scientific reports

OPEN

Robust consensus ordinal priority approach for improvisational emergency supplier selection under expert consensus ambiguity

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Emergencies are inherently uncertain, urgent, and complex, rendering improvisational emergency supplier selection (IESS) a demanding multi-attribute decision-making (MADM) problem. Existing methods are constrained by subjective or opaque expert weight assignments, inadequate handling of conflicting or uncertain opinions, and high computational demands that limit their practicality in time-sensitive contexts. To address these limitations, this study introduces a Robust Consensus Ordinal Priority Approach (OPA-RC) for IESS. The method derives nominal expert importance scores objectively through a consensus-building mechanism based on pairwise ranking concordance among experts. These scores are incorporated into a robust optimization framework via a budget-based ambiguity set, explicitly capturing the ambiguity in the nominal expert importance scores rather than relying on potentially subjective pre-assignment. The proposed model is then reformulated as a tractable linear program with a closed-form solution, combining computational efficiency with decision robustness. A scenario-based experiment is conducted to verify the effectiveness of OPA-RC, including result analysis, sensitivity analysis, and comparison analysis. The findings indicate that OPA-RC provides a transparent, robust, and computationally efficient decision-support tool, enabling reliable and resilient supplier selection under extreme disaster conditions.

Keywords Improvisational emergency supplier selection, Multi-attribute decision-making, Expert consensus, Robust optimization, Robust Consensus Ordinal Priority Approach (OPA-RC)

In recent decades, disasters, including natural hazards, public health crises, and large-scale industrial accidents, have grown in frequency, scale, and complexity, repeatedly disrupting social and economic systems[1]. These events often impair supply chains for critical resources such as medical equipment, protective gear, and daily necessities, directly reducing emergency response effectiveness and increasing population vulnerability[2]. For example, during the first month of the COVID-19 outbreak in Wuhan, hospitals experienced shortages exceeding 70 percent for N95 masks, 60 percent for ventilators, and 50 percent for diagnostic kits, delaying medical services and raising infection risks for frontline healthcare workers. Facing extreme time pressure and incomplete information, authorities had to identify alternative suppliers without prior contracts or established evaluation procedures, demonstrating that emergency supplier selection under extreme conditions differs fundamentally from conventional pre-planned procurement[3,4].

Despite insights from extreme events, existing research largely maintains a planning-oriented perspective on emergency supplier selection[5]. Most studies assume a pre-disaster context in which candidate suppliers, evaluation criteria, and decision preferences are defined in advance, and decisions occur under relatively stable conditions. In contrast, supplier selection during extreme disasters is inherently improvisational. Decisions must be made after the event, when supply networks are partially disrupted, information is incomplete or unreliable, and stakeholder preferences may shift rapidly. Decision-makers must evaluate suppliers while adapting criteria and reconciling diverse expert judgments in real time[6]. This study focuses on improvisational emergency supplier selection (IESS), which differs fundamentally from conventional pre-disaster approaches. IESS involves decision-making under severe time pressure, high uncertainty, and dynamically evolving constraints, where traditional planning frameworks are often inadequate.

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Recent research has extensively applied multi-attribute decision-making (MADM) approaches to emergency supplier selection, yet studies explicitly addressing IESS remain limited. Existing work primarily extends MADM methods but faces persistent issues with subjective and opaque expert weight assignments. Many approaches rely on predefined or arbitrarily elicited weights, overlook expert consensus, and fail to derive weights directly from rankings or preference data, reducing transparency and increasing susceptibility to bias. Current methods also inadequately address ambiguity in expert opinions[7]. Although grey system theory and fuzzy theory are used to model imprecise judgments, evaluations are often treated as deterministic, diluting inherent ambiguity and relying on single representative values rather than accounting for unfavorable yet plausible assessments. Some advanced optimization-based models incorporate uncertainty and disagreement, but their computational complexity limits practical application in time-critical emergencies, where rapid and reliable decisions are essential[8]. Overall, these limitations highlight a fundamental mismatch: existing IESS approaches either depend on subjective inputs, neutralize expert ambiguity too early, or impose modeling complexity incompatible with the urgency and reliability required for improvisational emergency decision-making.

The objective of this study is to establish an appropriate MADM framework for IESS that ensures transparency and consistency in evaluating expert influence; incorporates the ambiguity of expert evaluations in the decision process; and provides practical and reliable decision support under severe time pressure. To this end, we propose a Robust Consensus Ordinal Priority Approach (OPA-RC) designed for IESS based on Ordinal Priority Approach (OPA). The proposed approach determines the relative importance of experts using a consensus mechanism that captures agreement in ranking data and embeds these scores within a robust optimization framework to account for uncertainty in expert influence. This is then reformulated as a tractable linear program with a closed-form solution, ensuring computational efficiency while preserving decision robustness. The primary contributions of this study are as follows:

- **Methodology contribution:** OPA-RC enhances decision-making under extreme uncertainty by explicitly accounting for expert evaluation uncertainty and potential conflicts. Unlike conventional methods that rely on subjective or predefined weights, it offers a transparent and objective mechanism for assessing expert influence. By integrating these scores into a robust optimization framework and reformulating the model as a linear program with a closed-form solution, the approach achieves a rare combination of robustness and computational efficiency.
- **Practice contribution:** OPA-RC delivers a reliable and actionable MADM-support tool for time-sensitive emergency contexts. Its consensus-driven mechanism promotes fairness and transparency in expert participation, while robustness ensures dependable decisions under divergent opinions and incomplete information. This capability is critical for IESS, where rapid, interpretable, and resilient decisions are essential to mitigate disaster impacts and protect frontline responders.

The remainder of the paper is structured as follows. Section Literature review reviews the relevant literature. Section Preliminary presents preliminaries. Section Robust consensus ordinal priority approach introduces OPA-RC, describing its formulation and solution procedure. Section Scenario experiment reports a scenario-based experiment to demonstrate the applicability of OPA-RC, including result analysis, sensitivity analysis, and comparison analysis. Section Conclusion concludes this study and outlines directions for future research.

Literature review

In emergency situations, the rapid procurement of critical supplies is vital for effective response. Selecting suitable suppliers is central to this challenge and is commonly framed as a MADM problem[9]. Traditional approaches involve data collection, weight assignment, and ranking, and they perform well under stable conditions with ample time and reliable information[10,11]. However, these methods are designed for preparedness phases, assuming low time pressure and limited uncertainty. In contrast, post-disaster environments are highly dynamic, uncertain, and time-sensitive, limiting the effectiveness of conventional techniques. To address this gap, IESS emphasizes the need for rapid, robust, and consensus-based decisions under extreme conditions[5].

Current IESS research employs a range of MADM methods, including GRA[12], TOPSIS[13], VIKOR[14], TODIM[7], BWM[6], MARCOS[15], MABAC[16], MACBETH[17], and DEMATEL[18]. Due to the difficulty of obtaining reliable data in emergency contexts, most studies rely on subjective expert assessments, while few incorporate objective data. These subjective inputs often appear as evaluation scores[13,14], linguistic expressions[12], pairwise comparisons[10,19], or hybrid forms[6,7]. Given the inherent uncertainty of crises and limits of expert knowledge, these data are inherently ambiguous and imprecise. To address this, grey systems[12,20], fuzzy sets[7,21], and rough sets[15,22,23] have been applied to better represent and process subjective data. Aggregating expert opinions remains critical. While traditional approaches use algebraic methods such as weighted averages or geometric means[24], recent research emphasizes consensus-building and trust networks to enhance collective judgment reliability[7]. These aggregation methods also integrate the behavioral tendencies of DM, recognizing that experts display heterogeneous risk preferences under uncertainty. Behavioral decision theories, including prospect theory[9,25] and regret theory[14], have been incorporated to capture these effects. For example, some frameworks employ probabilistic hesitant fuzzy sets with clustering to assign expert weights in large groups, others combine belief distributions with advanced MADM models to manage incomplete information, and some integrate hesitant fuzzy linguistic data with game-theoretic methods[7] or probabilistic linguistic data with TODIM enhanced by prospect theory[26].

Despite advances in applying MADM methods to emergency supplier selection, significant limitations remain, especially for IESS. Existing studies often rely on subjective or arbitrarily assigned expert and attribute weights, commonly determined using AHP[27], DEMATEL[18], or BWM[19,28]. These approaches typically overlook expert consensus and fail to derive weights from ranking or preference data, producing opaque procedures prone to individual bias. Current methods also inadequately address ambiguity and disagreement in expert opinions. While fuzzy sets and grey systems are sometimes used to represent imprecise judgments[29], they often reduce evaluations to deterministic or aggregated values, diluting uncertainty and potentially ignoring unfavorable but plausible scenarios. This weakens decision robustness, particularly when expert opinions diverge. Furthermore, the computational demands of advanced robust MADM models limit their practical use in time-sensitive emergencies. Traditional robust optimization formulations often require complex reformulations, increasing computational cost and reducing responsiveness during improvisational decision-making[8,30]. Collectively, these limitations highlight a mismatch between existing MADM-based IESS methods and the practical demands of emergency response, where subjective inputs, insufficient handling of expert ambiguity, and high model complexity constrain transparency, reliability, and timeliness.

Preliminary

This section outlines the preliminaries of OPA, covering its formulation and properties, which serve as the basis for deriving OPA-RC.

OPA is a novel optimization-based technique for solving the MADM problems under incomplete or uncertain information[24]. By formulating a linear programming model, OPA derives weights for experts, attributes, and alternatives simultaneously within a normalized weight space constructed from ordinal preference data[31]. Because it relies on ordinal rankings rather than cardinal scores or pairwise comparisons, OPA reduces data collection burden, enhances stability, and eliminates the need for procedures such as data normalization, expert aggregation, or prior weight estimation[32]. These advantages have led to its growing adoption in both group and individual decision-making contexts, with applications reported in areas such as carbon emission efficiency analysis[33], supplier selection[5,34,35], project portfolio management[36,37], postal and logistics networks design[38], and emergency recovery planning[29].

Consider a classical MADM problem where DM selects the best option from a set of K alternatives, $\mathscr{K} = \{1, 2, \ldots, K\}$, evaluated under J attributes $\mathscr{J} = \{1, 2, \ldots, J\}$, by I experts $\mathscr{I} = \{1, 2, \ldots, I\}$. Each expert $i \in \mathscr{I}$ is first assigned a priority level $t_i \in [I]$ based on factors such as education and expertise. Then, expert *i* provides: (i) a ranking $s_{ij} \in [J]$ for attribute $j \in \mathscr{J}$, and (ii) a ranking $r_{ijk} \in [K]$ for alternative $k \in \mathscr{K}$ with respect to attribute *j*. In OPA, experts act independently; their ordinal judgments are aggregated without group discussion. Rankings follow the convention that 1 denotes the highest importance, 2 the next, and so forth.

To simplify notation, define the following sets:

$$
\begin{aligned}
\mathscr{X}^1 &:= \{(i, j, k, l) \in \mathscr{I} \times \mathscr{J} \times \mathscr{K} \times \mathscr{K} : r_{ijl} = r_{ijk} + 1,\ r_{ijk} \in [K - 1]\}, \\
\mathscr{X}^2 &:= \{(i, j, k) \in \mathscr{I} \times \mathscr{J} \times \mathscr{K} : r_{ijk} = K\}, \\
\mathscr{Y} &:= \{(i, j, k) \in \mathscr{I} \times \mathscr{J} \times \mathscr{K}\}.
\end{aligned} \tag{1}
$$

Let $A_{ijk}^{(r_{ijk})}$ denote the evaluation of alternative *k* on attribute *j* given by expert *i*, with rank r_{ijk}. Denote by w_{ijk} the corresponding weight. Within the same attribute and expert, a higher-ranked alternative dominates a lower-ranked one:

$$
A_{ijl}^{(r_{ijl})} \preceq A_{ijk}^{(r_{ijk})}, \quad \forall (i, j, k, l) \in \mathscr{X}^1, \tag{2}
$$

which implies

$$
w_{ijl} \le w_{ijk}, \quad \forall (i, j, k, l) \in \mathscr{X}^1. \tag{3}
$$

The feasible weight space is defined as

$$
\mathscr{W} := \left\{ w_{ijk} \ge 0 : \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} w_{ijk} = 1 \right\}, \tag{4}
$$

where all weights are non-negative and normalized to sum to one.

To capture the relative influence of experts and attributes, OPA introduces ranking multipliers. The marginal effect of weights is then expressed as

$$
\delta(\mathrm{w}) = \begin{cases} \delta^1(w_{ijk}) = t_i s_{ij} r_{ijk}(w_{ijk} - w_{ijl}) \ge 0, & \forall (i, j, k, l) \in \mathscr{X}^1, \\ \delta^2(w_{ijk}) = t_i s_{ij} r_{ijk} w_{ijk} \ge 0, & \forall (i, j, k) \in \mathscr{X}^2, \end{cases} \tag{5}
$$

which formalizes the marginal utility of weight increments. Any w satisfying Eq. (4) and Eq. (5) is consistent with experts' rankings. To differentiate preferences as much as possible, OPA formulates a max-min optimization problem:

$$
\max_{\mathrm{w} \in \mathscr{W}} \delta(\mathrm{w}). \tag{6}
$$

Applying the max-min approach yields the equivalent linear program:

$$
\begin{aligned}
\max_{\mathrm{w} \in \mathscr{W}, z} \quad & z \\
\text{s.t.} \quad & z \leq \delta^1(w_{ijk}), \quad \forall (i,j,k,l) \in \mathscr{X}^1, \\
& z \leq \delta^2(w_{ijk}), \qquad \forall (i,j,k) \in \mathscr{X}^2,
\end{aligned}
\tag{7}
$$

where z is the weight disparity scalar. This yields the original OPA model[24]:

$$
\begin{aligned}
\max_{\mathrm{w}, z} \quad & z \\
\text{s.t.} \quad & z \leq t_i s_{ij} r_{ijk} (w_{ijk} - w_{ijl}), \quad \forall (i,j,k,l) \in \mathscr{X}^1, \\
& z \leq t_i s_{ij} r_{ijk} w_{ijk}, \qquad\qquad \forall (i,j,k) \in \mathscr{X}^2, \\
& \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} w_{ijk} = 1, \\
& w_{ijk} \geq 0, \qquad\qquad\qquad\quad \forall (i,j,k) \in \mathscr{Y}.
\end{aligned}
\tag{8}
$$

In the cases with single DM, parameters linked to multiple experts can be omitted. Finally, the aggregated weights of experts, attributes, and alternatives are obtained as

$$
\begin{aligned}
W_i^{\mathscr{I}} &= \sum_{j=1}^{J} \sum_{k=1}^{K} w_{ijk}^*, \quad \forall i \in \mathscr{I}, \\
W_j^{\mathscr{J}} &= \sum_{i=1}^{I} \sum_{k=1}^{K} w_{ijk}^*, \quad \forall j \in \mathscr{J}, \\
W_k^{\mathscr{K}} &= \sum_{i=1}^{I} \sum_{j=1}^{J} w_{ijk}^*, \quad \forall k \in \mathscr{K}.
\end{aligned}
\tag{9}
$$

Robust consensus ordinal priority approach

In this section, we propose OPA-RC to perform consensus-based robust evaluation of alternatives in IESS. Specifically, we first introduce the basic OPA-RC framework, then present a tractable reformulation, and finally examine its theoretical properties.

We begin with building the framework of OPA-RC. In practice, DMs are often asked to pre-rank experts by importance, a process that is inherently subjective and susceptible to bias, while experts' rankings may be unstable or conflicting. To address these issues, OPA-RC derives expert importance scores through a consensus-building mechanism based on the similarity of expert rankings, recognizing that correlation-based measures alone may be unreliable and should serve only as a reference[39]. Accordingly, OPA-RC integrates these consensus-based scores into a robust optimization framework via an ambiguity set, enhancing resilience to ranking uncertainty and eliminating the need for subjective pre-assignment of expert importance.

In OPA-RC, a nominal expert importance vector $\hat{\boldsymbol{\tau}}$ is first obtained from the degree of consensus among experts' ranking information. The underlying rationale is that experts whose rankings are more consistent with the group consensus are considered more reliable and thus assigned relatively higher nominal importance. To account for potential instability and conflicts in ranking information, as well as the limited reliability of correlation-based consensus measures, expert importance is treated as uncertain. Let $\tilde{\boldsymbol{\tau}} = (\tilde{\tau}_1, \ldots, \tilde{\tau}_I)$ denote a realization of expert importance scores that may deviate from the nominal values $\hat{\boldsymbol{\tau}}$ within a prescribed ambiguity set $\mathscr{U}(\hat{\boldsymbol{\tau}})$. Building on OPA in Eq. (8), OPA-RC is formulated as

$$
\begin{aligned}
\max_{\mathrm{w}, z} \quad & z \\
\text{s.t.} \quad & z \leq \tilde{\tau}_i s_{ij} r_{ijk} (w_{ijk} - w_{ijl}), \quad \forall \tilde{\tau} \in \mathscr{U}(\hat{\tau}),\ \forall (i,j,k,l) \in \mathscr{X}^1, \\
& z \leq \tilde{\tau}_i s_{ij} r_{ijk} w_{ijk}, \qquad\qquad \forall \tilde{\tau} \in \mathscr{U}(\hat{\tau}),\ \forall (i,j,k) \in \mathscr{X}^2, \\
& \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} w_{ijk} = 1, \\
& w_{ijk} \geq 0, \qquad\qquad\qquad\qquad\qquad\qquad \forall (i,j,k) \in \mathscr{Y},
\end{aligned}
\tag{10}
$$

which seeks a solution that remains feasible and optimal under the worst-case realization of $\tilde{\boldsymbol{\tau}}$ within the ambiguity set $\mathscr{U}(\hat{\boldsymbol{\tau}})$, thereby enhancing robustness against ambiguity and conflicts.

The key to implementing OPA-RC lies in the construction of the ambiguity set $\mathscr{U}(\hat{\boldsymbol{\tau}})$. In this study, we develop a budget-based ambiguity set by leveraging the similarity among attribute rankings s_{ij} provided by different experts. Given that the available data are rankings, Kendall's coefficient of concordance is used to measure similarity between expert rankings. Instead of a single global concordance, we calculate pairwise Kendall-based concordance values for all expert pairs to capture the structure of agreement at the expert level. For each pair (i, j), Kendall's concordance $W_{ij} \in [0, 1]$ is computed from their attribute rankings, with higher values indicating stronger agreement. Aggregating all pairwise concordances forms an expert similarity matrix. Using this structure, the nominal expert importance vector $\hat{\boldsymbol{\tau}} = (\hat{\tau}_1, \ldots, \hat{\tau}_I)$ is derived by averaging each expert's concordance with all other experts, so that experts whose rankings align more closely with the group consensus receive higher nominal importance.

Definition 1 Let $\hat{\boldsymbol{\tau}} = (\hat{\tau}_1, \ldots, \hat{\tau}_I)$ denote the nominal expert importance scores derived from the correlation of attribute rankings. The budget-based ambiguity set of $\tilde{\tau}$ is defined as

$$\mathscr{U}(\hat{\boldsymbol{\tau}}) = \left\{ \tilde{\boldsymbol{\tau}} \in \mathbb{R}_+^I : \ |\tilde{\tau}_i - \hat{\tau}_i| \leq \gamma_i, \ \forall i = 1, \ldots, I, \ \sum_{i=1}^{I} \frac{|\tilde{\tau}_i - \hat{\tau}_i|}{\gamma_i} \leq \Gamma \right\}, \tag{11}$$

where $0 \leq \gamma_i < \hat{\tau}_i$ is the maximum allowable deviation for expert *i*, and $\Gamma \geq 0$ is the uncertainty budget that controls the deviation of $\tilde{\boldsymbol{\tau}}$ from its nominal value $\hat{\boldsymbol{\tau}}$.
To preserve practical interpretability, γ is required to satisfy $\gamma < \hat{\tau}$, which ensures that the perturbed expert importance scores remain nonnegative and that deviations from the nominal consensus-based estimates stay within a plausible range. It is important to note that γ does not represent a DM-assigned importance level. Instead, it characterizes the uncertainty associated with the objectively derived nominal expert importance score $\hat{\tau}$. The exact value of γ is not uniquely determined and may vary across decision contexts, reflecting different levels of confidence in the nominal scores. Rather than prescribing a fixed rule for γ, it is specified within a reasonable range based on the problem setting, and its impact, together with the uncertainty budget Γ, is systematically examined through sensitivity analysis (see Section Parameter perturbation). This design follows the standard budgeted uncertainty framework, in which individual deviations are locally bounded while the overall level of conservatism is jointly controlled.

Building on this ambiguity set, the next step is to derive a tractable reformulation of OPA-RC. Specifically, we embed $\mathscr{U}(\hat{\boldsymbol{\tau}})$ into the original OPA framework and reformulate the resulting robust counterpart so that the worst-case impact of uncertain expert weights can be explicitly characterized and efficiently solved.

Proposition 1 *OPA-RC in Eq. (10) with the budget-based ambiguity set defined in Definition 1 is equivalent to the following deterministic linear programming problem:*

$$\begin{aligned} \max_{\mathrm{w}, z} \quad & z \\ \text{s.t.} \quad & z \leq \underline{\tau}_i s_{ij} r_{ijk} (w_{ijk} - w_{ijl}), && \forall (i,j,k,l) \in \mathscr{X}^1, \\ & z \leq \underline{\tau}_i s_{ij} r_{ijk} w_{ijk}, && \forall (i,j,k) \in \mathscr{X}^2, \\ & \sum_{i=1}^{K} \sum_{j=1}^{J} \sum_{k=1}^{M} w_{ijk} = 1, \\ & w_{ijk} \geq 0, && \forall (i,j,k) \in \mathscr{Y}, \end{aligned} \tag{12}$$

where for each expert i the worst-case lower bound is attained as

$$\underline{\tau}_i = 1 - \max\{0, \ \hat{\tau}_i - \gamma_i \min\{1, \Gamma\}\}. \tag{13}$$

Proof The proof details are provided in Supplementary Material.

Proposition 1 provides an explicit characterization of worst-case expert weights, showing precisely how nominal importance scores are adjusted under individual deviations and the overall budget of uncertainty. This closed-form result not only enhances interpretability by clarifying the extent to which each expert's influence may deteriorate in adverse scenarios, but also establishes a key theoretical contribution: the robust counterpart of OPA-RC remains a deterministic linear program, thereby ensuring both robustness and computational tractability. Beyond this tractable reformulation, an even stronger property holds: OPA-RC admits a closed-form optimal solution.

Associate each alternative index $k \in \mathscr{K}$ with its ranking position r_{ijk} and define the index set:

$$\mathscr{Z} := \{(i,j,r) : i \in \mathscr{I}, \ j \in \mathscr{J}, \ r \in \mathscr{R}\}. \tag{14}$$

Then, OPA-RC can be equivalently reformulated as[8]

$$\begin{aligned} \max_{\bar{\boldsymbol{w}}, z} \quad & z, \\ \text{s.t.} \quad & RU_r^{ROC} z \leq \underline{\tau}_i s_{ij} \bar{w}_{ijr}, && \forall (i,j,r) \in \mathscr{Z}, \\ & \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{r=1}^{R} \bar{w}_{ijr} = 1, \\ & \bar{w}_{ijr} \geq 0, && \forall (i,j,r) \in \mathscr{Z}, \end{aligned} \tag{15}$$

where $U_r^{ROC} = \left(\sum_{h=r}^{R} \frac{1}{h}\right)/R$ denotes the rank order centroid weight for the r-th ranked alternative.

Theorem 1 *OPA-RC admits the following unique closed-form solution:*

$$z^* = \left(\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{r=1}^{R} \frac{RU_r^{ROC}}{\underline{\tau}_i s_{ij}} \right)^{-1}, \tag{16}$$

and

$$\bar{w}_{ijr}^* = \frac{RU_r^{ROC} z^*}{\underline{\tau}_i s_{ij}}, \quad \forall (i,j,r) \in \mathscr{Z}. \tag{17}$$

Proof The proof details are provided in Supplementary Material. □

Theorem 1 establishes that OPA-RC admits explicit unique closed-form solutions for both the optimal weight disparity scalar and the associated weights. This is one of the most attractive features of the model, as it implies that the solution can be obtained directly through explicit analytical expressions without resorting to numerical optimization. After obtaining the optimal solution $(z^*, \bar{\boldsymbol{w}}^*)$, the components $\bar{w}_{ijr}^*$ are mapped to w_{ijk}^* in order to derive the corresponding weights of experts, attributes, and alternatives according to Eq. (9). The following corollary characterizes how this robust solution compares with the nominal OPA without robustness.

Corollary 1 *Let $z_{\text{OPA-RC}}^*$ and z_{OPA}^* denote the optimal weight disparity scalars of OPA-RC and OPA, respectively. Then*

$$z_{\text{OPA-RC}}^* \leq z_{\text{OPA}}^*. \tag{18}$$

Proof The proof details are provided in Supplementary Material.

Corollary 1 implies that the optimal weight disparity scalar under OPA-RC is always no greater than that under OPA. This finding underscores a fundamental trade-off: robustness against parameter uncertainty is achieved at the expense of reduced nominal performance. Specifically, the conservative adjustment in worst-case weights embodies DMs' ambiguity aversion, resulting in more balanced allocations rather than an exclusive pursuit of performance maximization.

The following Procedure 1 presents the implementation steps of OPA-RC. When implementing OPA-RC, it is important to note that the consensus constraint introduces additional robustness parameters (γ, Γ), but the overall computational complexity remains polynomial and comparable to that of the original OPA.

Step 1: Identify the elements of decision-making.
Determine the expert set $\mathscr{K}$, attribute set $\mathscr{J}$, and alternative set $\mathscr{I}$.
Step 2: Collect ranking information.
for each expert $i \in \mathscr{I}$ **do**
    Obtain the ranking s_{ij} of each attribute $j \in \mathscr{J}$ and the ranking r_{ijk} of each alternative $k \in \mathscr{K}$ under attribute $j \in \mathscr{J}$.
end for
Step 3: Construct nominal expert importance scores.
Compute the average Kendall's W coefficient across experts' attribute rankings to obtain the nominal expert importance scores $\hat{\boldsymbol{\tau}} = (\hat{\tau}_1, \ldots, \hat{\tau}_I)$.
Step 4: Construct the ambiguity set.
Construct the budget-based ambiguity set $\mathscr{U}(\hat{\boldsymbol{\tau}})$ according to Definition 1, with deviation parameters $\boldsymbol{\gamma}$ and uncertainty budget Γ.
Step 5: Reformulate the robust optimization problem.
Embed $\mathscr{U}(\hat{\boldsymbol{\tau}})$ into OPA and derive the robust counterpart in Eq. (10).
Obtain the equivalent deterministic linear program in Eq. (12).
Step 6: Solve for the optimal weights.
Apply the closed-form solution in Theorem 1 to compute the optimal solution z^* and $\bar{w}_{ijr}^*$.
Step 7: Aggregate decision outcomes.
Calculate expert weights $\boldsymbol{w}^{\mathscr{K}}$, attribute weights $\boldsymbol{w}^{\mathscr{J}}$, and alternative weights $\boldsymbol{w}^{\mathscr{I}}$.

Procedure 1. Implementation steps of OPA-RC.

Scenario experiment

Scenario description

To evaluate the applicability of OPA-RC in IESS, we design a scenario experiment based on the 2023 Turkey-Syria Earthquake. On February 6, 2023, a 7.8-magnitude earthquake struck southeastern Turkey and northern Syria, causing widespread building collapses, transportation disruptions, and failures in electricity and communication systems. These cascading effects generated urgent demand for medical supplies, food, shelter, and heating equipment. The disaster's unprecedented scale and sudden onset quickly exceeded the capacity of pre-identified suppliers, forcing emergency authorities and international organizations to rapidly redesign the supply network. Decision-making under these conditions faced severe time pressure, high uncertainty, and multiple stakeholder involvement. Unlike traditional case studies that retrospectively describe events, this study uses a scenario experiment to reconstruct the disaster context and test the proposed model. This design provides a controlled yet realistic evaluation, allowing assessment of how the robust approach handles uncertainty and consensus, and highlighting its advantages over existing methods in practical emergency decision-making.

In this scenario experiment, 15 emergency suppliers (A1–A15) were selected for evaluation. These candidates included national logistics firms, international NGO warehouses, regional pharmaceutical companies, and local commercial enterprises. Their capabilities varied significantly. Some suppliers offered reliable cross-border transportation and broad geographic coverage at higher costs, while local warehouses enabled rapid response but faced limited stock. International humanitarian organizations could provide large-scale donations of essential goods but often encountered customs and coordination delays. This heterogeneity highlights the trade-offs that must be systematically considered in supplier selection.

To ensure comprehensive assessment, eight criteria were considered:

- **Response speed (C1)**: the ability of suppliers to mobilize and deliver emergency resources promptly after a disaster occurs.
- **Delivery reliability (C2)**: the consistency and dependability of suppliers in fulfilling commitments without delays or disruptions.
- **Geographic coverage (C3)**: the extent to which suppliers can provide services across the affected regions, including remote or hard-to-reach areas.
- **Operation sustainability (C4)**: the capacity of suppliers to maintain continuous operations and stable resource provision over an extended response period.
- **Collaborative experience and credibility (C5)**: prior cooperation with emergency agencies and established trustworthiness in disaster relief.
- **Availability (C6)**: the immediacy and sufficiency of emergency supplies that can be mobilized at short notice.
- **Quality (C7)**: the standard and safety of the supplied resources, ensuring they meet emergency requirements.
- **Cost-effectiveness (C8)**: the balance between supply costs and the efficiency of resource delivery in crisis contexts.

To capture diverse perspectives on emergency supplier selection, we convened a panel of five experts with extensive experience in disaster response and logistics management. The panel included representatives from the Turkish Disaster and Emergency Management Authority, the Turkish Ministry of Health, the International Red Cross, a local government agency, and a leading logistics company. These experts were chosen to ensure coverage of both public and private sector perspectives and to balance operational and strategic considerations. Their relative authority and involvement in disaster response operations were prioritized as follows: E5 > E3 > E1 > E4 > E2. Each expert evaluated the key attributes for emergency supplier selection and ranked a set of candidate suppliers accordingly. The evaluation captured both the perceived importance of each attribute and the comparative performance of suppliers under realistic emergency scenarios. Data were collected via structured questionnaires and follow-up interviews to clarify ambiguous responses and ensure consistency. All judgments were systematically recorded, and the resulting attribute and supplier rankings form the primary dataset for the OPA-RC analysis.

Scenario result

Figure 1 presents the pairwise Kendall's W heatmap among experts. Coefficients range from 0.8690 to 1.000, indicating overall strong agreement in their rankings. E1 shows particularly high concordance with most other experts, while the lowest agreement occurs between E3 and E4, reflecting some divergence. Even so, the minimum pairwise consistency exceeds 0.8690, demonstrating a high level of group consensus. Consistently, the final expert weights from OPA-RC follow a similar pattern: E1 holds the highest weight (0.2355), followed by E2 (0.2165), E5 (0.1932), E4 (0.1833), and E3 (0.1716), as shown in Fig. 2a.

Figure 2b presents the attribute weights derived from OPA-RC. Response speed (C1) (0.2832) and delivery reliability (C2) (0.2470) together account for over half of the total weight, highlighting that IESS decisions are primarily driven by the ability to deploy resources rapidly and deliver them without disruption, as failures in these areas directly amplify human and economic losses. Once these time-sensitive requirements are met, geographic coverage (C3) (0.1385) becomes the next critical factor, indicating that spatial accessibility and network flexibility provide strategic advantages, especially in widespread or infrastructure-constrained disasters. Operation sustainability (C4) (0.0906), collaborative experience and credibility (C5) (0.0788), and availability (C6) (0.0601) carry moderate weights, suggesting that long-term stability, inter-organizational trust, and inventory readiness primarily support risk mitigation but cannot offset deficiencies in speed or reliability during immediate response. In contrast, quality (C7) (0.0547) and cost-effectiveness (C8) (0.0471) are least emphasized, reflecting a conscious shift from conventional procurement priorities and indicating that DMs accept higher

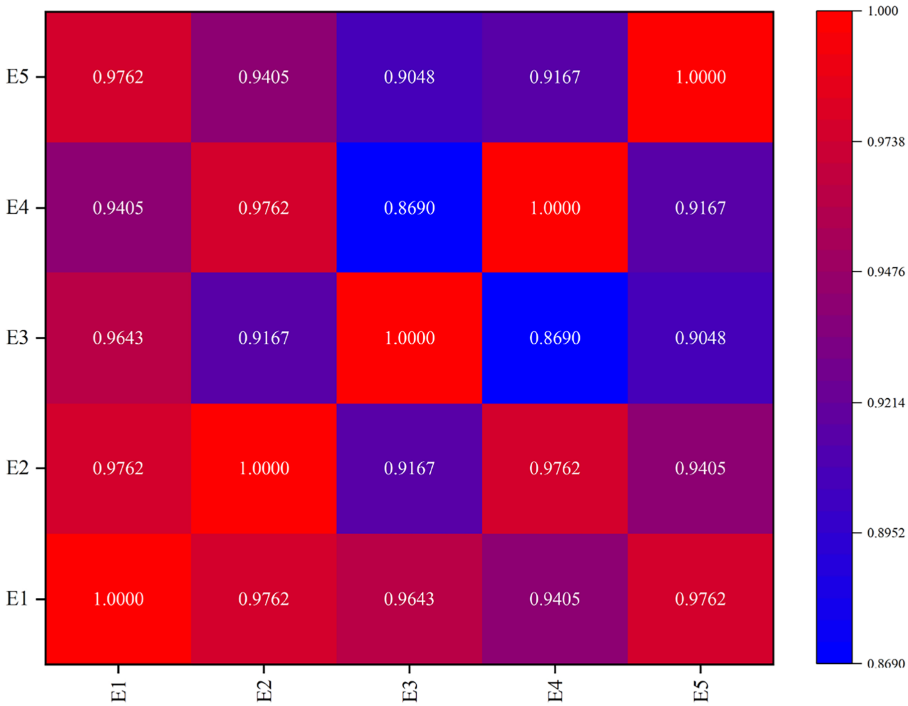
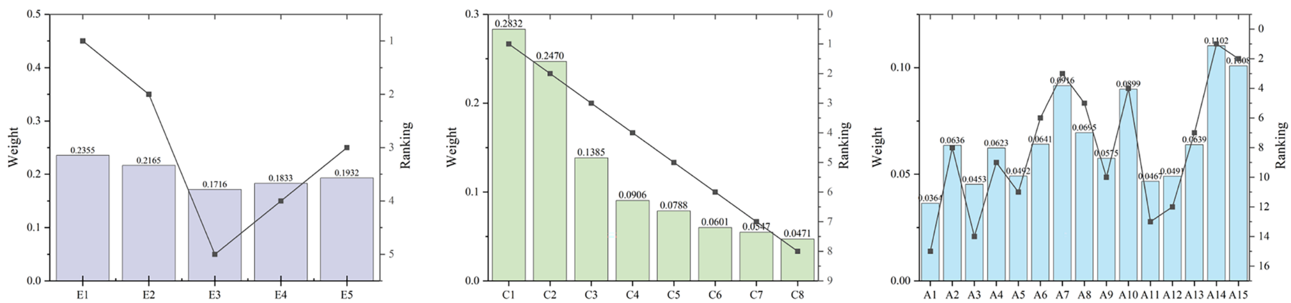


Fig. 1. Pairwise Kendall's *W* heatmap among experts.



(a) Expert **(b)** Attribute **(c)** Alternative

Fig. 2. Weight and ranking results of the case IESS.

costs and potential quality trade-offs to ensure rapid and reliable delivery, underscoring the key distinction between emergency supplier selection and routine procurement under urgent conditions.

Figure 2c shows the alternative weights derived from OPA-RC. Alternatives A14 (0.1102) and A15 (0.1008) are the top-ranked suppliers, followed by A7 (0.0916) and A10 (0.0899), primarily due to their strong performance on the most influential attributes, response speed and delivery reliability, which dominate the overall weighting. The pronounced strengths of A14 and A15 in these dimensions reflect superior rapid mobilization and reliable logistics, aligning with the urgency and risk sensitivity of disaster response and explaining their lead despite smaller differences in secondary attributes. Mid-ranked alternatives such as A8 (0.0695), A6 (0.0641), A13 (0.0639), and A2 (0.0636) show balanced but less distinctive performance; moderate limitations in speed, reliability, or geographic coverage prevent them from matching top-tier suppliers, positioning them as suitable backup or complementary options. Lower-ranked alternatives, including A3 (0.0453) and A1 (0.0364), underperform on critical, time-sensitive attributes, and their better scores on less influential criteria such as cost or quality do not compensate for these weaknesses, highlighting a key insight: in IESS, rapid response and reliable delivery cannot be offset by conventional procurement strengths.

Sensitivity analysis

This section presents a sensitivity analysis of OPA-RC, comprising two parts. The first examines parameter perturbation by varying the ambiguity set size to assess its impact on result robustness. The second addresses input perturbation, modifying alternative rankings to evaluate the stability of the derived solutions.

Parameter perturbation
This section evaluates the robustness of OPA-RC under parameter perturbations and derives practical insights for emergency supplier selection[40]. Individual uncertainty budgets γ_i and the overall budget Γ were varied by $\pm5\%$, $\pm10\%$, and $\pm15\%$, and the resulting changes in alternative weights and ranking stability were assessed.

The analysis shows that perturbations in both individual and overall budgets produce consistent structural effects, confirming the theoretical derivation of the lower consensus bound ($\underline{\tau}$). Across all scenarios, the average worst-case consensus parameter $\underline{\tau}$ ranged from 0.0966 to 0.1610 around a baseline of 0.1295, while the optimal disparity z^* varied between 0.00852 and 0.0103, representing a relative change of 19.03%. These results indicate that γ and Γ exert comparable influence on consensus robustness, supporting the stability of OPA-RC under moderate uncertainty. Ranking stability was preserved for the top- and bottom-ranked suppliers, with only up to four mid-ranked alternatives shifting positions under the $\pm10\%$ perturbation. Table 1 presents the floating ratio of alternative weights, showing the largest fluctuations in specific alternatives, such as A15. Under more conservative settings with increased uncertainty budgets, top-ranked supplier weights decreased slightly, with corresponding increases for lower-ranked alternatives. This pattern indicates that OPA-RC balances robustness and fairness, preventing excessive weight concentration on a few suppliers and highlighting candidates suitable for secondary or complementary deployment.

The parameter perturbation results indicate that the model's consensus measures scale proportionally with changes in individual and overall uncertainty budgets, confirming that γ and Γ exert similar structural effects. Notably, top- and bottom-ranked suppliers remain stable across all perturbations, demonstrating that critical suppliers are resilient to moderate fluctuations. In contrast, mid-ranked alternatives are more sensitive, as small changes in uncertainty budgets can shift their relative positions. This differential sensitivity suggests that the ranking of key suppliers is robust, whereas secondary suppliers are more context-dependent.

Input perturbation
This section evaluates the sensitivity of OPA-RC to perturbations in alternative rankings. Perturbed samples are generated by treating the original ranking as the mean and adding noise with variance 0.5. For each sample, alternative weights and the resulting rankings are calculated. The overall distribution of weights across samples is summarized using the mean, standard deviation, minimum, maximum, and the 25%, 50%, and 75% quantiles.

The input perturbation analysis confirms that fluctuations in alternative rankings do not affect expert or attribute weights. This property, consistent with the analytical solution of OPA-RC, indicates that input perturbations only alter the allocation of weights among alternatives without impacting higher-level decision parameters. Figure 3 presents the resulting alternative weights. As shown in Table 2, mean weights remain close to baseline values, and standard deviations are small, mostly below 0.005, indicating limited variability across samples. Minimum-maximum ranges are narrow, showing that no alternative experiences substantial deviations under noisy inputs. For instance, top-ranked alternatives A2 and A13 exhibit high mean weights (0.0752 and 0.0754) with stable dispersion. In contrast, A1 and A5 show slightly larger fluctuations, indicating moderate sensitivity. Quartile statistics further confirm robustness, with interquartile ranges tightly concentrated, typically within 0.004 to 0.006, ensuring the central 50% of weight realizations remain highly stable.

The input perturbation analysis shows that variations in alternative rankings mainly influence weight allocation among alternatives without affecting higher-level decision parameters. Small standard deviations and narrow interquartile ranges indicate that OPA-RC maintains the relative weight structure under noisy inputs, with top alternatives retaining high mean weights and low dispersion, while lower-ranked alternatives exhibit minor variability. These results suggest that the method effectively filters input noise, ensuring stable decision outcomes.

Alternative	15%	10%	5%	-5%	-10%	-15%
A1	0.25%	0.17%	0.09%	-0.09%	-0.19%	-0.29%
A2	0.05%	0.03%	0.02%	-0.02%	-0.04%	-0.07%
A3	-0.07%	-0.05%	-0.03%	0.03%	0.06%	0.09%
A4	-0.34%	-0.23%	-0.12%	0.13%	0.27%	0.41%
A5	0.31%	0.21%	0.11%	-0.12%	-0.24%	-0.37%
A6	0.26%	0.18%	0.09%	-0.10%	-0.20%	-0.32%
A7	0.36%	0.25%	0.13%	-0.14%	-0.29%	-0.45%
A8	0.81%	0.55%	0.28%	-0.30%	-0.63%	-0.97%
A9	0.45%	0.31%	0.16%	-0.17%	-0.35%	-0.55%
A10	-0.01%	-0.01%	0.00%	0.00%	0.01%	0.01%
A11	-0.01%	-0.01%	0.00%	0.01%	0.01%	0.02%
A12	0.09%	0.06%	0.03%	-0.04%	-0.07%	-0.12%
A13	-0.43%	-0.30%	-0.15%	0.17%	0.34%	0.54%
A14	-0.25%	-0.17%	-0.09%	0.09%	0.19%	0.29%
A15	-0.82%	-0.56%	-0.29%	0.31%	0.64%	1.00%

Table 1. Floating ratio of alternative weights under budget perturbations.

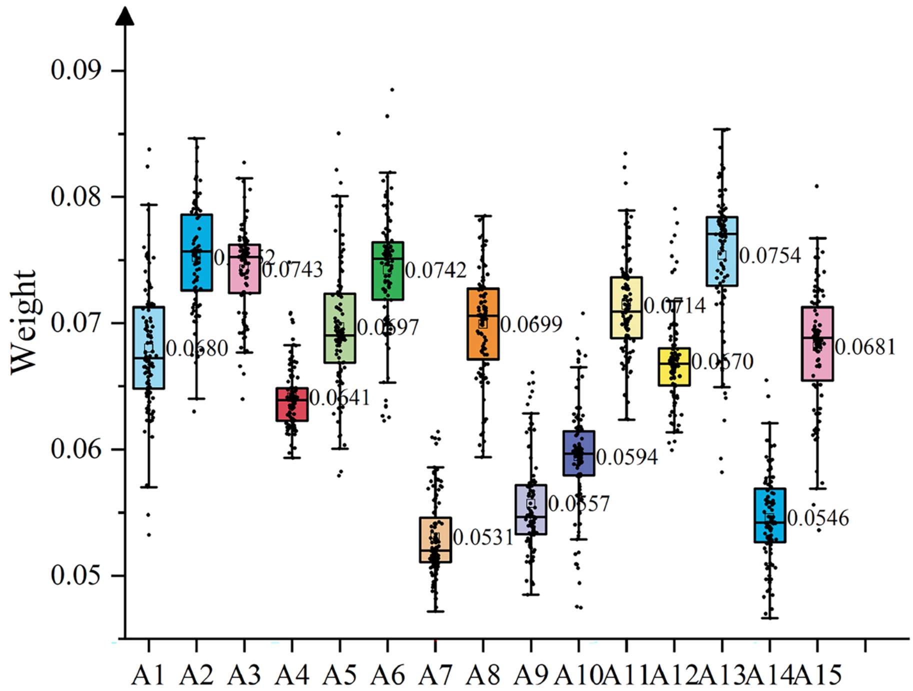


Fig. 3. Alternative weight results under ranking perturbations.

Alternative	Mean	Std	Min	Max	25% quartile	50% quartile	75% quartile
A1	0.0680	0.0052	0.0532	0.0838	0.0648	0.0672	0.0712
A2	0.0752	0.0042	0.0630	0.0846	0.0726	0.0757	0.0785
A3	0.0743	0.0034	0.0640	0.0827	0.0724	0.0753	0.0762
A4	0.0641	0.0025	0.0593	0.0748	0.0623	0.0639	0.0648
A5	0.0697	0.0051	0.0579	0.0850	0.0669	0.0690	0.0723
A6	0.0742	0.0047	0.0622	0.0885	0.0719	0.0751	0.0764
A7	0.0531	0.0032	0.0472	0.0614	0.0511	0.0520	0.0544
A8	0.0699	0.0043	0.0594	0.0785	0.0673	0.0706	0.0727
A9	0.0557	0.0040	0.0485	0.0704	0.0533	0.0547	0.0572
A10	0.0594	0.0043	0.0475	0.0708	0.0580	0.0597	0.0614
A11	0.0714	0.0040	0.0624	0.0835	0.0688	0.0709	0.0736
A12	0.0670	0.0036	0.0599	0.0791	0.0651	0.0668	0.0680
A13	0.0754	0.0053	0.0582	0.0853	0.0731	0.0771	0.0784
A14	0.0546	0.0036	0.0466	0.0655	0.0527	0.0542	0.0568
A15	0.0681	0.0048	0.0536	0.0809	0.0656	0.0688	0.0711

Table 2. Statistics results of alternative weights under ranking perturbations.

Comparison analysis

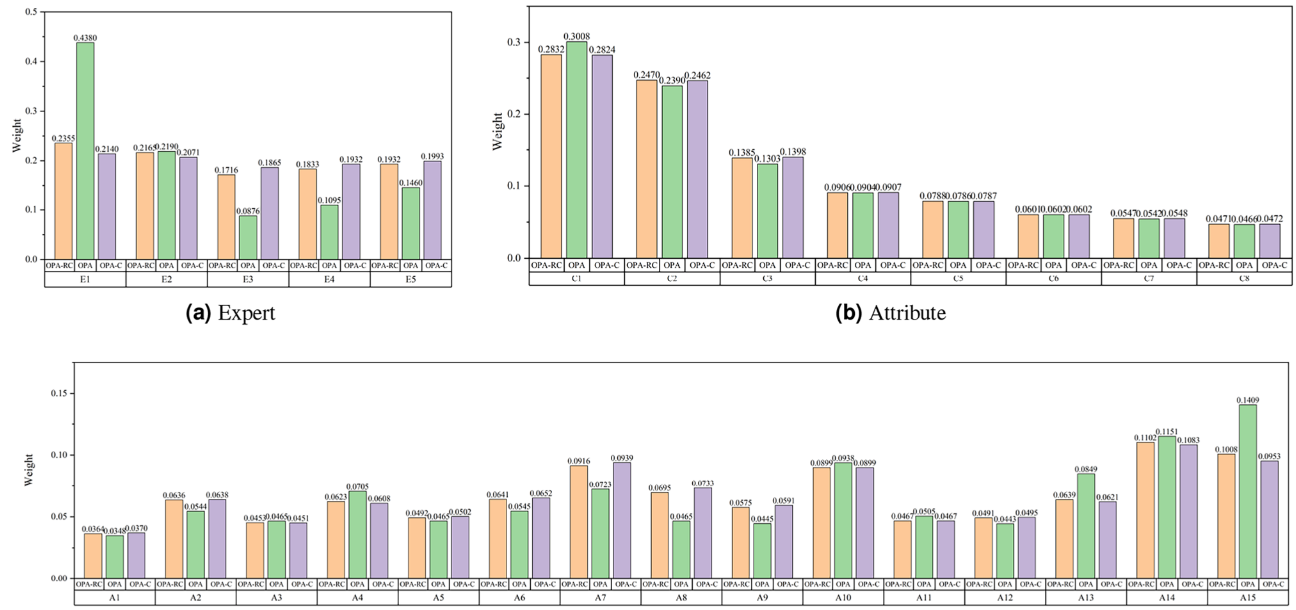
This section compares the proposed OPA-RC with two benchmarks: OPA and a consensus-adjusted variant, OPA-C. All methods are applied to the same ranking data. The comparison considers expert weight dispersion, attribute importance distribution, ranking stability, uncertainty management, and computational efficiency.

We include OPA and its consensus-adjusted variant as benchmarks:

- **OPA**[24]: Expert weights are assigned directly from pre-specified ranks ρ_i, with smaller values indicating higher importance:

$$\tau_i^{\mathrm{OPA}} = \rho_i, \quad i = 1, \ldots, I, \tag{19}$$

which are treated as deterministic and do not reflect expert consensus.



(a) Expert **(b)** Attribute

(c) Alternative

Fig. 4. Weight comparison among different models.

- **Corrected OPA (OPA-C)**[29]: To incorporate consensus, each expert rank ρ_i is adjusted via a nonlinear transformation based on the mean Kendall's W value $\bar{W}_i$:

$$\tau_i^{\text{OPA-C}} = \rho_i^{\frac{(1-\bar{W}_i)\cdot c}{\log(I)}}, \quad i = 1, \ldots, I, \tag{20}$$

where $c = 1.9912$ calibrates the effect of consensus. This method partially accounts for agreement among experts but still produces point estimates.

The rationale for selecting these benchmarks is twofold. First, OPA represents the original method and serves as a natural baseline. Second, OPA-C is, to our knowledge, the only variant that explicitly incorporates expert consensus. Notably, it alters OPA's internal structure rather than combining it with external techniques, making it a structurally distinct extension.

Figure 4 presents the comparative results. In expert weight allocation, OPA shows large disparity, assigning 0.438 to E1 while compressing E3–E5 below 0.12. OPA-C reduces this imbalance but remains skewed. OPA-RC produces a narrower range (0.171–0.236), reflecting both differences in authority and uncertainty in expert influence. For attribute importance, all methods identify response speed (C1) and delivery reliability (C2) as dominant. OPA overemphasizes C1 (0.301) and underweights C2 (0.239). OPA-C partially corrects this bias, whereas OPA-RC delivers a more balanced allocation (0.283 for C1, 0.247 for C2) and smoother distribution across secondary criteria, aligning with the multi-objective nature of emergency response. Regarding alternative ranking, all methods agree on top- and bottom-ranked suppliers but differ in mid-tier positions. OPA's deterministic weights produce unstable rankings for alternatives with weak consensus. OPA-C improves stability but remains sensitive to parameter calibration. OPA-RC achieves the highest consistency, especially among mid-ranked suppliers, due to its worst-case-oriented treatment of expert weight uncertainty. Methodologically, OPA and OPA-C handle uncertainty implicitly or partially, while OPA-RC explicitly models uncertainty in expert influence through robust optimization. Despite this enhancement, OPA-RC remains computationally tractable via linear reformulation and closed-form solutions, making it suitable for time-critical emergency contexts.

Currently, MADM methods for emergency supplier selection fall into two categories. Weighting methods, such as OPA, AHP, BWM, and FUCOM, assign weights to experts, criteria, or alternatives. Ranking-based methods, including TOPSIS, VIKOR, PROMETHEE, and ELECTRE, derive preferences from decision matrices. The proposed OPA-RC integrates both weighting and ranking, addressing key limitations of conventional approaches. Unlike ranking methods that require complete decision matrices, OPA-RC relies solely on accessible ranking data, reducing collection costs and limiting the impact of incomplete or low-quality inputs. Unlike traditional weighting methods, which often depend on subjective or pre-specified expert weights, OPA-RC objectively derives expert importance scores from ranking data through a consensus mechanism and embeds them within a robust optimization framework. This approach removes arbitrary weight assignments, incorporates expert agreement, and explicitly accounts for uncertainty and potential conflicts, features largely absent in OPA and its corrected variants. OPA-RC also produces balanced distributions of expert and attribute weights, stabilizes alternative rankings, and enhances interpretability, fairness, and decision robustness.

In summary, OPA-RC provides the following advantages:

- Relies on accessible ranking data, avoiding prespecified weights or complete decision matrices.
- Follows a robust optimization framework that incorporates objectively derived expert importance scores with consensus, accounting for ambiguity while reducing subjectivity.
- Maintains computational efficiency through linear program reformulation.
- Produces balanced, stable, and interpretable weights and rankings, making it particularly suitable for IESS under severe time pressure.

Conclusion

This study introduces OPA-RC to address critical challenges in IESS, including severe uncertainty and conflicting expert opinions. OPA-RC derives expert importance scores through a consensus mechanism based on ranking similarity and embeds these scores within a robust optimization framework. Unlike traditional MADM methods, it eliminates subjective weight assignments and directly integrates consensus-driven rankings into a tractable linear model with a closed-form solution, ensuring transparency and computational efficiency. The key innovation of OPA-RC lies in combining consensus measurement with robust optimization, preserving the diversity of expert views while ensuring solution resilience under worst-case scenarios. Practically, this framework provides DMs with a reliable tool to manage uncertainty and time pressure in emergency contexts. By enabling rapid, transparent, and robust supplier selection, OPA-RC helps reduce supply chain risks and mitigate potential losses in disaster response. Overall, this study advances IESS by offering a valuable decision support tool for practitioners in high-stakes emergency management.

The scenario experiments offer several managerial insights for emergency supplier selection. First, DMs should prioritize suppliers' rapid mobilization and reliable delivery, as these capabilities critically determine effective disaster response, outweighing traditional factors such as cost or quality. The findings support a tiered supplier strategy, with top-ranked suppliers serving as primary responders and mid-ranked but stable alternatives acting as backup or complementary options to enhance resilience. The robustness of leading suppliers under both parameter and input perturbations indicates that early identification of a small set of decisive suppliers can reduce risk and support confident decision-making despite uncertainty or incomplete information. Additionally, the redistribution of weights under conservative uncertainty settings emphasizes the value of maintaining a diversified supplier portfolio to avoid dependence on a single entity. Finally, the high expert consensus achieved through structured, ranking-based evaluation demonstrates the managerial benefit of systematic, multi-stakeholder elicitation processes, which efficiently aggregate judgments while preserving consistency and robustness under high-pressure conditions. Together, these insights provide practical guidance for designing agile, reliable, and uncertainty-resilient emergency procurement strategies.

It should be noted that the conclusions of this study are based on a limited scenario experiment, which may not fully reflect the diversity of real-world emergency contexts. First, the proposed model assumes independence among evaluation attributes, simplifying the decision process but potentially overlooking interactions between criteria. Future research could enhance OPA-RC by incorporating attribute interdependencies to improve realism and applicability. Second, the current model does not explicitly consider DMs' risk preferences, which play a crucial role in emergency settings where risk attitudes strongly influence judgments. Integrating risk preference modeling into OPA-RC represents a promising avenue for enabling more adaptive and context-sensitive supplier selection under extreme uncertainty. Third, although OPA-RC has been demonstrated with a moderate number of experts, real-world IESS often involves large-scale expert groups from diverse organizations and domains, introducing challenges in building consensus, resolving conflicts, and maintaining robustness. Future work could extend OPA-RC to large-scale group decision-making, potentially by incorporating clustering, opinion dynamics, or hierarchical consensus mechanisms.

Data availability

Data will be made available on request from the first author via email at: hezheng002@e.ntu.edg.sg.

Received: 30 September 2025; Accepted: 16 January 2026
Published online: 27 January 2026

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Funding
This research received no external funding.

Declarations

Competing interests
The authors declare no competing interests.

Additional information
Supplementary Information The online version contains supplementary material available at https://doi.org/10.1038/s41598-026-36876-6.

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