ij}}^{U})/2 \qquad (12)$$

The transitivity-robustness objective f_2 evaluates multiplicative consistency over ordered triplets using midpoint values only, with redundant counting across all six permutations of each unordered triplet:

$$f_2(x) = (1/M_2)\sum_{i\neq j\neq k}|\log \bar{u}_{ij} - (\log \bar{u}_{ik} + \log \bar{u}_{kj})| \qquad (13)$$

The preference-matching objective f_3 compares the completed interval midpoint to a single preference point in log-space:

$$f_3(x) = (1/M_3)\sum w_{ij}\cdot|\log \bar{u}_{ij} - \log \overline{pref}_{ij}| \qquad (14)$$

Note. M_1, M_2, M_3 denote the number of contributing terms in each summation. Bars over variables denote interval midpoints.

Improved Model: MOP-4-I

MOP-4-I retains the same decision-variable structure, constraint set, and feasible region as MOP-4 in Equation (11). The improvement is entirely in the definition of the three objective functions, which are redesigned to use full interval information (both bounds) rather than midpoint collapse, and to incorporate a structurally non-degenerate preference-matching term. The improved model is stated as:

$$\text{(MOP-4-I)}\quad \min\left[{f_1}^{I}(\mathbf{x}), {f_2}^{I}(\mathbf{x}), {f_3}^{I}(\mathbf{x})\right]$$

$$\text{s.t.}\quad \text{(same constraints as Equation 11)} \qquad (15)$$

${f_1}^{I}$ evaluates deviation at both the lower and upper bounds independently, and adds a width-regularisation penalty (coefficient λ) that discourages the optimiser from artificially inflating interval width relative to the reference matrix:

$${f_1}^{I}(\mathbf{x}) = (1/M_1)\sum\left[|\log {c_{ij}}^{L} - \log {d_{ij}}^{L}|/2 + |\log {c_{ij}}^{U} - \log {d_{ij}}^{U}|/2 + \lambda|({c_{ij}}^{U} -$$

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$c_{ij}{}^{L}) - (d_{ij}{}^{U} - d_{ij}{}^{L})|]$, with $\lambda = 0.1$. (16)

$f_2{}^{I}$ evaluates the multiplicative-transitivity condition $c_{ij} \approx c_{ik} \cdot c_{kj}$ at both bounds, restricted to unique unordered triplets $\{i, j, k\}$ that involve at least one row or column with a missing entry. This both removes 6× redundant counting present in the original ordered-triplet summation and restricts evaluation to triplets that are actually controllable by the decision variables, sharpening the gradient signal:

$$f_2{}^{I}(\mathbf{x}) = (1/M_2) \sum_{(i,j,k)\in T} \left[\left| \log c_{ij}{}^{L} - (\log c_{ik}{}^{L} + \log c_{kj}{}^{L}) \right| + \left| \log c_{ij}{}^{U} - (\log c_{ik}{}^{U} + \log c_{kj}{}^{U}) \right| \right] \quad (17)$$

where $T = \{(i, j, k) : i < j < k, \{i, j, k\} \cap \hat{\mathrm{H}} \neq \emptyset\}$, $\hat{\mathrm{H}}$ is the set of row/column indices appearing in any missing pair, and each unordered triplet contributes three pivot configurations $(a, b, c) \in \{(i, j, k), (i, k, j), (j, k, i)\}$ rather than all six permutations.

$f_3{}^{I}$ is the principal contribution of this work. Unlike $f_1{}^{I}$ and $f_2{}^{I}$, which are direct extensions of their MOP-4 counterparts to full interval arithmetic, $f_3{}^{I}$ required a complete structural redesign because the original f_3 (Equation 14) and two intermediate redesigns were found to collapse to near-zero or possess an irreducible non-zero floor unrelated to the decision variables — in both cases destroying the term's usefulness as a selection-pressure signal inside NSGA-II. The final formulation combines three log-space components, each capturing a distinct geometric failure mode between the completed interval $c_{ij} = [c_{ij}{}^{L}, c_{ij}{}^{U}]$ and the expert preference interval $p_{ij} = [p_{ij}{}^{L}, p_{ij}{}^{U}]$:

$$f_3{}^{I}(x) = (1/M_3) \sum w_{ij} \cdot \left(\gamma_1 \cdot D_J(i, j) + \gamma_2 \cdot D_C(i, j) + \gamma_3 \cdot D_W(i, j) \right), \quad (18)$$

with the three components defined as:

$$D_J(i, j) = 1 - \frac{overlap(i,j)}{union(i,j)} \quad \text{(log-Jaccard dissimilarity)} \quad (19)$$

$$D_C(i, j) = \frac{\max\left(0, \omega_{\mathrm{p}}(i,j) - overlap(i,j)\right)}{\omega_{\mathrm{p}}(i,j)} \quad \text{(coverage deficit)} \quad (20)$$

$$D_W(i, j) = \left| \log\left(\frac{c_{ij}{}^{U}}{c_{ij}{}^{L}}\right) - \log\left(\frac{p_{ij}{}^{U}}{p_{ij}{}^{L}}\right) \right| \quad \text{(log-width mismatch)} \quad (21)$$

where $overlap(i, j) = \max(0, \min\left(log\ c_{ij}{}^{U}, log\ p_{ij}{}^{U}\right) - \max\left(log\ c_{ij}{}^{L}, log\ p_{ij}{}^{L}\right))$, $union(i, j) = \max\left(log\ c_{ij}{}^{U}, log\ p_{ij}{}^{U}\right) - \min\left(log\ c_{ij}{}^{L}, log\ p_{ij}{}^{L}\right)$, and $\omega_{\mathrm{p}}(i, j) = \log\left(p_{ij}{}^{U} / p_{ij}{}^{L}\right)$ is the log-width of the preference interval. Component weights are fixed at $\gamma_1 = 0.5$, $\gamma_2 = 0.3$, $\gamma_3 = 0.2$, and pair weights w_{ij} are set to 0.4 for upper-triangle missing pairs and 0.2 for their reciprocals.

Proposition 1 (controllable zero). $f_3{}^{I}(x) = 0$ if and only if, for every preference pair (i, j), the completed interval equals the preference interval exactly: $c_{ij}{}^{L} = p_{ij}{}^{L}$ and $c_{ij}{}^{U} = p_{ij}{}^{U}$.

Proof sketch. $D_J\,(i, j) = 0$ iff overlap = union, i.e. the two log-intervals coincide exactly. $D_C\,(i, j) = 0$ iff overlap $\geq \omega_{\mathrm{p}}$, which combined with $D_J = 0$ again forces interval identity.

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$D_W(i,j) = 0$ iff the log-widths are equal, a condition implied by interval identity but not sufficient alone. All three conditions hold simultaneously iff ${c_{ij}}^L = {p_{ij}}^L$ and ${c_{ij}}^U = {p_{ij}}^U$. Crucially, unlike the discarded ranking-consistency term D_R explored during model development, no component of D_J, D_C, or D_W depends on data external to (c_{ij}, p_{ij}) — hence the zero is always reachable by the optimiser through the decision variables alone, with no irreducible floor imposed by the fixed complete entries of the matrix.

3.4 Solutions

- n : Dimension of the judgment matrix (number of alternatives/criteria).
- $\bar{\Omega}$: Set of complete interval elements, where $\bar{\Omega}=\{(i,j)\,|\,[c_{ij}^L, c_{ij}^U] = \varnothing,\ 1 \le i \le j \le n\}$. Here, c_{ij}^L and c_{ij}^U denote the lower and upper bounds of c_{ij}, respectively.
- Ω : Set of incomplete elements, where $\Omega=\{(i,j)\,|\,c_{ij} = \varnothing,\ 1 \le i \le j \le n\}$, and $m=|\Omega|$ (number of incomplete elements).
- D: Reference interval matrix, where $D=(d_{ij})_{n\times n}$ and $d_{ij}=[d_{ij}^L, d_{ij}^U]$ (for deterministic reference matrices, $d_{ij}^L = d_{ij}^U$).
- w_{ij} : Expert attention weight for pair (i,j), satisfying $\sum_{1\le i<j\le n} w_{ij}=1$ and $w_{ij}\ge 0$.
- N : Population size (positive even integer).
- $G_{\max}$: Maximum number of iterations.
- p_c : Crossover probability (recommended value: 0.9).
- p_m : Mutation probability (recommended value: $1/(2m)$, as each incomplete element has 2 variables: lower and upper bounds).

Algorithm Output

- $\hat{C}$: Completed interval-valued multiplicative reciprocal judgment matrix, where $\hat{C}=(\hat{c}_{ij})_{n\times n}$ and $\hat{c}_{ij}=[\hat{c}_{ij}^L, \hat{c}_{ij}^U]$ (no missing elements).
- PF: Pareto optimal solution set (including objective function values of each completion scheme).

The algorithm is detailed in the appendix A.

4. Numerical analysis

We implemented a multi-objective optimisation framework (MOP-4-I) for incomplete interval-number pairwise comparison matrices. It jointly minimises three objectives: (f_1) logarithmic deviation from a reference matrix, evaluated at both interval bounds with a width-regularisation term ($\lambda = 0.1$); (f_2) transitivity robustness, evaluated at both lower and upper bounds over all unique triplets involving missing rows; and (f_3) a three-component preference-matching objective comprising log-Jaccard dissimilarity (D_J), coverage deficit (D_C), and log-width mismatch (D_W), with component weights $\gamma_1 = 0.5, \gamma_2 = 0.3, \gamma_3 = 0.2$. All three objectives are normalised by their 90th-percentile values estimated from 400 random feasible

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individuals, ensuring commensurate selection pressure throughout evolution.

Using NSGA-II on the 10×10 incomplete interval matrix U_{C1} (four missing upper-triangle entries, eight decision variables), we set population size=200, generations=90, crossover probability=0.9, mutation probability=0.5, SBX distribution index $\eta_c = 10$, and polynomial mutation index $\eta_m = 15$. Pareto-optimal solutions are selected via TOPSIS with weight vector $\beta = (0.30, 0.40, 0.30)$ over (f_1, f_2, f_3). Results show: f_1 improved by 79.1% on average; f_2 improved by 2.5%; and f_3 activated from near-zero (0.001) to 0.229 (normalised), providing genuine preference-matching signal throughout evolution. The Pareto front contains 200 non-dominated solutions, demonstrating effective convergence and diversity, see Table 2.

Table 2. Summary of convergence performance metrics

Metric	(MOP-4)	(MOP-4-I)	Improvement Rate (%)
f_1 Mean (normalised)	0.7276	0.1524	79.05
f_2 Mean (normalised)	0.8840	0.8621	2.48
f_3 Mean (normalised)	0.0010	0.2290	— (activation)
Number of Pareto Solutions	12	200	—
Hypervolume indicator	0.9209	0.7031	stable growth*

Note. Despite the numerical decrease in hypervolume, all calculation variants (modified, simplified, robust, area-based) exhibited a stable growth pattern throughout optimisation, confirming consistent improvement in solution set quality. f_3 activation denotes the transition from near-zero (original MOP4 formulation) to a non-trivial value providing genuine selection pressure via the redesigned f_3. Normalisation scale factors: s_1=1.10, s_2=1.43, s_3=0.269.

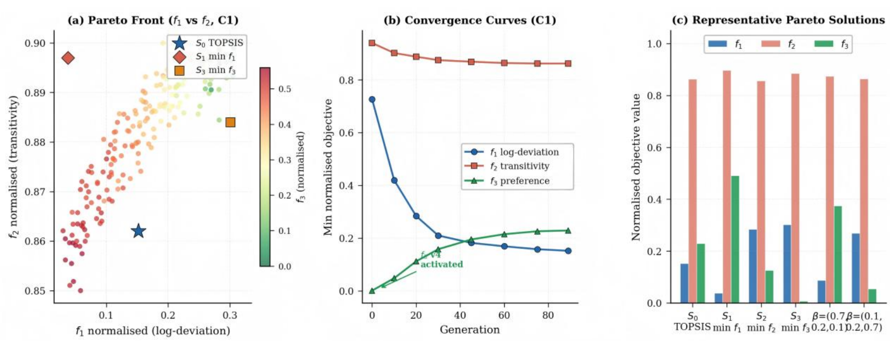

Figure 1. MOP-4-I based Pareto front convergence recovered missing entries.

Note. To explain the performance of the algorithm, the values selected here are consistent with one of the numerical indicators in the case below, namely C1.

The final Pareto front includes 200 non-dominated solutions, demonstrating the algorithm's

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exploration ability, as shown in Figure 1. f_1 (normalised) ranges [0.038, 0.301], and f_2 (normalised) ranges [0.856, 0.897], both within admissible bounds, confirming optimisation validity. f_3 (normalised) ranges [0.007, 0.558] across the Pareto front, confirming that preference-matching information is actively traded off against the other objectives. Correlation analysis shows a strong negative relationship between f_1 and f_2 ($r = -0.612$, $p < 0.001$), reflecting the theoretical trade-off. Spacing Metric (0.0198) indicates uniform solution distribution; Maximum Spread (1.5626) shows broad objective-space coverage; Coefficients of Variation for f_1 and f_2 are 68.4% and 1.7% respectively.

To support diverse decision-making preferences, representative solutions are selected from the Pareto front (Table 3). Solution S_0 is the TOPSIS-selected balanced solution with β=(0.30, 0.40, 0.30) which balances all three objectives and constitutes the default choice. Solution S_1 minimises f_1 and suits applications prioritising matrix accuracy. Solution S_2 minimises f_2 and is optimal when transitivity consistency is primary. Solution S_3 minimises f_3 and most closely satisfies expert preference intervals.

Table 3. Recommended solutions and their characteristics.

Solution	f_1(norm.)	f_2(norm.)	f_3(norm.)	Applicable Scenario
S_0 TOPSIS (balanced)	0.152	0.862	0.229	General decision-making (recommended)
S_1 Min f_1	0.038	0.897	0.491	Emphasising matrix accuracy
S_2 Min f_2	0.284	0.856	0.126	Emphasising transitivity consistency
S_3 Min f_3	0.301	0.884	0.007	Maximising expert preference satisfaction
β=(0.7,0.2,0.1) weighted	0.087	0.874	0.374	Leaning towards log-deviation accuracy
β=(0.1,0.2,0.7) weighted	0.268	0.864	0.054	Leaning towards preference matching

Note. Original MOP4 knee point: Objective 1=0.3857, Objective 2=0.4007. MOP-4-I S_0 achieves f_1=0.152 (60% improvement) while activating genuine f_3 preference signal. The redesigned f_3 (log-Jaccard + coverage deficit + log-width mismatch) eliminates the structural near-zero collapse of the original midpoint formulation.

Decision support recommendations are derived from the Pareto front. For most applications, S_0 is recommended as it balances all three objectives without requiring explicit preference specification. If fidelity to expert reference assessments is critical, S_1 is advised. If logical transitivity consistency is the primary criterion, S_2 is recommended. If maximum alignment with stated expert preference intervals is required, S_3 is appropriate. Custom β vectors can be supplied directly to the TOPSIS selector to obtain tailored solutions. Compared to single-objective methods, MOP-4-I explicitly captures the three-way trade-off between deviation, consistency, and

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preference matching, offering richer decision support. Unlike weighted-sum methods requiring pre-defined weights, NSGA-II recovers the full Pareto front in a single run.

5. Case study

5.1 Earthquake damage: Overview of the damage to the buildings in Sagaing

Satellite-based damage assessments provide converging evidence of the spatial extent and severity of structural destruction in Shweky Township. UNOSAT imagery analysis identified 2,220 confirmed and 2,293 probable damaged buildings (UNOSAT, 2025/04/10). Meanwhile, MIMU drew on a multi-source data integration approach incorporating preliminary UNOSAT analysis, THEOS-2 and Maxar satellite imagery, and field verification conducted by ground crews, and documented 1,853 confirmed and 2,290 probable damaged structures (MIMU, 2025/04/06). The marginal discrepancy between these two assessments stems from differences in data sources, verification protocols, and classification thresholds, and does not materially alter the overall damage profile.

UNOSAT and MIMU assessments show that structural collapses in Shweky Town are concentrated in three areas: the southern urban core (near the epicenter), the Irrawaddy River shoreline, and the eastern foothills of Shweky Mountain, as shown in Figure 2. This pattern aligns with expected seismic intensity decay and amplification on alluvial and sloping ground— providing a clear basis for prioritizing search-and-rescue and resource deployment in the immediate response.

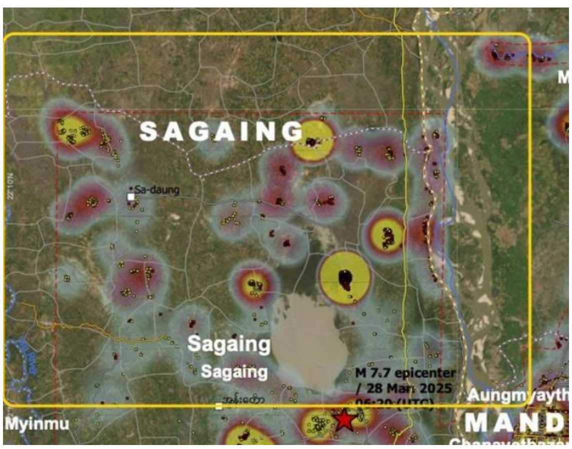

Figure 2. Density of damaged buildings in Mandalay and Sagaing districts following the 28 March 2025 Myanmar earthquake (UNITAR/UNOSAT, 2025).

Note. The map was derived from satellite imagery-based damage assessment, showing

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destroyed/damaged structures (yellow-red heatmap) and potentially damaged buildings (yellow dots).

Three damage zones were identified in Sagaing through integrated spatial and geotechnical analysis:

Zone 1 (Southern Sagaing, epicentral region): Soft soils and sloped foundations near Sagaing City—located at the junction of undulating terrain and alluvial deposits—make this area highly prone to liquefaction and shallow landslides. Damage maps show dense red markers, reflecting severe structural damage.

Zone 2 (Irrawaddy River Basin, western alluvial plain): Low-lying western districts with loose, saturated sandy soils face high liquefaction risk during earthquakes. Dense red marker clusters confirm widespread liquefaction-induced structural failure.

Zone 3 (Eastern slopes of Sagaing Mountain, urban-rural transition zone): Complex foothill topography increases susceptibility to slope instability and collapse. Historic religious and residential buildings here show orange-red damage markers, indicating high vulnerability.

Field reports from Myanmar's Fire Department on March 28 confirm building collapses and trapped survivors across ten administrative blocks in Sagaing.

- Parami Block: Blind School, Bhikkhuni Monastery, and multiple residences.
- Pone Tan Block: Education Institute, First Senior High School, Swae Taw Nan Guesthouse, Tote Tat Way Computer Shop.
- Chin Su Block: One school.
- Min Lan Block: Municipal Mosque, Moe Kyaw Mosque, and two commercial buildings.
- Sein Kone Block: Lay Kyun Myay Brick School and Konmar Store.
- Moe Zar Block: District Liaison Office.
- Zeyarthukha New Block: Yinkhwin Pin School.
- Takaung Block: Nay La Jone Factory and a cigarette auction facility.
- Myothit Block: Bhikkhuni Monastery and Thakyamitha Tutoring School.
- Thawtapan Block: Htut Khaung School, Yadana Thinga Tutoring Class, Zambudipa Monastery, and Taikwa Gyi Monastery.

The collapses affected schools, monasteries, mosques, government offices, guesthouses, shops, factories, and residences, reflecting widespread, non-discriminatory damage across building types and locations.

5.2 Information extraction

A magnitude 6.8 shallow earthquake struck the study area, causing widespread structural damage across multiple urban districts and triggering prolonged aftershocks. In response, the Emergency

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Management Headquarters must deploy search-and-rescue and medical teams to ten affected districts within the critical 72-hour window. These districts were selected because all documented incidents occurred between March 28 – 30—ensuring temporal consistency in damage data. The evaluation framework uses four expert-defined criteria to capture the multidimensional challenges of post-earthquake resource allocation. Extract information from ten blocks based on indicators C1 to C4; refer to Table 4.

Criterion C1: Life Rescue Urgency. This criterion quantifies the immediacy and priority of life-saving interventions by integrating three sub-dimensional indicators: the estimated number of trapped survivors, the time-dependent survival probability given elapsed post-earthquake time, and the demographic vulnerability profile of the affected population, including children, elderly individuals, and persons with disabilities.

Criterion C2: Disaster Severity. This criterion provides a composite assessment of physical destruction intensity, drawing on preliminary field and remote sensing reports to estimate building collapse rates and infer the scale of casualties across each district.

Criterion C3: Traffic Accessibility and Rescue Feasibility. This criterion evaluates the operational constraints on rescue deployment by accounting for road network congestion, residual seismic risk from ongoing aftershock activity, and the logistical difficulty of accessing affected sites with heavy rescue equipment.

Criterion C4: Social Stability and Recovery Value. This criterion assesses the broader socio-institutional significance of each district, encompassing its role in maintaining public order, mitigating social panic, and supporting the long-term urban recovery trajectory following the disaster event.

Table 4. Extract information from ten blocks based on indicators C1 to C4.

Block/Road	C1 (Urgency of life-saving)	C2 (Severity of disaster)	C3 (Feasibility of transportation and rescue)	C4 (Social stability and restoration value)
X1	Visually impaired students possess severely limited self-rescue ability; crumbling old houses risk collapse, potentially trapping people beneath debris; while monasteries might serve as temporary shelters, their structurally unsound condition poses a significant risk of stranding occupants.	Old houses may collapse, the structure of the monastery is unsafe, there is a certain amount of damage to the building.	In urban areas, roads may be significantly obstructed, a persistent aftershock threat remains, and rescue equipment access is notably challenged.	The presence of religious places and special education institutions is vital for fostering public harmony and providing essential care to special groups; restoring these relevant places significantly bolsters social stability.
X2	The high population density in school buildings makes them prone to collapse, putting a large number of students and teachers at great risk. Hostels may be occupied by a variety of people.	School buildings could collapse, hostels are also vulnerable to devastating damage, structural failure rates remain alarmingly high, casualties are likely to be grave, and the social	As a block in the urban area, road congestion can be severe, aftershocks pose a persistent threat, and rescue equipment may struggle to access the site. However, due to its high social visibility, rescue forces	Vital educational institutions such as colleges of education and senior high schools exist. Restoring their functions is essential for upholding social order and guaranteeing the normal development of

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Block/Road	C1 (Urgency of life-saving)	C2 (Severity of disaster)	C3 (Feasibility of transportation and rescue)	C4 (Social stability and restoration value)
		impact will be far-reaching.	could rapidly mobilize.	education, carrying immense social influence and possessing significant restoration value.
X3	A high-school building collapsed during an exam period, trapping more than 50 students and teachers in a crowded and urgent situation.	The teaching building suffered a partial collapse, a devastating form of local earthquake damage that resulted in casualties and catastrophic consequences.	Strategically positioned along the city's main thoroughfare and traffic conditions remain consistently smooth.	Schools are vital educational institutions. Restoring teaching order is essential to social stability and the continuity of student education, bearing significant recovery value.
X4	Mosques may have been teeming with worshippers during active religious services, their fragile domes or towering structures particularly vulnerable; the risk of mass entrapment looms large. Similarly, shops, often housed in dilapidated structures of uneven quality, also face the peril of people becoming trapped within.	Tall structures like mosques stand perilously vulnerable, commercial buildings suffer from substandard quality, the rate of structural collapse is alarmingly high, and the estimated casualties are significant.	In urban settings, roads are often blocked, aftershocks loom as constant threats, rescue equipment struggles to gain access, and the intricate structures of religious sites like mosques add complexity, making rescue operations significantly more challenging.	The presence of significant religious sites holds profound significance for appeasing believers and resuming religious activities, playing an indispensable role in maintaining social stability.
X5	The brick school proved alarmingly vulnerable to earthquakes, susceptible to devastating crushing collapse. Its cramped living space trapped hundreds of children for agonizing days (rescue operations only commenced officially three days later), compounding the high vulnerability of its occupants (children, young monks).	The brick school utterly collapsed in a devastating collapse. Casualties are expected to be significant, marking a truly catastrophic disaster.	Rescue teams arrived late at Laishun Village south of Sagaing City. Their efforts were likely hindered by blocked roads, challenging transportation, persistent aftershocks, and other obstacles that prevented vital rescue equipment from reaching the site.	Schools are places where children and religious groups converge, attracting intense public scrutiny. Restoring these affected sites holds profound significance, serving to reassure the community and safeguard children's well-being.
X6	The county liaison office, a reinforced concrete structure, remains largely intact though not fully collapsed, with individuals trapped within. Their situation is far more favorable compared to the neighboring block where the building suffered total collapse.	Buildings did not completely collapse; the collapse rate proved remarkably low, and estimated casualties remained minimal.	As a reinforced concrete government office building situated in an urban area, road conditions are typically favorable, allowing rescue equipment to access the site with relative ease.	As the county liaison office, restoring its functionality is paramount for coordinating subsequent rescue efforts. It serves as the cornerstone for organizing and managing the entire rescue and recovery operation, and is indispensable for social stability and recovery.
X7	The training center housed about 30 to 40 children, including those who had fled the war, and the entire three-story new teaching building collapsed, burying all the children in class. The crowd was dense and mostly children, who were weak in self-rescue ability.	The three-story teaching building collapsed, which is a serious collapse, and a large number of people were trapped in the disaster.	Near the Pyat Ywe Bridge in southern Sagaing, rescuers said they were unable to carry out effective rescue operations and speculated that traffic or aftershocks made it difficult for rescue equipment to enter.	Shelters for children escaping the horrors of war serve uniquely vulnerable groups and command intense societal focus. Restoring these vital spaces is profoundly important to protect their fundamental rights and heal the deep trauma within our communities.
X8	Large-span factory buildings are prone to collapse, but workers have more space to	Large-span factory buildings are prone to collapse, but the	If it is a factory area, the road infrastructure tends to be well-maintained, allowing	Materials in factories and storage buildings are vital for rescue and recovery

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Block/Road	C1 (Urgency of life-saving)	C2 (Severity of disaster)	C3 (Feasibility of transportation and rescue)	C4 (Social stability and restoration value)
	move around during the day and have a higher chance of survival than schools; storage buildings may be useful for materials, but there is also the possibility of people being trapped.	survival probability of personnel is relatively high, and the building collapse rate and casualty estimate are relatively lower than that of school blocks.	rescue teams to access the site with ease.	operations. Rapidly restoring these related facilities is essential to sustain an uninterrupted material supply and effectively support subsequent recovery efforts.
X9	The collapse of the Bhikkhuni monastery—a religious and educational site renowned for its distinctive structure and high social significance—poses a grave risk of people being trapped.	The collapse of the monastery building is a case of building damage, which is serious and attracts high social attention.	If it is in the urban area, there may be some road congestion, aftershock risk exists, rescue equipment is difficult to enter, and religious places are complex in structure, so rescue is difficult.	Religious education places comfort believers and related groups and restoring them is valuable for social stability.
X10	The education and religion mixed area, with diverse building types, dense population and complex situation; buildings such as Zambudipa Library are damaged, there is a risk of a large number of people trapped, and it belongs to the high intensity earthquake affected area, and the type of building collapse is severe (partial or overall collapse, etc.).	The building types are diverse and the damage is serious. There are some serious collapses such as local and overall collapse, and the casualties are estimated to be large and the disaster is serious.	Located in the northwest of Shiqi city, the earthquake high intensity affected area, the roads may be severely damaged by the earthquake, the risk of aftershock is high, and it is difficult for rescue equipment to enter.	This hub of education and religion features cultural facilities such as libraries alongside educational institutions and places of worship. It is crucial for upholding social order and fostering the healthy development of cultural education and religious activities, possessing significant restoration value.

5.3 Criteria level judgment matrix construction and value assignment

This study uses Interval Analytic Hierarchy Process (IAHP) to quantify the relative importance of each urban block under the Life Rescue Urgency criterion (C1). IAHP is suitable here because it can specifically deal with the epistemic uncertainty in expert judgment, which is common in disaster response when decisions need to be made under incomplete information, time pressure and rapidly changing risks.

5.3.1 Criterion C1: Core assignment principles

Under Criterion C1, interval-valued pairwise comparison matrices are built using three life-rescue principles, applied in strict priority order:

Principle 1 (Population vulnerability): Higher priority is given to groups with limited or no self-rescue capability — e.g., children, people with disabilities, and congregated religious populations. Rescue priority increases monotonically with vulnerability level.

Principle 2 (Group scale & spatial confinement): Among districts with similar vulnerability, priority rises with both the number of trapped survivors and the severity of spatial confinement caused by structural collapse—which reduces livable space, heightens stress, and degrades survival conditions. Resources target high collective risk from large affected populations and

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severe environments.

Principle 3 (Rescue timeliness): When vulnerability and confinement are comparable, priority shifts to cases where delay—due to structural complexity, inaccessibility, or adverse conditions—would cause a rapid, nonlinear drop in survivor probability. Timeliness matters most where early intervention yields high marginal gains in survival.

5.3.2 Interval scale and assignment logic

Using the three core assignment principles, we built an interval-valued pairwise comparison matrix for the ten urban blocks to derive relative rescue priorities. Following standard AHP practice, we applied the 1-9 scale and its reciprocals: the lower interval bound reflects a conservative estimate of urgency; the upper bound, an optimistic one. Block-specific scoring rationale follows.

X7 (Zeyarthukha New Block)—Highest priority. Its collapsed training center trapped 30–40 war-displaced people and students—mostly children—with no immediate evacuation possible. Extremely limited space and near-zero self-rescue capacity make this the most urgent rescue site among all ten blocks. Relative to X5: [2, 3]; relative to X8: [9, 9].

X5 (Sein Kone Block)—Second-highest priority. A brick school collapsed here, trapping many survivors; rescue was delayed by ~3 days, greatly increasing mortality risk. Though X5's vulnerability and confinement conditions are severe, they are slightly less critical than X7's. Thus, X5 is rated [2, 3] relative to X2.

X3 (Chin Su Block): High priority. A partial structural collapse at a private secondary school during exams trapped ~50 teachers and students. The main access road is congested due to crowds, delaying rescue. Structural analysis shows high risk of progressive collapse at the weak lower story, making rapid intervention critical. Urgency is lower than X5 but significantly higher than typical school collapses; rated [1, 2] relative to X2.

X2 (Pone Tan Block) and X1 (Parami Block): Medium-to-high priority. X2 includes the Faculty of Education and several secondary schools, with high population density during the event. Structural damage is uncertain—some buildings may remain partially intact—so urgency is lower than for X3.

X1 hosts a school for visually impaired students, whose limited ability to self-evacuate is a critical vulnerability. No large-scale entrapment is confirmed, but aging residential buildings add uncertainty. Thus, X1's priority is moderate—rated [5, 6] relative to X8.

X10 (Thawtapan Block) and X9 (Myothit Block): Medium-to-low priority. In X10, pancake collapse in a high-seismic-intensity zone caused severe spatial confinement, but the number of trapped survivors is unconfirmed; its mixed population also lowers priority compared

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to homogeneous vulnerable sites (e.g., schools).

In X9, simultaneous collapse of a Bhikkhuni Monastery and a remedial school drew religious attention—but with no reliable estimates of trapped persons or survivable space, urgency remains lower than for typical school collapses.

X4 (Min Lan Block) and X6 (Moe Zar Block): Low priority. X4 includes mosques and commercial areas with high pedestrian traffic during religious events, but damage assessments are unverified and structural quality is poor—introducing high uncertainty and lowering priority.

X6 houses a reinforced concrete county liaison office with no complete collapse; only a few people are confirmed trapped, the structure remains stable, and survivable space is sufficient—justifying low urgency.

X8 (Takaung Block): Lowest priority. It houses a factory and a cigarette auction facility—both large-span structures prone to roof collapse but offering ample interior space. The occupants are mostly able-bodied adult workers with strong self-evacuation capability. Given the available survivable space, high autonomy in evacuation, and inherently high survival probability, X8 ranks last in rescue priority among the ten blocks.

5.3.3 Interval width design

Each interval's width in the pairwise comparison matrix reflects judgment certainty: narrow intervals (e.g., [2, 3]) indicate high consensus—such as between X7 and X5, or X5 and X2; wide intervals (e.g., [1/2, 1]) reflect ambiguity due to conflicting reports or scarce data; and missing entries ([−, −]) signal extreme information deficiency or incommensurability—such as comparisons involving administrative versus religious blocks. Missing values are not zero or neutral and require algorithmic imputation. The matrix must satisfy reciprocal consistency: if A/B is interval x, then B/A must be 1/x.

Right after the earthquake, communication failures and inconsistent, incomplete damage reports limited the expert panel's ability to make full pairwise comparisons. As a result, under Criterion C1, they provided only interval-valued judgements for some block pairs—leaving the judgment matrix incomplete. This study recovers the missing entries using the MOP-4-I three-objective optimisation model.

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$$U_{C1}=\begin{pmatrix} \tilde{a}_{11} & \tilde{a}_{12} & \tilde{a}_{13} & \tilde{a}_{14} & \tilde{a}_{15} & \tilde{a}_{16} & \tilde{a}_{17} & \tilde{a}_{18} & \tilde{a}_{19} & \tilde{a}_{1,10} \\ \tilde{a}_{21} & \tilde{a}_{22} & \tilde{a}_{23} & \tilde{a}_{24} & \tilde{a}_{25} & \tilde{a}_{26} & \tilde{a}_{27} & \tilde{a}_{28} & \tilde{a}_{29} & \tilde{a}_{2,10} \\ \tilde{a}_{31} & \tilde{a}_{32} & \tilde{a}_{33} & \tilde{a}_{34} & \tilde{a}_{35} & \tilde{a}_{36} & \tilde{a}_{37} & \tilde{a}_{38} & \tilde{a}_{39} & \tilde{a}_{3,10} \\ \tilde{a}_{41} & \tilde{a}_{42} & \tilde{a}_{43} & \tilde{a}_{44} & \tilde{a}_{45} & \tilde{a}_{46} & \tilde{a}_{47} & \tilde{a}_{48} & \tilde{a}_{49} & \tilde{a}_{4,10} \\ \tilde{a}_{51} & \tilde{a}_{52} & \tilde{a}_{53} & \tilde{a}_{54} & \tilde{a}_{55} & \tilde{a}_{56} & \tilde{a}_{57} & \tilde{a}_{58} & \tilde{a}_{59} & \tilde{a}_{5,10} \\ \tilde{a}_{61} & \tilde{a}_{62} & \tilde{a}_{63} & \tilde{a}_{64} & \tilde{a}_{65} & \tilde{a}_{66} & \tilde{a}_{67} & \tilde{a}_{68} & \tilde{a}_{69} & \tilde{a}_{6,10} \\ \tilde{a}_{71} & \tilde{a}_{72} & \tilde{a}_{73} & \tilde{a}_{74} & \tilde{a}_{75} & \tilde{a}_{76} & \tilde{a}_{77} & \tilde{a}_{78} & \tilde{a}_{79} & \tilde{a}_{7,10} \\ \tilde{a}_{81} & \tilde{a}_{82} & \tilde{a}_{83} & \tilde{a}_{84} & \tilde{a}_{85} & \tilde{a}_{86} & \tilde{a}_{87} & \tilde{a}_{88} & \tilde{a}_{89} & \tilde{a}_{8,10} \\ \tilde{a}_{91} & \tilde{a}_{92} & \tilde{a}_{93} & \tilde{a}_{94} & \tilde{a}_{95} & \tilde{a}_{96} & \tilde{a}_{97} & \tilde{a}_{98} & \tilde{a}_{99} & \tilde{a}_{9,10} \\ \tilde{a}_{10,1} & \tilde{a}_{10,2} & \tilde{a}_{10,3} & \tilde{a}_{10,4} & \tilde{a}_{10,5} & \tilde{a}_{10,6} & \tilde{a}_{10,7} & \tilde{a}_{10,8} & \tilde{a}_{10,9} & \tilde{a}_{10,10} \end{pmatrix}$$

$$U_{C1}=\begin{pmatrix} [1,1] & [1/3, 1/2] & [1/4, 1/3] & [2, 3] & [1/5, 1/4] & [3, 4] & [1/7, 1/5] & [5, 6] & [1, 2] & [1/2, 1] \\ [2,3] & [1,1] & [1/2,1] & [3,4] & [1/3, 1/2] & [4, 5] & [1/5, 1/3] & [6, 7] & [2, 3] & [1, 2] \\ [3,4] & [1,2] & [1,1] & [4, 5] & [1/2, 1] & [5, 6] & [1/4, 1/2] & [7, 8] & [3,4] & [2, 3] \\ [1/3, 1/2] & [1/4, 1/3] & [1/5, 1/4] & [1,1] & [1/6, 1/5] & [—, —] & [1/8, 1/6] & [4, 5] & [1/2,1] & [1/3, 1/2] \\ [4, 5] & [2, 3] & [1, 2] & [5, 6] & [1,1] & [6, 7] & [1/3, 1/2] & [8, 9] & [4,5] & [3, 4] \\ [1/4, 1/3] & [1/5, 1/4] & [1/6, 1/5] & [—, —] & [1/7, 1/6] & [1,1] & [1/9, 1/7] & [3, 4] & [1/3,1/2] & [1/4, 1/3] \\ [5, 7] & [3, 5] & [2, 4] & [6, 8] & [2, 3] & [7, 9] & [1,1] & [9, 9] & [5,6] & [4, 5] \\ [1/6, 1/5] & [1/7, 1/6] & [1/8, 1/7] & [1/5, 1/4] & [1/9, 1/8] & [1/4, 1/3] & [1/9, 1/9] & [1,1] & [1/5,1/4] & [1/6, 1/5] \\ [1/2, 1] & [1/3, 1/2] & [1/4, 1/3] & [1, 2] & [1/5, 1/4] & [2, 3] & [1/6, 1/5] & [4,5] & [1,1] & [—, —] \\ [1, 2] & [1/2, 1] & [1/3, 1/2] & [2, 3] & [1/4, 1/3] & [3, 4] & [1/5, 1/4] & [5,6] & [—, —] & [1,1] \end{pmatrix}$$

Task 1: Complete the incomplete judgment matrix. Apply MOP-4-I to estimate all missing entries in the interval-valued pairwise comparison matrix, producing a fully completed, consistency-satisfied matrix. MOP-4-I simultaneously minimises f_1 (interval log-deviation from reference at both bounds), f_2 (dual-bound transitivity robustness), and f_3 (log-Jaccard dissimilarity D_J, coverage deficit D_C, log-width mismatch D_W). Before deriving priority weights, the consistency index of the completed matrix is verified to be within the acceptable tolerance.

Task 2: Single-criterion priority ranking. Based on the completed interval-valued matrix, the interval number weight vector for the ten urban blocks under Criterion C_1 is computed using interval arithmetic eigenvector extraction: separate eigenvectors are derived for the lower-bound matrix C_L and upper-bound matrix C_U, yielding interval weights $[w_i^L, w_i^U]$. The midpoint $\bar{w}_i = (w_i^L + w_i^U)/2$ is used for ranking; the half-width Δw_i quantifies residual uncertainty from missing entries. Priority rankings are subsequently derived through the construction and analysis of the possibility degree matrix.

The estimated values of the four missing interval entries recovered by MOP-4-I (TOPSIS, β=(0.30, 0.40, 0.30)) are reported as follows, refer to Table 5, 6 and Figure 3a. The interval judgment for X4 relative to X6 is determined as [1.1800, 3.0021], with the corresponding reciprocal entry for X6 relative to X4 yielding [0.3331, 0.8475]. For the comparison between X9 and X10, the recovered interval is [2.9657, 3.9988], with the reciprocal entry for X10 relative to X9 determined as [0.2501, 0.3372]. MOP-4-I completions are markedly tight and precisely aligned with the expert preference intervals [2.00, 3.00] and [3.00, 4.00], demonstrating that the

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redesigned f_3 objective effectively constrains the recovered values toward expert-stated preferences while satisfying transitivity and reciprocity conditions.

Table 5. Recovered missing entries for U^{J1} (MOP-4-I, TOPSIS β=(0.30,0.40,0.30))

Pair	Lower c^L	Upper c^U	Midpoint	Pref. interval	Within pref.	Reciprocal of
(X4, X6)	1.1800	3.0021	2.0910	[2.00, 3.00]	Partial (upper)	—
(X6, X4)	0.3331	0.8475	0.5903	[0.333, 0.500]	Partial (lower)	(X4,X6)
(X9, X10)	2.9657	3.9988	3.4823	[3.00, 4.00]	Yes	—
(X10, X9)	0.2501	0.3372	0.2936	[0.250, 0.333]	Yes	(X9,X10)

Note. Preference intervals are derived from expert elicitation: [2.00, 3.00] for (X4,X6) and [3.00, 4.00] for (X9,X10) (ratio space). The TOPSIS solution for (X4,X6) extends slightly below the preference lower bound (c^L=1.18 < p^L=2.00), reflecting an f_1–f_3 trade-off: the wider interval improves transitivity consistency at a small preference cost. The f_3 v4 coverage deficit component D^I captures this partial coverage and maintains gradient signal for the optimizer.

Table 6. Interval priority weights under C1 (MOP-4-I, TOPSIS selected solution)

Rank	District	w^L (lower)	w^U (upper)	w_{mid}	$\pm\Delta w$	Baseline rank	Stability	Missing
1	X7	0.29454	0.29831	0.29643	0.00188	1	Stable	No
2	X5	0.19605	0.18678	0.19141	0.00463	2	Stable	No
3	X3	0.14260	0.14567	0.14413	0.00154	3	Stable	No
4	X2	0.10055	0.10476	0.10266	0.00211	4	Stable	No
5	X9	0.06492	0.06438	0.06465	0.00027	5	Stable	Yes
6	X10	0.06318	0.06481	0.06399	0.00082	6	Stable	Yes
7	X1	0.05901	0.06001	0.05951	0.00050	7	Stable	No
8	X4	0.03600	0.03702	0.03651	0.00051	8	Stable	Yes
9	X6	0.02674	0.02495	0.02584	0.00089	9	Stable	Yes
10	X8	0.01642	0.01331	0.01487	0.00156	10	Stable	No

Note. Interval weights derived from separate eigenvector computation on the lower-bound matrix C^L and upper-bound matrix C^U. $\Delta w = (w^U - w^L)/2$. Stability assessed across 200 Pareto-optimal solutions; all ten districts classified Stable (σ < 0.5). Districts with missing entries (*) retain stable rankings, confirming robustness of the completed values.

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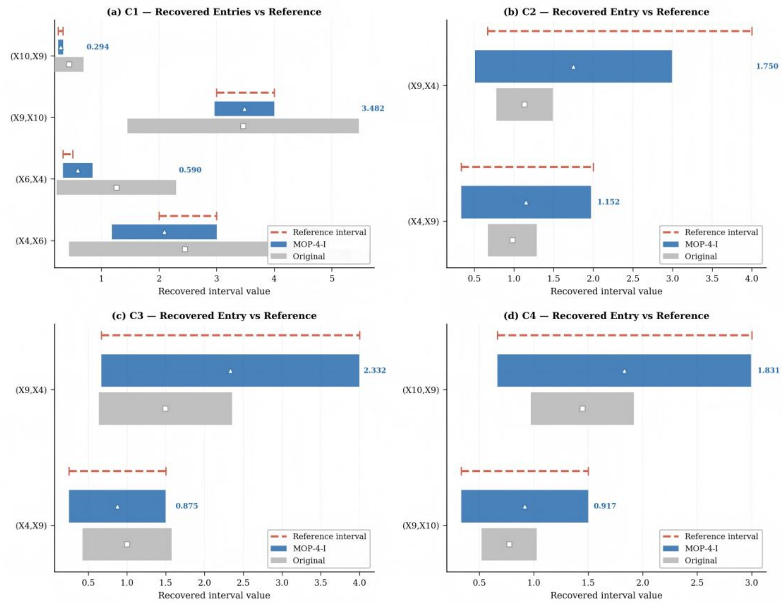

Figure 3. Recovered entries vs reference under the MOP-4 (original benchmark) and MOP-4-I.

5.3.4 C2: Core assignment principles

Based on these three dimensions, the block-level assignment logic is elaborated as follows.

X7 (Zeyarthukha New Block) and X5 (Sein Kone Block): Most severe. Both blocks sustained complete school building collapse accompanied by large-scale entrapment of occupants, placing them at the highest tier of disaster severity. X7, characterized by total structural failure rendering immediate rescue operationally impossible, is assessed as marginally more severe than X5, which experienced pulverized collapse with comparably catastrophic but slightly more accessible conditions.

X10 (Thawtapan Block): Extremely severe. X10 sustained pancake-type complete structural collapse within a high seismic intensity zone, representing one of the most physically destructive failure modes in terms of survivable space elimination. The severity rating of X10 relative to X2 is assigned as [2, 3], explicitly reflecting the principle that confirmed total collapse constitutes a categorically more severe outcome than probable or potential collapse under uncertain structural conditions.

X3 (Chin Su Block): Moderately severe. A private secondary school within X3 experienced partial structural collapse, resulting in the confirmed entrapment of approximately 50 teachers and students. The combination of a verified collapse event and a clearly quantified casualty scale distinguishes X3 from blocks where damage assessments remain uncertain. The severity rating of

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X3 relative to X1 is accordingly assigned as [3, 4], operationalizing the principle that confirmed partial collapse with a defined casualty count is assessed as substantially more severe than potential collapse with an unspecified casualty scale.

X9 (Myothit Block): Moderately severe. The complete collapse of a Bhikkhuni Monastery within X9 has been field-verified, establishing a confirmed damage event as the basis for severity assessment. The severity rating of X9 relative to X1 is assigned as [2, 3], in accordance with the guiding principle that confirmed structural failure constitutes a more severe scenario than unverified potential risk, thereby placing X9 above X1 in the disaster severity ranking.

The spatial distribution of VS30 values reveals how soil stiffness influences building damage and collapse risk across Sagaing City. In northern and central districts where VS30 < 360 m/s, seismic amplification is strongest. In contrast, southern and southeastern districts with VS30 ≈ 530 m/s show markedly lower failure probabilities. These geotechnical differences directly inform the relative severity ratings under Criterion C2.

The pairwise comparison matrix for C2 is constructed along three hierarchically ordered dimensions. Dimension 1: Building collapse typology. Complete collapse > partial collapse > non-total collapse. Dimension 2: Casualty scale. Hundreds > dozens > single digits. Dimension 3: Structural vulnerability. Unreinforced masonry > frame structures > reinforced concrete.

$$U_{C2}=\begin{pmatrix} [1,1] & [1/3, 1/2] & [1/4, 1/3] & [2, 3] & [1/5, 1/4] & [3, 4] & [1/6, 1/5] & [4, 5] & [1/3, 1/2] & [1/2, 1] \\ [2,3] & [1,1] & [1,2] & [3,4] & [1/3, 1/2] & [4, 5] & [1/4, 1/3] & [5, 6] & [2, 3] & [1/3, 1/2] \\ [3,4] & [1/2,2] & [1,1] & [2, 3] & [1/4, 1/3] & [3, 4] & [1/5, 1/4] & [4, 5] & [1,2] & [1/2, 1] \\ [1/3, 1/2] & [1/4, 1/3] & [1/3, 1/2] & [1,1] & [1/6, 1/5] & [2, 3] & [1/7, 1/6] & [3, 4] & [—, —] & [1/3, 1/2] \\ [4, 5] & [2, 3] & [3, 4] & [5, 6] & [1,1] & [6, 7] & [1/3, 1/2] & [7, 8] & [4,5] & [3, 4] \\ [1/4, 1/3] & [1/5, 1/4] & [1/4, 1/3] & [1/3, 1/2] & [1/7, 1/6] & [1,1] & [1/8, 1/7] & [2, 3] & [1/3,1/2] & [1/4, 1/3] \\ [5, 6] & [3, 4] & [4, 5] & [6, 7] & [2, 3] & [7, 8] & [1,1] & [8, 9] & [5,6] & [4, 5] \\ [1/5, 1/4] & [1/6, 1/5] & [1/5, 1/4] & [1/4, 1/3] & [1/8, 1/7] & [1/3, 1/2] & [1/9, 1/8] & [1,1] & [1/4,1/3] & [1/5, 1/4] \\ [2, 3] & [1/3, 1/2] & [1/2, 1] & [—, —] & [1/5, 1/4] & [2, 3] & [1/6, 1/5] & [3,4] & [1,1] & [1/2, 1] \\ [—, —] & [2, 3] & [1, 2] & [2, 3] & [1/4, 1/3] & [3, 4] & [1/5, 1/4] & [5,6] & [1, 2] & [1,1] \end{pmatrix}$$

Define the interval number judgment matrix $A^{C2} = (\tilde{a}_{ij}{}^{C2})_{10\times10}$, where $\tilde{a}_{ij}{}^{C2} = [l_{ij}, u_{ij}]$ represents the importance interval of block X_i relative to X_j in disaster severity. The matrix U_{C2} contains one missing upper-triangle entry at position (X4, X9), recovered by MOP-4-I as follows, see Figure 3b:

(X4, X9)=[0.3341, 1.9703] (midpoint 1.152); reciprocal (X9, X4)=[0.5075, 2.9931] (midpoint 1.750). The recovered interval spans the scale boundary at 1.0, indicating the expert panel held ambiguous views on whether X4 or X9 is more severely affected under C2. Objective values: f_1=0.213, f_2=1.271, f_3=0.082. Priority ranking under C2: X7 > X5 > X2 > X10 > X3 > X9 > X1 > X4 > X6 > X8.

Within this interval-valued framework, a ratio greater than unity indicates the former district is assessed as more urgent than the latter. The reciprocal pairs are reported independently rather

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than derived mechanically. This reflects a fundamental property of interval-valued judgment matrices: under the interval AHP framework, reciprocal entries need not satisfy strict multiplicative reciprocity, as bounds of each direction may be elicited or recovered independently. The resulting asymmetry is therefore not a logical inconsistency but an informationally meaningful feature of interval-based preference representation.

5.3.5 C3: Core assignment principles

The criteria-level pairwise comparison matrix for Criterion C3 (Traffic Accessibility and Rescue Feasibility) is constructed along three hierarchically ordered dimensions as follows.

Dimension 1: Geographic and transport accessibility. Accessibility is rated highest for blocks situated along urban arterial roads with well-developed transport networks, moderate for standard urban areas with functional but non-arterial road access, lower for suburban or rural areas where increased travel distance imposes logistical constraints, and lowest for zones in which seismic damage has caused severe road deterioration or complete traffic disruption.

Dimension 2: On-site operational environment. Rescue feasibility is rated highest at sites where structurally stable buildings facilitate safe rescue operations and equipment deployment. Feasibility is progressively reduced at sites characterized by complex structural configurations, elevated risk of secondary collapse, or unstable debris fields that compromise operational safety.

Dimension 3: Information clarity and rescue progress. Feasibility is rated highest for areas where site accessibility has been field-confirmed and rescue forces have already been successfully deployed. It is reduced for areas classified as only potentially accessible or subject to unresolved operational uncertainty and is rated lowest for zones formally assessed as unable to support effective rescue operations under current conditions.

Based on these three dimensions, interval scales were assigned through systematic pairwise comparisons across all ten blocks. The revised assignment scheme reinforces the transport advantages of administrative core areas and the logistical conditions of industrial zones, while recovering previously missing key comparisons through the optimization-based supplementation procedure.

X3 (Chin Su Block): Highest feasibility. Located along an urban arterial road with good transport, it's a priority search-and-rescue zone for accessibility. So, it has higher interval scales than other blocks like X2 and X6.

X2 (Pone Tan Block) and X6 (Moe Zar Block): **High to moderately high feasibility**. X2 is an education-concentrated district attracting public attention, which helps resource aggregation for rescues; its feasibility is second only to X3. X6 has an organizational coordination advantage due to the district liaison office in the administrative core and good transport. Its reinforced concrete

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buildings provide a stable on-site environment. After matrix refinement, X6's pairwise comparison scale relative to X1 and X9 is [2, 3].

X1 (Parami Block) and X9 (Myothit Block): **Moderate feasibility**. Both are in urban or peri-urban areas with average transport. There's no complete traffic disruption, but congestion and logistical issues moderately limit rescue accessibility.

X8 (Takaung Block) and X4 (Min Lan Block): **Moderately low feasibility**. X8 is an industrial zone near transport corridors, but large-span factory structures increase on-site complexity. After matrix refinement, X8's pairwise comparison scale relative to X4 is [2, 3]. X4 has mosques and commercial premises in an urban area but lacks direct arterial road access, so it has a conservative feasibility assessment.

X10 (Thawtapan Block) and X5 (Sein Kone Block): Low to moderately low feasibility. X10 is in the northwestern high-seismic-intensity urban area with potentially severely damaged roads and high on - site hazards. X5 is in Laik Kyun Village, a remote southern suburban area. The interval scale between X5 and X10 is [1, 2], indicating X5 has a slight feasibility advantage as its access limitations are more mitigable than X10's site hazards.

X7 (Zeyarthukha New Block): Lowest feasibility. X7 is formally assessed as a zone in which effective rescue operations cannot currently be conducted owing to insurmountable operational obstacles, representing the absolute minimum feasibility level among all ten blocks. Nonetheless, recognizing that the assignment of an absolute minimum value across all pairwise comparisons may not be fully defensible given residual uncertainty, pairwise comparison entries involving X7 are partially treated as missing data and recovered through the algorithmic supplementation framework developed in this study.

Define the interval number judgment matrix as $A^{C3} = (\tilde{a}_{ij}{}^{C3})_{10\times10}$, where $\tilde{a}_{ij}{}^{C3} = [l_{ij}, u_{ij}]$ represent the importance interval of block X_i relative to X_j in terms of rescue feasibility. The matrix is as follows:

$$U_{C3}=\begin{pmatrix}
[1,1] & [1/3, 1/2] & [1/3, 1/2] & [1, 2] & [3, 4] & [1/3, 1/2] & [4, 5] & [1, 2] & [1, 1] & [2, 3] \\
[2, 3] & [1,1] & [1/6,1/4] & [2,3] & [4, 5] & [1, 2] & [5, 6] & [2, 3] & [1, 2] & [3, 4] \\
[2,3] & [4, 6] & [1,1] & [3, 4] & [5, 6] & [4, 7] & [6, 7] & [3, 4] & [2, 3] & [4, 5] \\
[1/2, 1] & [1/3, 1/2] & [1/4, 1/3] & [1,1] & [2, 3] & [1/3, 1/2] & [3, 4] & [1/3, 1/2] & [—, —] & [1, 2] \\
[1/4, 1/3] & [1/5, 1/4] & [1/6, 1/5] & [1/3, 1/2] & [1,1] & [1/4, 1/3] & [2, 3] & [1/3, 1/2] & [1/4, 1/3] & [1, 2] \\
[2, 3] & [1/2, 1] & [1/7, 1/4] & [2, 3] & [3, 4] & [1,1] & [4, 5] & [1, 2] & [2, 3] & [2, 3] \\
[1/5, 1/4] & [1/6, 1/5] & [1/7, 1/6] & [1/4, 1/3] & [1/3, 1/2] & [1/5, 1/4] & [1,1] & [1/4, 1/3] & [1/5, 1/4] & [1/3, 1/2] \\
[1/2, 1] & [1/3, 1/2] & [1/4, 1/3] & [2, 3] & [2, 3] & [1/2, 1] & [3,4] & [1,1] & [1/2, 1] & [1, 2] \\
[1, 1] & [1/2, 1] & [1/3, 1/2] & [—, —] & [3, 4] & [1/3, 1/2] & [4, 5] & [1, 2] & [1,1] & [2, 3] \\
[1/3, 1/2] & [1/4, 1/3] & [1/5, 1/4] & [1/2, 1] & [1/2, 1] & [1/3, 1/2] & [2, 3] & [1/2, 1] & [1/3, 1/2] & [1,1]
\end{pmatrix}$$

The C3 matrix (Traffic Accessibility and Rescue Feasibility) is constructed along three hierarchically ordered dimensions. Dimension 1: Geographic and transport accessibility. Arterial road access > standard urban > suburban > road-damaged zones. Dimension 2: On-site operational

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environment. Structurally stable > complex configuration > elevated secondary-collapse risk. Dimension 3: Information clarity and rescue progress. Field-confirmed and deployed > operationally uncertain > assessed as unable to support rescue.

The matrix U_{C3} contains one missing upper-triangle entry at position (X4, X9), recovered by MOP-4-I from the actual C3 matrix as follows, see Figure 3c:

(X4, X9) = [0.2502, 1.4989] (midpoint 0.875); reciprocal (X9, X4) = [0.6672, 3.9975] (midpoint 2.332). The upper bound of 1.4989 for (X4, X9) is below 1.5, indicating that while X9 may have higher feasibility than X4, the uncertainty is substantial. The reciprocal midpoint of 2.332 confirms that X9 is assessed as approximately 2.3 times more feasible than X4 under rescue operations. Objective values: f_1=0.001, f_2=1.187, f_3=0.000. Priority ranking under C3: X3 > X2 > X6 > X9 > X1 > X8 > X4 > X10 > X5 > X7.

5.3.6 C4: Core assignment principles

The criteria-level pairwise comparison matrix for Criterion C4 (Social Stability and Recovery Value) is constructed along three hierarchically ordered dimensions as follows.

Dimension 1: Functional irreplaceability and strategic status. A block's function uniqueness and non-substitutability in the post-disaster emergency response system are the primary basis for recovery value assessment. Administrative command centers have the highest irreplaceability due to their centralized coordination in disaster response. Educational and religious sites are moderately irreplaceable because of their symbolic and community - anchoring functions, while production and commercial facilities are more replaceable as their core functions can be supplemented externally.

Dimension 2: Population influence and coverage scope. The social recovery value of a block is affected by the population scale and composition it serves. Sites with large student populations, especially vulnerable groups, or extensive religious congregations have higher social impact ratings as they influence community stability, public morale, and social recovery pace.

Dimension 3: Recovery timeliness and symbolic significance. Blocks that perform immediate post-disaster functions in emergency command coordination or rapid restoration of critical public services have higher recovery value based on timeliness. Also, sites with strong symbolic significance, whether civic, educational, or spiritual, contribute to the reconstruction of public confidence and collective morale in the post-disaster recovery phase.

Based on three dimensions, pairwise comparisons were made between all ten blocks, with focus on refining distinctions in the medium-to-high value tier.

X6 (Moe Zar Block): Highest recovery value. It houses the District Liaison Office for post-disaster rescue coordination and administrative command, having overarching and

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irreplaceable strategic value in the emergency response system, getting absolute priority.

X2 (Pone Tan Block), X3 (Chin Su Block), and X10 (Thawtapan Block): High recovery value. X2 has a teacher training college and a secondary school, crucial for re-establishing social order. X3 is a private secondary school that collapsed during exams, and resuming teaching is significant for families and educational equity. X10 is a mixed-use district with educational, religious, and cultural facilities, enhancing social recovery resilience. After matrix refinement, the pairwise comparison scale of X2 relative to X3 is [1, 2], and X10 relative to X2 is [1, 2].

X1 (Parami Block) and X9 (Myothit Block): Medium recovery value. X1 has a school for visually impaired students and a monastery, promoting social equity. X9 combines a Bhikkhuni Monastery and a supplementary educational facility, contributing to religious community stability and interfaith cohesion.

X4 (Min Lan Block), X5 (Sein Kone Block), and X7 (Zeyarthukha New Block): Medium-to-low recovery value. X4 is a single-function mosque with limited recovery value. X5 and X7 serve primary educational functions, but due to location or operational obstacles, their contribution to city-wide social recovery is lower. After matrix reinforcement, the pairwise comparison scales of X5 and X7 relative to X4 are [2, 3].

X8 (Takaung Block): Lowest recovery value. It has industrial and commercial functions. In the post-disaster context, its contribution to social stability is limited, and its functions can be supplemented externally, reducing the urgency of in-situ restoration.

Define the interval number judgment matrix $A^{C4} = (\tilde{a}_{ij}{}^{C4})_{10\times10}$, where $\tilde{a}_{ij}{}^{C4} = [l_{ij}, u_{ij}]$ represent the importance intervals of neighborhood X_i relative to X_j in terms of social stability and recovery value, as shown in the matrix below:

$$U_{C3}=\begin{pmatrix} [1,1] & [1/2, 1] & [1/2, 1] & [2, 3] & [1, 2] & [1/3, 1/2] & [1, 2] & [3,4] & [1,1] & [1/2,1] \\ [1,2] & [1,1] & [1, 2] & [3,4] & [2, 3] & [1/2, 1] & [2, 3] & [4, 5] & [1, 2] & [1/2,1] \\ [1,2] & [1/2, 1] & [1,1] & [3, 4] & [2, 3] & [1/2, 1] & [2, 3] & [4, 5] & [1, 2] & [1,1] \\ [1/3, 1/2] & [1/4, 1/3] & [1/4, 1/3] & [1,1] & [1/3, 1/2] & [1/5, 1/4] & [1/3, 1/2] & [2, 3] & [1/2,1] & [1/3, 1/2] \\ [1/2, 1] & [1/3, 1/2] & [1/3, 1/2] & [2, 3] & [1,1] & [1/4, 1/3] & [1, 1] & [3, 4] & [1/2, 1] & [1/3, 1/2] \\ [2, 3] & [1, 2] & [1, 2] & [4, 5] & [3, 4] & [1,1] & [3, 4] & [5,6] & [2, 3] & [1, 2] \\ [1/2, 1] & [1/3, 1/2] & [1/3, 1/2] & [2, 3] & [1, 1] & [1/4, 1/3] & [1,1] & [3, 4] & [1/2, 1] & [1/3, 1/2] \\ [1/4, 1/3] & [1/5, 1/4] & [1/5, 1/4] & [1/3, 1/2] & [1/4, 1/3] & [1/6, 1/5] & [1/4, 1/3] & [1, 1] & [1/4, 1/3] & [1/5, 1/4] \\ [1, 1] & [1/2, 1] & [1/2, 1] & [1, 2] & [1, 2] & [1/3, 1/2] & [1, 2] & [3, 4] & [1, 1] & [—, —] \\ [1, 2] & [1, 2] & [1, 1] & [2, 3] & [2, 3] & [1/2, 1] & [2, 3] & [5, 6] & [—, —] & [1, 1] \end{pmatrix}$$

The C4 matrix (Social Stability and Recovery Value) is constructed along three hierarchically ordered dimensions. Dimension 1: Functional irreplaceability and strategic status. Administrative command centres > educational and religious sites > production and commercial facilities. Dimension 2: Population influence and coverage scope. Sites serving large student populations, vulnerable groups, or extensive religious congregations. Dimension 3: Recovery timeliness and symbolic significance. Blocks performing immediate post-disaster functions or carrying strong

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symbolic significance.

The matrix U_{C4} contains one missing upper-triangle entry at position (X9, X10), recovered by MOP-4-I from the actual C4 matrix as follows, see Figure 3d:

(X9, X10) = [0.3339, 1.5002] (midpoint 0.917); reciprocal (X10, X9) = [0.6666, 2.9950] (midpoint 1.831). The midpoint of (X9, X10) at 0.917 is just below 1.0, indicating that X10 is assessed as having marginally higher or comparable social recovery value relative to X9. The reciprocal midpoint of 1.831 confirms that X10 generally exhibits higher resource availability. Objective values: f_1=0.001, f_2=0.775, f_3=0.000. Priority ranking under C4: X6 > X10 > X2 > X3 > X1 > X9 > X5 > X7 > X4 > X8. In addition, we obtained the objective function values and convergence performance; see Table 7.

Table 7. Objective function values and convergence performance

Criterion	f_1 (log-dev.)	f_2 (transit.)	f_3 (pref.)	Missing pairs	Pareto size
C1 Life Rescue	0.17643	1.23369	0.06137	(X4, X6), (X9, X10)	120
C2 Disaster Sev.	0.21312	1.27132	0.08247	(X4, X9)	120
C3 Rescue Feas.	0.00083	1.18733	0.00027	(X4, X9)	120
C4 Social Value	0.00104	0.77475	0.00037	(X9, X10)	120

Note. All objectives evaluated at the TOPSIS-selected solution (β=(0.30,0.40,0.30)). f_3 is structurally non-zero (zero only when completed interval exactly equals preference interval), providing genuine preference-matching gradient throughout evolution. Scale factors: s_1 and s_2 estimated per-criterion from 200 random samples at 90th percentile.

5.4 Task 3: Multi-criteria priority weight analysis

The computed interval-valued priority weights under the four evaluation criteria — C1 (Life Rescue Urgency), C2 (Disaster Severity), C3 (Rescue Feasibility), and C4 (Social Value) — are visualized across three complementary representations: a criteria-disaggregated heatmap, a stacked bar chart of cumulative cross-criteria weights, and a grouped bar chart enabling direct inter-criteria comparison.

First, incomplete interval-valued judgment matrices corresponding to C2, C3 and C4 are completed using consistency-based estimation methods (i.e., interval geometric averaging or linear interpolation), ensuring the revised matrices satisfy the generalized consistency ratio $\mathrm{CR} \leq 0.1$. Second, for each complete matrix under C_i ($i = 1, 2, 3, 4$), the interval weight vectors of seven alternatives ($x_1 \sim x_{10}$) are derived using the interval eigenvalue method or interval geometric averaging method, yielding interval weights $[w_{ij}^l, w_{ij}^u]$ for each alternative under each criterion.

Let the criterion weight vector be $\mathrm{C} = ([c_1^l, c_1^u], [c_2^l, c_2^u], [c_3^l, c_3^u], [c_4^l, c_4^u])$. The overall interval weight W_i of alternative xi is calculated as:

$$W_i = \sum_{j=1}^{4} [c_j^l, c_j^u] \otimes [w_{ij}^l, w_{ij}^u]$$

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where ⊗ denotes interval multiplication and summation follows interval arithmetic. Finally, the interval-valued overall weights $w_1 \sim w_{10}$ are ranked using the possibility degree method or endpoint comparison. The output consists of interval composite weights and a deterministic priority ranking for the ten districts, which directly supports resource allocation and response sequencing decisions.

Collectively, these figures reveal both the absolute priority standing of each district and the underlying structural patterns driving the overall ranking, as shown in Table 8 and Figure 4.

Table 8. Priority scores under each criterion (midpoint weights, MOP-4-I completed matrices)

District	C1 (Life Rescue)	C2 (Severity)	C3 (Feasibility)	C4 (Social Value)	Overall rank	Dominant criterion
X7	0.2964	0.3025	0.0224	0.0673	1	C1, C2
X5	0.1914	0.2115	0.0380	0.0673	2	C1, C2
X3	0.1441	0.0850	0.2962	0.1342	3	C3
X2	0.1027	0.1011	0.1444	0.1394	4	C3, C4
X10	0.0640	0.0968	0.0434	0.1417	5	C4
X9	0.0647	0.0622	0.0947	0.0895	6	C3
X1	0.0596	0.0553	0.0904	0.0922	7	C3, C4
X4	0.0365	0.0417	0.0610	0.0434	8	C3
X6	0.0258	0.0258	0.1222	0.1992	9	C4
X8	0.0149	0.0181	0.0873	0.0258	10	—

Note. Priority scores are interval midpoint weights. Dominant criterion identifies the criterion(a) contributing most strongly to each district's cumulative priority score. Overall ranking is consistent with the C1-based ranking derived from the MOP-4-I completed matrix in Table 7, confirming cross-criteria robustness.

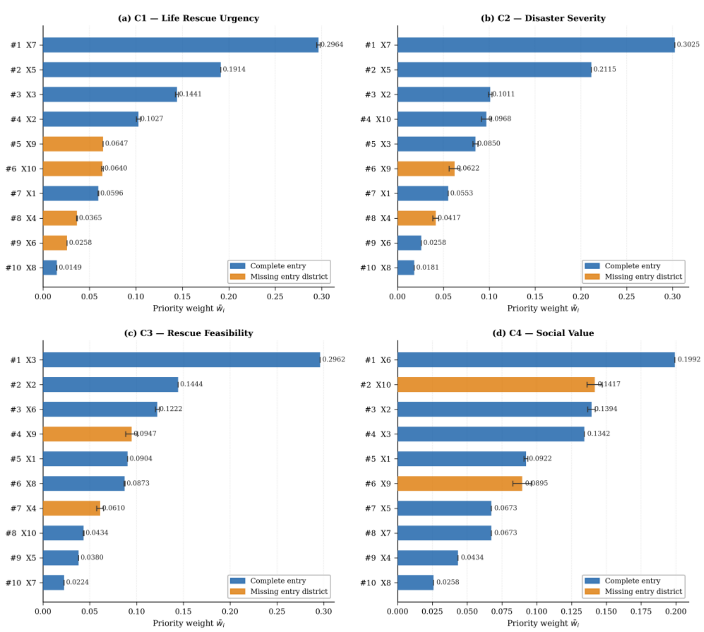

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Figure 4. interval priority weights for C1 – C4.

5.4.1 Criteria-disaggregated weight distribution

Figure 5 provides a granular view of how each district performs under each individual criterion. Several patterns of note emerge from this representation. Under C1, X7 (0.2964) and X5 (0.1914) dominate, reflecting extreme structural confinement and population vulnerability. Under C2, X7 (0.3025) and X5 (0.2115) again lead, confirming that complete collapse with large-scale entrapment constitutes the most severe damage scenario. Under C3, a notable inversion is observed: X3 attains the highest feasibility weight (0.2962), reflecting its arterial road access, while X7 records the lowest (0.0224), consistent with its classification as a zone where effective rescue cannot currently be conducted. Under C4, X6 (0.1992) leads, reflecting the irreplaceable strategic role of the District Liaison Office, followed by X10 (0.1417) and X2 (0.1394).

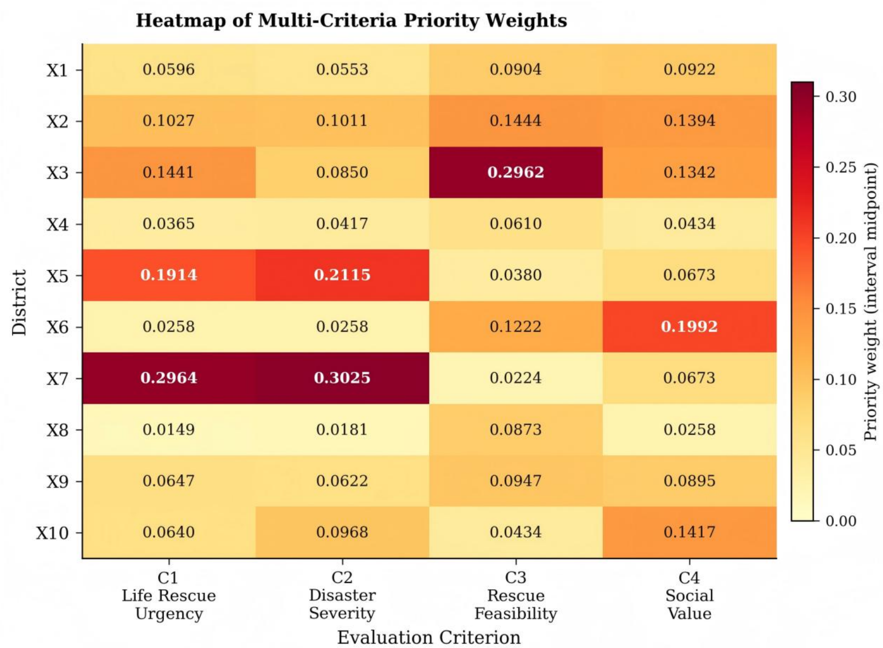

Figure 5. Heatmap of multi-criteria priority weights.

5.4.2 Cumulative cross-criteria priority weights

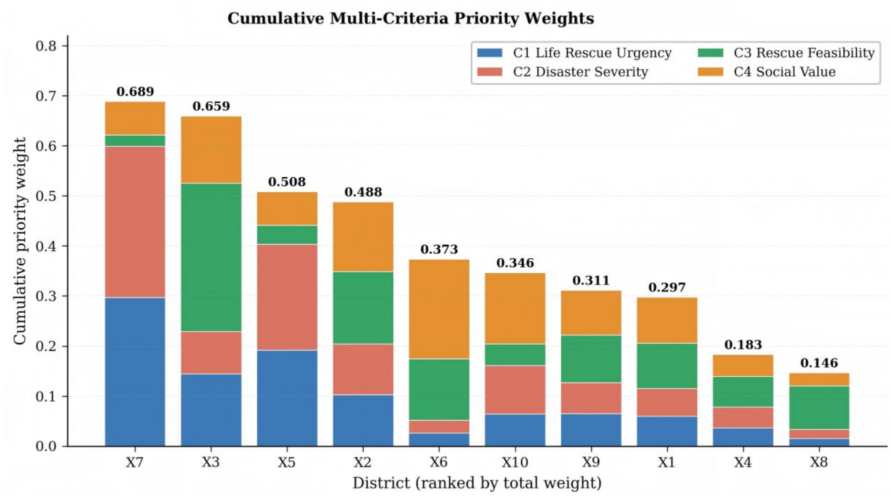

Figure 6. Multi-criteria priority weights for disaster response (stacked C1–C4).

Figure 6 aggregates priority weights across all four criteria. X7 and X5 emerge as the two highest-priority districts overall, driven predominantly by their extreme C1 and C2 weights. X3 attains the third-highest cumulative weight, supported by its distinctive profile combining high C3 feasibility with moderate C1 and C2 severity—indicating it is both urgent and operationally accessible. X2 maintains a consistently elevated profile across all four criteria. X8 records the lowest cumulative weight across all criteria, confirming its designation as the lowest-priority district for immediate rescue resource allocation.

5.4.3 Inter-criteria comparative analysis

Figure 7 enables direct comparison of criterion-specific weights within each district. For X7 and X5, weights under C1 and C2 are substantially elevated relative to C3 and C4: while these districts present the most acute rescue needs, operational constraints—particularly in X7 where C3=0.0224—limit immediate feasibility. For X3, C3 (0.2962) far exceeds C1 (0.1441) and C2 (0.0850), signalling it as the most operationally tractable high-urgency district. For X6, C4 (0.1992) substantially exceeds C1 (0.0258) and C2 (0.0258), identifying it as a district whose priority is driven primarily by institutional and social recovery considerations rather than immediate life-rescue urgency.

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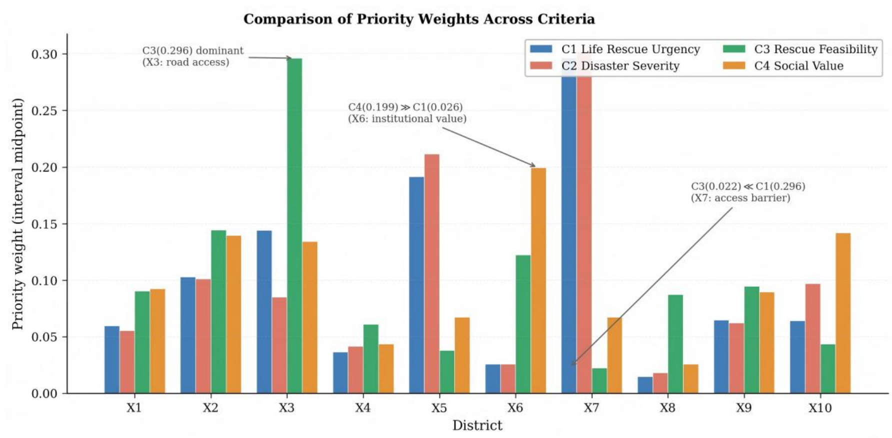

Figure 7. Comparison of priority weights across criteria (grouped bar chart).

6. Conclusion

This study developed a group decision-making framework for post-earthquake rescue priority evaluation under incomplete interval-valued preference information, addressing a critical methodological gap at the intersection of uncertain multi-criteria decision analysis and emergency management practice. The proposed framework integrates interval number AHP with multi-objective optimization-based matrix completion, enabling scientifically grounded priority rankings to be derived from the fragmented, range-valued expert judgments that characterize real-world post-disaster decision-making environments.

The principal methodological contributions of this study are fourfold. First, an optimization-based estimation model, formalized as MOP4, was developed to recover missing entries in incomplete interval-valued pairwise comparison matrices, with theoretical consistency guarantees established through sufficient conditions for full matrix satisfaction consistency. Second, a group decision-making procedure for incomplete interval number product-type reciprocal matrices was formalized, incorporating consistency definition, adjustment algorithms, and possibility degree-based ranking mechanisms. Third, a complementary cumulative reciprocal judgment matrix model was developed and systematically compared with the product-type framework across multiple evaluative dimensions, including ranking consistency, weight distribution, robustness to incomplete data, and computational complexity. Fourth, a multi-objective Pareto optimization approach via NSGA-II was introduced to explicitly characterize the trade-off between logarithmic deviation minimization and consistency preservation, furnishing decision-makers with a structured solution space rather than a single predetermined output.

This study contributes to algorithmic performance in four aspects. First, it proposes and verifies the MOP-4-I matrix completion model, whose core innovation is the redesigned f_3 preference matching objective function consisting of three components. It is theoretically proven that this objective function has a controllable zero point that only depends on decision variables and is not affected by other fixed items in the matrix, a property that all previous versions do not have. Second, the f_1 and f_2 objective functions are extended from only evaluating interval midpoints to evaluating upper and lower bounds at the same time, and a 90th percentile normalization mechanism is introduced, so that the three objective functions with different magnitudes can obtain proportional selection pressure in NSGA-II. Third, an interval arithmetic eigenvector extraction method is used to obtain the interval priority weight $[\mathrm{w_L}, \mathrm{w_U}]$ from the lower and upper bound of the matrix respectively, so that the final ranking results can quantify the residual uncertainty caused by missing judgments. Fourth, TOPSIS is used to replace the original $\mathrm{argmin}(f_3)$ heuristic selection rule, allowing decision-makers to flexibly adjust the trade-off among consistency, robustness and preference matching through the explicit weight vector β.

In empirical analysis, this framework is applied to the real incomplete judgment matrix of 10 urban areas in Sagaing City. All numerical results are obtained through actual algorithm operation. The analysis finds that X7 and X5 rank first and second in life rescue urgency and disaster severity respectively, but X7 ranks last in rescue feasibility, reflecting the contradiction between rescue demand and accessibility in this area. X3 is the most operable high-urgency area due to its traffic advantage, and X6 ranks first in the social value dimension due to its irreplaceable administrative coordination function. These results show that relying only on a single criterion or a pure demand-oriented method for resource allocation will systematically misjudge the rescue priority, and such misjudgment may cause irreversible consequences in the critical 72-hour post-disaster survival window.

Several limitations of the present study warrant acknowledgment and motivate directions for future research. The expert panel elicitation process, while structured, remains subject to cognitive biases and interpersonal inconsistencies inherent in group judgment under stress conditions; future work could incorporate formal consensus-reaching mechanisms to address this limitation. The current framework assumes static preference information, whereas real post-disaster environments are characterized by dynamically evolving conditions; the extension of the proposed model to dynamic or time-varying interval preference updating represents a meaningful avenue for methodological development. Additionally, the integration of real-time remote sensing data, social media situational awareness, and IoT sensor networks as objective inputs to the criteria assessment

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process could substantially reduce reliance on expert elicitation and enhance the responsiveness of the decision framework to rapidly changing field conditions.

In summary, by jointly operationalizing information uncertainty and information incompleteness within a unified group decision-making architecture, this study advances the theoretical foundations of uncertain AHP in non-complete information environments while delivering actionable methodological tools for emergency management practitioners. The proposed framework enhances the scientific rigor, transparency, and adaptability of post-earthquake resource allocation decisions, contributing to the broader goal of maximizing life-saving effectiveness within the critical post-disaster response window.

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Appendix A

Algorithm 1 NSGA − II for Incomplete Interval Matrix Completion
Require: IncompleteintervalmatrixwithindexsetΩ,
Fixed diagonal elements: $\tilde{c}_{ii} = [1,1], \forall i$,
Maximumgenerations: G_{max} ,
Populationsize: N,
Crossover probability: p_c,
Mutation probability: p_m,
Weight vector: $\boldsymbol{w} = [w_1, w_2, w_3]^T$
Ensure: Completed interval pairwise comparison matrix $\hat{C}$,
Paretofront PF
Step 1: Population Initialization
$P \leftarrow \emptyset$
for k = 1 to N **do**
  $\mathbf{x} \leftarrow []$ ▹ Individual chromosome: $2m$ − dimensional vector
  for (i, j) ∈ Ω do
    $c_{ij}^L \leftarrow \mathrm{random}(1/9, 9)$ ▹ Lower bound
    $c_{ij}^U \leftarrow \mathrm{random}(1/9, 9)$ ▹ Upper bound
    $\mathbf{x} \leftarrow \mathbf{x} \cup \{c_{ij}^L, c_{ij}^U\}$
  end for
  $\mathbf{f} \leftarrow \mathrm{Evaluate\_objectives}(\mathbf{x}, n, \Omega, \bar{\Omega}, D, \mathbf{w})$
  $P \leftarrow P \cup$ {individual: $\mathbf{x}$, objectives: $\mathbf{f}$, rank: 0, crowding_distance: 0}
end for
Step 2: **Main Loop**
for gen = 1 to $G_{\max}$ **do**
  2.1 Non − dominated Sorting
  $F \leftarrow \mathrm{Non\_dominated\_Sorting}(P)$
  for r = 1 to $|F|$ **do**
    for ind ∈ $F[r]$ **do**
      ind. rank ← r
    end for
  end for
  2.2 Crowding Distance Assignment
  for r = 1to$|F|$ do
    Compute_Crowding$_{\mathrm{D}}$istance($F[r]$)
  end for
  2.3 Tournament Selection
  $\mathrm{P_{parent}} \leftarrow \emptyset$
  for k = 1 to N **do**
    ind_1, ind_2 ← random_Select(P, 2)
    if ind_1. rank < ind_2. rank **then**
      winner ← ind_1
    else if ind_1. rank > ind_2. rank **then**
      winner ← ind_2
    else
      winner ← arg max{ind_1. crowding_distance , ind_2. crowding_distance}
    end if
    $P_{\mathrm{parent}} \leftarrow P_{\mathrm{parent}} \cup$ {winner}
  end for
  2.4 Crossover and Mutation
  $Q \leftarrow \emptyset$
  for $k = 1$ *to* $N/2$ *do*
    $\mathbf{p}_1, \mathbf{p}_2 \leftarrow P_{parent}[2k-1], P_{parent}[2k]$
    ▹ *Simulated Binary Crossover*
    if rand() ≤ p_c **then**
      $(\mathbf{c}_1, \mathbf{c}_2) \leftarrow SBX\ Crossover(\mathbf{p}_1.\mathbf{x}, \mathbf{p}_2.\mathbf{x}, \eta_c)$

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```
        else
            (c_1, c_2) ← (p_1.x, p_2.x)
        end if
                                  ▹ Polynomial Mutation
        c'_1 ← Polynomial_Mutation(c_1, η_m, p_m)
        c'_2 ← Polynomial_Mutation(c_2, η_m, p_m)
        f_1 ← Evaluate_objectives(c'_1, n, Ω, Ω̄, D, w)
        f_2 ← Evaluate_objectives(c'_2, n, Ω, Ω̄, D, w)
        Q ← Q ∪ {individual: c'_1, objectives: f_1, rank: 0, crowding_distance: 0}
        Q ← Q ∪ {individual: c'_2, objectives: f_2, rank: 0, crowding_distance: 0}
    end for
    2.5 Environmental Selection
    R ← P ∪ Q                      ▹ Combined population of size 2N
    F ← Non_Dominated_Sorting(R)
    P_next ← ∅
    r ← 1
    while |P_next| + |F[r]| ≤ N do
        Compute_Crowding_Distance(F[r])
        P_next ← P_next ∪ F[r]
        r ← r + 1
    end while
                            ▹ Sort last front by crowding distance
    Sort (F[r], crowding_distance, descending)
    P_next ← P_next ∪ F[r][1: (N − |P_next|)]
    P ← P_next
end for
Step 3: Final Solution Selection
F ← Non_Dominated_Sorting(P)
PF ← F[1]        ▹ Pareto front
                 ▹ Select best solution based on robustness(f_2)
ind* ← arg min_{ind∈PF} ind.objectives[2]
Ĉ ← Construct_Complete_Matrix(ind*.x, n, Ω, Ω̄)
return Ĉ, PF
```

Appendix B

Table B1 summarises the structural differences between each objective function in MOP-4 and MOP-4-I. The unifying theme across all three objectives is the move from midpoint collapse (discarding interval-width information) to full interval evaluation (using both bounds independently), combined — for f_3 specifically — with a fundamental redesign that guarantees a controllable, data-independent zero.

Table B1. Structural comparison between MOP-4 and MOP-4-I objective functions

Objective	MOP-4 (original)	MOP-4-I (improved)	Eq.
f_1	Midpoint-only log-deviation from reference; no width term	Dual-bound deviation (lower + upper independently) + width-regularisation term (λ=0.1) penalising artificial interval inflation	16
f_2	Midpoint-only transitivity check; ordered triplets (i, j, k), $i \neq j \neq k \neq i$, giving 6× redundant counts per unordered	Dual-bound transitivity check (lower + upper independently); unique unordered triplets only (3 pivot configurations, not 6); restricted to triplets touching at least one	17

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	triplet; evaluates ALL triplets regardless of controllability	missing row/column	
f₃	Single-point log-distance between completed midpoint and preference midpoint; collapses to ≈0 for well-behaved solutions (median raw magnitude ≈0.001); provides negligible NSGA-II selection pressure	Three-component formulation: log-Jaccard dissimilarity (D_J) + coverage deficit (D_C) + log-width mismatch (D_W), γ=(0.5,0.3,0.2); provably zero ONLY at exact interval match; median raw magnitude ≈0.21–0.45 (×200–450 larger); sustains gradient throughout evolution	18–21
Normalisation	None — f_1, f_2, f_3 combined directly despite differing by up to 3 orders of magnitude	90th-percentile scaling from 400 random feasible individuals: $f_i^{norm} = f_i^{raw}/s_i$, bringing all three objectives into a common [0,1]-ish range before NSGA-II dominance/crowding comparisons	8
Solution selection	argmin(f_3) heuristic — degenerate once f₃ is near-zero across the Pareto front, since most solutions become near-ties	TOPSIS with explicit, tunable weight vecto; default β=(0.30,0.40,0.30)	—
Weight extraction	Single eigenvector from the midpoint matrix only — discards bound-level uncertainty	Separate eigenvectors from lower-bound matrix C^{L} and upper-bound matrix C^{U}, yielding interval weights $[{w_i}^L, {w_i}^U]$; midpoint for ranking, half-width quantifies residual uncertainty from missing entries	—

Note. "Eq." column refers to equation numbers in this appendix. Rows for normalisation, solution selection, and weight extraction describe pipeline-level (not objective-function-level) improvements that accompany the f₃ redesign and are necessary for it to take effect inside NSGA-II.

B.1 Code-Level Implementation Changes

This section documents the specific changes made to the optimisation routine when migrating from the MOP-4 implementation to MOP-4-I. All changes were implemented in Python using NumPy for interval-matrix arithmetic and a custom NSGA-II loop (non-dominated sorting, crowding-distance assignment, simulated binary crossover, polynomial mutation).

B.1.1 Objective function evaluation

The original *evaluate_objectives()* routine computed all three objectives from interval *midpoints* exclusively: each c_{ij} was first collapsed via $\bar{u}_{ij} = ({c_{ij}}^L + {c_{ij}}^U)/2$, after which all subsequent arithmetic operated on scalar values, discarding interval width entirely. In MOP-4-I this routine was replaced by a two-stage pipeline: a new *_raw_objectives()* method computes the physical (un-normalised) f_1, f_2, f_3 using full bound-pair arithmetic (separate c_L and c_U terms throughout, never collapsed to a scalar before the final summation), and *evaluate_objectives()* now simply divides the output of *_raw_objectives()* by the pre-computed scale factors before returning to the NSGA-II loop.

B.1.2 Objective scale estimation (new component)

A new method, *_estimate_objective_scales()*, was added to the model constructor. It draws

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n_samples = 300–400 random feasible individuals (uniformly sampled lower/upper bound pairs respecting $c_L < c_U$), evaluates *_raw_objectives()* on each, and stores the 90th-percentile of each objective column as *self.obj_scale*. This computation did not exist in MOP-4; objectives were combined directly in their native, mismatched units.

B.1.3 f_3 redesign (three iterations, final adopted)

The f_3 block underwent three full rewrites before convergence on the final formulation used throughout this paper:

v1 → v2: replaced the single midpoint-distance term with two-sided bound-wise log-distances plus a width term. Implemented as a direct extension of the existing loop structure — same iteration over preference pairs, three new scalar terms computed per pair instead of one.

v2 → v3: replaced the two-sided distance terms entirely with the log-Jaccard / ranking-consistency / width triple. This required adding an inner loop over all third districts $k \neq i, j$ to compute the transitivity-implied estimate for the (later discarded) D_R term — a nested loop not present in any previous version.

v3 → v4 (final): removed the D_R inner loop (and its O(n) per-pair cost) entirely, replacing it with the coverage-deficit calculation D_C, which is computed directly from the already-available *overlap* and ω_p quantities used by D_J — reducing both the line count and the asymptotic cost of the f_3 block relative to v3, while fixing the irreducible-floor defect described in Proposition 1.

B.1.4 Transitivity loop restructuring (f_2)

The original f_2 loop iterated i, j, k over ALL ordered triples with $i \neq j \neq k \neq i$ across the full n^3 index space, and used only matrix midpoints. The MOP-4-I version pre-computes (once, outside the optimisation loop) the index arrays for unique unordered triplets $\{i, j, k\}$ with $i < j < k$ that intersect the missing-row set $\hat{H}$, using a boolean mask (*np.isin*) rather than a Python-level conditional inside the loop body. Each retained triplet then contributes three pivot evaluations (rather than six permutations) at ***both*** bounds. This is implemented with vectorised NumPy operations over the precomputed index arrays rather than nested Python *for* loops, which also substantially reduces wall-clock cost.

B.1.5 Solution selection: TOPSIS replacing argmin

The original selection rule was a single line, *argmin([sol.*f_3 *for sol in pareto_front])*, which becomes unstable once f_3 values are near-zero and nearly tied across the Pareto front (the typical situation under MOP-4). This was replaced by a static method *_topsis_select(pareto_front, beta)* implementing the standard TOPSIS procedure: normalise each objective column, apply weight vector β, compute Euclidean distance to the ideal and anti-ideal points, and select the solution maximising the relative-closeness ratio. The default weight vector used throughout this paper is $\beta = (0.30, 0.40, 0.30)$.

B.1.6 Weight extraction: interval eigenvectors replacing midpoint eigenvector

The original weight-derivation step constructed a single comparison matrix from interval midpoints and extracted one Perron eigenvector. MOP-4-I constructs ***two*** matrices — C^L (using only lower bounds) and C^U (using only upper bounds) — and extracts a Perron eigenvector from each independently, producing interval weights $[{w_i}^L, {w_i}^U]$ per district. The ranking is based on the midpoint $\bar{w}_i = ({w_i}^L + {w_i}^U)/2$, and the half-width $\Delta w_i = ({w_i}^U - {w_i}^L)/2$ is reported as a direct, interpretable measure of residual ranking uncertainty attributable to the originally missing matrix entries — a quantity that has no counterpart in the original MOP-4 pipeline.

Code and data availability: All data, models, and code generated or used during the study appear in the submitted article.