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LARGE-SCALE EMERGENCY SUPPLIER SELECTION CONSIDERING LIMITED RATIONAL BEHAVIORS OF DECISION MAKERS AND RANKING ROBUSTNESS

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Abstract. Selecting emergency suppliers from a wide range of candidates based on their performance under each criterion can be regarded as a multi-criterion decision making (MCDM) problem. Existing MCDM models to solve the emergency supplier selection problem ignored situations where large-scale suppliers exist, the influence of criteria weights on the robustness of ranking results, and the influence of psychology of regret aversion and disappointment aversion on decision results. To make up for these deficiencies, this paper proposes an MCDM model to solve emergency supplier selection problem with large-scale alternatives. Firstly, to avoid the influence of criteria weights on ranking of alternatives, the Robustness, Correlation, and Standard Deviation (ROCOSD) method is introduced to determine objective weights of criteria based on three objectives. Secondly, the τ-balanced clustering method is applied to cluster large-scale alternatives into balanced clusters. Next, considering the psychology of regret aversion and disappointment aversion of decision makers, a two-stage method is proposed to rank alternatives, which identifies the optimal alternative within each cluster and forms a new cluster consisting of these optimal alternatives in the first stage, and selects the optimal alternative from the new-formed cluster in the second stage. A numerical case is given to validate the proposed model.

Keywords: emergency supplier selection, large-scale alternatives, multi-criterion decision-making, regret theory, disappointment theory, τ-balanced clustering method, ROCOSD method.

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1. Introduction

Emergencies encompass sudden natural disasters, accidents, public health events and social security events. Natural disasters caused by various uncontrollable forces (such as natural phenomena, geological disasters, meteorological disasters) can inflict severe economic and societal damage necessitating emergency measures (Liu et al., 2023b). According to the Statistics of Natural Disasters in 2022 released by the Ministry of Emergency Management[1], China experienced floods, droughts, hailstorms, earthquakes and geological catastrophes, typhoons, freezing temperatures with snowfall hazards, sandstorms, forest and grassland fires as well as marine disasters. In 2022, a total of 112 million people were affected by natural

[1] https://www.mem.gov.cn/xw/yjglbgzdt/202301/t20230113_440478.shtml

disasters such that 554 people were dead or missing, 2.428 million people were relocated, 47 thousand houses collapsed and 796 thousand houses were damaged to different degrees. Effective emergency management plays an indispensable role in reducing and mitigating the impact of such devastating events. The provision of emergency materials is crucial for effectively responding to emergencies. Selecting emergency suppliers from a number of candidates to supply emergency materials is an important measure to mitigate the damage.

Generally, decision makers (DMs) need to make emergency decisions at short notice using partial or incomplete information, especially in the early stage of a disaster, and a wrong decision may cause serious consequences (Yu & Lai, 2011). Selecting emergency suppliers from a wide range of candidates based on their performance under each criterion can be regarded as a multi-criterion decision making (MCDM) problem (Ulutaş et al., 2021). Nowadays, with the development of information technology, the number of alternatives and experts involved in decision-making problems shows a significant upward trend (Zhou et al., 2020). Large-scale decision-making problems have drawn extensive attention of scholars (Zuo et al., 2020; Wan et al., 2020; Zhou et al., 2023). Existing large-scale decision-making models focused on dimensionality reduction (Liu et al., 2022b), social relationship analysis among experts (Du et al., 2020; Zhou et al., 2022) and behavior management (Li et al., 2021; Chao et al., 2021). However, these models only centred around large-scale experts. In some practical problems, especially in emergency decision making problems (Xu et al., 2019) and group buying in e-commerce (Efremova & Lotov, 2009), large-scale alternatives are involved. The aforementioned models are not suitable for these problems with large-scale alternatives. How to deal with MCDM problems with large-scale alternatives is a valuable and challenging topic.

In addition, most MCDM methods, such as PROMETHEE (Brans & Vincke, 1985) and TOPSIS (Qin et al., 2017) are mainly based on the expected utility theory (Von Neumann & Morgenstern, 1944) that assumes DMs are completely rational. The psychology of DMs, such as loss aversion, regret aversion and disappointment aversion, makes individuals not completely rational when making decisions (Yin et al., 2019). van Dijk and Zeelenberg (2002) concluded that even closely related emotions such as regret and disappointment have distinctive effects on DMs' decision behaviors: the experience of disappointment makes people feel more powerless than the experience of regret; compared with regret, disappointment is more related to other person agency and circumstances agency but less related to self-agency. Most of the extant models (Zhao et al., 2022; Zhan et al., 2023) considering DMs' bounded rational behaviors applied the regret theory (RT) to reflect the influence of psychology of regret aversion on decision results, but ignored psychology of disappointment aversion, which may lead to biases of ranking results of alternatives. How to avoid the influence of regret aversion and disappointment aversion of DMs on decision results is a problem worthy of study.

Moreover, traditional MCDM methods primarily focused on selecting the optimal alternative based on comprehensive performance of each alternative, which can be obtained by integrating criteria weights and the performance of the alternative under various criteria (Alvarez et al., 2021). The robustness of ranking results of alternatives, referring to the ability of ranking of alternatives to cope with uncertainties including those that may not be anticipated, depends not only on the ranking mechanism, but also criteria weights (Wallenius et al., 2008). Owing to inherent cognitive limitations of individuals, ensuring complete accuracy in determining criteria weights becomes challenging. Existing objective weighting methods based on decision matrices, such as the Criteria Importance through Intercriteria Correlations (CRITIC) (Dialoulaki et al., 1995; Peng & Huang, 2020) and Entropy-based method (Ye, 2010), essentially rely on the conflict between intercriteria. However, these methods failed to consider the impact of changing criteria weights on ranking robustness. Alterations in criteria weights may lead to the change of ranking results and further affect the robustness of ranking results (Jessop, 2004; Danielson & Ekenberg, 2017). In such circumstances, developing a weight determination method to avoid the influence of imprecise criteria weights on ranking robustness holds significant importance.

Regarding the first research challenge on large-scale alternatives, clustering is an effective technique for reducing the dimensionality of extensive datasets by grouping similar data into clusters. Existing clustering methods can be categorized into two groups: the first group is that the balanced cluster results cannot be generated, such as the K-means (De Smet & Guzman, 2004), fuzzy C-means (Ozer, 2005), Adaptive Consistency Propagation (ACP) (Li et al., 2020). These clustering methods can produce good clustering results, but they fail to generate balanced clusters that have similar size. The deficiency limits their applicability. The second group includes algorithms that can achieve balanced clustering results, such as the Hungarian algorithm (Kuhn, 1955) and Balanced K-Means for Clustering (Franti et al., 2014). These methods can generate balanced clusters well, but they suffer from high time complexity. By contrast, the τ-balanced clustering method (Lin et al., 2022) can produce balanced clustering results, and the time complexity of the algorithm is small. Therefore, this paper uses the τ-balanced clustering method to classify large-scale alternatives into several clusters. In this way, an MCDM problem with large-scale alternatives is turned into an MCDM problem with limited-scale groups of alternatives.

In response to the second research challenge regarding limited rational behaviors of DMs, we simultaneously consider the influence of DMs' regret aversion and disappointment aversion psychology on decision results. Drawing upon the regret theory (Bell, 1982) and disappointment theory (DT) (Bell, 1985), we propose a perceived utility function of DMs for alternatives, which incorporates a utility function, regret-rejoicing function and disappointment-elation function. Based on the proposed perceived utility function, a two-stage method is proposed to rank alternatives, which identifies the optimal alternative within each cluster and forms a new group of alternatives consisting of the optimal alternatives in the first stage, and selects the optimal alternative from the new-formed group in the second stage.

The Robustness, Correlation, and Standard Deviation (ROCOSD) method (Pala, 2023) determines criteria weights by considering the robustness of ranking of alternatives, correlation between criteria, and standard deviations of criteria. To reduce the influence of criteria weights on the robustness of ranking results, this paper introduces the ROCOSD method to assign values to criteria according to three objectives. The first goal is to minimize the overall maximum divergence between criteria weights and the ratio of the standard deviation of each criterion to the sum of the standard deviations of all criteria. Maximizing divergence between criteria weights and the ratio of the correlation coefficient of each pair of criteria to the sum of the correlation coefficients of all criteria is the second objective. The third goal is to maximize the minimum change in any criteria weight that leads to a reversal of the ranking of alternatives. Applying the ROCOSD method to determine criteria weights can ensure the robustness of the ranking results, which is important for the validity of decision results.

Based on the above analysis, this study proposes an MCDM model for large-scale emergency suppliers selection considering DMs' psychology of regret aversion and disappointment aversion, and the influence of criteria weights on the robustness of ranking results. This paper conducts the following innovative work:

(1) The $\tau-$ balanced clustering method is applied to cluster large-scale alternatives into several clusters. In this way, the MCDM problem with large-scale alternatives is turned into an MCDM problem with limited-scale groups of alternatives, which reduces the difficulty of decision making.

(2) A perceived utility function of DMs for alternatives is proposed, which consists of the utility function, regret-rejoicing function and disappointment-elation function. The perceived utility function can reflect DMs' psychology of regret aversion and disappointment aversion on decision results.

(3) The ROCOSD method is applied to determine objective weights of criteria. The criteria weighting method considers the standard deviation, correlation coefficient and robustness of ranking, simultaneously. Then, a two-stage method is proposed to rank alternatives, which identifies the optimal alternative within each cluster and forms a new group of alternatives consisting of these optimal alternatives in the first stage, and selects the optimal alternative from the new-formed group in the second stage. In this way, it can ensure that the comprehensive perceived utility value of the selected best alternative is maximum.

The rest of this paper is organized as follows: Section 2 reviews relevant methods used in this study, including emergency supplier selection, the regret theory and disappointment theory. Section 3 demonstrates the proposed MCDM model. Section 4 validates the practicability of the proposed model and presents discussions. The last section concludes this study.

2. Literature review

Before introducing the MCDM model, this section reviews the advances of emergency supplier selection in Section 2.1 and then reviews the regret theory and disappointment theory in Section 2.2.

2.1. Advances of emergency supplier selection

The significance of emergency supplier assessment and selection has led researchers to propose host of studies. Table 1 summarizes relevant literature. As it can be seen from Table 1, these methods can be divided into three categories: the first category is programming-based approach, such as the goal programming method (Azadi et al., 2013); the second category is efficiency evaluation-based approach, such as data envelopment analysis (DEA) (Kraude et al., 2023); the last category is MCDM techniques, such as PROMETHEE method (Brans & Vincke, 1985), VIKOR method (Opricovic & Tzeng, 2004) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Qin et al., 2017). Among these three categories, MCDM techniques are the most widely used methods.

Scholars have proposed MCDM models (Su & Meng, 2017; Fei et al., 2021) and MCGDM models (Wang & Cai, 2017; Liu et al., 2023a) to deal with the emergency supplier selection problem. However, these models ignored DMs' limited rational behaviors. Although some MCDM methods that took DMs' limited rational behaviors into consideration (Liu et al., 2022c;

Zhang et al., 2022) were proposed, they ignored the influence of criteria weights on the robustness of ranking results. What's more, to our knowledge, there is no literature focused on solving the emergency supplier selection problem that involves large-scale suppliers. However, with the development of information technology and the change of decision-making environment, the number of emergency suppliers shows a significant upward trend. Therefore, it is urgent to develop an MCDM method that considers both the correlation between criteria and limited rational behaviors of DMs to solve an emergency supplier selection problem with large-scale alternatives.

Table 1. Summary of MCDM methods for emergency supplier selection

Category	Reference	Method(s)	Application area	Large-scale alternatives or not	Criteria are independent or not	Consider psychological factors or not
Programming-based approach	Azadi et al. (2013)	Goal programming method	Supplier selection	No	No	No
Efficiency evaluation-based approach	Sabouhi et al. (2018)	DEA	Supplier selection	No	No	No
MCDM techniques	Su and Meng (2017)	Entropy weighted TOPSIS method	Emergency procurement suppliers selection	No	Yes	No
	Wang and Cai (2017)	VIKOR	Emergency supplier selection	No	Yes	No
	Hu and Dong (2019)	Stochastic programming	Relief supplies selection	No	Yes	No
	Qin et al. (2021)	LINMAP and Even swaps method	Emergency logistics supplier selection	No	Yes	No
	Fei et al. (2021)	Dempster-Shafer theory	Emergency medical supplier selection	No	No	No
	Li et al. (2022)	Fuzzy SWARA and actor analysis method	Emergency epidemic prevention materials suppliers selection	No	No	No
	Liu et al. (2022c)	IBCSMDM and TODIM	Emergency medical supplier selection	No	No	Yes
	Zhang et al. (2022)	CRITIC, Cumulative prospect theory	Emergency supplies supplier selection	No	No	Yes
	Liu et al. (2023a)	TOPSIS	Emergency material supplier selection	No	Yes	No

Abbreviations: "AWARA" – stepwise weigt assessment ratio analysis, "IBCSMDM" – ISM-BWM-Cosine Similarity-viration Method, "CPT" – cumulative prospect theory.

The selection of the right emergency supplier requires comprehensive consideration of different criteria. Thus, the determination of criteria plays an important role in supplier selection. Based on existing literature (Wang et al., 2016; Qin et al., 2017; Li et al., 2022), the evaluation criteria system of emergency suppliers established in this study is shown in Table 2.

Table 2. Emergency suppliers' evaluation criteria system

Main criteria	Explanation	Sub-criteria
c_1 Flexible supply capacity	The emergency response speed and resource allocation ability of an enterprise, reflecting the response ability of the enterprise in the face of emergency events	Technical support capacity
		Emergency resource allocation level
		Emergency response speed
		Emergency organization capacity
c_2 Delivery capacity	The strong interaction ability of a supplier can guarantee the quantity, timeliness and accuracy of the supply	Emergency inventory level
		Supplier completeness
		Emergency processing speed
		Delivery accuracy
c_3 Price	The cost of purchasing emergency supplies	Agreement discount
		Price stability
c_4 Quality	The quality of emergency materials decides the quality of emergency rescue	Qualification rate of emergency suppliers
		Quality certification system
		Facilities and equipment
		Engineering technology level

2.2. Regret theory and disappointment theory

By explicitly incorporating regret into expected utility theory, the regret theory was proposed by Bell (1982) and Loomes and Sugden (1982) to explain and depict individual decision making behaviors under the premise of ignoring the independence axiom. It focuses on DMs' regret about wrong decisions. The regret theory is based on the intuition that DMs, when choosing a risky object, are concerned not only with the rewards they receive, but also with the rewards they forgo, that is, the rewards they would have received if they had made a different choice. The regret theory is characterized by two functions: a utility function capturing attitudes toward outcomes and a regret-rejoicing function capturing the effect of regret. Let a_i imply the result obtained by selecting alternative x_i (i = 1, 2, ..., m). The most extant literature applied $v(a_i) = (a_i)^{\theta}$ as the utility function of alternative x_i, where the parameter θ (0 < θ < 1) implies the risk aversion parameter of a DM. $R(v(a_i) - v(a^*)) = 1 - e^{\delta(v(a_i) - v(a^*))}$ was used in most literature to represent the regret-rejoice function of choosing alternative x_i, where the parameter δ (0 < δ < +∞) denotes the regret aversion parameter provided by a DM. When $v(a_i) > v(a^*)$, the DM will feel joy; otherwise, the DM will feel regret. Then, the perceived utility of the DM choosing alternative x_i can be calculated by $U(x_i) = v(a_i) + R(v(a_i) - v(a^*))$, where $a^* = \max\left\{a_i \middle| i = 1, 2, \ldots, m\right\}$. Based on utility function and regret-rejoicing function, the regret theory can explain many empirical violations of expected utility (Loomes & Sugden, 1982). The key to explaining these violations is the psychological intuition that most DMs have an innate aversion to regret. The intuitive content and explanatory power of regret theory make it well suited for real-world applications, such as new energy investment (Peng et al., 2019), reverse auction (Liao et al., 2020), medical decision (Wang et al., 2022, 2023) and emergency decision making (Xue et al., 2023). These literatures applied the regret theory to reflect the bounded rationality of DMs, ignored DMs' psychology of disappointment aversion.

Regret is caused by DMs' subjective wrong decision, which leads to a better alternative than the actual choice. By contrast, disappointment is caused by the decision-making environment, which has multiple results, but the actual result is poor due to the influence of the external decision-making environment (Bell, 1985). Let $s_1, s_2, \dots, s_L$ be possible outcomes of alternative x_i with corresponding probabilities $pro_{s_1}, pro_{s_2}, \dots, pro_{s_L}$. When the actual outcome is s_t, the disappointment-elation value of a DM who chooses alternative x_i is $D(v(a_i^{s_t}) - v(\bar{a}_i)) = 1 - \lambda^{(v(a_i^{s_t}) - v(\bar{a}_i))}$, where $v(\bar{a}_i) = \frac{1}{L}\sum_{l=1}^{L} v(a_i^{s_l})$, and the parameter λ ($0 < \lambda < +\infty$) denotes the regret aversion parameter provided by DMs. When $v(a_i^{s_t}) > v(\bar{a}_i)$, DMs will feel elation; otherwise, DMs will feel disappointment. Since the disappointment theory can explain DMs' emotional and behavioral reactions in the face of the gap between expected and actual results, it has been widely used after it was proposed. For example, Liu et al. (2022a) proposed an improved MULTIMOORA method to evaluate distance education quality based on the disappointment theory. Ruan et al. (2023) proposed a two-sided matching decision-making method of electricity sales packages based on the disappointment theory. However, as far as we know, the disappointment theory has not been applied to emergency decision making.

In emergency decision-making, the severity of emergencies will change as time goes on. When the impact of external environment leads to poor decision-making results, the generated disappointment will affect final decision-making results. Therefore, it is necessary to consider DMs' psychology of disappointment aversion and regret aversion when selecting emergency suppliers.

3. An RT-DT-ROCOSD model for emergency decision making problems with large-scale alternatives

Selecting emergency suppliers from large-scale candidates based on their performance under criteria can be regarded as an MCDM problem with large-scale alternatives denoted as $X = \{x_1, x_2, \dots, x_m\}$ ($m \geq 20$). Let a set of criteria be denoted as $C = \{c_1, c_2, \dots, c_n\}$ and their weight vector be $w = (w_1, w_2, \dots, w_n)^T$. Let $\{s_1, s_2, \dots, s_L\}$ denote the state of the emergency, and pro_{s_l} imply the probability that an emergency event is in the state s_l, satisfying $\sum_{l=1}^{L} pro_{s_l} = 1$. The matrix $P^{s_l} = (p_{ij}^l)_{m \times n}$ denotes the evaluation matrix when an emergency event is in state s_l, where p_{ij}^l implies the evaluation value of alternative x_i under criterion c_j corresponding to state s_l.

In the selection process, the decision results may be biased due to limited rational behaviors of DMs, and the robustness of ranking results for alternatives can be influenced by criteria weights. To address these issues, this section proposes an MCDM model to select appropriate emergency suppliers with large-scale alternatives considering DMs' psychology of regret aversion and disappointment aversion, as well as the influence of criteria weights on the robustness of ranking results. Specifically, Section 3.1 applies the ROCOSD method to obtain objective weights of criteria. Section 3.2 describes the method of dimensionality reduction for large-scale alternatives based on the τ-balanced clustering method. Section 3.3 introduces the regret theory and disappointment theory to obtain the comprehensive perceived utility of alternatives, and alternatives are ranked based on the comprehensive perceived utilities of alternatives. A summary of the proposed model is presented in Section 3.4.

3.1. Determine criteria weights based on the ROCOSD method

The evaluation of emergency suppliers involves both benefit criteria and cost criteria. Criteria are often incomparable when they are expressed in different scales. Thus, the decision matrix P should be normalized into a standard scale, which can be achieved by Eq. (1), where $\hat{p}_{ij}^{l}$ denotes the normalized evaluation value of alternative x_i under criterion c_j corresponding to state s_l. Then, integrate the evaluation values of each alternative under each criterion corresponding to different states of an emergency event to obtain the comprehensive decision matrix $P=(p_{ij})_{m\times n}$, where $p_{ij}=\sum_{l=1}^{L} pro_{s_l}\hat{p}_{ij}^{l}$, denoting the evaluation value of alternative x_i under criterion c_j corresponding to state s_l. The overall utility of alternative x_i can be calculated as $S_i=\sum_{j=1}^{n} w_j p_{ij}$, $i=1,2\ldots,m$.

$$\hat{p}_{ij}^{l}=\begin{cases}\dfrac{p_{ij}^{l}-\min\left\{p_{ij}^{l}\,\middle|\,i\in 1,2,\ldots,m\right\}}{\max\left\{p_{ij}^{l}\,\middle|\,i\in 1,2,\ldots,m\right\}-\min\left\{p_{ij}^{l}\,\middle|\,i\in 1,2,\ldots,m\right\}}, & \text{if } c_j \text{ is a benefit criterion}\\[2ex] \dfrac{\max\left\{p_{ij}^{l}\,\middle|\,i\in 1,2,\ldots,m\right\}-p_{ij}^{l}}{\max\left\{p_{ij}^{l}\,\middle|\,i\in 1,2,\ldots,m\right\}-\min\left\{p_{ij}^{l}\,\middle|\,i\in 1,2,\ldots,m\right\}}, & \text{if } c_j \text{ is a cost criterion}\end{cases}. \tag{1}$$

Due to complexity of decision environment and cognition deficiencies of DMs, it is difficult to ensure the complete accuracy of criteria weights. To avoid the reversal of ranking results of alternatives caused by incomplete accuracy of criteria weights, the influence of criteria weights on the robustness of ranking results of alternatives should be emphasized when determining criteria weights. Let MS_{ig-j} denote the maximum amount of tolerable change on w_j that does not lead to rank reversal between alternatives x_i and x_g. It can be determined by Eq. (2). Eq. (3) ensures that the criterion weight w_j is positive:

$$MS_{ig-j}=\frac{S_i-S_g}{p_{ij}-p_{gj}}, i\neq g; \tag{2}$$

$$w_j-MS_{ig-j}\geq 0. \tag{3}$$

In addition, the amount of information contained in criteria, which can reflect importance of criteria, is proportional to the discrete size of the data. Therefore, the standard deviation of evaluation values of criteria can be used to evaluate the information level contained in each criterion when determining criteria weights. The standard deviation σ_j of criterion c_j can be obtained by Eq. (4):

$$\sigma_j=\sqrt{\frac{1}{m}\sum_{i=1}^{m}(p_{ij}-\frac{1}{m}\sum_{i=1}^{m}p_{ij})^2}, j=1,2,\ldots,n. \tag{4}$$

What's more, if a criterion has a low correlation with other criteria, it contains high information about alternatives and thus should be assigned a high weight. The correlation coefficient ρ_{jr} of criterion c_j and criterion c_r can be calculated by Eq. (5):

$$\rho_{jr} = \frac{\sum_{i=1}^{m}(p_{ij} - \frac{1}{m}\sum_{i=1}^{m} p_{ij})(p_{ir} - \frac{1}{m}\sum_{i=1}^{m} p_{ir})}{\sqrt{\sum_{i=1}^{m}(p_{ij} - \frac{1}{m}\sum_{i=1}^{m} p_{ij})^2 \cdot \sum_{i=1}^{m}(p_{ir} - \frac{1}{m}\sum_{i=1}^{m} p_{ir})^2}}, \; j,r = 1,2,\ldots,n. \tag{5}$$

Based on the above analysis, Model 1, a mix-integer linear programming model, can be established to determine criteria weights. In Model 1, constraints C1 and C2 are used to indicate whether Eq. (3) has been satisfied, where b_{ig-j} is an auxiliary binary variable to identify if any change in w_j can lead to rank reversal between alternatives x_i and x_g. If it is satisfied, $b_{ig-j} = 0$, indicating that changing the criterion weight could result in rank reversal; otherwise, there is no possible of rank reversal. In constraints C3 and C4, if MS_{ig-j} is positive, $a_{ig-j} = 1$; else, $a_{ig-j} = 0$. Constraints C5 and C6 are used to restrict *MMSV* to less than MS_{ig-j}, where *MMSV* denotes the minimum of maximum stable values. Constraints C7 and C8 are used to restrict *MDSDR* that denotes the maximum divergence between criteria weights and the ratio of the standard deviation of each criterion to the sum of the standard deviations of all criteria. Constraints C9 and C10 are applied to restrict *MDCCR* that denotes maximum divergence between criteria weights and the ratio of the correlation coefficient of each pair of criteria to the sum of the correlation coefficients of all criteria. Constraint C12 ensures that the sum of criteria weights is 1.

Model 1 Min $\{MDSDR + MDCCR - MMSV\}$

$$\begin{cases}
C1: w_j + Hb_{ig-j} - MS_{ig-j} \ge 0, \; (i,g = 1,2,\ldots,m, \forall j = 1,2,\ldots,n, for \; i < g) \\
C2: w_j - H(1 - b_{ig-j}) - MS_{ig-j} \le 0, \; (i,g = 1,2,\ldots,m, \forall j = 1,2,\ldots,n, for \; i < g) \\
C3: MS_{ig-j} - Ha_{ig-j} \le 0, \; (i,g = 1,2,\ldots,m, \; \forall j = 1,2,\ldots,n, for \; i < g) \\
C4: MS_{ig-j} + H(1 - a_{ig-j}) \ge 0, \; (i,g = 1,2,\ldots,m, \; \forall j = 1,2,\ldots,n, for \; i < g) \\
C5: Ha_{ig-j} - MS_{ig-j} \ge MMSV, \; (i,g = 1,2,\ldots,m, \; \forall j = 1,2,\ldots,n, for \; i < g) \\
C6: Hb_{ig-j} + H(1 - a_{ig-j}) + MS_{ig-j} \ge MMSV, \; (i,g = 1,2,\ldots,m, \; \forall j = 1,2,\ldots,n, \; for \; i < g) \\
C7: w_j - (\frac{\sigma_j}{\sum_{j=1}^{n} \sigma_j}) \le MDSDR, \; (\forall j = 1,2,\ldots,n) \\
C8: -w_j + (\frac{\sigma_j}{\sum_{j=1}^{n} \sigma_j}) \le MDSDR, \; (\forall j = 1,2,\ldots,n) \\
C9: w_j - (\frac{\sum_{r=1}^{n}(1 - \rho_{jr})}{\sum_{j=1}^{n}\sum_{r=1}^{n}(1 - \rho_{jr})}) \le MDCCR, \; (j,r = 1,2,\ldots,n) \\
C10: -w_j + (\frac{\sum_{r=1}^{n}(1 - \rho_{jr})}{\sum_{j=1}^{n}\sum_{r=1}^{n}(1 - \rho_{jr})}) \le MDCCR, \; (j,r = 1,2,\ldots,n) \\
C11: \sum_{j=1}^{n} w_j = 1, \; (j = 1,2,\ldots,n) \\
b_{ig-j} \in \{0,1\}, \; (i,g = 1,2,\ldots,m, \; \forall j = 1,2,\ldots,n, \; for \; i < g) \\
a_{ig-j} \in \{0,1\}, \; (i,g = 1,2,\ldots,m, \; \forall j = 1,2,\ldots,n, \; for \; i < g) \\
w_j \ge 0, \; j = 1,2,\ldots,n \\
MDSDR, \; MDCCR, \; MMSV \ge 0.
\end{cases}$$

3.2. Cluster large-scale alternatives based on the K-means clustering method

After determining criteria weights, we deal with large-scale alternatives. As discussed above, the basic idea of dealing with MCDM problems involving large-scale alternatives is dimensionality reduction, transforming an MCDM problem with large-scale alternatives into a general MCDM problem with limited-scale groups of alternatives. Based on this idea, this part applies the τ-balance clustering method to cluster large-scale alternatives into several clusters.

Let $A_i = (p_{i1}, p_{i2}, \dots, p_{in})^T$ denote the evaluation vector corresponding to alternative x_i, for i = 1, 2, ..., m. Firstly, calculate parameters B_{ls} and B_{lc} by Eqs. (6) and (7), respectively, which are introduced to constrain the size of each cluster and the number of the largest clusters to produce a τ-balanced clustering result, respectively. K implies the number of clusters and it is determined in advance according to the actual situation.

$$B_{lc} = \frac{m - K\lceil m/K \rceil}{\tau} + K; \tag{6}$$

$$B_{ls} = \frac{m - B_{lc}\tau}{K} + \tau. \tag{7}$$

Then, identify initial cluster centroids. A common way to determine the initial cluster is to select them at random. However, the initial cluster centroids will affect the clustering effect. In this regard, we use the idea of the max-min method (Gonzalez, 1984). In the max-min method, the first cluster centroid c^1 is selected randomly. Then, the point that is at the greatest distance from the first centroid is selected as the second cluster centroid c^2. Compute the distances of the remaining points to the current two centroids. The point that has the nearest distance is selected as the third cluster centroid c^3. This procedure is continued until K centroids are selected.

Next, assign alternatives to clusters by Model 2, where c^k is the centroid of cluster C^k and $\left|C^k\right|$ is the number of alternatives in cluster C^k. $I(\left|C^k\right| = B_{ls})$ is an indicator function and it returns 1 if the Boolean expression $\left|C^k\right| = B_{ls}$ is true, otherwise, it returns 0. $dis(A_i, c^k) = \sqrt{\sum_{j=1}^{n}(p_{ij} - c_{ij}^k)^2}$ is a predefined distance function for measuring the difference of alternative x_i and centroid $c^{k,t}$. We update centroids of clusters by Eq. (8). The cluster assigning and updating process are repeated until the sum of difference of the distance between alternatives and its centroids in two successive iterations is less than a predefined threshold. In this case, all clusters are stabilized. Equation (9) emphasizes the stop condition for the cluster algorithm, where parameter ς is a very small number which is usually set as 0.001.

Model 2 $C^{k,t}(A_i) = \underset{c^1,c^2,\dots,c^k}{\arg\min} \sum_{k=1}^{K} \sum_{x_i \in C^k} dis(A_i, c^{k,t})$

$$\text{Subject to } \begin{cases} \left|C^k\right| \le B_{ls},\ k = 1, 2, \dots, K \\ \sum_{k=1}^{K} I(\left|C^k\right| = B_{ls}) \le B_{lc} \end{cases}$$

$$c_{ij}^{k,t+1} = \frac{1}{\left|C^{k,t}\right|} \sum_{x_i \in C^{k,t}} p_{ij}, j = 1, 2, \cdots, n; \tag{8}$$

$$\frac{\sum_{i=1}^{m}\sum_{k=1}^{K}\left|dis(A_i,c^{k,t+1})-dis(A_i,c^{k,t})\right|}{m\cdot K}\le\varsigma. \quad (9)$$

3.3. Rank alternatives based on the RT-DT

The psychology of regret aversion and disappointment aversion may affect their decision behaviors, and further affect decision results. Based on regret theory and disappointment theory, a two-stage approach is proposed to rank alternatives. In the first stage, we identify the optimal alternative within each cluster based on the RT-DT to form a group consisting of optimal alternatives and select the optimal alternative from the new-formed group in the second stage.

Stage 1: Identify the optimal alternative within each cluster based on RT-DT

To reduce the difficulty of selection process, we use the following rule to eliminate alternatives whose performance is significantly lower than other alternatives.

Elimination Rule: When the performance value of alternative x_a is not worse than alternative x_b corresponding to each criterion, i.e $\hat{p}_{aj}^{l}\ge\hat{p}_{bj}^{l},\forall j\in\{1,2,\ldots,n\}$, alternative x_a must be better than alternative x_b, and we eliminate the inferior alternative x_b. Similarly, if alternative x_i within a cluster C^k performs better than other alternatives corresponding to each criterion, the alternative is the best alternative for the cluster C^k. When the best alternative within the cluster C^k cannot be determined according to the rule, we can select the best alternative from the remaining alternatives within the cluster by using the following proposed method.

First, calculate the utility value matrix $V^l=\left(v_{ij}^{l}\right)_{m\times n}$, where v_{ij}^{l} implies the performance of alternative x_i under criterion c_j corresponding to state s_l, which can be obtained based on the power utility function by Eq. (10):

$$v_{ij}^{l}=(\hat{p}_{ij}^{l})^{\theta},\ \ x_i\in C^k. \quad (10)$$

Regret-rejoicing is produced by the comparison of decision results when choosing different alternatives under the same state. If DMs find that the results of the unselected alternatives are better than those of the selected alternatives, they will experience regret; otherwise, they will experience rejoicing. The regret-rejoicing value of DMs in choosing alternative x_i instead of x_* under criterion c_j corresponding to state s_l can be obtained by Eq. (11):

$$r_{ij}^{l}=1-e^{-\delta(v_{ij}^{l}-v_{*j}^{l})},\ \ v_{*j}^{l}=\max_{x_i\in C^k}\left\{v_{ij}^{l}\right\}. \quad (11)$$

Disappointment-elation is produced by the comparison of the results corresponding to different states under the same alternative. When the actual result is poor among several results due to the influence of the decision environment, DMs will be disappointed, and vice versa. The disappointment-elation matrix $D^l=(d_{ij}^{l})_{m\times n}$ can be obtained by Eq. (12):

$$d_{ij}^{l}=1-\lambda^{(v_{ij}^{l}-v_{ij}^{*})},\ v_{ij}^{*}=\frac{1}{L}\sum_{l=1}^{L}v_{ij}^{l}. \quad (12)$$

Then, we can obtain comprehensive utility matrix $CU^l=(cu_{ij}^{l})_{m\times n}$ where cu_{ij} denotes comprehensive utility value of alternative x_i under criterion c_j, which can be calculated by Eq. (13).

The comprehensive perceived utility of alternative x_i can be calculated by Eq. (14). According to the comprehensive perceived utilities of alternatives, the optimal alternative of each cluster can be selected, denoted as $x_{1*}, x_{2*}, \ldots, x_{K*}$, where x_{k*} implies the best alternative in the cluster C^k. Then, the optimal alternatives from each cluster constitute a new group, denoted as C^*. If more than one optimal alternative exists in a cluster, these alternatives are clustered into the optimal alternative cluster C^*.

$$cu_{ij}^l = v_{ij}^l + r_{ij}^l + d_{ij}^l; \tag{13}$$

$$G_i = \sum_{l=1}^{L} \sum_{j=1}^{n} pro_{s_l} w_j cu_{ij}^l. \tag{14}$$

Stage 2: Select the optimal alternative from the new-formed group.

Calculate the utility of the performance of alternative x_{k^*} under criterion c_j corresponding to state s_l based on the power utility function by Eq. (15). Calculate the regret-rejoicing value in choosing the alternative x_{k^*} instead of x_{**} under criterion c_j can be obtained by Eq. (16). Obtain the disappointment-elation value by Eq. (17). According to Eq. (18), the comprehensive utility of alternative x_{k^*} under criterion c_j consisting of utility, regret-rejoicing value and disappointment-elation value can be calculated. The comprehensive perceived utility of alternative x_{k^*} can be calculated by Eq. (19). According to the comprehensive perceived utilities of optimal alternatives, we can obtain the ranking of alternatives.

$$v_{k^*j}^l = (\hat{p}_{k^*j}^l)^{\theta}, x_{k^*} \in C^*; \tag{15}$$

$$r_{k^*j}^l = 1 - e^{-\delta(v_{k^*j}^l - v_{**j}^l)}, v_{**j}^l = \max_{x_{k^*} \in C^*} \left\{ v_{k^*j}^l \right\}; \tag{16}$$

$$d_{k^*j}^l = 1 - \lambda^{(v_{k^*j}^l - v_{k^*j}^*)}, \; v_{k^*j}^* = \frac{1}{L} \sum_{l=1}^{L} v_{k^*j}^l; \tag{17}$$

$$cu_{k^*j}^l = v_{k^*j}^l + r_{k^*j}^l + d_{k^*j}^l; \tag{18}$$

$$G_{k^*} = \sum_{l=1}^{L} \sum_{j=1}^{n} pro_{s_l} w_j cu_{k^*j}^l. \tag{19}$$

3.4. Summary of the proposed method

The specific procedure of the proposed method is summarized in Algorithm 2 and the framework of the proposed method is displayed in Figure 1.

Algorithm 2

Input: A set of original decision matrices P^{s_l}, the probability that an emergency event is in the state s_l, the number of clusters K, parameters τ, ς, θ, δ and λ.

Output: The ranking of alternatives.

Step 1: According to Eqs (2)–(5), construct Model 1 and then calculate criteria weights by solving Model 1.

Step 2: Select K centroids by using the idea of the max-min method. Assign alternatives to the clusters by Model 2 and update centroids by Eq. (8).

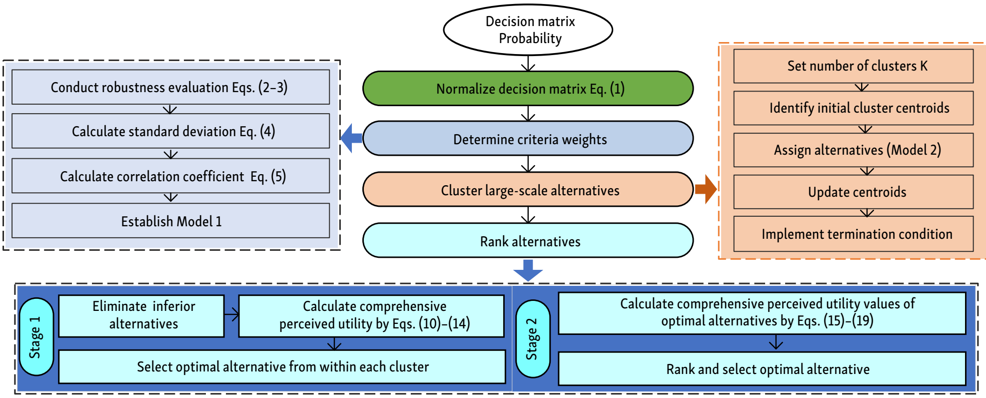


Figure 1. The flow chart of the proposed model

Step 3: Judge the termination condition of iteration and cluster alternatives into several clusters.

Step 4: Eliminate the inferior alternatives based on the Elimination Rule.

Step 5: Calculate utilities of alternatives by Eq. (10), regret-rejoicing values and disappointment-elation values by Eqs (11) and (12), respectively. Obtain comprehensive utility of alternative x_{i^*} under criterion by Eq. (13) and the comprehensive perceived utility of alternatives by Eq. (14). According to the comprehensive perceived utility of alternatives, select the optimal alternative of each cluster.

Step 6: By Eqs (15)–(19), calculate the comprehensive perceived utilities of alternatives within the optimal alternative cluster C^*. Then, rank optimal alternatives based on the comprehensive utilities of alternatives and select the best alternative. End.

4. Case study: A strategical selection of emergency material suppliers

This section employs a numerical example of emergency material supplier selection to demonstrate the effectiveness of the proposed method. Sensitivity analysis and comparative analysis are given to illustrate merits of the proposed method.

4.1. Case description

In recent years, emergency events are constantly emerging, such as earthquakes, typhoons, landslides, mudslides, river pollution, mine explosions, which causes major and devastating blows to human beings. Especially, in the western part of Sichuan Province in China, the topography and geological structure are complicated, which makes the types of geological disasters diverse. The main disaster is a large debris flow, which is often sudden and fierce, and its harm degree is more extensive and serious than that of a single collapse, landslide and flood. Emergency resource is important for people evacuation and property rescue when such emergency events occur. The sudden and high variation in the occurrence of emergency aggravate the uncertainty, complexity and fuzziness of the information environment. In such circumstance, selecting appropriate emergency material suppliers quickly and effectively is of great practical value for timely supply.

Suppose that a large debris flow occurs suddenly in a certain place in Sichuan Province. After field investigation by geological experts and analysis of landslide evolution trend, the emergency event faces two states of "medium landslide" (s_1) and "large landslide" (s_2) and the probability of these two states occurring in the next few days is 0.4 and 0.6, respectively, i.e $pro_{s_1} = 0.4$, $pro_{s_2} = 0.6$. Due to the sudden occurrence, the material reserve is short of sufficient materials. Therefore, the government urgently needs to select a suitable supplier from 20 emergency material suppliers, denoted as $\{x_1, x_2, \ldots, x_{20}\}$ to provide adequate emergency materials. To evaluate these suppliers comprehensively, a multi-disciplinary expert from within the government to assess the performance of these 20 suppliers under four criteria describes in Section 3.1. It is assumed that the criteria are benefit oriented, and the larger the value, the better the performance of the alternative under the criterion. The evaluation matrix of the expert is put in Appendix A.1.

Considering traditional MCDM problems mainly deal with small-scale alternatives of around 3–5 alternatives (Zhou et al., 2020), we set K = 4, that is, cluster large-scale alternatives into 4 clusters. We set τ = 1, that is, the size difference between any two clusters is less than or equal to 1. In addition, we set parameters θ = 0.88, δ = 0.3 (Wang et al., 2020), λ = 0.8 (Laciana & Weber, 2008).

4.2. Resolving process

This section applies the proposed method to address the problem. First, according to Model 1, we can obtain criteria weights as $w_1 = 0.2297$, $w_2 = 0.2047$, $w_3 = 0.2792$, $w_4 = 0.2864$. Second, classify the large-scale alternatives into different clusters. Using the τ-balanced clustering method, the 20 alternatives are grouped into four clusters: $C^1 = \{x_1, x_3, x_4, x_8, x_{19}\}$ $C^2 = \{x_2, x_{10}, x_{12}, x_{15}, x_{17}\}$, $C^3 = \{x_5, x_6, x_{16}, x_{18}, x_{20}\}$, $C^4 = \{x_7, x_9, x_{11}, x_{13}, x_{14}\}$. Then, identify the optimal alternative within each cluster based on the RT-DT. First, according to Rule 1, the optimal alternative within each cluster is not determined. Then, according to Rule 2, alternative x_{20} in cluster C^3 performs better than alternative x_{18} under each criterion. Therefore, eliminate the inferior alternative x_{18}. Similarly, alternative x_{13} in cluster C^4 performs better than alternative x_9 under each criterion. Therefore, eliminate the inferior alternative x_9. Then, we apply the proposed MCDM method to calculate the combined performance values of alternatives within each cluster, respectively. According to Eqs (9)–(12), the utility value, regret-rejoice values, disappointment-elation values, and comprehensive utilities of alternatives within cluster C^1 can be obtained. The results are shown in Table A.2 – Table A.4 in Appendix and Table 3, respectively. By Eq. (13), the comprehensive perceived utility values of alternatives within cluster C^1 can be calculated as G_1 = 0.63, G_3 = 0.52, G_4 = 0.59, G_8 = 0.61, G_{19} = 0.62. According to the comprehensive perceived utilities of the alternatives, we can obtain the ranking of alternatives within cluster C^1 as $x_1 \succ x_{19} \succ x_8 \succ x_4 \succ x_3$. Therefore, the optimal alternative in cluster C^1 is alternative x_{19}.

Similarly, the results of cluster C^2 are shown in Table A.5 – Table A.7 in Appendix A and Table 4, respectively. By Eq. (13), the comprehensive perceived utilities of alternatives within cluster C^2 can be calculated and the results are as G_2 = 0.41, G_{10} = 0.46, G_{12} = 0.43, G_{15} = 0.491, G_{17} = 0.490. According to the comprehensive perceived utilities of alternatives, we can obtain the ranking of alternatives within cluster C^2 as $x_{15} \succ x_{17} \succ x_{10} \succ x_{12} \succ x_2$. Therefore, the optimal alternative in cluster C^2 is alternative x_{15}.

The results of cluster C^3 are shown in Table A.8 – Table A.10 in Appendix A and Table 5, respectively. By Eq. (13), the comprehensive perceived utilities of alternatives within cluster C^3 can be calculated as G_5 = 0.59, G_6 = 0.63, G_{16} = 0.57, G_{20} = 0.61. According to the comprehensive perceived utilities of alternatives, we can obtain the ranking of alternatives within cluster C^3 as $x_6 \succ x_{20} \succ x_5 \succ x_{16}$. Therefore, the optimal alternative in cluster C^3 is alternative x_6.

The results of cluster C^4 are shown in Table A.11 – Table A.13 in Appendix A and Table 6, respectively. By Eq. (13), the comprehensive perceived utilities of alternatives within cluster C^4 can be calculated as G_7 = 0.44, G_{11} = 0.53, G_{13} = 0.57, G_{14} = 0.51. According to the comprehensive perceived utilities of alternatives, we can obtain the ranking of alternatives within cluster C^4 as $x_{13} \succ x_{11} \succ x_{14} \succ x_7$. Therefore, the optimal alternative in cluster C^4 is alternative x_{13}.

According to the above results, we can obtain a new optimal alternative cluster $C^* = \left\{x_6, x_{13}, x_{15}, x_{19}\right\}$. The results of cluster C^* are shown in Table A.14 – Table A.16 in Appendix A and Table 7, respectively. The comprehensive perceived utilities of the alternatives within cluster C^* can be calculated by Eq. (19) as G_1 = 0.58, G_6 = 0.56, G_{13} = 0.49, G_{15} = 0.39. According to the comprehensive perceived utilities of alternatives, we can obtain the ranking of alternatives within cluster C^* as $x_1 \succ x_6 \succ x_{13} \succ x_{15}$. Therefore, the optimal alternative is alternative x_1.

Table 3. The comprehensive utilities of alternative x_i under criterion c_j corresponding to state s_l within cluster C^1

cu_{ij}^l	s_1				s_2			
	c_1	c_2	c_3	c_4	c_1	c_2	c_3	c_4
x_1	0.73	0.69	0.33	0.86	0.68	0.65	0.36	0.79
x_3	0.65	0.67	0.33	0.92	0.21	0.36	0.34	0.78
x_4	0.68	0.64	0.36	0.86	0.48	0.63	0.34	0.80
x_8	0.58	0.69	0.32	0.92	0.56	0.63	0.34	0.85
x_{19}	0.77	0.62	0.46	0.91	0.48	0.63	0.26	0.91

Table 4. The comprehensive utilities of alternative x_i under criterion c_j corresponding to state s_l within cluster C^2

cu_{ij}^l	s_1				s_2			
	c_1	c_2	c_3	c_4	c_1	c_2	c_3	c_4
x_2	0.22	0.29	0.82	0.41	0.12	0.22	0.68	0.41
x_{10}	0.21	0.19	0.86	0.55	0.23	0.15	0.87	0.42
x_{12}	0.21	0.21	0.82	0.47	0.15	0.23	0.68	0.48
x_{15}	0.36	0.35	0.78	0.54	0.29	0.29	0.66	0.55
x_{17}	0.19	0.21	0.88	0.56	0.26	0.24	0.80	0.54

Table 5. The comprehensive utilities of alternative x_i under criterion c_j corresponding to state s_l within cluster C^3

cu_{ij}^l	s_1				s_2			
	c_1	c_2	c_3	c_4	c_1	c_2	c_3	c_4
x_5	0.93	0.86	0.33	0.30	0.78	0.79	0.48	0.47
x_6	0.91	0.91	0.18	0.44	0.91	0.91	0.46	0.44
x_{16}	0.85	0.80	0.34	0.44	0.85	0.77	0.32	0.44
x_{20}	0.83	0.85	0.35	0.47	0.86	0.85	0.45	0.46

Table 6. The comprehensive utilities of alternative x_i under criterion c_j corresponding to state s_l within cluster C^4

cu_{ij}^l	s_1				s_2			
	c_1	c_2	c_3	c_4	c_1	c_2	c_3	c_4
x_7	0.75	0.61	0.16	0.59	0.43	0.50	0.14	0.54
x_{11}	0.82	0.73	0.13	0.58	0.76	0.63	0.14	0.61
x_{13}	0.83	0.77	0.11	0.70	0.82	0.62	0.13	0.73
x_{14}	0.71	0.59	0.19	0.84	0.64	0.57	0.12	0.59

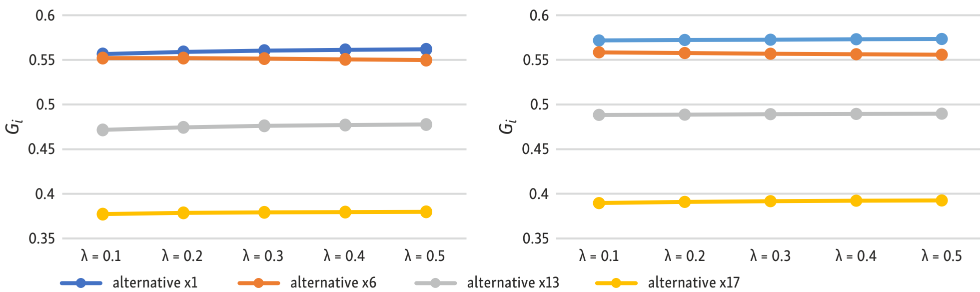
Table 7. The comprehensive utilities of alternative x_i under criterion c_j corresponding to state s_l within cluster C^*

cu_{ij}^l	s_1				s_2			
	c_1	c_2	c_3	c_4	c_1	c_2	c_3	c_4
x_1	0.68	0.62	0.22	0.87	0.61	0.57	0.24	0.82
x_6	0.91	0.91	0.04	0.31	0.91	0.91	0.39	0.33
x_{13}	0.81	0.72	-0.09	0.69	0.79	0.54	–0.06	0.70
x_{15}	0.18	0.17	0.80	0.44	0.09	0.09	0.70	0.47

4.3. Sensitivity analysis

In this section, we carry out sensitivity analysis to discuss the influence of disappointment aversion parameter λ on the results derived by the proposed method.

To verify the impact of DM's disappointment aversion psychology on decision results, we keep the regret aversion parameter unchanged, that is, $\delta = 0.3$. The value of disappointment parameter λ changes from 0.1 to 1, and observe the change of the comprehensive perceived utilities of alternatives and the optimal alternative of each cluster. The results are shown in Table B.1 in Appendix B and Figure 2. According to Eq. (11), we can find that when $\lambda = 1$, the disappointment-elation values of alternatives corresponding to DMs are 0, i.e, the psychology of disappointment aversion corresponding to DMs is not taken into account. The optimal alternative for cluster C^2 is alternative x_{15}. In addition, it can be seen from Figure 2 that, when $\lambda \in \{0.6, 0.7, 0.8, 0.9, 1\}$, as the value of λ increases, the optimal alternative within each cluster does not change, and the comprehensive utilities of alternatives in cluster C^* gradually increase. When $\lambda \in \{0.1, 0.2, 0.3, 0.4, 0.5\}$, the optimal alternative in cluster C^2 changes from



Note: "G_i" refers to the comprehensive perceived utility of alternative x_i.

Figure 2. Values of G_i of alternatives in cluster C

alternative x_{15} to alternative x_{17}. Therefore, the DMs' disappointment aversion psychology can affect decision-making results, and it is necessary to consider both the regret aversion and disappointment aversion psychology of DMs.

4.4. Comparative analysis

In this section, we conduct the following comparative analysis to illustrate the advantages of our proposed method.

(1) Compared with existing objective weighting methods, such as the CRITIC (Dialoulaki et al., 1995) and entropy-based method (Ye, 2010), the weight determination method adopted in this paper offers a more comprehensive approach to ensure the robustness of decision results. This study not only considers the influences of criteria weights on ranking results, but also considers correlation between criteria and standard deviations of criteria, thus ensuring the robustness of decision-making results.

(2) Compared with existing MCDM models that were proposed to solve the emergency supplier selection problem (Su & Meng, 2017; Wang & Cai, 2017; Hu & Dong, 2019), the model proposed in this paper considers the influence of DMs' psychological factors on decision-making results. Xue et al. (2023) considered DMs' regret aversion, but they ignored the impact of DMs' disappointment aversion on decision-making results. Our model considered not only the influence of DMs' regret aversion on decision-making results, but also the disappointment aversion psychology, thus increasing the credibility of decision-making results.

From this research, we can draw the following management implications:

(1) The MCDM model proposed in this paper overcomes the shortcomings of existing research. The proposed method focused on the influence of DMs' psychological factors on the emergency decision making results. In emergency decision-making, DMs' psychological factors such as regret avoidance and disappointment avoidance may affect decision-making results. Considering these psychological factors can help DMs make informative decisions and reduce the level of regret and disappointment. In addition, changes in the decision-making environment increase the number of alternatives that need to be evaluated. Applying the clustering method proposed in this paper to reduce the dimension of large-scale alternatives provides a new perspective for dealing with large-scale alternatives.

(2) For a major emergency such as debris flow, the available information for emergency decision-making is typically incomplete and inaccurate, and the trajectory of the event remains uncertain. In this case, the cognitive abilities and subjective factors of DMs significantly influence their choice of emergency alternatives, thereby indirectly impacting the effectiveness of plan implementation. DMs often exhibit behavioral characteristics associated with regret avoidance and disappointment avoidance during risk decision-making processes.

5. Conclusions

This paper proposed an MCDM model to address the issue of emergency supplier selection with large-scale alternatives, taking into account DMs' psychology of regret aversion and disappointment aversion, as well as the impact of criteria weights on the robustness of ranking results. In this model, we introduced a method that simultaneously considers robustness, criteria correlation and standard deviation to determine objective weights of criteria, thereby mitigating the influence of criteria weights on decision results. Additionally, by leveraging clustering techniques such as τ-balanced clustering method, we classify large-scale alternatives into different groups to transform MCDM problems with large-scale alternatives into general MCDM problems, so as to enhance decision-making efficiency. Furthermore, considering the joint influence of regret and disappointment behaviors of DMs on decision results, a two-stage method was proposed to rank alternatives, which identifies the optimal alternative within each cluster to form a group consisting of optimal alternatives in the first stage, and selects the optimal alternative from the new-formed group in the second stage.

The proposed model used the idea of clustering to divide large-scale alternatives into different subgroups, which provides a variety of new ideas for solving decision-making problems involving large-scale alternatives. In addition, the proposed model took into account both regret aversion and disappointment aversion of DMs, which makes up for the deficiency of only considering regret aversion of DMs in the existing literatures. However, in the case study of this paper, the regret aversion parameter δ and disappointment aversion parameter λ were determined subjectively. In the future, we will study the extraction of DMs' regret and disappointment aversion parameters based on their preferences through preference disaggregation (Fernández et al., 2017; Madhooshiarzanagh & Abi-Zeid, 2021).

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Author contributions

Xiaofang Li and Huchang Liao proposed the original idea and conceived the study. Xiaofang Li, Huchang Liao and Romualdas Baušys were responsible for developing the method, collecting and analyzing the data. Xiaofang Li, Huchang Liao and Edmundas Kazimieras Zavadskas were responsible for data interpretation. Xiaofang Li and Huchang Liao wrote the first draft of the article. Romualdas Baušys and Edmundas Kazimieras Zavadskas revised the paper.

Disclosure statement

The authors have no competing financial, professional, or personal interests from other parties that are related to this paper.

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APPENDIX

A. The evaluation matrices of experts are as follows:

Table A1. The evaluation of expert e_1

p_{ij}^l	s_1				s_2			
	c_1	c_2	c_3	c_4	c_1	c_2	c_3	c_4
x_1	0.7	0.65	0.31	0.85	0.65	0.62	0.31	0.8
x_2	0.2.	0.25	0.8	0.4	0.13	0.2	0.7	0.4
x_3	0.61	0.62	0.31	0.9	0.3	0.4	0.3	0.8
x_4	0.65	0.61	0.33	0.85	0.5	0.6	0.3	0.81
x_5	0.91	0.85	0.3	0.3	0.8	0.8	0.42	0.41
x_6	0.9	0.9	0.2	0.4	0.9	0.9	0.4	0.4
x_7	0.72	0.6	0.13	0.6	0.5	0.5	0.11	0.55
x_8	0.58	0.65	0.3	0.9	0.55	0.6	0.3	0.85
x_9	0.75	0.6	0.1	0.65	0.65	0.55	0.1	0.6
x_{10}	0.2	0.18	0.85	0.5	0.2	0.15	0.85	0.41
x_{11}	0.8	0.7	0.11	0.6	0.75	0.6	0.11	0.6
x_{12}	0.2	0.2	0.8	0.45	0.15	0.2	0.7	0.45
x_{13}	0.81	0.73	0.1	0.7	0.8	0.6	0.1	0.7
x_{14}	0.7	0.59	0.15	0.8	0.65	0.55	0.1	0.6
x_{15}	0.31	0.3	0.77	0.5	0.25	0.25	0.68	0.51
x_{16}	0.85	0.8	0.3	0.4	0.85	0.78	0.31	0.4
x_{17}	0.19	0.2	0.86	0.52	0.22	0.21	0.8	0.5
x_{18}	0.8	0.82	0.25	0.35	0.82	0.8	0.3	0.38
x_{19}	0.72	0.6	0.4	0.9	0.5	0.6	0.25	0.9
x_{20}	0.83	0.85	0.31	0.42	0.85	0.85	0.4	0.41

Table A2. The utility of alternative x_i under criterion c_j corresponding to state s_l within cluster C^1

v_{ij}^l	s_1				s_2			
	c_1	c_2	c_3	c_4	c_1	c_2	c_3	c_4
x_1	0.73	0.68	0.36	0.87	0.68	0.66	0.36	0.82
x_3	0.65	0.66	0.36	0.91	0.35	0.45	0.35	0.82
x_4	0.68	0.65	0.38	0.87	0.54	0.64	0.35	0.83
x_8	0.62	0.68	0.35	0.91	0.59	0.64	0.35	0.7
x_{19}	0.75	0.64	0.45	0.91	0.54	0.64	0.30	0.91

Table A3. The regret-rejoicing value of alternative x_i under criterion c_j corresponding to state s_l within cluster C^1

r_{ij}^l	s_1				s_2			
	c_1	c_2	c_3	c_4	c_1	c_2	c_3	c_4
x_1	–0.01	0.00	–0.03	–0.01	0.00	0.00	0.00	–0.03
x_3	–0.03	–0.01	–0.03	0.00	–0.11	–0.07	0.00	–0.03
x_4	–0.02	–0.01	–0.02	–0.01	–0.04	–0.01	0.00	–0.02
x_8	–0.04	0.00	–0.03	0.00	–0.03	–0.01	0.00	–0.01
x_{19}	0.00	–0.01	0.00	0.00	–0.04	–0.01	–0.02	0.00

Table A4. The disappointment-elation value of alternative x_i under criterion c_j corresponding to state s_l within cluster C^1

d_{ij}^l	s_1				s_2			
	c_1	c_2	c_3	c_4	c_1	c_2	c_3	c_4
x_1	0.01	0.00	0.00	0.01	–0.01	0.00	0.00	–0.01
x_3	0.03	0.02	0.00	0.01	–0.03	–0.02	0.00	–0.01
x_4	0.02	0.00	0.00	0.00	–0.02	0.00	0.00	0.00
x_8	0.00	0.01	0.00	0.00	0.00	–0.01	0.00	–0.01
x_{19}	0.02	0.00	0.02	0.00	–0.02	0.00	–0.02	0.00

Table A5. The utility of alternative x_i under criterion c_j corresponding to state s_l within cluster C^2

v_{ij}^l	s_1				s_2			
	c_1	c_2	c_3	c_4	c_1	c_2	c_3	c_4
x_2	0.24	0.30	0.82	0.45	0.17	0.24	0.73	0.45
x_{10}	0.24	0.22	0.87	0.54	0.24	0.19	0.87	0.46
x_{12}	0.24	0.24	0.82	0.50	0.19	0.24	0.73	0.50
x_{15}	0.36	0.35	0.79	0.54	0.30	0.30	0.71	0.55
x_{17}	0.23	0.24	0.88	0.56	0.26	0.25	0.82	0.54

Table A6. The regret-rejoicing value of alternative x_i under criterion c_j corresponding to state s_l within cluster C^2

r_{ij}^l	s_1				s_2			
	c_1	c_2	c_1	c_2	c_1	c_2	c_1	c_2
x_2	–0.03	–0.02	–0.02	–0.04	–0.04	–0.02	–0.04	–0.03
x_{10}	–0.03	–0.04	0.00	–0.01	–0.02	–0.03	0.00	–0.03
x_{12}	–0.03	–0.03	–0.02	–0.02	–0.03	–0.02	–0.04	–0.02
x_{15}	0.00	0.00	–0.02	–0.01	0.00	0.00	–0.05	0.00
x_{17}	–0.04	–0.03	0.00	0.00	–0.01	–0.01	–0.01	0.00

Table A7. The disappointment-elation value of alternative x_i under criterion c_j corresponding to state s_l within cluster C^2

d_{ij}^l	s_1				s_2			
	c_1	c_2	c_1	c_2	c_1	c_2	c_1	c_2
x_2	0.01	0.01	0.01	0.00	–0.01	–0.01	–0.01	0.00
x_{10}	0.00	0.00	0.00	0.01	0.00	0.00	0.00	–0.01
x_{12}	0.01	0.00	0.01	0.00	–0.01	0.00	–0.01	0.00
x_{15}	0.01	0.01	0.01	0.00	–0.01	–0.01	–0.01	0.00
x_{17}	0.00	0.00	0.01	0.00	0.00	0.00	–0.01	0.00

Table A8. The utility of alternative x_i under criterion c_j corresponding to state s_l within cluster C^3

v_{ij}^l	s_1				s_2			
	c_1	c_2	c_1	c_2	c_1	c_2	c_1	c_2
x_5	0.92	0.87	0.35	0.35	0.82	0.82	0.47	0.46
x_6	0.91	0.91	0.24	0.45	0.91	0.91	0.45	0.45
x_{16}	0.87	0.82	0.35	0.45	0.87	0.80	0.36	0.45
x_{20}	0.85	0.87	0.36	0.47	0.87	0.87	0.45	0.46

Table A9. The regret-rejoicing value of alternative x_i under criterion c_j corresponding to state s_l within cluster C^3

r_{ij}^l	s_1				s_2			
	c_1	c_2	c_1	c_2	c_1	c_2	c_1	c_2
x_5	0.00	–0.01	0.00	–0.04	–0.03	–0.03	0.00	0.00
x_6	0.00	0.00	–0.03	–0.01	0.00	0.00	–0.01	0.00
x_{16}	–0.02	–0.03	0.00	–0.01	–0.01	–0.03	–0.03	0.00
x_{20}	–0.02	–0.01	0.00	0.00	–0.01	–0.01	–0.01	0.00

Table A10. The disappointment-elation value of alternative x_i under criterion c_j corresponding to state s_l within cluster C^3

d_{ij}^l	s_1				s_2			
	c_1	c_2	c_1	c_2	c_1	c_2	c_1	c_2
x_5	0.01	0.01	–0.01	–0.01	–0.01	–0.01	0.01	0.01
x_6	0.00	0.00	–0.02	0.00	0.00	0.00	0.02	0.00
x_{16}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
x_{20}	0.00	0.00	–0.01	0.00	0.00	0.00	0.01	0.00

Table A11. The utility of alternative x_i under criterion c_j corresponding to state s_l within cluster C^4

v_{ij}^l	s_1				s_2			
	c_1	c_2	c_1	c_2	c_1	c_2	c_1	c_2
x_7	0.75	0.64	0.17	0.64	0.54	0.54	0.14	0.59
x_{11}	0.82	0.73	0.14	0.64	0.78	0.64	0.14	0.64
x_{13}	0.83	0.76	0.13	0.73	0.82	0.64	0.13	0.73
x_{14}	0.73	0.63	0.19	0.82	0.68	0.59	0.13	0.64

Table A12. The regret-rejoicing value of alternative x_i under criterion c_j corresponding to state s_l within cluster C^4

r_{ij}^l	s_1				s_2			
	c_1	c_2	c_1	c_2	c_1	c_2	c_1	c_2
x_7	–0.02	–0.04	–0.01	–0.06	–0.09	–0.03	0.00	–0.04
x_{11}	0.00	–0.01	–0.01	–0.06	–0.01	0.00	0.00	–0.03
x_{13}	0.00	0.00	–0.02	–0.03	0.00	0.00	0.00	0.00
x_{14}	–0.03	–0.04	0.00	0.00	–0.04	–0.01	0.00	–0.03

Table A13. The disappointment-elation value of alternative x_i under criterion c_j corresponding to state s_l within cluster C^4

d_{ij}^l	s_1				s_2			
	c_1	c_2	c_1	c_2	c_1	c_2	c_1	c_2
x_7	0.02	0.01	0.00	0.01	–0.02	–0.01	0.00	–0.01
x_{11}	0.01	0.01	0.00	0.00	–0.01	–0.01	0.00	0.00
x_{13}	0.00	0.01	0.00	0.00	0.00	–0.01	0.00	0.00
x_{14}	0.01	0.00	0.01	0.02	–0.01	0.00	–0.01	–0.02

Table A14. The utility of alternative x_i under criterion c_j corresponding to state s_l within cluster C^*

v_{ij}^l	s_1				s_2			
	c_1	c_2	c_1	c_2	c_1	c_2	c_1	c_2
x_1	0.73	0.68	0.36	0.87	0.68	0.66	0.36	0.82
x_6	0.91	0.91	0.24	0.45	0.91	0.91	0.45	0.45
x_{13}	0.83	0.76	0.13	0.73	0.82	0.64	0.13	0.73
x_{15}	0.36	0.35	0.80	0.54	0.30	0.30	0.71	0.55

Table A15. The regret-rejoicing value of alternative x_i under criterion c_j corresponding to state s_l within cluster C^*

r_{ij}^l	s_1				s_2			
	c_1	c_2	c_1	c_2	c_1	c_2	c_1	c_2
x_1	–0.06	–0.07	–0.14	0.00	–0.07	–0.08	–0.11	0.00
x_6	0.00	0.00	–0.18	–0.13	0.00	0.00	–0.08	–0.12
x_{13}	–0.02	–0.05	–0.22	–0.04	–0.03	–0.09	–0.19	–0.03
x_{15}	–0.18	–0.18	0.00	–0.10	–0.20	–0.20	0.00	–0.08

Table A16. The disappointment-elation value of alternative x_i under criterion c_j corresponding to state s_l within cluster C^*

d_{ij}^l	s_1				s_2			
	c_1	c_2	c_1	c_2	c_1	c_2	c_1	c_2
x_1	0.01	0.00	0.00	0.01	–0.01	0.00	0.00	–0.01
x_6	0.00	0.00	–0.02	0.00	0.00	0.00	0.02	0.00
x_{13}	0.00	0.01	0.00	0.00	0.00	–0.01	0.00	0.00
x_{15}	0.01	0.01	0.01	0.00	–0.01	–0.01	–0.01	0.00

B. The comprehensive utilities of alternatives with the optimal alternative cluster C^*

Table B1. The comprehensive utilities of alternatives with the optimal alternative cluster C^*

G_i	x_1	x_6	x_{13}	x_{17}
λ = 0.1	0.5565	0.552	0.4716	0.3773
λ = 0.2	0.5589	0.552	0.4744	0.3785
λ = 0.3	0.5603	0.5513	0.476	0.3791
λ = 0.4	0.5612	0.5505	0.4769	0.3795
λ = 0.5	0.5619	0.5498	0.4777	0.3798
G_i	x_1	x_6	x_{13}	x_{15}
λ = 0.6	0.5718	0.5584	0.4883	0.3897
λ = 0.7	0.5724	0.5577	0.4887	0.391
λ = 0.8	0.5727	0.557	0.4891	0.3916
λ = 0.9	0.5731	0.5564	0.4894	0.3922
λ = 1.0	0.5734	0.5558	0.4897	0.3926