Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

A hybrid MADM method considering expert consensus for emergency recovery plan selection: Dynamic grey relation analysis and partial ordinal priority approach

Renlong Wang

School of Emergency Management Science and Engineering, University of Chinese Academy of Sciences, Beijing 100049, China

ARTICLE INFO

Keywords:
Muti-attribute decision making (MADM)
Emergency recovery plan selection
Expert consensus
Dynamic Grey Relation Analysis (DGRA)
Partial Ordinal Priority Approach (POPA)

ABSTRACT

Emergency recovery plan selection (ERPS) is critical for managing post-disaster recovery and ensuring long-term societal stability. However, current multi-attribute decision-making (MADM) research on ERPS is limited and lacks consideration of Pareto-optimal solutions and expert consensus resulting from multi-stakeholder involvement. Therefore, this study proposes a hybrid Dynamic Grey Relation Analysis and Partial Ordinal Priority Approach (DGRA-POPA) model for ERPS. The proposed approach employs stable and easily accessible ranking data as inputs. DGRA is first utilized to extract consistency in attribute preferences among experts and serves as the basis for determining expert rankings. Considering expert consensus and information distribution, preference modification coefficients are derived and embedded into POPA. Through decision-weight optimization, partial-order cumulative transformation, and dominance structure generation, the weights for experts, attributes, and alternatives are determined along with a Hasse diagram. This diagram offers Pareto-optimal and suboptimal alternatives and alternative clustering information. The proposed approach is demonstrated using the ERPS after the Manchester Stadium attack. Sensitivity and comparative analyses with ten different MADM methods validate the effectiveness. Overall, the proposed approach enhances ERPS transparency, stability, and robustness by identifying Pareto-optimal alternatives while considering expert consensus and information distribution.

1. Introduction

In contemporary society, people are confronted with a diverse and recurrent array of disaster threats stemming from natural, anthropogenic, or compounded factors that exert extensive and far-reaching effects [1]. In this high-risk environment, selecting the appropriate emergency recovery plans is crucial for emergency decision-making (EDM), transcending mere temporary solutions in the aftermath of disasters and entailing pivotal strategic choices that affect long-term societal stability and sustainable development. Emergency recovery plan selection (ERPS) presents several challenges. First, the efficacy of disaster emergency recovery plans remains elusive to precise capture or measurement through evaluation attributes [2]. Second, ERPS necessitates the consideration of consensus and discord among various stakeholders who usually have divergent goals, values, and prioritized factors and frequently encounter intricate coordination and tradeoffs in achieving consensus [3]. Thus, ERPS embodies immediate measures to address prevailing disasters and crucial strategic decisions that demand comprehensive consideration of long-term development and societal welfare. In

E-mail address: 13127073530@163.com.

https://doi.org/10.1016/j.ins.2024.120784
Received 9 January 2024; Received in revised form 21 May 2024; Accepted 24 May 2024

such situations, multi-attribute decision-making (MADM) is promising as an approach for addressing ERPS. MADM techniques can effectively address complex decision problems involving conflicts among attributes, diverse data formats, high uncertainty, and the involvement of multiple stakeholders [4]. Specifically, for ERPS, the optimal plan from among all feasible emergency recovery plans is possible to identify by utilizing MADM techniques and considering various decision attributes.

The extensive use of MADM methods in EDM has led to studies on their application in diverse scenarios, such as emergency logistics planning and evaluation, emergency supplier selection, emergency capacity evaluation, and emergency operation decision-making. The present research on EDM primarily relies on classical MADM methods, such as GRA [5,6], TOPSIS [5], VIKOR [7], TODIM [8,9], ELECTRE [10], BWM [9,11], MARCOS [12], and MABAC [13]. Most studies rely on decision data based on expert opinions, such as subjective linguistic values, evaluation scores, and pairwise comparison values, to address the challenge of acquiring objective data in EDM [4]. To effectively handle the ambiguity and uncertainty in expert subjective opinions, some studies have adopted the grey system theory [14], fuzzy set theory [10,15] and rough set theory [13,16] to process expert opinions. These studies typically utilize weighting methods (e.g., AHP [17], DEMATEL [18], and BWM [9,11]) to determine the weights of experts and attributes beforehand. Subsequently, algebraic logic, such as weighted and fuzzy averages, is applied to aggregate expert opinions. Few studies have considered expert consensus and information distribution in expert opinion aggregation to account for the involvement of multiple stakeholders [19,20].

A literature review shows that the focus on ERPS is relatively limited in EDM. However, ERPS differs significantly from other emergency decisions, as it involves long-term strategic considerations and complex systemic impacts. Furthermore, current research on MADM in EDM commonly overlooks potential Pareto-optimal solutions (i.e., partial-order relations among alternatives) in decision-making [21]. This is because MADM methods often project multiple attributes onto a comprehensive evaluation attribute, leading to total-order ranking results. However, Pareto-optimal solutions can effectively enhance the transparency, stability, and robustness of decision-making, which is crucial for addressing uncertainties in ERPS. Notably, the empirical evidence shows that ranking data can perform well in the face of high uncertainty [22]. Ranking data are more stable and easier to obtain than other types of subjective decision data. Ranking data only require experts to answer which alternative is better without specifying the degree. Therefore, incorporating ranking data into ERPS as decision data is a promising approach.

The Ordinal Priority Approach (OPA) is a novel MADM technique based on linear programming [23]. This approach utilizes ranking data reflecting expert preferences as decision data, which can be considered a potentially powerful basis for addressing ERPS within the context of MADM. By solving a linear programming model, this approach can simultaneously determine the weights for experts, attributes, and alternatives by applying alternative weights used for ranking. The advantages of this approach are its ability to dispense with data standardization, expert opinion aggregation, and predetermined weights, making it a comprehensive MADM method capable of assigning weights and ranking alternatives. Currently, OPA and its extensions have been applied in areas such as blockchain technology evaluation [24], supplier selection [25], and project portfolio selection [26]. However, the current focus of OPA and its extensions is on improving the ability to address uncertainty in decision data, leaving a research gap regarding expert consensus and information distribution. In addition, similar to most MADM methods, OPA overlooks the potential Pareto-optimal solutions in decision-making.

Given the practical demand for ERPS and the current status of MADM in EDM, and OPA in particular, this study proposes a new MADM method for ERPS with the following features: (1) utilizing more readily available and stable ranking data as input, (2) eliminating the need for data standardization or predetermined weights, (3) considering expert consensus and information distribution, and (4) being capable of identifying potential Pareto-optimal solutions. Therefore, this study proposes hybrid Dynamic Grey Relation Analysis (DGRA) and Partial Ordinal Priority Approach (POPA) models for ERPS under a group decision-making scenario. The hybrid DGRA-POPA model integrates DGRA to extract data on expert consensus and information distribution on attributes more accurately than traditional Grey Relation Analysis (GRA), forming a reference for expert ranking. By incorporating preference modification coefficients derived from expert consensus and information distribution, the modified POPA determines how to weight experts, attributes, alternatives, and the dominance structure among the alternatives. Notably, the dominance structure of alternatives, called a Hasse diagram, can provide insights into Pareto-optimal and suboptimal alternatives and alternative clustering information. This study showcases the application of the model in selecting post-disaster recovery plans after the Manchester Stadium attack, accompanied by sensitivity and comparative analyses to validate its effectiveness.

The remainder of this paper is organized as follows: Section 2 reviews the literature on the MADM method in ERPS. Section 3 presents the hybrid DGRA-POPA model. Section 4 presents an ERPS of the Manchester Stadium attack as an illustrative example of the proposed approach. Section 5 validates the proposed approach. Section 6 discusses the managerial implications, advantages, and insights relevant to the proposed approach. Finally, Section 7 presents the conclusions and outlines directions for future research.

2. Literature review

EDM aims to effectively plan resources, organize actions, improve disaster prevention and emergency response efficiency, minimize losses, and ensure public safety [27]. Achieving this goal requires crucial support from scientific EDM technology. Over the past decade, MADM has emerged as a beneficial tool in the EDM field. Furthermore, MADM is considered a powerful tool for addressing complex decision-making problems and can handle challenges such as goal conflicts, data diversity, and the high uncertainty inherent in EDM [4]. Current research on MADM in EDM mainly focuses on emergency capability evaluation, emergency logistics and facility planning, emergency supplier selection, and emergency response plan selection. These studies primarily adopted classic MADM methods, such as GRA [5,6], TOPSIS [5], VIKOR [7], TODIM [8,9], ELECTRE [10], BWM [9,11], MARCOS [12], and MABAC [13].

Regarding decision data, given the challenges in obtaining data for EDM, few studies to date have utilized objective decision data

[12,28]. Most studies synthesize expert opinions in the form of subjective linguistic values [5,6,8], subjective evaluation scores [19,20], and subjective pairwise comparison values [7,9]. For example, Wang et al. [9] assessed the optimal solutions in a multi-department emergency collaboration within a multi-granularity extended probabilistic linguistic term set framework using the BWM-TODIM approach. Saner et al. [7] evaluated the hospital emergency capabilities in various contexts based on the Bayesian BWM-VIKOR. Su et al. [8] applied the TODIM method, which integrates probabilistic linguistic term sets and prospect theory for emergency supplier selection. Furthermore, considering the lack of relevant information or specialized expertise in specific contexts among experts, several studies have improved input data quality using grey system theory [14], fuzzy set theory [10,15] and rough set theory [13,16]. Wang et al. [28] used WSR methodology to assess the locations of emergency medical facilities by applying the TOPSIS-BWM method based on interval type-2 fuzzy sets. Zhang et al. [6] introduced a novel approach utilizing spherical fuzzy sets as model inputs and established a spherical fuzzy GRA based on the CPT method for emergency supplier selection. Additionally, Liu et al. [10] proposed an integrated decision-support model combining a double-hierarchy hesitant fuzzy linguistic term set with the ELECTRE II method to address the issue of emergency supplier selection.

In terms of weight acquisition, the current MADM in EDM mainly utilizes weighting methods, such as AHP [17], DEMATEL [18], and BWM [9,11], to obtain expert and attribute weights in advance. Subsequently, averaging techniques such as weighted, geometric, and fuzzy averages are employed to aggregate expert opinions. However, this approach only assimilates expert opinions based on algebraic logic and fails to reflect individual expert opinions accurately [23]. Numerous studies have consider decision-makers' risk preferences to incorporate prospect theory and regret theory into the EDM process [6,29]. However, few studies have considered incorporating expert consensus into the EDM to handle multiple stakeholder involvement [19,20]. Liu et al. [19] proposed a dynamic consensus model utilizing a dual-trust relationship-based social network (DTRSN) for emergency response plan selection, and by employing a fuzzy clustering feedback mechanism, Li et al. [20] adjusted the expert consensus and integrated the TOPSIS method to achieve optimal emergency response plan selection.

Notably, although the issue of ERPS in the field of emergency management is equally crucial, substantial research is lacking. ERPS, as part of post-disaster long-term strategy selection, possesses distinct characteristics compared to other EDM. Specifically, emergency recovery plans focus more on long-term recovery, reconstruction, and enhancement, necessitating the consideration of more complex factors and long-term effects [30]. This amplifies the uncertainties for experts when assessing the long-term performance of emergency recovery plans based on evaluation attributes, thus requiring more flexible and robust approaches to reach a resolution. An ERPS involves multiple stakeholders with diverse interests and perspectives [3]. When formulating recovery plans, seeking expert consensus amid stakeholder needs and expectations is imperative to ensure these plans are feasible and sustainable. However, current ERPS research lacks sufficient consideration of expert consensus and the characteristics of information distribution among expert groups. Additionally, analyzing the Pareto-optimal alternatives within the ERPS can enhance the stability and transparency of decision outcomes [31]. Pareto-optimal alternatives aid in comprehending and balancing the tradeoffs among evaluation attributes and the potential for achieving optimal outcomes under diverse circumstances. Thus, when addressing unforeseen scenarios or uncertainties in ERPS, opting for a particular solution among Pareto-optimal alternatives may offer superior coping capabilities in one or more aspects. Nevertheless, this analytical aspect has been overlooked in the current MADM research in EDM.

Opting for more stable and readily available ranking data as decision data for MADM has emerged as a promising way of addressing ERPS. Some studies have indicated that establishing dominant relationships (ranking data) among alternatives is easier and more reliable than establishing subjective semantic values, evaluation scores, and comparative values [22]. This is because experts only need to answer "which one is better" without determining the extent of their differences [23].

Therefore, this study is based on a novel MADM technique, the OPA, with ranking data as the model input for addressing the ERPS [23]. This approach is applicable across various MADM scenarios, enabling the determination of weights and rankings for experts, attributes, and alternatives in both the group and individual decision processes [25]. It concurrently resolves a linear programming model and derives weights and rankings for experts, attributes, and alternatives [32]. Compared with methods such as FUCOM [33], LBWA [34], and DIBR [35], OPA is a more versatile approach that addresses the problems of attribute and expert weight acquisition and alternative ranking in MADM. In addition, unlike ranking methods like TODIM [9], MARCOS [12], and MABAC [13], OPA does not require data standardization, expert opinion aggregation, or pre-obtained weights for experts and attributes. This holds great potential for decision scenarios with limited objective data and high uncertainty, particularly in ERPS. Currently, extensions of OPA primarily focus on enhancements in handling uncertainty in expert opinions, including robust OPA [26], grey OPA [25], fuzzy OPA [32,36], and rough-set OPA [37]. Although TOPSIS-OPA has been applied to address large-scale group decision problems, its main emphasis remains on addressing missing values in group decision-making [38]. However, pertinent research is lacking on expanding OPA to consider expert consensus and information distribution. Moreover, a research gap exists in the consideration of potential Pareto-optimal solutions in decision-making with respect to OPA.

Considering the characteristics of ERPS and the current research status of MADM in EDM, particularly focusing on the gaps in OPA, this study proposes an extended OPA model suitable for ERPS. The model should effectively identify potential Pareto-optimal solutions while considering expert consensus and information distribution. Furthermore, the proposed approach should effectively address the high uncertainty and multi-stakeholder participation issues in ERPS, while enhancing decision transparency, stability, and robustness.

3. Methodology

This section focuses on elucidating the theoretical background and deriving the proposed hybrid DGRA-POPA model. An overview of the notations used in the proposed approach is provided in Table 1.

3.1. Dynamic grey relation analysis

GRA was introduced by *Julong Deng* in the 1980s and is a pivotal component of grey system theory [39]. GRA is applicable when data are incomplete and exhibit substantial uncertainty, as it identifies the correlation among variables to reveal inherent patterns and trends. However, most current research on GRA commonly adopts an arbitrary approach by setting one of its key parameters (i.e., the distinguishing coefficient) to 0.5. This setting lacks an adequate theoretical foundation or validation reflecting a conventional empirical practice [40]. Therefore, DGRA, proposed by Javed et al. [41] is a novel GRA model that utilizes an objective optimal dynamic distinguishing coefficient estimation technique. Unlike traditional GRA models, DGRA employs an objective technique to estimate the optimal distinguishing coefficient, thereby addressing the subjective selection by decision-makers of the value 0.5. Therefore, DGRA is employed to enhance POPA by deriving and integrating expert preference consensus and information distribution. This operation facilitates the acquisition of more accurate information regarding expert consensus than the traditional GRA methods.

Initially, a reference series is constructed in this study that reflects experts' collective preferences. Given that the decision data for the proposed approach comprise ranking data, this study employs the commonly utilized rank order centroid (ROC) weights to amalgamate expert preferences [42]. Specifically, experts' attribute preferences are leveraged as a benchmark by employing ROC-weighted voting to form a series that represents expert preferences for attributes. The rationale for utilizing ROC weights lies in their utilization of ranking data, which aligns with the input data format of the proposed approach. Moreover, ROC demonstrates superior accuracy compared to other rank-ordered methods, such as RS, RR, and EW. Furthermore, it exhibits a high correlation with the outcomes of precise numerical methods. The ROC weights for each ranking are computed based on **Eq. (1)** as follows:

$$w_r^{ROC} = \frac{1}{n}\sum_{k=r}^{n}\frac{1}{k} \quad \forall r \in [n] \tag{1}$$

where r is the ranking index and n is the number of attributes.

Given the comparison ranking series of attributes provided by each expert $RC = (rc_{1k}, \ldots, rc_{jk}, \ldots rc_{nk}), \forall k \in E$, the frequency of the attribute rankings across the expert group is computed. Finally, these statistics undergo ROC-weighted summation and ranking to derive a reference series $RC^* = \left(rc_1^*, \cdots, rc_j^*, \cdots, rc_n^*\right)$ reflecting the expert group's attribute preferences.

The grey relational variator within the DGRA, which is the core factor leading to changes in the dynamic distinguishing coefficient, is subsequently identified. The grey relational variator contains a local form for each alternative (denoted as φ_{jk}) and a global form for all alternatives (denoted as ϕ_j). Given the reference series RC^* and the comparison series RC, the local grey relational variator (φ_{jk}) is determined using **Eq. (2)** as follows:

$$\varphi_{jk} = \frac{\left|rc_j^* - rc_{jk}\right|}{\max_k \max_j \left|rc_j^* - rc_{jk}\right|} \quad \forall j, k \tag{2}$$

Table 1
Nomenclature.

Type	Notation	Definition
Index	i	Index of alternatives $(1, \ldots, i, \ldots, m)$
	j	Index of attributes $(1, \ldots, j, \ldots, n)$
	k	Index of experts $(1, \ldots, k, \ldots, p)$
Parameter	re_k	Ranking of the expert k
	rc_{jk}	Ranking of the attribute j given by the expert k
	ra_{ijk}	Ranking of the alternative i on the attribute j given by the expert k
Set	A	Set of alternatives $\forall i \in A$
	C	Set of attributes $\forall j \in C$
	E	Set of experts $\forall k \in E$
Variable	w_r^{ROC}	Rank order centroid weight assigned to the ranking r
	φ_{jk}	Local grey relational variator of the expert k of the attribute j
	ϕ_j	Global grey relational variator of the attribute j
	ξ_j	Dynamic distinguishing coefficient of the attribute j
	h	Continuous multiplier of dynamic distinguishing coefficient
	γ_k	Dynamic grey relational coefficient of the expert k on the attribute j
	Γ_k	Dynamic grey relational grade of the expert k
	Z	Objective function
	W_{ijk}^{ra}	Weight of the alternative i for the attribute j with the ranking of ra_{ijk} under the preferences of the expert k
Partial-order theory-related notation	$(A, \preccurlyeq_{POCT})$	Partial-order cumulative transformation set (POCTS) of alternatives
	PR^{POCT}	POCTS in binary matrix form
	$A_{i,POCT}^{+}$	Upper set of the alternative i of POCTS
	$A_{x,POCT}^{-}$	Lower set of the alternative i of POCTS
	$A_{x,POCT}^{\neq}$	Incomparable set of the alternative i of POCTS
	GS^{POCT}	General skeleton matrix of POCTS

The global grey relational variator (ϕ_j) is the average of the local grey relational variators (φ_{jk}) among the experts, as shown in **Eq. (3)**:

$$\phi_j = \frac{1}{m}\sum_{k=1}^{m}\varphi_{jk} \quad \forall j \tag{3}$$

Essentially, the dynamic distinguishing coefficient (ξ_j) is the unique scaling of the global grey relational variator (i.e., $\xi_j = h\phi_j$), in which the unique continuous multiplier (h) defines the relative position of each coefficient in the dynamic distinguishing coefficient (ξ_j).

Lemma 1. [41]. *If* $0 \leqslant \phi_j \leqslant 1$*, then* $\phi_j \leqslant \xi_j \leqslant (1+b)\phi_j$*, where* $b \in \mathbb{R}^+$.

According to ***Lemma 1****, the unique continuous multipliers* $h \in [1, 1+b]$ *and* $b = 1$ *provide sufficient space for the dynamic distinguishing coefficient (*ξ_j*) to reasonably distinguish between high- and low-variance data.*

Therefore, when calculating the optimal dynamic distinguishing coefficient, the optimal value of the continuous multiplier (h) formed during the iterative process must be estimated. The precise optimal value of the continuous multiplier (h) is calculated by solving the linear programming model shown in **Eq. (4)** as follows:

$$\begin{aligned}
\max \quad & \sum_{j=1}^{n}\xi_j \\
\text{s.t.} \quad & \xi_j = h\phi_j && \forall j \\
& \phi_j = \frac{\frac{1}{m}\left|rc_j^* - rc_{jk}\right|}{\max\limits_k \max\limits_j \left|rc_j^* - rc_{jk}\right|} && \forall j \\
& h\phi_j \leqslant 1 && \forall j \\
& h \in [1,2]
\end{aligned} \tag{4}$$

By solving **Eq. (4)**, the optimal continuous multiplier (h) is obtained, and the dynamic distinguishing coefficient ($\xi_1, \xi_2, \cdots, \xi_n$) can be calculated accordingly.

The dynamic grey relational coefficient (γ_{jk}) between the reference and comparison series can be calculated with **Eq. (5)** as follows:

$$\gamma_{jk} = \frac{\min_k \min_j |rc_j^* - rc_{jk}| + \xi_j \max_k \max_j \left|rc_j^* - rc_{jk}\right|}{|rc_j^* - rc_{jk}| + \xi_j \max_k \max_j \left|rc_j^* - rc_{jk}\right|} \quad \forall j, k \tag{5}$$

The dynamic grey relational grade (Γ_k) is calculated from **Eq. (6)**:

$$\Gamma_k = \frac{1}{n}\sum_{j=1}^{n}\gamma_{jk} \quad \forall k \tag{6}$$

The dynamic grey relational grade is a benefit-based indicator and $\Gamma_k \in (0,1]$, with larger values indicating more important experts resulting from group preference consistency. Thus, the experts are ranked based on the dynamic gray correlation grade (Γ_k) for each expert to obtain $RE = (re_1, \ldots, re_k, \ldots, re_p)$. Notably, given that POPA inherently lacks the capability for group decision-making adjustments, expert consensus and information distribution reflected by the dynamic grey relational grade are utilized to refine POPA.

3.2. Partial ordinal priority approach

POPA is an innovative MADM approach grounded in linear programming, partial-order theory, and graph theory [43]. Specifically, it builds upon OPA by integrating partial-order theory, thereby representing a partial-order extension of OPA. Overall, this study expands the original OPA model by incorporating considerations of expert consensus and information distribution, further utilizing partial-order cumulative transformation and structural generation to identify potential Pareto-optimal alternatives in decision-making. The proposed approach calculates the weights of experts, attributes, and alternatives, and generates a Hasse diagram containing the dominance structure of the alternatives. This Hasse diagram provides information on Pareto-optimal alternatives, sub-optimal alternatives, and hierarchical clustering.

3.2.1. Weight calculation considering expert consensus and information distribution

Following the DGRA computation, dynamic grey relational grades (Γ_k) and expert rankings (RE) based on consensus are derived. Consequently, this study further explores the characteristics of information distribution within dynamic grey relational grades to enhance the weight calculation process of the original OPA model. This refinement is designed to enhance the accuracy and practicality of the proposed approach in group decision-making. The weight calculation procedure for the proposed approach relies primarily on the original OPA model, as detailed in Appendix B.

Initially, this study designs a preference-modification coefficient based on expert consensus and information distribution, which can be integrated into the proposed approach. This coefficient can be precisely determined through a linear transformation of the dynamic grey relational grades, as shown in **Eq.** (7). In the proposed approach, the preference modification coefficient serves as a crucial parameter for quantifying the extent of expert preference fluctuations.

$$c_k = (1 - \Gamma_k) \times \frac{1.9912}{\log p} \quad \Gamma_k \in \left(0, 1\right) \tag{7}$$

where k is the index of the experts, Γ_k denotes the dynamic grey relational grade of expert k, and p is the number of experts.

Theorem 1. *The value of preference modification coefficients of experts based on dynamic grey relational grades (Γ_k) can be determined by the following linear function:*

$$c_k = (1 - \Gamma_k) \times \frac{1.9912}{\log p} \tag{8}$$

Proof of Theorem 1. Given the extreme scenario in which $\Gamma_{k_1} = 0.99$ and $\Gamma_{k_2} = 0.01$, the maximum degree of variation in expert preferences is depicted. Considering the original OPA model, parameter re_{k_1} of expert k_1 with the best ranking (i.e., 1^{st}) equals to $1^{c_{k_1}}$, and parameter re_{k_2} of expert k_2 with the worst ranking (i.e., p^{th}) equals to $p^{c_{k_2}}$. Thus, the objective of the model is to find the maximum difference between the input parameters (i.e., $1^{c_{k_1}}$ and $p^{c_{k_2}}$) when Γ_{k_1} and Γ_{k_2} have the maximum variation. Then, the following model is then constructed:

$$\begin{array}{ll} \max & Z \\ \text{s.t.} & 1^{c_{k_1}} \times (\Gamma_{k_1} - \Gamma_{k_2}) \geqslant Z \\ & p^{c_{k_2}} \times \Gamma_{k_2} \geqslant Z \\ & p^{c_{k_2}} \geqslant 1 \end{array} \tag{9}$$

After solving **Eq.** *(9), we obtain:*

$$p^{c_{k_2}} = 98 \Rightarrow \log(p^{c_{k_2}}) = \log 98 \Rightarrow c_{k_2} \times \log p = 1.9912 \Rightarrow c_{k_2} = \frac{1.9912}{\log p} \tag{10}$$

Therefore, the preference modification coefficient is $c_k \in [0, 1.9912/\log p]$. *Regarding the information distribution of the expert consensus, when* $\Gamma_k < 1 - \log p/1.9912$, *the preference modification coefficient has the amplification effect for individual experts, and when* $\Gamma_k > 1 - \log p/1.9912$, *it has a suppression effect. Thus,* ***Theorem 2*** *is proved.*

By incorporating the preference modification coefficient into the original OPA model, a decision-weight optimization model that accounts for expert consensus and information distribution is formulated, as shown in **Proposition 1**.

Proposition 1. *Given the dynamic grey relational grades (Γ_k) and rankings of experts (re_k) and attributes (rc_{jk}) and the alternatives for each attribute (ra_{ijk}) experts provide independently, the decision-weight optimization model considering expert consensus and information distribution is formulated as* **Eq.** *(11) as follows:*

$$\begin{array}{lll} \max & Z & \\ \text{s.t.} & Z \leq re_k^{c_k}\left(rc_{jk}\left(ra_{ijk}\left(W_{ijk}^{ra=r} - W_{ijk}^{ra=r+1}\right)\right)\right) & \forall i, j, k \\ & Z \leq re_k^{c_k}\left(rc_{jk}\left(ra_{ijk}\left(W_{ijk}^{ra=m}\right)\right)\right) & \forall i, j, k \\ & \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{p} W_{ijk}^{ra} = 1 & \\ & c_k = \left(1 - \mathit{\Gamma}_k\right) \times \frac{1.9912}{\log p} & \forall k \\ & W_{ijk}^{ra} \geq 0 & \end{array} \tag{11}$$

After solving **Eq.** (11), **Eq.** (12) provides the formulations for computing the weights of the alternatives, attributes, and experts.

$$W_i^A = \sum_{j=1}^{n}\sum_{k=1}^{p} W_{ijk}^{ra} \quad \forall i$$
$$W_j^C = \sum_{i=1}^{m}\sum_{k=1}^{p} W_{ijk}^{ra} \quad \forall j \tag{12}$$
$$W_k^E = \sum_{i=1}^{m}\sum_{j=1}^{n} W_{ijk}^{ra} \quad \forall k$$

Through the derivation process described above, a decision-weight optimization model is developed that is capable of simultaneously obtaining the weights of experts, attributes, and alternatives while considering expert consensus and information distribution. Compared to other traditional MADM methods, the proposed approach requires no data normalization or pre-acquisition of weight techniques. Notably, the preference modification coefficient proposed in **Theorem 1** may amplify or suppress the individual expert effect. However, when integrating the preference modification coefficient into the decision-weight optimization model described in **Proposition 1**, the relative effects of all expert coefficients are essential to consider. For example, if the preference modification coefficients of all experts are generally above a certain threshold, the resulting amplification will be relatively weakened in the decision weight optimization model compared to the impact on an individual expert. This observation underscores the significance of accounting for group effects when designing a decision-weight optimization model to ensure the precision and efficiency of the decision-making process.

However, the computed alternative weights merely project numerous attributes onto a single comprehensive evaluation attribute. Consequently, the outcomes lack stability when handling scenarios involving potential Pareto-optimal alternatives, which is a common challenge in most MADM methods [21]. To address this challenge, in the proposed approach, the weight calculation outcomes undergo a partial-order cumulative transformation and structural generation that incorporate information on attribute weights.

3.2.2. Partial-order cumulative transformation and structural generation

In the proposed approach, the core of partial-order cumulative transformation and structural generation lies in constructing a partial-order set containing attribute weight information. Theoretically, the crucial aspect of this process is ensuring that the newly constructed partial-order set maintains order-preserving properties, meaning that the dominant structure of any two alternatives within the partial-order set will consistently reflect the relative superiority or inferiority in the original data. In management practice, this process should offer greater flexibility than the partial-order set formed based on strict Pareto-optimality conditions for each attribute, as well as demonstrate stronger robustness than the total-order set constructed on a single projection comprehensive attribute derived from the decision-weight optimization model. Moreover, this process should effectively identify the potential Pareto-optimal solutions in the decision-making process. Thus, the fundamental partial-order theory necessary to facilitate the above operation is introduced in this section.

Definition 1.. (*Partial-order Relation*) *Let R be a binary relation on set X, denoted as $R \subset X \times X$ (R is a subset of the Cartesian product of X with itself). R is defined as a partial order relation on set X, if it satisfies the following properties:*

(1) Self-reversibility: R is self-reversible if for $\forall x \in X$, xRx holds.
(2) Transmissibility: R is transmissible if for $\forall x, y, z \in X$, $xRy, yRz \Rightarrow xRz$ holds.
(3) Anti-symmetry: R is antisymmetric if for $\forall x, y \in X$, $xRy, yRx \Rightarrow x = y$ holds.

Definition 2.. (*Total-order Relation*) *Partial-order relation R on set X is defined as the total-order relation on the set X if it satisfies the strong completeness (*i.e., *$xRy \vee yRx$ for $\forall x, y \in X$).*

Notably, the partial-order relation is a relatively flexible relationship, allowing for equivalence between alternatives (i.e., when it is impossible to distinguish between superiority or inferiority among them across all considered attributes) or incomparability (i.e., when one alternative is superior in specific attributes, while another is superior in others, without sufficient information to judge the overall superiority comprehensively). When evaluating alternative set A based on the utility derived from attribute set C, the partial-order and total-order relations yield partial-order sets (denoted as $(A, \preccurlyeq_C)$) and total-order sets (denoted as $(A, \leqslant_C)$), respectively.

Definition 3.. (*Lower Set and Upper Set of Partial-order Set*) *Given the partial-order set $(A, \preccurlyeq_C)$, for $\forall x \in A$, $A_{x,C}^- = \{y | y \preccurlyeq_C x, y \in A\}$ is defined as the lower set of X on the partial-order set $(A, \preccurlyeq_C)$, whereas $A_{x,C}^+ = \{y | x \preccurlyeq_C y, y \in A\}$ is defined as the upper set of X on the partial-order set $(A, \preccurlyeq_C)$.*

Definition 4.. (*Order-preserving Mapping of Partial-order Set*) *Let $(A, \preccurlyeq_{C_1})$ and $(B, \preccurlyeq_{C_2})$ be the partial-order set, and function $f : A \to B$ is the mapping function. If $x \preccurlyeq_{C_1} y \Rightarrow f(x) \preccurlyeq_{C_2} f(y)$ holds for $\forall x, y \in A$, then function f is defined as the order-preserving mapping of the partial-order set $(A, \preccurlyeq_{C_1})$.*

Definition 5.. (*Inclusion Relation in Partial-order Set*) *Let A_{x,C_1}^- and B_{x,C_2}^- be the lower set of X on the partial-order sets $(A, \preccurlyeq_{C_1})$ and $(B, \preccurlyeq_{C_2})$, respectively. If $A_{x,C_1}^- \subseteq B_{x,C_2}^-$ holds for $\forall x \in A$, then the partial-order set $(A, \preccurlyeq_{C_1})$ is the subset of the partial-order set $(B, \preccurlyeq_{C_2})$, denoted as $(A, \preccurlyeq_{C_1}) \subseteq (B, \preccurlyeq_{C_2})$.*

As the first step of the partial-order cumulative transformation, the weights of the alternatives must be calculated across all attributes, as outlined in ***Eq. (13)****:*

$$W_{ij}^{AC} = \sum_{k=1}^{p} W_{ijk}^{ra} \quad \forall i, j \tag{13}$$

In the total-order set originating from the single-projection comprehensive attribute W^A is denoted as $(A, \leqslant_{SPCA})$, and the partial-order set originating from the strict Pareto-optimality judgment of W^{AC} denoted as $(A, \preccurlyeq_{AC})$. Notably, the partial-order set based on the strict Pareto-optimality condition refers to the formation of a partial-order relationship by directly examining the dominance structure of alternatives across all attributes. Subsequently, the partial-order cumulative transformation set of the proposed approach is constructed as shown in ***Definition 5****.*

Definition 6.. (*Partial-order Cumulative Transformation Set*) *Given that the attributes in W^{AC} are arranged in descending order by weight* (i.e.*, the weight of each attribute obtained from the weight calculation process of the proposed approach is $W_{j_1} \geqslant W_{j_2} \geqslant \cdots \geqslant W_{j_n}$), the partial-order cumulative transformation weight can be calculated using* ***Eq.*** *(14). Then, the partial-order set originating from the partial-order cumulative transformation weight is defined as the partial-order cumulative transformation set (POCTS) of $(A, \preccurlyeq_{AC})$, denoted as $(A, \preccurlyeq_{POCT})$:*

$$W_{ij}^{POCT} = \sum_{j=1}^{l} W_{ij} \quad \forall l \in [n] \text{ and } \forall i, j \tag{14}$$

The expression for the partial-order cumulative transformation weight in the matrix form shown in ***Eq.*** *(15) as follows:*

$$W^{POCT} = W^{AC} H = \begin{pmatrix} W_{i_1 j_1}^{AC} & W_{i_1 j_1}^{AC} + W_{i_1 j_2}^{AC} & \cdots & W_{i_1 j_1}^{AC} + W_{i_1 j_2}^{AC} + \cdots + W_{i_1 j_n}^{AC} \\ W_{i_2 j_1}^{AC} & W_{i_2 j_1}^{AC} + W_{i_2 j_2}^{AC} & \cdots & W_{i_2 j_1}^{AC} + W_{i_2 j_2}^{AC} + \cdots + W_{i_2 j_n}^{AC} \\ \vdots & \vdots & \ddots & \vdots \\ W_{i_m j_1}^{AC} & W_{i_m j_1}^{AC} + W_{i_m j_2}^{AC} & \cdots & W_{i_m j_1}^{AC} + W_{i_m j_2}^{AC} + \cdots + W_{i_m j_n}^{AC} \end{pmatrix} \tag{15}$$

$$H = \begin{pmatrix} 1 & 1 & \cdots & 1 \\ 0 & 1 & \cdots & 1 \\ 0 & 0 & \ddots & \vdots \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

Comparing the magnitudes of the row vectors of W^{POCT} yields the POCTS in binary matrix form $PR^{POCT} = \left[pr_{i_1 i_2}^{POCT}\right]_{m \times m}$, and its element $pr_{i_1 i_2}^{POCT}$ is determined using ***Eq.*** *(16) as follows:*

$$pr_{i_1 i_2}^{POCT} = \begin{cases} 1, & \text{if } W_{i_1 j}^{POCT} \geqslant W_{i_2 j}^{POCT} \quad \forall i_1, i_2 \in A \text{ and } \forall j \\ 0, & \text{otherwise} \end{cases} \tag{16}$$

Theorem 2. *If $(A, \preccurlyeq_{POCT})$ is the partial-order cumulative transformation set of $(A, \preccurlyeq_{AC})$, then $(A, \preccurlyeq_{AC}) \subseteq (A, \preccurlyeq_{POCT})$.*

Proof of Theorem 2. *See Appendix B.*

Theorem 3. *If $(A, \preccurlyeq_{POCT})$ is the partial-order cumulative transformation set of $(A, \preccurlyeq_{AC})$, then for $\forall i_1, i_2 \in A$, when $i_1 \preccurlyeq_C i_2$ exists on $(A, \preccurlyeq_{AC})$, $W_{i_1 j}^{POCT} \leqslant W_{i_2 j}^{POCT}$ holds.*

Proof of Theorem 3. *See Appendix B.*

Theorems 2 and 3 confirm that POCTS exhibits order-preserving properties. Notably, the last column of the partial-order cumulative transformation weight is equivalent to W^A, which is derived from the decision-weight optimization model that incorporates expert consensus and information distribution. Hence, according to **Definition 2** of the total-order relationship, $(A, \preccurlyeq_{AC}) \subseteq (A, \preccurlyeq_{POCT}) \subseteq (A, \leqslant_{SPCA})$ holds. This articulation theoretically demonstrates that POCTS negotiates a trade-off between partial-order relations under strict Pareto optimality and the total-order relation derived from a single projection comprehensive attribute, thus forging a more robust dominance structure.

However, the POCTS in binary matrix form contains redundant information on dominance structures, leading to unnecessary complexity and information overload in decision-making. Therefore, this study further optimizes dominance structures through the transitivity of partial-order relations and generates a Hasse diagram with dominant hierarchy structures, which can effectively reduce information redundancy. Crucially, the generated structure reveals Pareto-optimal alternatives, suboptimal alternatives, and their hierarchical clustering information, offering decision-makers a more stable and transparent mechanism for evaluating decision outcomes.

Proposition 2. *Dominant Hierarchy Extraction of Partial-order Cumulative Transformation Set in Binary Matrix Form.*

Based on ***Definition 3****, the lower, upper, and incomparable set of $\forall x \in A$ of POCTS in binary matrix form can be identified by* ***Eq.*** *(17) as follows:*

$$A^{-}_{i_1,POCT} = \left\{ i_2 \middle| pr^{POCT}_{i_1 i_2} = 1, i_2 \in A \right\}$$
$$A^{+}_{i_1,POCT} = \left\{ i_2 \middle| pr^{POCT}_{i_2 i_1} = 1, i_2 \in A \right\} \tag{17}$$
$$A^{-}_{i_1,POCT} = A - A^{-}_{i_1,POCT} - A^{+}_{i_1,POCT}$$

Regarding the dominant hierarchy extraction based on non-dominant ascending, if $\left(A^{-}_{i_1,POCT} \cup \{i_1\}\right) \cap \left(A^{+}_{i_1,POCT} \cup \{i_1\}\right) = \left(A^{-}_{i_1,POCT} \cup \{i_1\}\right)$ *holds for* $i_2 \in A$*, then* i_2 *is positioned at the top layer. Subsequently, the rows and columns corresponding to* i_2 *in* PR^{POCT} *are deleted. The above process is iterated, positioning* i_2 *from top to bottom, until all alternatives in* PR^{POCT} *are eliminated.*

To streamline the dominance structure, edge contraction is performed to obtain the general skeleton matrix of POCTS (GS^{POCT}), as shown in **Eq.** (18). The operations in **Eq.** (18) are Boolean operations.

$$GS^{POCT} = \left(PR^{POCT} + I\right)^{'} - \left(\left(PR^{POCT}\right)^{'}\right)^{2} - I \tag{18}$$

Finally, the proposed approach derives the Hasse diagram of the dominance structure of the alternatives by substituting a general skeleton matrix into the extracted dominant hierarchy. The dominance of alternatives within the general skeleton matrix indicates transitivity. The top-level alternatives in the hierarchy represent Pareto-optimal alternatives, and the alternatives at the same level show no comparability.

3.3. Steps of the proposed approach

This section aims to clarify the operational procedures of the proposed hybrid DGRA-POPA model, as shown in Fig. 1. Based on Fig. 1, detailed explanations are provided below for each step.

Step 1: Identify the experts, attributes, and alternatives in decision-making. This phase involves collecting decision-making data, including rankings of attributes and alternatives under each attribute, independently provided by experts.

Step 2: Calculate the ROC weights for each ranking allocation using **Eq.** (1). Then, the ROC-weighted sum is computed based on the frequency of the attribute ranking to establish the reference sequence RC^{*}, which reflects the expert consensus. Next, determine the grey relational variator (φ_{jk} and ϕ_j), dynamic distinguishing coefficient (ξ_j), and dynamic Grey relational grade (Γ_k) using **Eqs.** (2) to (6). Finally, sort the experts in descending order of their dynamic grey relational grades to obtain RE.

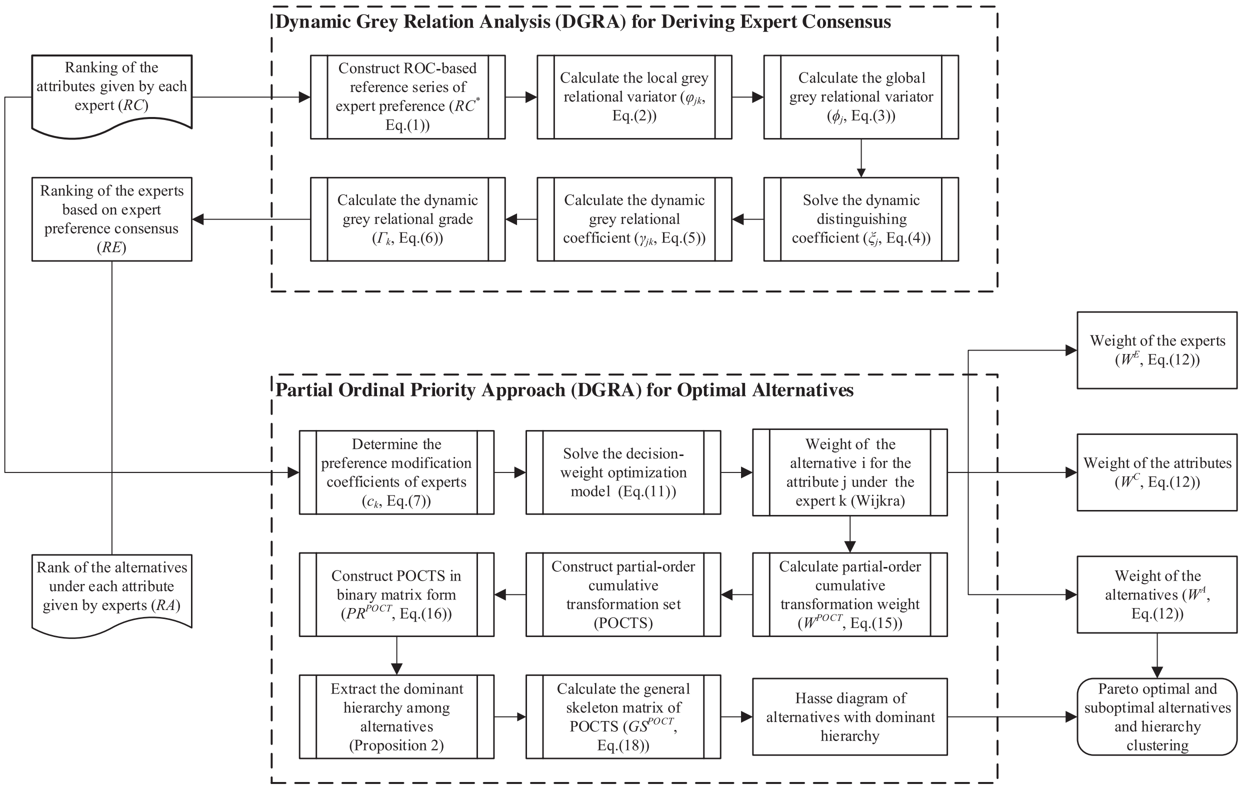

Fig.1. The steps of the proposed hybrid DGRA-POPA model.

Step 3: Utilize the dynamic grey relational grade (Γ_k) to calculate the preference modification coefficients (c_k) of experts with **Eq. (7)**. Formulate and solve **Eq. (11)** to determine the weight (W_{ijk}^{ra}) of alternative i for attribute j with the ranking of ra_{ijk} under the preferences of expert k. Finally, calculate the weights of experts, attributes, and alternatives (W^E, W^C, W^A) according to **Eq. (12)**.

Step 4: Apply partial-order cumulative transformation according to **Eqs.** (13) to (15). Construct the POCTS in binary matrix form (PR^{POCT}) using **Eq. (16)**. Extract the dominant hierarchy based on **Proposition 2** and derive the general skeleton matrix (GS^{POCT}) of the POCTS using **Eq. (18)**. Finally, substitute the general skeleton matrix (GS^{POCT}) into the extracted dominant hierarchy to generate the Hasse diagram of alternatives.

4. Case study

4.1. Case description

This study utilizes the ERPS of the Manchester Stadium attack as a case study to showcase and validate the proposed hybrid DGRA-POPA model. Manchester Stadium, a top-tier sports arena, has cutting-edge facilities that accommodate up to 75,000 spectators. However, on the evening of May 22, 2017, a tragic terrorist attack occurred at Manchester Stadium when a suicide bomber detonated an explosive device within the stadium premises after a music concert, resulting in 22 deaths and over 500 injuries. This attack is regarded as one of the most severe terrorist assaults in the UK in recent years, prompting global attention and condemnation and sparking more comprehensive discussions on terrorism worldwide.

The “Manchester Stadium Inquiry Volume Two: Emergency Response” report highlights numerous shortcomings across the response protocols of emergency service agencies [44]. First, deficiencies arise from leadership aptitude and command training. Consequently, insufficiencies can be observed in refining emergency response procedures, fostering interagency collaboration, ensuring ample medical equipment, and facilitating effective information exchange. Additionally, deficiencies linked to the Operation Plato initiative involve inadequate training, unclear role delineation, and mishandled media interactions. Following the report analysis, ten emergency recovery plans were devised to address the identified issues and recommend improvements for emergency response at Manchester Stadium, as presented in Table C1. These plans include emergency healthcare administration, information management, procedural enhancements, and personnel training. Key ERPS stakeholders are the Greater Manchester Resilience Forum, Greater Manchester Police, North West Ambulance Service, British Transport Police, and North West Fire Control.

4.2. Attributes for emergency recovery plan selection and data collection

This study utilizes a literature analysis method to systematically identify attributes for evaluating emergency recovery enhancement plans for Manchester Stadium. These attributes evaluate recovery plans from the perspectives of enhancing emergency capabilities and intrinsic attributes. Table 2 summarizes the attributes, related descriptions, and references that should be considered when selecting emergency recovery plans. Regarding emergency capacity enhancement, the research has increasingly emphasized the crucial role that resilience plays in emergency management when facing highly uncertain, dynamic, and complex disasters. The widely accepted 4R resilience theory subdivides a system’s recovery capabilities into robustness, redundancy, speed, and resourcefulness. Thus, this study utilizes the 4R resilience theory as a guiding framework for the ERPS. Moreover, the inherent attributes of these plans, such as feasibility and cost-effectiveness, are commonly regarded as pivotal. Furthermore, sustainability must be considered when choosing emergency recovery plans. As underscored at the United Nations’ 2016 World Humanitarian Summit, a significant interplay and correlation exist between humanitarian actions and Sustainable Development Goals. Given these factors, establishing sustainable long-term emergency recovery plans becomes exceedingly imperative. After identifying the plans and attributes, five decision-making experts representing critical stakeholders, are engaged to offer their rankings of attributes and plans as input data for the proposed approach, as presented in Table D1 and D2.

Table 2
Attributes for emergency response plan selection.

Measurement	Attribute	Description	Reference
Emergency capability enhancement	Robustness	The plan ensures consistent and dependable execution of emergency response plans across diverse situations.	[45,46]
	Redundancy	The plan improves adaptability in addressing diverse unforeseen events within the emergency response.	
	Rapidity	The plan enhances the efficiency and speed of the emergency response.	
	Resourcefulness	The plan enhances the availability of essential supplies, personnel, and other resources required for the emergency response.	
Inherent attribute	Feasibility	The practicality and feasibility of plan implementation in real-world settings.	
	Cost-effectiveness	The equilibrium between implementation costs and achieving the desired benefits of the plan.	
	Sustainability	The sustainability and stability of long-term plan implementation.	

4.3. Results analysis

According to **Step 1**, the reference series of attribute rankings derived from expert consensus is determined as follows:

$$RC^{*} = (2, 6, 1, 5, 3, 4, 7) \tag{19}$$

Based on **Eq.** (3), in **Step 2**, the global grey relational variator (ϕ_j) corresponding to each attribute can be calculated as follows:

$$\phi_j = (0.3000, 0.3000, 0.2500, 0.3000, 0.4000, 0.5000, 0.3500) \tag{20}$$

A linear programming model is constructed to compute the optimal dynamic distinguishing coefficient (ξ_j) and continuous multiplier (h) according to **Eq.** (4) as follows:

$$\begin{array}{ll} \max & \xi_1 + \xi_2 + \xi_3 + \xi_4 + \xi_5 + \xi_6 + \xi_7 \\ \text{s.t.} & \xi_1 = 0.3000 \times h; \xi_2 = 0.3000 \times h; \xi_3 = 0.2500 \times h; \xi_4 = 0.3000 \times h \\ & \xi_5 = 0.4000 \times h; \xi_6 = 0.5000 \times h; \xi_7 = 0.3500 \times h \\ & \xi_1, \xi_2, \xi_3, \xi_4, \xi_5, \xi_6, \xi_7 \leqslant 1 \\ & 1 \leqslant h \leqslant 2 \end{array} \tag{21}$$

This was obtained by solving **Eq.** (21); the continuous multiplier $h = 2$ and the optimal dynamic distinguishing coefficients for each attribute are shown in **Eq.** (22) as follows:

$$\xi_j = (0.6000, 0.6000, 0.5000, 0.6000, 0.8000, 1.0000, 0.7000) \tag{22}$$

The dynamic grey relational grade of each expert (Γ_k) is calculated according to **Eqs.** (5) and (6).

$$\Gamma_k = (0.6360, 0.7752, 0.7676, 0.6526, 0.7809) \tag{23}$$

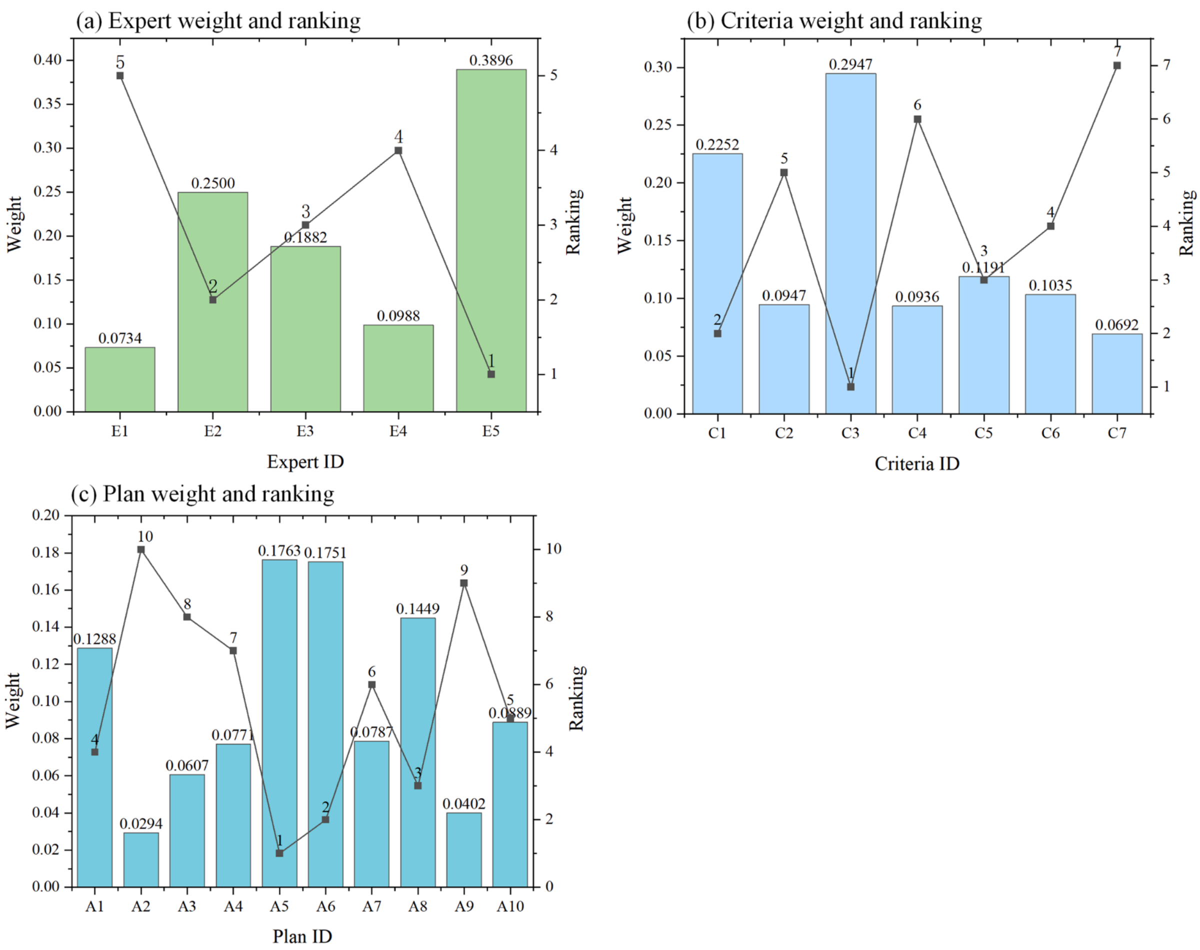

Fig.2. The weight calculation results of the ERPS case study.

The expert ranking is obtained accordingly as $RE = (5, 2, 3, 4, 1)$.

According to **Eq. (7)**, in **Step 3**, the preference modification coefficient is determined as follows:

$$c_k = (1.0369, 0.6403, 0.6622, 0.9898, 0.6241) \tag{24}$$

The findings reveal notably higher dynamic grey relational grades for E2, E3, and E5, with scores of 0.7752, 0.7676, and 0.7809, respectively, displaying marginal disparities. Conversely, E1 and E4 exhibit relatively low grades of 0.6360 and 0.6526, respectively. Notably, owing to inadequate consistency and information distribution surpassing threshold 1, the preference modification coefficients suppress the weight assigned to E1, signifying diminished weight allocation. However, the preference modification coefficients amplify the weights of E2, E3, and E4, for which information distribution falls below the threshold of 1.

Subsequently, the ranking of attributes and alternatives under each attribute the experts have provided, along with the calculated preference modification coefficients and expert rankings, are incorporated into the decision-weight optimization model, as shown in **Eq. (11)**. Fig. 2 illustrates the weight calculation results for experts, attributes, and alternatives (detailed results are available in Table E1). Among these attributes, the most critical factors are rapidity (C3) and robustness (C1) enhancement, with weights of 0.2947 and 0.2252, respectively. Feasibility (C5), cost-effectiveness (C6), redundancy (C2), and resourcefulness enhancement (C4) follow closely, with weights of 0.1191, 0.1035, 0.0947, and 0.0936, respectively. Conversely, the weight for sustainability (C7) is relatively low at 0.0692. Therefore, within the decision-making process for emergency recovery plans, enhanced rapidity and robustness are important factors. Notably, the sustainability of emergency recovery plans has yet to receive adequate attention, with experts leaning more towards focusing on the attributes directly associated with emergency capacity enhancement. The results in Fig. 2 **(c)** reveal relatively high weights for A1, A5, A6, and A8, with A5 and A6 exhibiting similar weights. Consequently, there is a need to develop the partial-order-based dominance structure among plans further to differentiate between various plans, thereby enabling more reliable decision-making.

Subsequently, a partial-order accumulation transformation is performed on the alternative weights according to **Eq. (14)**. Table 3 shows the results.

The POCTS in binary matrix form is obtained according to **Eq. (16)**, and the results are presented in Table F1. A Hasse diagram with the dominant hierarchy of alternatives is then generated by applying **Proposition 2** to extract the dominant hierarchy and perform edge contraction operations using **Eq. (18)**. The computational results are listed in Table F2.

The results in Fig. 3 show that A1, A5, and A6 emerge as Pareto-optimal plans, whereas A8 does not. The core reason behind the status of A5 as a Pareto-optimal plan lies in its significant enhancement effects on rapidity and resourcefulness, coupled with its higher overall weight. Conversely, the strength of A6 lies in its outstanding performance in improving robustness and ability to compensate for its deficiency in rapidity compared with A5. A1 is a Pareto-optimal plan because of its absolute advantage in enhancing rapidity, which is the most critical attribute. However, A1 demonstrates significant divergence in overall weight consideration compared to A5 and A6, which cautions against prioritization. Consequently, by recommending A5 and A6 as optimal choices, decision-makers may ultimately select either based on preference. In addition, A8 is deemed a suboptimal alternative to A5 and A6, whereas A10 is a suboptimal alternative to A1, A5, and A6, collectively. This indicates that, for scenarios in which A1, A5, or A6 cannot be feasibly implemented, a certain level of tolerance exists for the loss of effectiveness, allowing for a suitable suboptimal alternative to be selected.

5. Model validation

5.1. Sensitivity analysis

5.1.1. Overall sensitivity results analysis

Analyzing the sensitivity of the input data or parameters is a crucial numerical method for evaluating the effectiveness of MADM methods. This study uses expert preference consistency and information distribution to acquire expert rankings and adjust preferences to construct the hybrid DGRA-POPA model. Therefore, this study focuses on the sensitivity analysis of expert rankings. A total of 120 sensitivity analysis experiments are conducted by completely permuting the rankings of the five experts. The sensitivity analysis outputs the results, including the weights of experts, attributes, and alternatives, and the frequency of becoming Pareto-optimal

Table 3
The partial-order cumulative transformation weights in the ERPS case study.

	W_{i3}^{POCT}	W_{i1}^{POCT}	W_{i5}^{POCT}	W_{i6}^{POCT}	W_{i2}^{POCT}	W_{i4}^{POCT}	W_{i7}^{POCT}
A1	0.0636	0.0962	0.1011	0.1069	0.1212	0.1255	0.1288
A2	0.0046	0.0138	0.0170	0.0205	0.0238	0.0281	0.0294
A3	0.0171	0.0268	0.0312	0.0414	0.0476	0.0568	0.0607
A4	0.0261	0.0334	0.0427	0.0528	0.0554	0.0715	0.0771
A5	0.0584	0.0911	0.1112	0.1246	0.1462	0.1643	0.1763
A6	0.0339	0.0980	0.1252	0.1433	0.1557	0.1626	0.1751
A7	0.0272	0.0315	0.0443	0.0608	0.0662	0.0692	0.0787
A8	0.0280	0.0649	0.0898	0.1091	0.1254	0.1358	0.1449
A9	0.0056	0.0245	0.0265	0.0291	0.0302	0.0345	0.0402
A10	0.0303	0.0397	0.0500	0.0540	0.0655	0.0824	0.0889

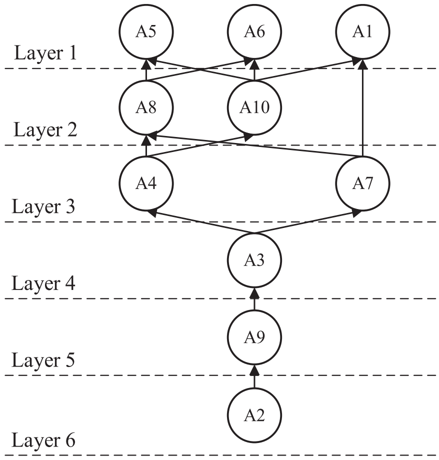

Fig.3. The Hasse diagram of the ERPS case study.

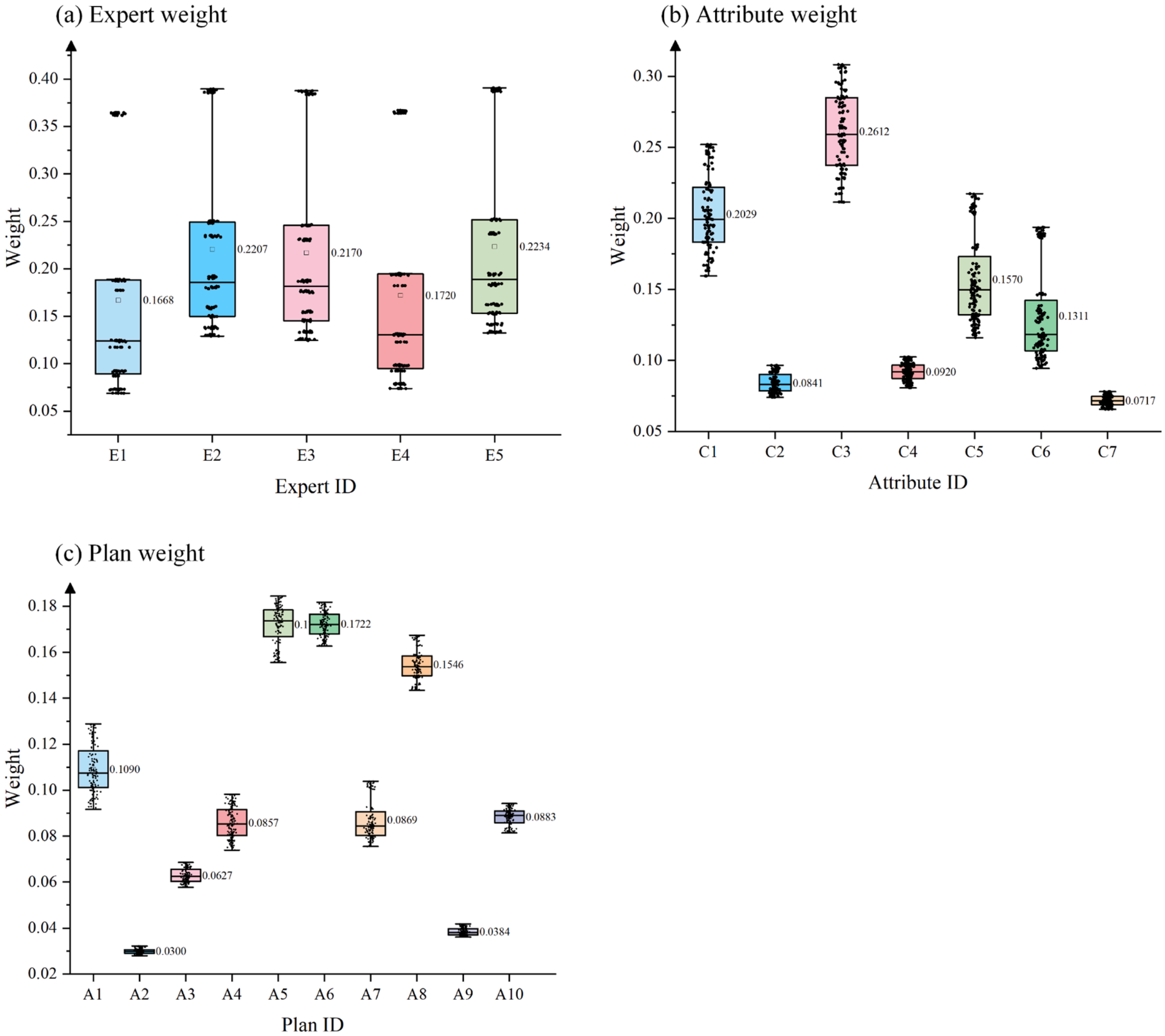

Fig.4. Box plots of the computed weights.

alternatives in the Hasse diagram. Fig. 4 and Table 4 depict the box plots and descriptive statistics of the computed outcomes.

The boxplot analysis of the expert weights (Fig. 4**(a)**) shows that the weights of E2, E3, and E5 are relatively concentrated and higher, whereas the weights of E1 and E4 exhibit lower and closer values. Specifically, the average weight of E5 is the highest at 0.2234, followed by E2 and E3 with average weights of 0.2207 and 0.2170, respectively. In comparison, E4 and E1 exhibit lower average weights of 0.1720 and 0.1668, respectively. The extreme values of the expert weights demonstrate a distribution trend similar to the averages, whereby E2, E3, and E5 possess larger and closely situated extreme weights, whereas E1 and E4 have smaller and relatively closer extreme weights. Considering the preference modification coefficients, a consistent alignment can be observed between the distribution of expert weights, their respective rankings, and the preference modification coefficients of the experts. This phenomenon highlights the influential regulatory role of preference-modification coefficients in the context of complete permutations in expert rankings.

The boxplot of attribute weights (Fig. 4**(b)**) shows that the weight distribution is within a reasonable range, that is, within 1.5 times the interquartile range (IQR) indicated by the whiskers of the boxplot. Regarding the average weight values, C3 has the highest average weight value at 0.2612. Subsequently, C1, C5, and C6 have average weights of 0.2029, 0.1570, and 0.1311, respectively. In contrast, the weights of C4, C2, and C7 are relatively low and similar, with values of 0.0920, 0.0841, and 0.0717, respectively. Regarding the variability of the weights, the coefficients of variation for C5 and C6 reached 0.1932 and 0.2456, respectively, exceeding the threshold of 0.15. This indicates that significant outliers exist in the weights of C5 and C6, suggesting that some experts may prefer these attributes. Furthermore, the kurtosis of all the attribute weights is less than zero, indicating that the weight distribution is flatter and broader than a normal distribution, with a thinner tail and fewer extreme values. All attributes except C4 show positive skewness, indicating that the right tail of the weight distribution is longer and that most weight values are concentrated in the lower range. Among these, C1, C2, C5, and C6 exhibit prominent positive skewness characteristics, whereas the distributions of C3 and C7 are relatively symmetrical.

Based on the analysis of the average weights of the alternatives, A5 has the highest average value of 0.1744, followed closely by A6 with an average value of 0.1722. A8 and A1 rank third and fourth, with average weights of 0.1546 and 0.1090, respectively. The average weights of A4, A7, and A10 range between 0.0857 and 0.0883. The remaining three alternatives (A2, A3, and A9) have relatively lower weights. Concerning the coefficient of variation, all alternative weights had values less than 0.15, indicating that they fall within the normal range. The kurtosis of the alternative weights, similar to that of the attribute weights, displays a flatter characteristic than a normal distribution. Notably, A5 and A10 exhibit negative skewness, whereas the other alternatives show positive skewness. This suggests that the weights of A5 and A10 are concentrated in the higher-value region, with fewer weights distributed towards the lower end. However, although A5 has a higher mean weight than A6, its greater volatility reduces its stability as the optimal choice.

Furthermore, following the conventional practice of MADM, decision-makers often preferentially select A5, A6, and A8, in that order. However, the statistical analysis of the various experiments shows that A6 appears as the Pareto-optimal alternative 120 times, indicating its consistent selection as the Pareto-optimal alternative across all permutations of expert rankings. A5 closely follows with 113 occurrences. This phenomenon aligns with the result that A6 exhibits greater weight stability than A5. Despite A8 ranking lower with only 32 occurrences, A1, which has significant differences in mean weight compared to A8, is the Pareto-optimal solution 34 times. This suggests that while A8 may have a much higher average weight than A1, it often serves as a suboptimal choice compared to

Table 4
Descriptive statistics of the computed outcomes.

	Mean	Max	Min	Standard deviation	Variance	Skewness	Kurtosis	Coefficient of variation	Frequency of being Pareto optimal
E1	0.1668	0.3647	0.0689	0.1061	0.0113	1.0710	−0.3718	0.6361	–-
E2	0.2207	0.3896	0.1291	0.0914	0.0084	0.9787	−0.4959	0.4141	–-
E3	0.2170	0.3877	0.1246	0.0924	0.0085	0.9817	−0.4924	0.4258	–-
E4	0.1720	0.3670	0.0739	0.1047	0.0110	1.0577	−0.3905	0.6089	–-
E5	0.2235	0.3907	0.1325	0.0906	0.0082	0.9768	−0.4980	0.4055	–-
C1	0.2029	0.2520	0.1595	0.0261	0.0007	0.3725	−0.8723	0.1286	–-
C2	0.0841	0.0965	0.0741	0.0065	0.0000	0.4353	−1.0442	0.0768	–-
C3	0.2612	0.3083	0.2115	0.0282	0.0008	0.0121	−1.2003	0.1080	–-
C4	0.0920	0.1025	0.0808	0.0060	0.0000	−0.1112	−0.9096	0.0648	–-
C5	0.1570	0.2173	0.1161	0.0303	0.0009	0.7632	−0.6722	0.1932	–-
C6	0.1311	0.1938	0.0945	0.0322	0.0010	0.9732	−0.4660	0.2456	–-
C7	0.0717	0.0781	0.0657	0.0035	0.0000	0.0695	−1.1128	0.0491	–-
A1	0.1090	0.1288	0.0917	0.0103	0.0001	0.3378	−0.9652	0.0947	34
A2	0.0300	0.0322	0.0279	0.0012	0.0000	0.2368	−0.8145	0.0395	0
A3	0.0628	0.0686	0.0578	0.0031	0.0000	0.3199	−1.0577	0.0486	0
A4	0.0857	0.0982	0.0739	0.0067	0.0000	0.0938	−1.1751	0.0784	0
A5	0.1721	0.1845	0.1556	0.0082	0.0001	−0.6007	−0.7942	0.0478	114
A6	0.1722	0.1818	0.1627	0.0052	0.0000	0.0678	−0.9725	0.0302	120
A7	0.0870	0.1039	0.0755	0.0086	0.0001	0.8478	−0.5659	0.0986	0
A8	0.1546	0.1674	0.1435	0.0068	0.0000	0.3405	−0.7359	0.0437	32
A9	0.0384	0.0418	0.0361	0.0017	0.0000	0.6104	−0.8916	0.0438	0
A10	0.0883	0.0942	0.0814	0.0036	0.0000	−0.4378	−0.8218	0.0407	0

A5 and A6, whereas A1 demonstrates advantages that A5 and A6 lack in specific contexts. This highlights the capability of the hybrid DGRA-POPA model to enhance decision stability and transparency through partial-order cumulation transformation and structured generation.

5.1.2. Sensitivity results analysis of representative scenarios

This section focuses on selecting representative sensitivity analysis scenarios for further explanation to enhance the credibility of the results. The representative scenarios encompass both similar and extremely inverse scenarios. The test of similar scenarios (denoted as ST) entails grouping proximate experts via preference modification coefficients, and arranging permutations of expert rankings within the same group to generate varied similar scenarios. This study specifically presents a sensitivity analysis of similar scenarios for expert groups E2, E3, and E5. Similar scenarios of expert rankings and their designations are illustrated in Table 5, and the corresponding results are shown in Fig. 5 and Table 6.

From the expert weight results in Fig. 5**(b)**, significant disparities in the weights of E2, E3, and E5 across different similar scenarios can be observed, while the weights for E1 and E4 remain relatively stable. Regarding the attribute weights and rankings (Fig. 5**(a)**), there is relative stability across different scenarios, with the attribute rankings of scenarios ST1, ST2, ST3, and ST4 aligning with the rankings in control scenario G. However, in scenario ST5, a reversal occurs in the rankings of C2 and C4. The alternative rankings (Fig. 5**(c)**) exhibit relative stability across similar scenarios, whereas the rankings of A1, A2, A3, A8, A9, and A10 remain consistent. The focal point of contention in the alternative rankings is related to A5 and A6. In scenarios ST1 and ST2, in contrast to control scenario G, the rankings of A5 and A6 are reversed primarily because of a decrease in the weight of C3 and an increase in C1 compared with control scenario G. In the case study, the advantage of A5 over A6 lies primarily in C3, whereas the advantage of A6 lies in C1, which is in accordance with the reverse ranking of A5 and A6. Furthermore, Table 6 shows that, within the Hasse diagram across all similar scenarios, both A5 and A6 are identified as Pareto-optimal alternatives. Thus, the sensitivity analysis results in similar scenarios indicate the stability of the outcomes of the proposed hybrid DGRA-POPA model.

The extreme inverse scenario (denoted as ET) represents an extreme case in which expert rankings are entirely inverted compared with the control scenario, indicating the highest degree of disturbance in expert ranking. Thus, in the extreme inverse scenario, the expert ranking stands for (1, 4, 3, 2, 5), and the results are depicted in Figs. 6 and 7.

Based on the results shown in Fig. 6**(a)**, notable disparities exist when the expert weights between the extreme inverse scenarios are compared. However, because of the impact of the preference modification coefficient, the maximum variance in expert weights in the extreme inverse scenario (0.2292) is less than that in the control scenario (0.3162). Regarding the attribute weights (Fig. 6**(b)**), C2, C4, and C7 demonstrate marginal discrepancies between the extreme inverse and control scenarios. Nevertheless, a reversal can be observed in the ranking of the weights for C1, C5, C2, and C4. Similarly, the effect of the preference modification coefficient reduces the discrepancies in the attribute weights in the extreme inverse scenario. Regarding the alternative ranking (Fig. 6**(c)**), A5, A6, and A8 remain the top three; however, A1 has dropped in rank from fourth to sixth. Based on an analysis of the extreme inverse scenario's partial-order-based dominance structure, the Pareto-optimal alternative has clearly shifted from the original A1, A5, and A6 to A5, A6, and A8, with A1 becoming a suboptimal alternative to A5. A8 emerges as the Pareto-optimal alternative because of its notable performance in C5 and the increased weight of C5 in the extreme inverse scenario, compensating for its gap with A5 and A6 in C6. The descent of A1 to become a suboptimal alternative to A5 arises from a significant decrease in the weights of E2 and E5, which previously considered A1 to excel in C3, leading to the inferior performance of A1 in C3 compared to A5 in the extreme inverse scenario.

Notably, whether in similar or extreme inverse scenarios, both A5 and A6 can emerge as Pareto-optimal alternatives through the generated Hasse diagram despite the potential for reversals in weight-based total-order rankings. In addition, the preference modification coefficients effectively modulate and diminish the differences in the weight outcomes under extreme disturbances. Consequently, sensitivity analyses across similar and extreme inverse scenarios suggest that the proposed hybrid DGRA-POPA model is stable.

5.2. Comparison analysis

To conduct a comparative analysis of the hybrid DGRA-POPA model, first, the expert weight results of the proposed approach are compared with those of the original OPA model. The relevance of this comparison reflects the proposed approach, which improves the decision-weight optimization of the original OPA model by integrating expert consensus and information distribution. Mirroring the sensitivity analysis, the comparison analysis is conducted with complete permutation operations on the expert rankings within the original OPA model, generating 120 distinct experimental scenarios. Fig. 8 shows the results for the expert weights.

For the original OPA model, the computed expert weights display an interesting phenomenon. Specifically, the statistical indicators of the five experts' weights are entirely consistent, with an average value of 0.2. These findings are attributed to the expert weight allocation of the original OPA model, which is based on the experts' rankings only. This study adopts a comprehensive permutation

Table 5
The designations and expert rankings of similar scenarios.

	G	ST1	ST2	ST3	ST4	ST5
Expert ranking	(5, 2, 3, 4, 1)	(5, 1, 2, 4, 3)	(5, 1, 3, 4, 2)	(5, 2, 1, 4, 3)	(5, 3, 1, 4, 2)	(5, 3, 2, 4, 1)

Note: G denotes the control group, which is same expert ranking with the case study section.

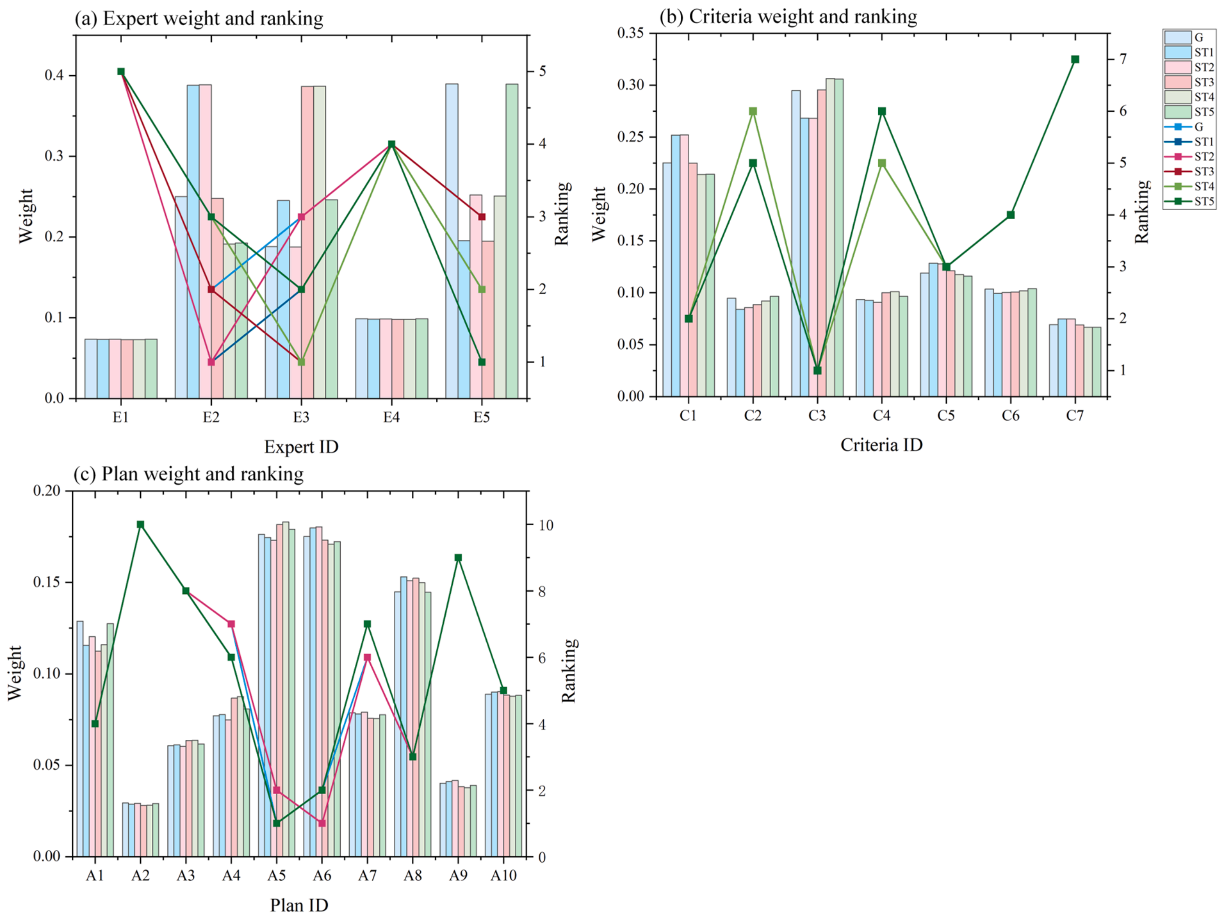

Fig.5. The weight calculation results of the similar scenarios.

Table 6
The Pareto-optimal and suboptimal alternatives of similar scenarios.

	Intersection of all scenario	G	ST1	ST2	ST3	ST4	ST5
Pareto optimal alternative	A5, A6	A1	--	A1	--	--	--
Suboptimal alternative	A8	A7, A10	A1	A7, A10	A1	A1	A1

ranking technique, creating uniform chances and occurrences for each expert across all rankings and leading to the equalization of the average weights among experts. However, in the proposed approach, expert weights are not fixed but exhibit fluctuations around the reference value of 0.2. Specifically, the mean weights of E2, E3, and E5 are higher than 0.2, which is directly related to their relatively high preference-correction coefficients. This indicates that the hybrid DGRA-POPA model can effectively capture and reflect individual differences in decision-making by introducing preference modification coefficients, thereby achieving more refined weight adjustments.

In this section, the alternative ranking results of the proposed approach based on the case scenarios are compared with those of other MADM methods. OPA, TOPSIS, VIKOR, TODIM, COPRAS, CARDIS, MOORA, MABAC, MAIRCA, and MARCOS are selected as the representative benchmarking methods. Notably, the most effective method for demonstrating the validity of the results of the proposed approach is to examine whether the ranking outcomes are reversed compared with the original OPA model, as both take ranking data as input. However, the rationale for choosing other methods is because of their status as prevalent benchmarks in MADM and their frequent application in ERPS research. These methods rely on decision matrices as input data and require attribute weights to be acquired beforehand. Making comparisons using these methods allows for a broader generalization of the analysis and underscores the advantages of the proposed approach in simultaneously determining the weights for experts, attributes, and alternatives.

As for the initial input of the comparison analysis, OPA utilizes expert-provided rankings of attributes and alternatives under each attribute (Tables E1 and E2) and expert rankings based on dynamic grey relational degrees as input data. For other MADM methods that utilize decision matrices as inputs, W^{AC} as derived from the proposed approach is decomposed into attribute weights and utilities

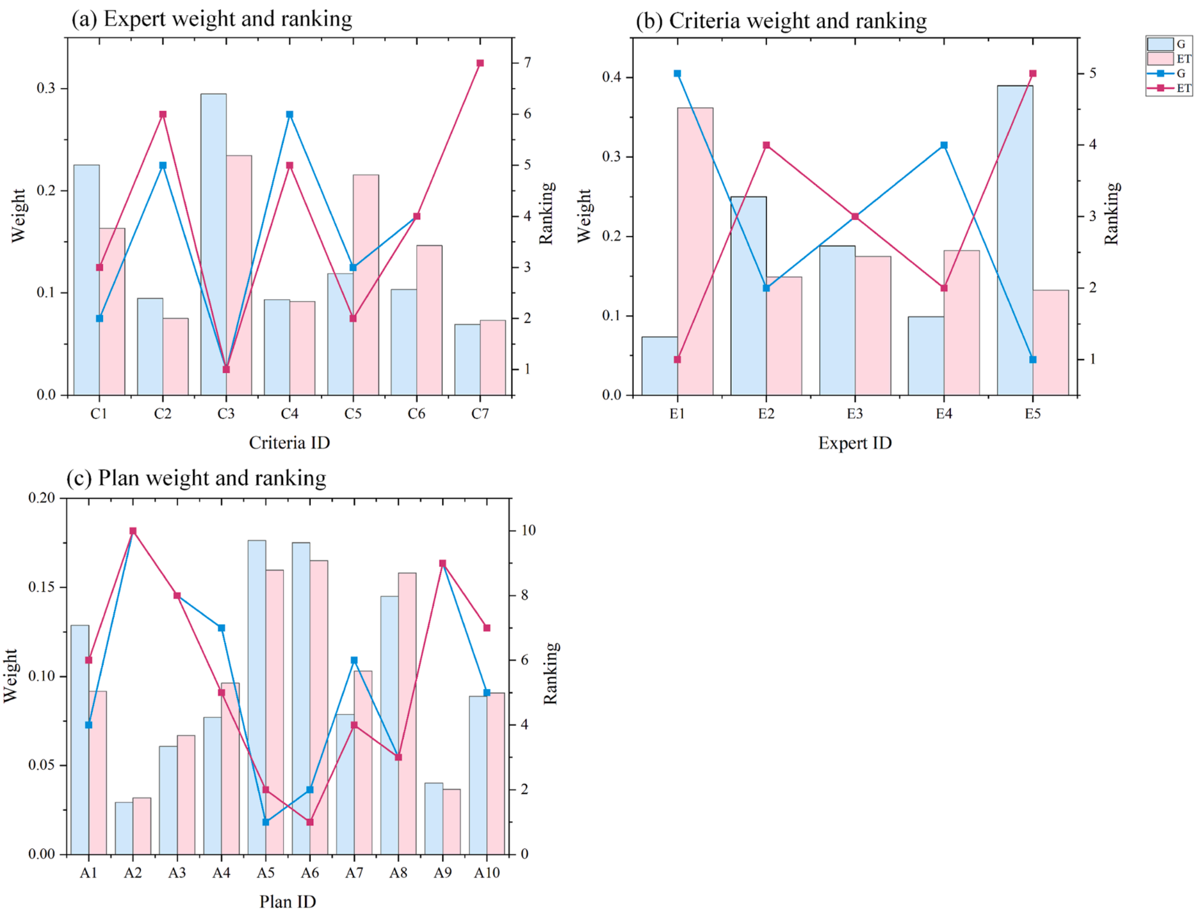

Fig.6. The weight calculation results of the extreme inverse scenario.

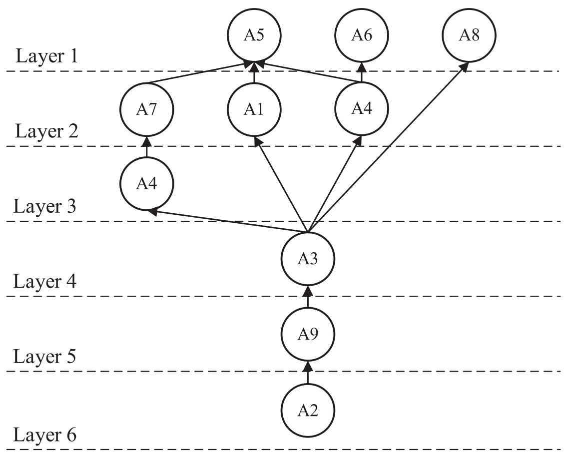

Fig.7. Hasse diagram of the extreme inverse scenario.

of alternatives across attributes (i.e., $W_{ij}^{AC} = W_j^C \times V_{ij}^{AC}$). The rationality of this decomposition stems from W^{AC} representing the consolidated expert opinions on alternative weights across various attributes with a total weight equal to one. Therefore, extracting the attribute weights calculated in the proposed approach allows the utility of each alternative to be determined for the respective attributes. As discussed above, Table 7 is then utilized as input for the other MADM methods. However, soliciting new decision data from experts introduces additional decision information and increases the uncertainty and cost implications. In contrast, the proposed

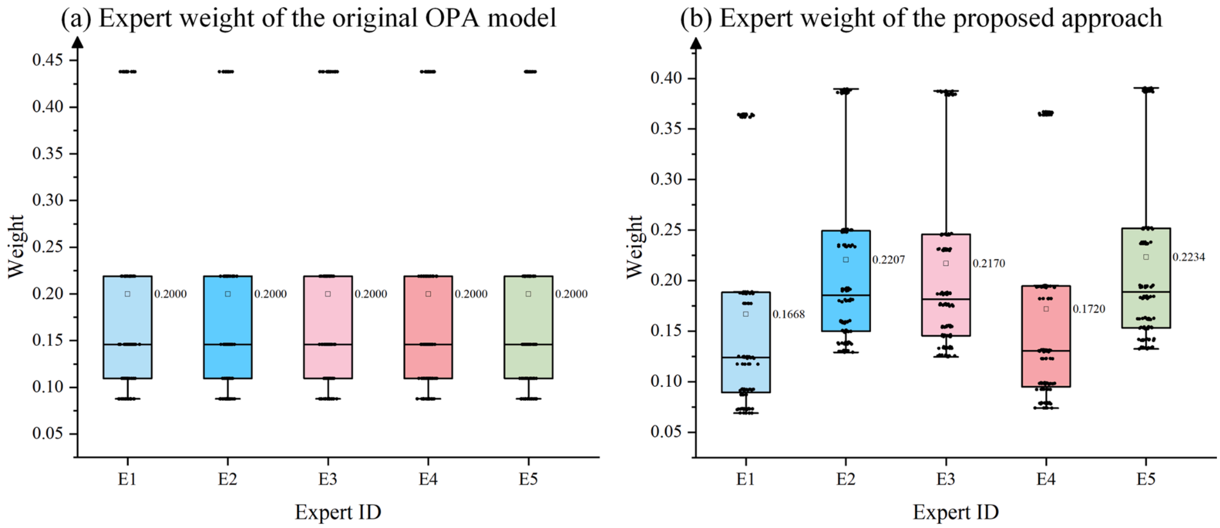

Fig.8. Box plots of computed expert weights.

Table 7
Decision data for the MADM methods using a decision matrix.

	C1	C2	C3	C4	C5	C6	C7
A1	0.2826	1.0157	0.3431	1.1425	1.0178	1.2131	1.8607
A2	0.0205	0.1462	0.0576	0.2187	0.1999	0.2718	0.4241
A3	0.0757	0.2826	0.1060	0.4429	0.3996	0.5490	0.8764
A4	0.1157	0.3532	0.1450	0.5643	0.4657	0.6912	1.1137
A5	0.2591	0.9618	0.3772	1.3317	1.2279	1.5880	2.5468
A6	0.1505	1.0346	0.4248	1.5317	1.3079	1.5714	2.5303
A7	0.1209	0.3331	0.1504	0.6495	0.5562	0.6685	1.1365
A8	0.1242	0.6857	0.3046	1.1665	1.0530	1.3129	2.0940
A9	0.0248	0.2592	0.0899	0.3112	0.2538	0.3337	0.5801
A10	0.1345	0.4190	0.1697	0.5769	0.5500	0.7966	1.2841
Attribute weight	0.2252	0.0947	0.2947	0.0936	0.1191	0.1035	0.0692

approach endeavors to achieve relatively stable decision outcomes using minimal decision information (i.e., ranking data) in highly uncertain ERPS scenarios.

Fig. 9 illustrates the ranking outcomes of the alternatives using different methods. The specific rankings of the top four alternatives

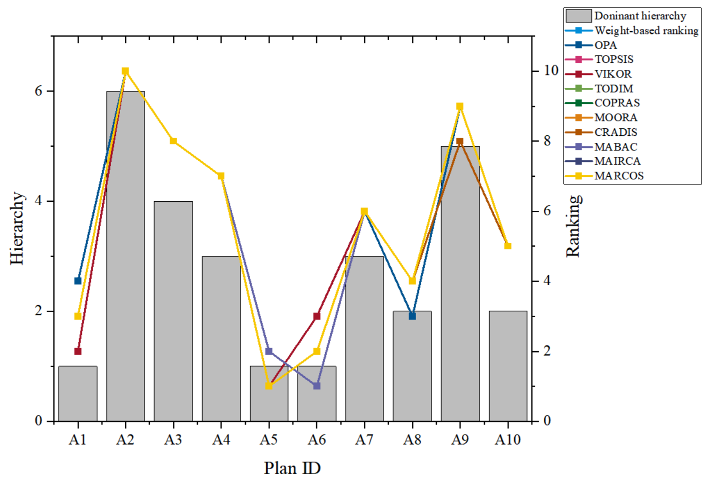

Fig.9. Ranking results of multiple MADM methods.

(A1, A5, A6, and A8) exhibit divergence. Methods excluding VIKOR, TODIM, and MABAC rank A5 first and A6 second. Conversely, TODIM and MABAC assign first place to A6, while A5 is in second place. VIKOR positions A5 first, A1 second, and A6 third. As for A1 and A8, the proposed approach aligns with OPA, placing A1 third and A8 fourth. Except for VIKOR, the other methods rank A1 fourth and A8 third. These outcomes are effectively resolved within the dominance hierarchy of the proposed approach, as A1, A5, and A6 occupy the first layer, indicating they are Pareto-optimal solutions. This aligns with the sensitivity analysis findings, wherein the average weight of A8 substantially exceeds that of A1, although without a significant difference in how frequently they are Pareto-optimal solutions. However, the original OPA model cannot provide such insights. Thus, the analysis validates the effectiveness and stability of the proposed approach for ERPS.

6. Discussion

6.1. Managerial implications for emergency recovery plan selection

This section discusses the managerial implications, where A5 and A6 emerge as Pareto-optimal solutions in the case study, serving as references for other ERPS decision-makers. The emergency recovery enhancement measures of A6 include establishing a joint medical rescue center, creating an emergency information-sharing platform, setting up a unified emergency command center, developing an emergency collaboration mechanism, and conducting regular drills and simulations. Compared with that of A5, implementing the emergency recovery plan of A6 is expected to significantly improve the emergency response system's redundancy, speed, and resource availability, as reflected in three main aspects. First, by establishing joint medical rescue and emergency command centers, the plan effectively integrates and optimizes existing resources, and builds a more robust emergency response system. This provides more alternative solutions and resources in the event of emergencies but also significantly enhances system redundancy, ensuring that sufficient resources are available at critical moments. Second, creating an emergency information-sharing platform ensures the rapid circulation of crucial information, significantly reducing delays in information transmission. The operation of the joint command center further achieves quick dispatching and decision-making regarding emergency resources, thus significantly accelerating the overall response. Finally, through cross-departmental and cross-regional collaboration mechanisms, the plan effectively breaks down existing information silos and resource barriers, thereby achieving efficient resource sharing and utilization. Regular drills and simulations continue to optimize resource allocation, ensuring the rapid mobilization of necessary resources in emergencies and improving resource availability.

Regarding A5, its measures primarily include developing effective casualty evacuation plans, enhancing emergency record management systems, formulating policies and operational standards for emergency command transitions, establishing emergency collaboration mechanisms, and conducting regular drills and simulations. Compared to A6, this plan excels in economic efficiency, sustainability, and enhanced robustness of future emergency capabilities. Economically, although initial investments are required for system development, personnel training, and resource integration, measures such as implementing effective casualty evacuation plans and strengthening emergency record management systems can significantly reduce additional losses due to the mishandling of emergencies, thereby saving costs and maximizing benefits. Moreover, by establishing emergency collaboration mechanisms and transparent policies for emergency command transitions, the plan promotes the effective integration of cross-departmental and cross-regional resources, prevents resource duplication and waste, and enhances resource utilization efficiency, thereby reducing overall operational costs. Regarding sustainability, the plan provides a solid institutional guarantee for emergency management through institutionalized and standardized measures, such as formulating policies and operational standards for emergency command transitions, establishing long-term emergency collaboration mechanisms, and ensuring emergency measure continuity and stability. Regular drills and simulations help test and refine existing emergency plans while increasing an organization's adaptability and flexibility to new situations. This will ensure that emergency management systems can continuously adapt to future changes and challenges. Collectively, these measures enhance the speed and efficiency of emergency response, strengthen an organization's capability to handle diverse emergencies and improve the robustness of emergency management systems, ensuring an efficient and effective response to various uncertainties.

6.2. Advantages of and insights from the proposed approach

Currently, MADM methods are primarily categorized into two types: (1) weighting methods such as AHP, Entropy, FUCOM, LBWA, BWM, and DEMATEL, and (2) ranking methods, including TOPSIS, TODIM, ELECTRE, PROMETHEE, COPRAS, CARDIS, MOORA, MABAC, MAIRCA, and MARCOS. The hybrid DGRA-POPA model proposed in this study reflects a comprehensive MADM approach. Unlike traditional weighting methods that calculate weights for experts, attributes, and alternatives for ranking separately, the proposed approach concurrently determines the weights for experts, attributes, and alternatives without requiring any pre-obtained weights, thereby offering a distinct advantage over conventional ranking methods.

Furthermore, compared with methods that use pairwise comparison values (e.g., AHP, BWM, DEMATEL, and FUCOM) and those that utilize decision matrices (e.g., TOPSIS, TODIM, MOORA, MABAC, and MARCOS), the proposed approach relies on easily obtainable and stable ranking data as the decision-making basis. This is particularly pertinent in the ERPS domain on which this study focuses, where ranking data offer an effective strategy for managing uncertainty when facing poor quality or inaccessible decision matrices. Additionally, the proposed approach does not require any data normalization techniques, which often directly affect the computational results of methods based on decision matrices. Compared to pairwise comparisons, acquiring ranking data is more straightforward, requiring answers to "which is better" rather than "by how much," significantly reducing the costs and time associated with collecting decision data.

This study crucially incorporates expert consensus and Pareto-optimality analysis into the proposed approach. DGRA is applied to extract an expert consensus. Furthermore, the original OPA model is utilized to derive a preference modification coefficient based on expert consensus and information distribution, which is then integrated into the decision weight optimization model. Notably, the method for expert consensus extraction is not limited to DGRA; any expert consensus measurement within the range of (0,1) and characterized as a benefit attribute can be adjusted using the proposed modification operation, as derived from Theorem 1. This study validates these findings through sensitivity and comparative analyses with the weight results of the original OPA model. Furthermore, this study utilizes a partial-order cumulative transformation and a structured generation method for the decision-weight optimization model to identify potential Pareto-optimal alternatives. This demonstrates the order-preserving nature of partial-order cumulative transformation and its relationship with the partial-order set based on strict Pareto optimality and the total-order set based on a single projected comprehensive attribute. Thus, the model theoretically demonstrates that partial-order cumulative transformation can enhance the stability and robustness of decision outcomes. This study also proposes a Hasse diagram with hierarchical clustering, which effectively improves decision robustness and transparency. The results are validated based on sensitivity and comparative analyses. Therefore, analyzing potential Pareto-optimal alternatives in MADM enhances decision transparency, stability, and robustness, which current MADM methods often overlook. Additionally, the partial-order cumulative transformation and structural generation provided in this study can offer insights into portfolio selection problems in decision-making through Pareto-optimal alternatives, suboptimal alternatives, and clustering information.

Overall, the hybrid DGRA-POPA model offers the following advantages:

(1) It utilizes readily accessible and stable ranking data as inputs for the model.
(2) It obviates the need for any data normalization and weight pre-acquisition techniques.
(3) It introduces a decision-weight optimization model that considers expert consensus and information distribution.
(4) It identifies potential Pareto-optimal solutions in decision-making through partial-order cumulative transformation and structural generation.

However, different MADM methods have relative advantages in terms of their applicability. The hybrid DGRA-POPA model is more suitable for situations with high uncertainty and a lack of reliable decision data. When decision-makers are confident in the pairwise comparison values and decision matrices experts provide, MADM methods that fully reflect relative dominance and distance are recommended. In cases where decision-makers face a wealth of accurate decision data, big-data-driven decision-making methods are recommended to obtain more precise outcomes.

7. Conclusion

In today’s high-risk society, selecting emergency recovery plans is crucial, as it effectively mitigates the potential negative effects of unforeseen events, thus ensuring the resilience and capacity of society to cope with extreme weather disasters, terrorist attacks, and infectious diseases. However, in selecting strategies in the future, appropriate emergency recovery plans often encounter uncertainties regarding the long-term performance of attributes and require engagement from multiple stakeholders. Consequently, when determining these plans, addressing uncertainties and instabilities in the assessment process and aligning the consensus with discrepancies among multiple stakeholders becomes a key challenge. Therefore, this study proposes a hybrid DGRA-POPA model for ERPS that utilizes DGRA to extract a more accurate consensus from expert preferences regarding attributes and subsequently provides a reference for expert ranking. Preference modification coefficients are derived based on the consensus among the expert group and its information distribution characteristics are integrated into POPA. Ultimately, the modified POPA applies decision-weight optimization modeling, partial-order cumulative transformation, and structural generation to determine weights for experts, attributes, and alternatives, and establish a Hasse diagram of alternatives. This diagram offers insights into Pareto-optimal alternatives, suboptimal alternatives, and hierarchical clustering information. Thus, this study provides an illustrative application of the proposed approach to the selection of post-disaster emergency recovery enhancement plans for the Manchester Stadium attack. The hybrid DGRA-POPA model is validated through a sensitivity analysis of expert rankings and comparative analysis with 10 traditional MADM methods, demonstrating stability, robustness, and transparency in decision-making, while proving its effectiveness and reliability in addressing complex decision-making issues.

The primary contribution of this study is the introduction of the hybrid DGRA-POPA model, which effectively addresses the challenge of ERPS by considering expert consensus, information distribution, and potential Pareto-optimal alternatives. The proposed approach fills the gaps in considering expert consensus and Pareto-optimal alternatives in the original OPA model. The proposed approach relies on readily available and stable ranking data, simplifies data collection, and reduces time and costs. Through DGRA, the proposed approach extracts an expert consensus and then derives preference modification coefficients based on the original OPA model to enhance decision accuracy by incorporating expert opinion consistency. By integrating the weight determination and ranking processes, the proposed approach efficiently calculates the weights of the experts, attributes, and alternatives, thereby improving efficiency and consistency in the decision-making process. Furthermore, the proposed approach enhances the stability, robustness, and transparency of decision outcomes when identifying potential Pareto-optimal alternatives through partial-order cumulative transformation and Hasse diagram generation. Through theoretical analysis, insights are provided into integrating expert consensus and Pareto-optimal solution analysis into the original OPA model for MADM.

Finally, the results and conclusions were obtained within a limited context. Hence, further applications in various scenarios are required to validate their efficacy. Based on this study, future research could explore some critical areas in-depth. First, the integration of distance information into decision-weight optimization models based on the original OPA model deserves attention. Existing decision weight optimization methods rely on ranking data, which can only reflect relative superiority or inferiority without quantifying the degree of difference. This limitation indicates that the original OPA model fails to fully consider the potential distance information in the ranking data. Hence, integrating distance information into ranking data to improve the performance of decision-weight optimization models is an important direction for future research. However, although such integration methods improve the accuracy of decision results, they also impose higher requirements on the acquisition of decision data, potentially introducing more significant uncertainty and decision costs. Thus, future research could explore the utilization of social network analysis methods to characterize the opinions of a large expert pool, aiming to reveal consensus and divergence more accurately. In this process, considering the scale effects related to expert consensus and divergence may result in the construction of a complex social network consisting of positive (representing consensus) and negative (representing divergence) values, posing new challenges to the measurement of expert importance. Finally, the proposed approach is based on a critical assumption: the independence of the attributes. Given the potential correlations and interactions among attributes in the real world, future studies should consider the influence of these factors.

CRediT authorship contribution statement

Renlong Wang: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Conceptualization.

Declaration of competing interest

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

Data availability

The datasets utilized for this study can be founded in the Appendix or be requested from the first author at 13127073530@163.com.

Appendix A

The weight calculation in this study is primarily based on the modifications made to the original OPA model, which incorporates factors of expert consensus and information distribution. This section provides an introduction to the original OPA model, and its indices, sets, parameters, and variables are shown in Table A1.

Table A1
Notation definition of OPA.

Type	Notion	Definition
Index	i	Index of alternatives $(1,\ldots,i,\ldots,m)$
	j	Index of attributes $(1,\ldots,j,\ldots,n)$
	k	Index of experts $(1,\ldots,k,\ldots,p)$
Parameter	re_k	Ranking of the expert k
	rc_{jk}	Ranking of the attribute j under the preferences of the expert k
	ra_{ijk}	Ranking of the alternative i for the attribute j under the preferences of the expert k
Set	A	Set of alternatives $A = \{1,2,\ldots,i,\ldots,m\}$
	C	Set of attributes $C = \{1,2,\ldots,j,\ldots,n\}$
	E	Set of experts $E = \{1,2,\ldots,k,\ldots,p\}$
Variable	Z	Objective function
	W_{ijk}^{ra}	Weight of the alternative i for the attribute j of the ranking ra_{ijk} under the preferences of the expert k

Based on the identified attributes, experts, and alternatives, the decision maker initially assigns the ranking re_k to experts. Subsequently, each expert independently provides the ranking for each attribute rc_{jk} and the ranking for each alternative under each attribute ra_{ijk}. Utilizing the collected data, linear optimization model of OPA is formed to determine the weight W_{ijk}^{ra} of the alternative i for the attribute j of the ranking ra_{ijk} under the preferences of the expert k.

$$\begin{aligned}
\max \quad & Z \\
\text{s.t.} \quad & Z \leqslant re_k\left(rc_{jk}\left(ra_{ijk}\left(W_{ijk}^{ra=r} - W_{ijk}^{ra=r+1}\right)\right)\right) \quad \forall i,j,k \\
& Z \leqslant re_k(rc_{jk}\left(ra_{ijk}\left(W_{ijk}^{ra=m}\right)\right) \quad \forall i,j,k \\
& \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{p} W_{ijk}^{ra} = 1 \\
& W_{ijk}^{ra} \geqslant 0
\end{aligned} \tag{B1}$$

After solving **Eq.(B1)**, the weight of alternatives, attributes, and experts is calculated according to **Eq.(B2)**.

$$\begin{aligned}
W_i^A &= \sum_{j=1}^{n}\sum_{k=1}^{p} W_{ijk}^{ra} \quad \forall i \\
W_j^C &= \sum_{i=1}^{m}\sum_{k=1}^{p} W_{ijk}^{ra} \quad \forall j \\
W_k^E &= \sum_{i=1}^{m}\sum_{j=1}^{n} W_{ijk}^{ra} \quad \forall k
\end{aligned} \tag{B2}$$

Appendix B

Proof of Theorem 2. *Denote the lower set of* $i_1 \in A$ *on* $(A, \preccurlyeq_{AC})$ *and* $(A, \preccurlyeq_{POCT})$ *as* $A^-_{i_1,AC} = \{i_2 | i_2 \preccurlyeq_{AC} i_1, i_2 \in A\}$ *and* $A^-_{i_1,POCT} = \{i_2 | i_2 \preccurlyeq_{POCT} i_1, i_2 \in A\}$*, respectively. For* $\forall i_2 \in A^-_{i_1,AC}$*, there exists* $i_2 \preccurlyeq_{AC} i_1 \Leftrightarrow W_{i_2 j}^{AC} \leqslant W_{i_1 j}^{AC}, \forall j$*. It follows that* $\sum_{j=1}^{l} W_{i_2 j}^{AC} \leqslant \sum_{j=1}^{l} W_{i_1 j}^{AC}, l \in [n]$*, such that* $i_2 \in A^-_{i_1,POCT}$*, which implies that* $A^-_{i_1,AC} \subseteq A^-_{i_1,POCT}$*. By* ***Definition 5****,* $(A, \preccurlyeq_{AC}) \subseteq (A, \preccurlyeq_{POCT})$ *holds. Theorem 2 is proved.*

Proof of Theorem 3. *Prove by mathematical induction. Given* $a_{i_1} \preccurlyeq a_{i_2}$*, it is evident that*

$$W_{i_2 j_1}^{AC} - W_{i_1 j_1}^{AC} + \cdots + W_{i_2 j_n}^{AC} - W_{i_1 j_n}^{AC} \geqslant 0 \tag{C1}$$

It follows that

$$W_{j_1}^{C}(W_{i_2 j_1}^{AC} - W_{i_1 j_1}^{AC}) + W_{j_2}^{C}(W_{i_2 j_2}^{AC} - W_{i_1 j_2}^{AC}) + \cdots + W_{j_n}^{C}(W_{i_2 j_n}^{AC} - W_{i_1 j_n}^{AC}) \geqslant 0 \tag{C2}$$

When $r = 2$*, there exists* $W_{j_1}^C \geqslant W_{j_2}^C$*,* $W_{i_2 j_1}^{AC} \geqslant W_{i_1 j_1}^{AC}$ *such that*

$$W_{j_1}^{C}(W_{i_2 j_1}^{AC} - W_{i_1 j_1}^{AC}) \geqslant W_{j_2}^{C}(W_{i_2 j_1}^{AC} - W_{i_1 j_1}^{AC}) \tag{C3}$$

Then

$$\begin{aligned}
& W_{j_1}^{C}(W_{i_2 j_1}^{AC} - W_{i_1 j_1}^{AC}) + W_{j_2}^{C}(W_{i_2 j_2}^{AC} - W_{i_1 j_2}^{AC}) \geqslant \\
& W_{j_2}^{C}(W_{i_2 j_1}^{AC} - W_{i_1 j_1}^{AC}) + W_{j_2}^{C}(W_{i_2 j_2}^{AC} - W_{i_1 j_2}^{AC}) = \\
& \quad W_{j_2}^{C}(W_{i_2 j_1}^{AC} - W_{i_1 j_1}^{AC} + W_{i_2 j_2}^{AC} - W_{i_1 j_2}^{AC}) \geqslant 0
\end{aligned} \tag{C4}$$

When $r = l$*, there exists* $W_{j_{l-1}}^C \geqslant W_{j_l}^C$*,* $W_{i_2 j_1}^{AC} - W_{i_1 j_1}^{AC}, \cdots, W_{i_2 j_l}^{AC} - W_{i_1 j_l}^{AC}$ *such that*

$$\begin{aligned}
& W_{j_1}^{C}(W_{i_2 j_1}^{AC} - W_{i_1 j_1}^{AC}) + \cdots + W_{j_l}^{C}(W_{i_2 j_l}^{AC} - W_{i_1 j_l}^{AC}) \geqslant \\
& \quad W_{j_l}^{C}(W_{i_2 j_1}^{AC} - W_{i_1 j_1}^{AC} + \cdots + W_{i_2 j_l}^{AC} - W_{i_1 j_l}^{AC}) \geqslant 0
\end{aligned} \tag{C5}$$

Thus, when $r = n$*, there exists*

$$\begin{aligned}
& W_{j_1}^{C}(W_{i_2 j_1}^{AC} - W_{i_1 j_1}^{AC}) + \cdots + W_{j_n}^{C}(W_{i_2 j_n}^{AC} - W_{i_1 j_n}^{AC}) \geqslant \\
& \quad W_{j_n}^{C}(W_{i_2 j_1}^{AC} - W_{i_1 j_1}^{AC} + \cdots + W_{i_2 j_n}^{AC} - W_{i_1 j_n}^{AC})
\end{aligned} \tag{C6}$$

Based on the given premise that $W_{i_2 j_1}^{AC} - W_{i_1 j_1}^{AC} + \cdots + W_{i_2 j_n}^{AC} - W_{i_1 j_n}^{AC} \geqslant 0$*, it follows that*

$$\begin{aligned}
& W_{j_1}^{C}(W_{i_2 j_1}^{AC} - W_{i_1 j_1}^{AC}) + \cdots + W_{j_n}^{C}(W_{i_2 j_n}^{AC} - W_{i_1 j_n}^{AC}) \geqslant \\
& \quad W_{j_n}^{C}(W_{i_2 j_1}^{AC} - W_{i_1 j_1}^{AC} + \cdots + W_{i_2 j_n}^{AC} - W_{i_1 j_n}^{AC}) \geqslant 0
\end{aligned} \tag{C7}$$

Thus, $W_{i_1 j}^{POCT} \leqslant W_{i_2 j}^{POCT}$ *holds.* ***Theorem 3*** *is proved.*

Appendix C

Table C1
Emergency recovery plan of Manchester Stadium attack.

Improvement perspective	Sub-plan	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
Healthcare management	Establishing a joint medical rescue center	√	√	--	--	--	√	--	√	--	√
	Procuring medical equipment	--	--	√	--	--	--	--	--	√	--
	Establishing a medical equipment sharing program	--	--	--	√	--	--	√	--	√	--
	Developing an effective casualty transfer plan	--	--	--	--	√	--	√	--	--	--
Information management	Enhancing emergency record management systems	--	√	√	√	√	--	--	√	√	√
	Creating an emergency information sharing platform	√	√	--	√	--	√	√	--	--	--
Organization and procedure management	Establishing a joint emergency command center	--	--	--	--	--	√	√	--	--	--
	Developing collaborative mechanisms for emergency response	√	--	--	--	√	√	--	--	--	--
	Clarifying responsibilities of emergency organization members	--	--	√	--	--	--	--	--	--	√
	Developing policies and operational standards for emergency command handover	√	--	√	--	√	--	--	--	--	--
	Standardizing emergency service protocols	--	--	--	√	--	--	--	√	√	√
	Reviewing and improving major emergency response plans	--	√	--	--	--	--	--	√	--	--
Personnel training	Strengthening professional training for personnel	√	--	√	√	--	--	--	√	√	√
	Conducting regular drills and simulations	--	√	--	--	√	√	√	--	--	--

Appendix D

Table D1
Rankings of the attributes given by experts.

Expert ID	C1	C2	C3	C4	C5	C6	C7
E1	6	7	2	4	1	3	5
E2	1	6	2	5	3	7	4
E3	2	4	1	3	5	6	7
E4	3	6	4	7	2	1	5
E5	2	3	1	4	6	5	7

Table D2
Rankings of the plans under each attribute given by experts.

Expert ID	Plan ID	C1	C2	C3	C4	C5	C6	C7
E1	A1	2	6	7	4	8	10	6
	A2	9	9	10	8	9	3	7
	A3	8	7	9	2	6	4	2
	A4	5	8	4	3	5	1	3
	A5	4	4	3	1	7	2	8
	A6	1	1	5	7	2	5	9
	A7	10	2	1	10	3	7	1
	A8	3	3	6	9	1	6	10
	A9	6	10	8	6	10	8	4
	A10	7	5	2	5	4	9	5
E2	A1	4	5	1	10	7	6	8
	A2	8	9	10	4	9	10	10
	A3	6	7	9	2	10	7	7
	A4	9	8	6	3	6	8	6
	A5	3	4	4	1	1	4	5
	A6	1	1	7	8	3	1	1
	A7	10	6	3	9	4	2	3
	A8	2	2	5	6	2	3	2
	A9	5	10	8	7	8	9	9
	A10	7	3	2	5	5	5	4
E3	A1	3	1	7	5	7	5	9
	A2	9	9	10	8	6	8	8
	A3	10	7	3	9	8	9	6
	A4	8	8	2	3	4	10	7
	A5	4	2	1	2	3	3	2
	A6	1	3	5	7	1	1	3

(continued on next page)

Table D2 (*continued*)

Expert ID	Plan ID	C1	C2	C3	C4	C5	C6	C7
	A7	7	5	8	6	5	4	4
	A8	2	4	6	1	2	2	1
	A9	5	10	9	10	10	7	10
	A10	6	6	4	4	9	6	5
E4	A1	4	1	3	10	7	7	10
	A2	9	9	10	3	9	8	9
	A3	8	10	8	5	8	6	6
	A4	10	7	9	1	5	4	7
	A5	1	2	5	6	2	2	2
	A6	3	4	1	4	1	3	4
	A7	6	6	4	9	6	5	1
	A8	2	3	2	8	3	1	5
	A9	5	8	7	7	10	9	8
	A10	7	5	6	2	4	10	3
E5	A1	2	4	1	8	8	6	5
	A2	6	7	9	10	9	10	10
	A3	8	5	8	5	7	2	9
	A4	7	9	7	2	6	5	4
	A5	3	1	2	3	3	8	1
	A6	1	6	3	4	1	3	3
	A7	10	8	5	9	4	1	7
	A8	4	2	4	7	2	4	8
	A9	5	10	10	6	10	9	2
	A10	9	3	6	1	5	7	6

Appendix E

Table E1
Weight calculation results of the case ERPS.

		C1	C2	C3	C4	C5	C6	C7
E1	A1	0.0009	0.0003	0.0007	0.0008	0.0010	0.0001	0.0004
	A2	0.0001	0.0001	0.0001	0.0002	0.0006	0.0013	0.0003
	A3	0.0002	0.0002	0.0003	0.0014	0.0018	0.0010	0.0011
	A4	0.0004	0.0001	0.0016	0.0010	0.0024	0.0028	0.0008
	A5	0.0005	0.0004	0.0020	0.0021	0.0014	0.0018	0.0002
	A6	0.0014	0.0012	0.0012	0.0003	0.0055	0.0008	0.0001
	A7	0.0000	0.0008	0.0041	0.0001	0.0040	0.0005	0.0017
	A8	0.0007	0.0006	0.0009	0.0001	0.0083	0.0006	0.0001
	A9	0.0003	0.0000	0.0005	0.0005	0.0003	0.0003	0.0006
	A10	0.0002	0.0003	0.0027	0.0006	0.0031	0.0002	0.0005
E2	A1	0.0106	0.0014	0.0141	0.0002	0.0015	0.0009	0.0008
	A2	0.0032	0.0003	0.0005	0.0021	0.0007	0.0001	0.0002
	A3	0.0062	0.0008	0.0010	0.0037	0.0003	0.0007	0.0012
	A4	0.0020	0.0005	0.0031	0.0028	0.0021	0.0005	0.0016
	A5	0.0138	0.0018	0.0053	0.0056	0.0094	0.0015	0.0020
	A6	0.0282	0.0047	0.0023	0.0006	0.0046	0.0040	0.0071
	A7	0.0010	0.0010	0.0069	0.0004	0.0035	0.0027	0.0034
	A8	0.0186	0.0031	0.0041	0.0012	0.0062	0.0020	0.0046
	A9	0.0082	0.0002	0.0016	0.0009	0.0011	0.0003	0.0005
	A10	0.0046	0.0023	0.0093	0.0016	0.0027	0.0012	0.0026
E3	A1	0.0052	0.0053	0.0035	0.0020	0.0007	0.0010	0.0002
	A2	0.0008	0.0004	0.0007	0.0008	0.0009	0.0004	0.0003
	A3	0.0004	0.0009	0.0104	0.0005	0.0005	0.0003	0.0007
	A4	0.0012	0.0006	0.0140	0.0035	0.0016	0.0001	0.0005
	A5	0.0040	0.0035	0.0213	0.0047	0.0021	0.0017	0.0020
	A6	0.0106	0.0026	0.0061	0.0012	0.0043	0.0035	0.0015
	A7	0.0017	0.0015	0.0024	0.0016	0.0012	0.0013	0.0011
	A8	0.0070	0.0020	0.0047	0.0071	0.0028	0.0023	0.0030
	A9	0.0031	0.0002	0.0015	0.0002	0.0001	0.0006	0.0001
	A10	0.0023	0.0012	0.0080	0.0027	0.0003	0.0008	0.0009
E4	A1	0.0014	0.0019	0.0014	0.0001	0.0009	0.0018	0.0001
	A2	0.0003	0.0001	0.0001	0.0008	0.0004	0.0013	0.0002
	A3	0.0004	0.0001	0.0003	0.0005	0.0006	0.0025	0.0005
	A4	0.0001	0.0003	0.0002	0.0016	0.0016	0.0042	0.0004
	A5	0.0037	0.0012	0.0008	0.0004	0.0037	0.0073	0.0015

(*continued on next page*)

Table E1 (*continued*)

		C1	C2	C3	C4	C5	C6	C7
	A6	0.0018	0.0007	0.0028	0.0006	0.0056	0.0054	0.0008
	A7	0.0008	0.0004	0.0010	0.0001	0.0012	0.0032	0.0022
	A8	0.0024	0.0009	0.0018	0.0002	0.0027	0.0112	0.0006
	A9	0.0011	0.0002	0.0005	0.0003	0.0002	0.0008	0.0003
	A10	0.0006	0.0005	0.0006	0.0010	0.0021	0.0004	0.0011
E5	A1	0.0145	0.0055	0.0440	0.0013	0.0008	0.0019	0.0018
	A2	0.0049	0.0024	0.0032	0.0004	0.0005	0.0003	0.0002
	A3	0.0025	0.0042	0.0051	0.0032	0.0012	0.0058	0.0005
	A4	0.0036	0.0011	0.0072	0.0072	0.0016	0.0025	0.0024
	A5	0.0107	0.0147	0.0290	0.0054	0.0036	0.0010	0.0063
	A6	0.0220	0.0032	0.0215	0.0041	0.0073	0.0043	0.0031
	A7	0.0008	0.0017	0.0127	0.0008	0.0027	0.0088	0.0010
	A8	0.0082	0.0097	0.0165	0.0018	0.0048	0.0033	0.0007
	A9	0.0064	0.0005	0.0015	0.0024	0.0003	0.0006	0.0041
	A10	0.0016	0.0072	0.0097	0.0110	0.0021	0.0014	0.0014

Appendix F

Table F1
The POCTS in binary matrix form of the case ERPS.

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
A1	0	1	1	1	0	0	1	0	1	1
A2	0	0	0	0	0	0	0	0	0	0
A3	0	1	0	0	0	0	0	0	1	0
A4	0	1	1	0	0	0	0	0	1	0
A5	0	1	1	1	0	0	1	1	1	1
A6	0	1	1	1	0	0	1	1	1	1
A7	0	1	1	0	0	0	0	0	1	0
A8	0	1	1	1	0	0	1	0	1	0
A9	0	1	0	0	0	0	0	0	0	0
A10	0	1	1	1	0	0	0	0	1	0

Table F2
The general skeleton matrix of the case ERPS.

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
A1	0	0	0	0	0	0	0	0	0	0
A2	0	0	0	0	0	0	0	0	1	0
A3	0	0	0	1	0	0	1	0	0	0
A4	0	0	0	0	0	0	0	1	0	1
A5	0	0	0	0	0	0	0	0	0	0
A6	0	0	0	0	0	0	0	0	0	0
A7	1	0	0	0	0	0	0	1	0	0
A8	0	0	0	0	1	1	0	0	0	0
A9	0	0	1	0	0	0	0	0	0	0
A10	1	0	0	0	1	1	0	0	0	0

References

[1] R. Wang, E. Wang, L. Li, W. Li, Evaluating the effectiveness of the COVID-19 emergency outbreak prevention and control based on CIA-ISM, Int. J. Environ. Res. Public Health 19 (2022) 7146, https://doi.org/10.3390/ijerph19127146.

[2] A. Vafadarnikjoo, K. Chalvatzis, T. Botelho, D. Bamford, A stratified decision-making model for long-term planning: application in flood risk management in Scotland, Omega 116 (2023) 102803, https://doi.org/10.1016/j.omega.2022.102803.

[3] A.G. McClelland, D. Shaw, N. O'Grady, A. Fattoum, Recovery for development: a multi-dimensional, practice-oriented framework for transformative change post-disaster, J. Dev. Stud. 59 (2023) 1–20, https://doi.org/10.1080/00220388.2022.2130055.

[4] A. Nain, D. Jain, A. Trivedi, Multi-criteria decision-making methods: application in humanitarian operations, BIJ (2023), https://doi.org/10.1108/BIJ-11-2022-0673.

[5] J. Zhang, D. Huang, Q. You, J. Kang, M. Shi, X. Lang, Evaluation of emergency evacuation capacity of urban metro stations based on combined weights and TOPSIS-GRA method in intuitive fuzzy environment, Int. J. Disaster Risk Reduct. 95 (2023) 103864, https://doi.org/10.1016/j.ijdrr.2023.103864.

[6] H. Zhang, G. Wei, X. Chen, SF-GRA method based on cumulative prospect theory for multiple attribute group decision making and its application to emergency supplies supplier selection, Eng. Appl. Artif. Intel. 110 (2022) 104679, https://doi.org/10.1016/j.engappai.2022.104679.

[7] H.S. Saner, M. Yucesan, M. Gul, A Bayesian BWM and VIKOR-based model for assessing hospital preparedness in the face of disasters, Nat. Hazards 111 (2022) 1603–1635, https://doi.org/10.1007/s11069-021-05108-7.

[8] Y. Su, M. Zhao, C. Wei, X. Chen, PT-TODIM method for probabilistic linguistic MAGDM and application to industrial control system security supplier selection, Int. J. Fuzzy Syst. 24 (2022) 202–215, https://doi.org/10.1007/s40815-021-01125-7.
[9] X. Wang, X. Liang, X. Li, P. Luo, Collaborative emergency decision-making for public health events: an integrated BWM-TODIM approach with multi-granularity extended probabilistic linguistic term sets, Appl. Soft Comput. 144 (2023) 110531, https://doi.org/10.1016/j.asoc.2023.110531.
[10] Z. Liu, D. Wang, Y. Zhao, X. Zhang, P. Liu, An improved ELECTRE II-based outranking method for MADM with double hierarchy hesitant fuzzy linguistic sets and its application to emergency logistics provider selection, Int. J. Fuzzy Syst. 25 (2023) 1495–1517, https://doi.org/10.1007/s40815-022-01449-y.
[11] J. Zheng, Y.-M. Wang, K. Zhang, A case-driven emergency decision-making model based on probabilistic linguistic bidirectional projection, Comput. Ind. Eng. 187 (2024) 109844, https://doi.org/10.1016/j.cie.2023.109844.
[12] A. Memarpour Ghiaci, H. Garg, S. Jafarzadeh Ghoushchi, Improving emergency departments during COVID-19 pandemic: a simulation and MCDM approach with MARCOS methodology in an uncertain environment, Comput. Appl. Math. 41 (2022) 368, https://doi.org/10.1007/s40314-022-02080-1.
[13] P. Liu, Q. Pan, B. Zhu, X. Wu, Multi-attribute decision-making model based on regret theory and its application in selecting human resource service companies in the post-epidemic era, Inf. Sci. 649 (2023) 119676, https://doi.org/10.1016/j.ins.2023.119676.
[14] N. Zhang, H. Wang, Z. Gong, Dynamic multi-attribute grey target group decision model based on quantum-like Bayesian networks, Grey Systems: Theory and Application 14 (2024) 209–231, https://doi.org/10.1108/GS-08-2023-0072.
[15] J. Jiang, X. Liu, Z. Wang, W. Ding, S. Zhang, Large group emergency decision-making with bi-directional trust in social networks: a probabilistic hesitant fuzzy integrated cloud approach, Information Fusion 102 (2024) 102062, https://doi.org/10.1016/j.inffus.2023.102062.
[16] Z. Chen, W. Luo, An integrated interval type-2 fuzzy rough technique for emergency decision making, Appl. Soft Comput. 137 (2023) 110150, https://doi.org/10.1016/j.asoc.2023.110150.
[17] L. Yang, C. Li, L. Lu, T. Guo, Evaluation of port emergency logistics systems based on grey analytic hierarchy process, Journalof Intelligent & Fuzzy Systems 39 (2020) 4749–4761, https://doi.org/10.3233/JIFS-200674.
[18] X. Wu, H. Liao, A multi-stage multi-criterion group decision-making method for emergency management based on alternative chain and trust radius of experts, Int. J. Disaster Risk Reduct. 101 (2024) 104253, https://doi.org/10.1016/j.ijdrr.2024.104253.
[19] Z. Liu, W. Wang, P. Liu, Dynamic consensus of large group emergency decision-making under dual-trust relationship-based social network, Inf. Sci. 615 (2022) 58–89, https://doi.org/10.1016/j.ins.2022.09.067.
[20] G. Li, G. Kou, Y. Peng, Heterogeneous Large-scale group decision making using fuzzy cluster analysis and its application to emergency response plan selection, IEEE Transactions on Systems, Man, and Cybernetics: Systems 52 (2022) 3391–3403, https://doi.org/10.1109/TSMC.2021.3068759.
[21] M. Cao, Y. Hu, L. Yue, Research on variable weight CLIQUE clustering algorithm based on partial order set 1, J. Intell. Fuzzy Syst. (2023) 1–13, https://doi.org/10.3233/JIFS-230688.
[22] H. Wang, Y. Peng, G. Kou, A two-stage ranking method to minimize ordinal violation for pairwise comparisons, Appl. Soft Comput. 106 (2021) 107287, https://doi.org/10.1016/j.asoc.2021.107287.
[23] Y. Ataei, A. Mahmoudi, M.R. Feylizadeh, D.-F. Li, Ordinal priority approach (OPA) in multiple attribute decision-making, Appl. Soft Comput. 86 (2020) 105893, https://doi.org/10.1016/j.asoc.2019.105893.
[24] A. Mahmoudi, M. Sadeghi, L.M. Naeni, Blockchain and supply chain finance for sustainable construction industry: ensemble ranking using ordinal priority approach, Oper. Manag. Res. (2023), https://doi.org/10.1007/s12063-023-00374-z.
[25] A. Mahmoudi, X. Deng, S.A. Javed, N. Zhang, Sustainable supplier selection in megaprojects: grey ordinal priority approach, Bus. Strateg. Environ. 30 (2021) 318–339, https://doi.org/10.1002/bse.2623.
[26] A. Mahmoudi, M. Abbasi, X. Deng, A novel project portfolio selection framework towards organizational resilience: robust ordinal priority approach, Expert Syst. Appl. 188 (2022) 116067, https://doi.org/10.1016/j.eswa.2021.116067.
[27] N.M. AbdelAziz, K.A. Eldrandaly, S. Al-Saeed, A. Gamal, M. Abdel-Basset, Application of GIS and IoT technology based MCDM for disaster risk management: methods and case study, Decision Making: Applications in Management and Engineering 7 (2024) 1–36, https://doi.org/10.31181/dmame712024929.
[28] H. Wang, P. Luo, Y. Wu, Research on the location decision-making method of emergency medical facilities based on WSR, Sci. Rep. 13 (2023) 18011, https://doi.org/10.1038/s41598-023-44209-0.
[29] Q. Mao, J. Chen, J. Lv, S. Chen, Emergency plan selection for epidemic prevention and control based on cumulative prospect theory and hybrid-information MADM, Kybernetes 52 (2023) 1903–1933, https://doi.org/10.1108/K-08-2021-0736.
[30] M.L. Finucane, J. Acosta, A. Wicker, K. Whipkey, Short-term solutions to a long-term challenge: rethinking disaster recovery planning to reduce vulnerabilities and inequities, Int. J. Environ. Res. Public Health 17 (2020), https://doi.org/10.3390/ijerph17020482.
[31] D.E. Grierson, Pareto multi-criteria decision making, Adv. Eng. Inf. 22 (2008) 371–384, https://doi.org/10.1016/j.aei.2008.03.001.
[32] M. Sadeghi, A. Mahmoudi, X. Deng, X. Luo, Prioritizing requirements for implementing blockchain technology in construction supply chain based on circular economy: fuzzy ordinal priority approach, Int. J. Environ. Sci. Technol. 20 (2023) 4991–5012, https://doi.org/10.1007/s13762-022-04298-2.
[33] D. Pamučar, Ž. Stević, S. Sremac, A new model for determining weight coefficients of criteria in MCDM models: full consistency method (FUCOM), Symmetry 10 (2018), https://doi.org/10.3390/sym10090393.
[34] M. Žižović, D. Pamucar, New model for determining criteria weights: level based weight assessment (LBWA) model, Decision Making: Applications in Management and Engineering 2 (2019) 126–137, https://doi.org/10.31181/dmame1902102z.
[35] M. Deveci, D. Pamucar, I. Gokasar, D. Delen, Q. Wu, V. Simic, An analytics approach to decision alternative prioritization for zero-emission zone logistics, J. Bus. Res. 146 (2022) 554–570, https://doi.org/10.1016/j.jbusres.2022.03.059.
[36] M. Deveci, D. Pamucar, I. Gokasar, M. Köppen, B.B. Gupta, Personal mobility in metaverse with autonomous vehicles using Q-rung orthopair fuzzy sets based OPA-RAFSI model, IEEE Trans. Intell. Transp. Syst. 24 (2023) 15642–15651, https://doi.org/10.1109/TITS.2022.3186294.
[37] D. Pamucar, M. Deveci, I. Gokasar, M. Tavana, M. Köppen, A metaverse assessment model for sustainable transportation using ordinal priority approach and Aczel-Alsina norms, Technol. Forecast. Soc. Chang. 182 (2022) 121778, https://doi.org/10.1016/j.techfore.2022.121778.
[38] A. Mahmoudi, X. Deng, S.A. Javed, J. Yuan, Large-scale multiple criteria decision-making with missing values: project selection through TOPSIS-OPA, J. Ambient Intell. Hum. Comput. 12 (2021) 9341–9362, https://doi.org/10.1007/s12652-020-02649-w.
[39] J. Deng, Introduction to grey system theory, J. Grey Syst. 1 (1989) 1–24.
[40] A. Mahmoudi, S.A. Javed, S. Liu, X. Deng, Distinguishing coefficient driven sensitivity analysis of GRA model for intelligent decisions: application in project management, Technol. Econ. Dev. Econ. 26 (2020) 621–641, https://doi.org/10.3846/tede.2020.11890.
[41] S.A. Javed, A. Gunasekaran, A. Mahmoudi, DGRA: Multi-sourcing and supplier classification through dynamic grey relational analysis method, Comput. Ind. Eng. 173 (2022) 108674, https://doi.org/10.1016/j.cie.2022.108674.
[42] R.C. Burk, R.M. Nehring, An empirical comparison of rank-based surrogate weights in additive multiattribute decision analysis, Decis. Anal. 20 (2023) 55–72, https://doi.org/10.1287/deca.2022.0456.
[43] R. Wang, R. Shen, S. Cui, X. Shao, H. Chi, M. Gao, A novel multi-attribute decision-making approach for improvisational emergency supplier selection: partial ordinal priority approach, SSRN Journal (2024), https://doi.org/10.2139/ssrn.4708945.
[44] J. Saunders, Manchester arena inquiry volume 2 emergency response. report of the public inquiry into the attack on manchester arena on 22nd May 2017., (2022). https://manchesterarenainquiry.org.uk/report-volume-two#2.
[45] S. Chiossi, S. Tsolova, M. Ciotti, Assessing public health emergency preparedness: a scoping review on recent tools and methods, Int. J. Disaster Risk Reduct. 56 (2021) 102104, https://doi.org/10.1016/j.ijdrr.2021.102104.
[46] T.M. Carvalhaes, M.V. Chester, A.T. Reddy, B.R. Allenby, An overview & synthesis of disaster resilience indices from a complexity perspective, Int. J. Disaster Risk Reduct. 57 (2021) 102165, https://doi.org/10.1016/j.ijdrr.2021.102165.