symmetry

Article

A Large Group Emergency Decision Making Method Considering Scenarios and Unknown Attribute Weights

Pingping Wang [1] and Jiahua Chen [1,2,*]

[1] School of Economics, Management and Law, University of South China, Hengyang 421001, China
[2] Hunan Provincial Key Laboratory of Emergency Safety Technology and Equipment for Nuclear Facilities, Hengyang 421001, China
* Correspondence: chen.jiahua@usc.edu.cn

Abstract: Once an emergency event (EE) happens, emergency decision-making (EDM) plays a key role in mitigating the loss. EDM is a complex problem. Compared with conventional decision-making problems, more experts participate in decision-making. It usually has the feature of large group emergency decision-making (LGEDM). This paper proposes a large group emergency decision-making method based on Bayesian theory, relative entropy, and Euclidean distance, which is used for large group emergency decision-making with uncertain probabilities of occurrence, unknown attribute weights, and expert weights. In order to improve the accuracy of decision-making, Bayesian method is introduced into the calculation of scenario probability in the process of LGEDM. In the decision-making process, the experts' risk preference is considered. The experts' decision preference information is a symmetric and uniformly distributed interval value. The perceived utility values of the experts are obtained by introducing prospect theory. Euclidean distance is used to measure the contributions of experts to aggregation similarity, and different weights are given to experts according to their contributions. A relative entropy model with completely unknown weight information constraints is established to obtain attribute weights, which takes into account the differences of different alternatives under the same attribute and the differences between alternatives and the ideal solution. An example of nuclear power emergency decision-making illustrates the effectiveness of this method.

Keywords: large group emergency decision making; scenario; attribute weights; expert weights; Bayesian theorem; prospect theory; relative entropy

Citation: Wang, P.; Chen, J. A Large Group Emergency Decision Making Method Considering Scenarios and Unknown Attribute Weights. *Symmetry* **2023**, *15*, 223. https://doi.org/10.3390/sym15010223

Academic Editors: Dragan Pamucar, Željko Stević, Abbas Mardani and Edmundas Kazimieras Zavadskas

Received: 14 December 2022
Revised: 7 January 2023
Accepted: 10 January 2023
Published: 12 January 2023

1. Introduction

An emergency event (EE) refers to a sudden event that may cause casualties and losses [1]. In recent years, with the frequent occurrence of earthquakes, floods, rainstorms and other emergencies, human daily life and social development are affected to some extent. As emergency decision-making (EDM) plays a central role in mitigating accident losses, EDM has become an important research field of concern for scholars [2–6].

EDM is a complex problem. Compared with conventional decision-making problems, experts involved in decision-making tend to be more numerous, so it has the characteristics of large group decision-making (LGEDM), that is, the number of experts involved in decision-making is equal to or greater than 11 [7–10]. Nowadays, more and more decision-making problems involve many fields. For example, small group decision-making methods are no longer suitable for the needs of complex decision-making problems in social development. Many scholars began to study LGEDM. The procedure of LGEDM is: I assessments provided by the decision-making experts over alternatives are used for cluster analysis. The assessments and the expert weights are aggregated to get different aggregations, and then combined with the aggregation weights to get the final group decisions.

The existing LGEDM research is less, and mostly focuses on the decision-making risk, that is, the risk caused by the subjective factors of decision-makers. On the one hand, because the preference information expression of the decision-maker is uncertain, the implementation effect of the alternative has great uncertainty. On the other hand, due to the heterogeneity and large-scale nature of emergency decision-making groups, decision-making preference conflicts will inevitably occur. The greater the conflict, the lower the consensus level. In the case of a low consensus level, the aggregated comprehensive preference of the alternative has great uncertainty. Xu et al. [11] designed a large group emergency decision-making method considering individual language risk preference. Ding et al. [12] designed a collective method to aggregate the experts' individual preferences based on the principle of reasonable granularity. Xu et al. [13,14] proposed an improved consensus model and a dynamic consensus method based on the exit authorization mechanism. Xu et al. [15] put forward a consensus model of expert trust relationships based on social network analysis and preference risk based on interval intuitionistic fuzzy numbers.

In the emergency management and decision-making of major emergencies, due to the complexity of large-scale decision-making groups and emergency decision-making environment, emergency decision-making increasingly needs to comprehensively consider the implementation effect of alternatives under different scenarios, heterogeneous decision-making groups, and multi-attribute situations. However, most existing studies directly give the scenario probabilities, ignoring the impact of scenario uncertainty on decision-making [16]. In the actual decision-making process, the values of attribute weights play an important role in the ranking of alternatives [17]. Due to the complexity of objective things and the limitations of the decision-maker's own knowledge structure, it is often difficult for the experts to give accurate weights. The existing methods for calculating attribute weights include the minimum variance method [18], the least squares method [19], and the maximum Bayesian entropy method [20]. These methods only consider the use of the differences between alternatives to determine the role of an attribute but ignore the appeal for the ideal solution. Comprehensive assessments are obtained through the assessments of experts. Due to differences in theoretical knowledge and experience, the decision-making experts have different assessments and attitudes towards alternatives. Expert assessments and expert weights determine the final comprehensive assessments value. In the existing LGEDM research, most group decisions are based on the average value of decision experts' assessments [21,22], but in fact, the expert weights are different.

According to the previous limitations presented in current LGEDM methods, the aim of this paper is to propose a new LGEDM method that overcomes them. Such a method is able:

1. To improve the accuracy of probability by taking into account the scenario probabilities of LGEDM.
2. To obtain the best attribute weights by taking into account the difference between alternatives and the difference between alternatives and the ideal solution.
3. To assign different weights to experts by using Euclidean distance to measure the contributions of experts to aggregation similarity.

This paper presents a new LGEDM method. Bayesian theorem is introduced into the calculation of situation occurrence probabilities in the process of LGEDM, and a relative entropy model that takes into account the difference between alternatives, and the ideal alternative is constructed to obtain the attribute weights. The Euclidean distance is used to measure the contributions of decision-making experts to the aggregation similarity, and different weights are given to decision-making experts according to their contributions. This paper considers the psychological behavior of decision experts, and the experts' decision preference information is a symmetrical and evenly distributed interval value, and prospect theory is introduced to obtain the perceived utility of decision experts.

The outline of this paper is as follows: Section 2 briefly introduces Bayesian theorem, the prospect theory, and the relative entropy model, and briefly reviews the related work. A new LGEDM method will be presented in Section 3, which takes into account the above novelty. Section 4 provides a specific case of a nuclear power emergency to prove the feasibility and effectiveness of the proposed method. Section 5 provides the conclusions and future works of this paper.

2. Preliminaries

In this section, Bayesian theorem, prospect theory, and relative entropy will be briefly reviewed so that unfamiliar readers can understand our proposed method easily. In addition, some related works to illustrate the importance and necessity of this research are reviewed.

2.1. Bayesian Theorem in Emergency Decision-Making

Bayesian theorem was developed by the mathematician Bayes [23]. It is a standard method of applying observed phenomena in probability statistics to revise subjective judgments (prior probabilities) about probability distribution. In the process of EDM, Bayesian theorem can be used to modify the prior probabilities of scenario [24], which improves the accuracy of judging the occurrence probabilities of scenario.

At the initial stage of an EE, the decision-making experts do not know the real scenario, but the prior probabilities of the scenario are known. The prior probabilities of the scenario at the initial stage of the EE are obtained based on historical data or experience. The prior probabilities of the scenario at the EE development stage are the posterior probabilities of the previous stage. Assuming that the real emergency scenario is θ_k, but the probability that the decision-making experts judge it as μ_l is $p(\mu_l \mid \theta_k)$, and the real emergency scenario is θ_k, but the probability that the decision-making experts judge it as θ_k is $p(k = l)$, then the posterior probability that the emergency scenario is θ_k based on Bayesian theorem is:

$$p(\theta_k|\mu_l) = \frac{p(\mu_l|\theta_k)p(\theta_k)}{\sum_k^K p(\mu_l\big|\theta_k)p(\theta_k)} \tag{1}$$

In the constructed LGEDM method, Bayesian theorem will be used to calculate the occurrence probabilities of scenarios to improve the accuracy of experts' judgment on scenario probabilities. The aggregation conditional probabilities will be obtained by aggregating the scenario's conditional probabilities of experts. The group conditional probabilities will be obtained by aggregating the aggregation conditional probabilities, and the posterior probabilities of the scenario will be calculated by using Bayesian formula.

2.2. Prospect Theory in Emergency Decision-Making

In the face of the high uncertainty of EDM, the psychological role of decision-making experts cannot be ignored. Different from the expected utility theory, the prospect theory believes that people have different risk preferences in the face of gains and losses, will become risk seeking in the face of losses, and will become risk averse in the face of profits [25], so this paper considers the prospect theory to describe the psychological role of decision-makers. The prospect theory was put forward by D. Kahneman and A. Tversky in 1979 [26], and the prospect value function $v(\Delta x_i)$ reflects the perceived utility formed by the subject according to the value difference:

$$v(\Delta x_i) = \begin{cases} (\Delta x_i)^\alpha, & \Delta x_i \geq 0 \\ -\lambda(\Delta x_i)^\beta, & \Delta x_i < 0 \end{cases} \tag{2}$$

where $\Delta x_i = x_i - x_0$ represents the difference between the value x_i of the subject and reference point x_0 when event i occurs, α is the parameter with respect to gains, and β is the parameter associated with losses; $0 \leq \alpha, \beta \leq 1$. The larger the parameter value is, the less sensitive the subject is to the benefit or loss utility, and the greater the possibility that the subject is a risk seeker. λ denotes the parameter of risk aversion; $\lambda > 1$. The larger the parameter value is, the more sensitive the subject is to loss and the greater the degree of loss avoidance is. Generally, $\alpha = 0.88$, $\beta = 0.88$, and $\lambda = 1.25$.

In the constructed LGEDM method, prospect theory is used to calculate the perceived utility of experts. According to the experts' psychological reference value, the experts' psychological profit and loss value is calculated, and the perceived utility value is obtained by combining the risk preference coefficient of the experts.

2.3. Relative Entropy Model in Emergency Decision-Making

In information theory, the difference between the states A_i and B_i of two systems A and B can be measured by the Kullback–Leibler distance [27], that is:

$$C = \sum_{i=1}^{N} A_i \log \frac{A_i}{B_i} + (1 - A_i)\log\frac{(1 - A_i)}{(1 - B_i)} \tag{3}$$

C is called the relative entropy of the states of system A and B. The smaller the difference between the states of A and B, the smaller C is. In addition to measuring the distance between two random distributions, relative entropy can also handle the allocation of indicator weights in the multi-attribute indicator system evaluation [28].

In the constructed LGEDM method, the greater the difference between different alternatives under the same attribute, the weight given to this attribute is bigger. In contrast, the weight given to this attribute is smaller. At the same time, the gap between alternatives and the ideal solution needs to be as small as possible. Therefore, a relative entropy will be used to measure the difference between alternatives and calculate the optimal attribute weights.

2.4. Related Work

In order to demonstrate the importance and necessity of this study, we briefly reviewed the literature similar to this study.

In the existing EDM research, most of them consider the psychological behavior of decision makers. Wang et al. [29] proposed a GEDM method based on prospect theory, in which the decision-maker's preference information is interval value. Zhang et al. [30] proposed an EDM method based on PT and hesitation fuzzy set, which considers both the psychological behavior of experts and the hesitation of experts in the quantitative environment. Wang et al. [31] proposed a new GEDM method, which provides a consensus process to avoid divergence, and uses the fuzzy TODIM method based on prospect theory to consider the psychological behavior of decision-making experts.

Although the existing EDM research has made some achievements, they ignore an important fact that different emergency scenarios should be handled by using different measures, that is, the uncertainty of emergency scenarios will bring different impacts to decision-making. Liu et al. [30] proposed a scenario's representation model for emergency decision support, that is, a formal description of the object and its emergency state. This model is conducive to evaluating the severity and effectiveness of emergency decisions. Qie et al. [32] proposed a scenario modeling method for cascading disasters to support decision making for complex disaster emergency preparation and response. It can make effective emergency decisions under cascading disaster scenarios. Gupta et al. [33] considered the optimal alternative of resource allocation under different scenarios and proposed an EDM method based on game theory. On this basis, Zhang et al. [34] proposed an EDM method based on prospect theory and game theory, taking into account both the scenario and the decision-maker's psychological behavior. These studies all show that the emergency scenarios cannot be ignored.

The weights of decision-makers and attributes are unknown due to the complexity of GEDM. Zhang et al. [35] developed a deviation maximizing model to compute criteria weights and another compatibility maximizing model to calculate weights for decision makers. Liu et al. [36] proposed a novel intelligent optimization algorithm, a plant growth simulation algorithm, to integrate the different individual evaluations. Xu et al. [37] proposed a method to measure the rationality of experts and determine their weights using an interval consistency composed of the average consistency and standard deviation indices. Li et al. [38] proposed a method, and this method establishes a grey correlation analysis algorithm based on the objective evaluation value and subjective preference value of decision makers, which makes up for the shortcomings of traditional model's information loss and greatly improves the accuracy of EDM.

So far, the impact of scenario occurrence probabilities on the final decision are rarely considered in EDM research, and the calculation of attribute weights only considers the maximization of attribute deviation. Therefore, for the interval value LGEDM with uncertain occurrence probabilities of scenario, completely unknown attribute weights, and unknown decision-making expert weights, this paper proposes a LGEDM method based on Bayesian theory, relative entropy, and Euclidean distance. Bayesian theorem is introduced into LGEDM to improve the accuracy of scenario probabilities. The relative entropy model is constructed to calculate the attribute weights. The calculation of the attribute weights takes into account both the maximization of the difference between alternatives and the minimization of the difference between the alternative and the ideal solution. The Euclidean distance is used to measure the contributions of decision experts to the aggregation similarity, to calculate the weights of decision experts. This paper expresses the psychological role of experts using prospect theory.

3. A Large Group Emergency Decision-Making Method Considering Scenarios and Unknown Attribute Weights

This section introduces an LGEDM method considering scenarios and unknown attribute weights. This proposal is able: (1) to improve the accuracy of scenario uncertainty. (2) to calculate the attribute weights when the information is completely unknown. (3) to obtain expert weights according to the contributions of experts to aggregation similarity. (4) to take into account the psychological behavior of experts and the decision preference of interval number.

It consists of five main phases:

1. Definition framework. The main features, terminology, and expression domains utilized in the proposed LGEDM problem are defined.
2. Calculation of posterior probabilities of scenario. In this part, firstly, cluster analysis is carried out according to the conditional probabilities of the scenario, and the weights of experts are obtained by using the Euclidean distance. The aggregation conditional probabilities are obtained by aggregating the initial conditional probabilities and the expert weights, and the group conditional probabilities are obtained by aggregating the aggregation conditional probabilities and the aggregation weights. Secondly, the posterior probabilities are calculated by using Bayesian theorem and prior probabilities.
3. Calculation of the group prospect values. In this part, firstly, the perceived utility of the experts is calculated according to the decision interval and value function, and the initial prospect values of the experts are obtained by combining the posterior probabilities of scenario. Secondly, cluster analysis is carried out on the initial prospect values, and the expert weights are obtained by Euclidean distances. The aggregation prospect values are obtained by aggregating the initial prospect values and the expert weights, and the group prospect values are obtained by aggregating the aggregation prospect values and aggregation weights.
4. Calculation of attribute weights. The relative entropy model with completely unknown attribute weights is constructed, and the attribute weights are calculated by using Lagrange algorithm.
5. Ranking of alternatives. Combined with the group prospect values and attribute weights, the overall prospect values are obtained. Based on this, the ranking of alternatives is obtained. According to the ranking of alternatives, the experts can select the best or more suitable alternative to cope with the EE.

3.1. Definition Framework

The following notations that will be used in our proposal are defined below:

- $X = \{x_1, x_2, \ldots, x_i, \ldots, x_n\}$: refers to the set of different alternatives, in which x_{i} denotes the i-th alternative, $i = 1, 2, \ldots, n$.
- $E = \{e_1, e_2, \ldots, e_j, \ldots, e_m\}$, $m \geq 11$: refers to the set of the experts, in which e_j denotes the j-th decision expert, $j = 1, 2, \ldots, m$.
- $C = \{c_1, c_2, \ldots, c_l, \ldots, c_p\}$: refers to the set of criteria/attributes, in which cl denotes the l-th criterion/attribute, $l = 1, 2, \ldots, p$.
- $W = \{w_1, w_2, \ldots, w_l, \ldots, w_p\}$: refers to the weighting vector for the criteria, in which w_l denotes the criterion weight of the l-th criterion/attribute, $l = 1, 2, \ldots, p$.
- $\Omega_Z = \{Z^1, Z^2, \ldots, Z^h, \ldots, Z^k\}$: refers to the set of scenario conditional probability aggregations, in which Z^h denotes the h-th aggregation, $h = 1, 2, \ldots, k$. Clustering the conditional probabilities of scenario given by decision experts to form k aggregations, and the number of experts gathered in Z^h is n_h.
- $\Omega_R = \{R^1, R^2, \ldots, R^f, \ldots, R^O\}$: refers to the set of alternative assessment aggregations, in which Rf denotes the f-th aggregation, $f = 1, 2, \ldots, O$. Clustering the alternative assessments given by decision experts to form O aggregations, and the number of experts gathered in R^f is n_f.
- $\omega^{XE} = \{\omega_1{}^{XE}, \omega_2{}^{XE}, \ldots, \omega_m{}^{XE}\}$: refers to weighting vector of decision experts in assessing alternatives.
- $\omega^{XR} = \{\omega_1{}^{XR}, \omega_2{}^{XR}, \ldots, \omega_{nf}{}^{XR}\}$: refers to weighting vector of aggregations in assessing alternatives.
- $S = \{s_1, s_2, \ldots, s_t, \ldots, s_u\}$: refers to the set of different scenarios, in which s_t denotes the t-th scenario, $t = 1, 2, \ldots, u$. $p(s_t)$ is the prior probability of scenario s_t, $p_{\mathrm{j}}(s_d{}' \mid s_t)$ is the probability that the decision expert e_j determine the scenario as $s_d{}'$ under the real scenario s_t, $p^Z(s_d{}' \mid s_t)$ is the probability that the aggregation Z^h determine the scenario as $s_d{}'$ under the real scenario s_t, $p^G(s_d{}' \mid s_t)$ is the group conditional probability of scenario, and $p(s_t \mid s_d{}')$ is the posterior probability of the scenario s_t.
- $\omega^{PE} = \{\omega_1{}^{PE}, \omega_2{}^{PE}, \ldots, \omega_m{}^{PE}\}$: refers to weighting vector of decision experts in determining the condition probabilities.
- $\omega^{PZ} = \{\omega_1{}^{PZ}, \omega_2{}^{PZ}, \ldots, \omega_{nh}{}^{PZ}\}$: refers to weighting vector of aggregations in determining the condition probabilities.
- $a_{li}{}^{jt} = [a_{li}{}^{jtL}, a_{li}{}^{jtU}]$: refers to the assessment of the i-th alternative by the decision expert e_j under the scenario s_t and attribute c_l, belongs to the interval number, and the assessment matrix $A = [a_{li}{}^{jt}]_{m\times n\times u\times p}$ given by the decision experts is obtained.

3.2. Posteriori Probabilities of Scenario

3.2.1. Cluster Analysis of Scenario Conditional Probabilities

(1) Cluster the initial condition probabilities

Cluster analysis is a multivariate statistical method for studying problems. It refers to gathering similar elements into a category and classifying them by selecting certain indicators to analyze the differences between elements. The Euclidean distance between the scenario conditional probabilities of two decision experts e_{j1} and e_{j2} are calculated according to the initial scenario conditional probability matrix $P(s_d{}' \mid s_t) = [p_j(s_d{}' \mid s_t)]_{m\times u\times u}$:

$$d_p^{j1,j2} = d(p_{j1}(s'_d|s_t), p_{j2}(s'_d|s_t)) = \sqrt{(p_{j1}(s'_d|s_t) - p_{j2}(s'_d|s_t))^2} \tag{4}$$

The clustering algorithm matrix $D = [d_p{}^{j1,j2}]_{m\times m\times u\times u}$ is obtained, and the initial condition probability matrix $P(s_d{}' \mid s_t)$ is clustered by using the hierarchical clustering algorithm and the clustering algorithm matrix D to form k aggregations $\Omega_Z = \{Z^1, Z^2, \ldots, Z^h, \ldots, Z^k\}$. The idea of the hierarchical clustering algorithm is to calculate the distance between samples first, and the nearest points are merged into the same class each time. Then, the distance between classes is calculated, and the nearest classes are merged into a large class. Merging continues until a class is synthesized.

(2) Aggregation conditional probabilities

According to the majority principle, the more decision experts in the aggregation, the greater the weight given to the aggregation; on the contrary, the weight given to the aggregation is smaller. Therefore, the weight given for the aggregation Z^h is ${\omega_h}^{PZ} = n_h/m$. In the existing literature, the aggregation alternative assessments are mostly calculated by using the average value of experts' alternative assessments, but the aggregation alternative assessments are obtained by experts' alternative assessments and expert weights. In fact, the weights among experts are different, and it is inaccurate to take the average values of expert assessments as the aggregation assessments. Therefore, this paper proposes to use the Euclidean distance to measure the contribution of experts to the aggregation similarity to calculate the expert weights; ${\omega_{hq}}^{PE}$ $(0 < q < n_h)$ is the weight of the q-th expert in the aggregation Z^h to determine the scenarios:

$$\omega_{hq}^{PE} = \frac{\sum_{j2=1}^{n_h}\left(1 - d_p^{j1,j2}\right)}{\sum_{j1=1}^{n_h}\sum_{j2=1}^{n_h}\left(1 - d_p^{j1,j2}\right)} \tag{5}$$

According to the initial scenario condition probabilities and the weights of decision experts, the aggregation condition probabilities $p_h^Z(s'_d|s_t) = \sum_{q=1}^{n_h} \omega_{hq}^{PE} p_{hq}(s'_d\big|s_t)$ are obtained, and then the aggregation condition probability matrix $P^Z({s_d}' \mid s_t) = [p^Z({s_d}' \mid s_t)]_{k\times u\times u}$ $(h = 1, 2, \ldots, k)$ is obtained.

(3) Group conditional probabilities

According to the aggregation conditional probabilities and aggregation weights, the group conditional probabilities $p_h^G(s'_d|s_t) = \sum_{h=1}^{k} \omega_h^{PZ} p_h^Z(s'_d\big|s_t)$ are obtained, and then the group conditional probability matrix $P^G({s_d}' \mid s_t) = [p^G({s_d}' \mid s_t)]_{u\times u}$ is obtained.

3.2.2. Calculation of Posterior Probabilities

Bayesian theorem is used to obtain the scenario posterior probabilities:

$$p(s_t|s'_d) = \frac{p^G(s'_d|s_t)p(s_t)}{\sum_{t=1}^{u} p^G(s'_d|s_t)p(s_t)} \tag{6}$$

And then the scenario posterior probability matrix $P(s_t \mid s_d\prime) = [p(s_t \mid s_d\prime)]_{u\times u}$ is obtained.

3.3. Group Prospect Values of Alternative Assessments

3.3.1. Perceived Utility Matrix

According to the interval number of the i-th alternative assessed by the decision expert e_j under the scenario s_t and attribute c_l, the assessment matrix $A = [{a_{li}}^{jt}]_{m\times n\times u\times p}$ given by the decision experts is obtained. The alternative assessments are standardized to obtain the standardized matrix $B = [{b_{li}}^{jt}]_{m\times n\times u\times p}$ according to the attributes' type. The standardized formulas of benefit type and cost type, respectively, are:

$$\begin{cases} b_{li}^{jtL} = \dfrac{a_{li}^{jtL} - \min\left\{a_{li}^{jtL}\right\}}{\max\left\{a_{li}^{jtU}\right\} - \min\left\{a_{li}^{jtL}\right\}} \\ b_{li}^{jtU} = \dfrac{a_{li}^{jtU} - \min\left\{a_{li}^{jtL}\right\}}{\max\left\{a_{li}^{jtU}\right\} - \min\left\{a_{li}^{jtL}\right\}} \end{cases} \tag{7}$$

$$\begin{cases} b_{li}^{jtL} = \frac{\max\left\{a_{li}^{jtU}\right\} - a_{li}^{jtU}}{\max\left\{a_{li}^{jtU}\right\} - \min\left\{a_{li}^{jtL}\right\}} \\ b_{li}^{jtU} = \frac{\max\left\{a_{li}^{jtU}\right\} - a_{li}^{jtL}}{\max\left\{a_{li}^{jtU}\right\} - \min\left\{a_{li}^{jtL}\right\}} \end{cases} \tag{8}$$

According to the normalized matrix $B = [b_{li}{}^{jt}]_{m\times n\times u\times p}$, the real numbers as the reference points are selected to obtain the difference $\Delta b_{li}^{jtL} = b_{li}^{jtL} - \overline{b_{li}^{jt}}$, $\Delta b_{li}^{jtU} = b_{li}^{jtU} - \overline{b_{li}^{jt}}$ between the alternative assessments and the reference points under different scenarios and attributes, and the difference matrix $[\Delta b_{li}{}^{jt}]_{\mathrm{m\times n\times u\times p}}$. Assuming that an alternative assessment is subject to uniform distribution within the decision-making interval $[b_{li}{}^{jtL}, b_{li}{}^{jtU}]$, the random probability density function of the alternative assessments is:

$$\begin{cases} f_{li}^{jt}(x) = \frac{1}{b_{li}^{jtU} - b_{li}^{jtL}}, & \Delta b_{li}^{jtL} \le x \le b_{li}^{jtU}, \quad \overline{\mathrm{b}_{li}^{\mathrm{jt}}} \le b_{li}^{jtL} \le b_{li}^{jtU}, \quad b_{li}^{jtL} \le b_{li}^{jtU} \le \overline{\mathrm{b}_{li}^{\mathrm{jt}}} \\ f_{li}^{jt}(x) = \begin{cases} \frac{1}{\overline{\mathrm{b}_{li}^{jt}} - b_{li}^{jtL}}, & \Delta b_{li}^{jtL} \le x \le 0 \\ \frac{1}{b_{li}^{jtU} - \overline{\mathrm{b}_{li}^{\mathrm{jt}}}}, & 0 \le x \le \Delta b_{li}^{jtU} \end{cases}, & b_{li}^{jtL} \le \overline{\mathrm{b}_{li}^{\mathrm{jt}}} \le b_{li}^{jtU} \end{cases} \tag{9}$$

The perceived utility values are calculated by combining the value function of the prospect value theory:

$$\Delta v_{li}^{jt} = \begin{cases} \int_{\Delta b_{li}^{jtL}}^{\Delta b_{li}^{jtU}} x^{a} \frac{1}{b_{li}^{jtU} - b_{li}^{jtL}} dx, & \Delta b_{li}^{jtU} \ge 0, \Delta b_{li}^{jtL} \ge 0 \\ \int_{\Delta b_{li}^{jtL}}^{\Delta b_{li}^{jtU}} -\lambda(-x)^{\beta} \frac{1}{b_{li}^{jtU} - b_{li}^{jtL}} dx, & \Delta b_{li}^{jtU} \le 0, \Delta b_{li}^{jtL} \le 0 \\ \int_{\Delta b_{li}^{jtL}}^{0} -\lambda(-x)^{\beta} \frac{1}{\overline{\mathrm{b}_{li}^{\mathrm{jt}}} - b_{li}^{jtL}} dx + \int_{0}^{\Delta b_{li}^{jtU}} x^{a} \frac{1}{b_{li}^{jtU} - \overline{\mathrm{b}_{li}^{\mathrm{jt}}}} dx, & \Delta b_{li}^{jtU} \ge 0, \Delta b_{li}^{jtL} \le 0 \end{cases} \tag{10}$$

3.3.2. Prospect Values of Decision Experts

The decision experts determine the current scenario. If the scenario is determined to be $s_d{}'$, the prospect values of the alternative assessments will be calculated under the posterior probabilities of scenario:

$$v_{li}^{j} = \sum_{t=1}^{u} \Delta v_{li}^{jt} p_t(s_t | s_d') \tag{11}$$

Then the prospect value matrix $V_{li}{}^{j} = [v_{li}{}^{j}]_{m\times n\times p}$ is obtained.

3.3.3. Prospect Values Clustering

(1) Cluster prospect values

According to the prospect value matrix $V_{li}{}^{j} = [v_{li}{}^{j}]_{m\times n\times p}$, the Euclidean distance between the prospect values of two decision experts e_{j1} and e_{j2} is calculated by:

$$d_V^{j1,j2} = d\left(v_{li}^{j1}, v_{li}^{j2}\right) = \sqrt{\left(v_{li}^{j1} - v_{li}^{j2}\right)^2} \tag{12}$$

The clustering algorithm matrix $D = [d_V{}^{j1,j2}]_{m\times m\times n\times p}$ is obtained, and the scenario's prospect values are clustered by using the hierarchical clustering algorithm and the clustering algorithm matrix D to form O aggregations. The idea of the hierarchical clustering algorithm is to calculate the distance between samples first, and the nearest points are merged into the same class each time. Then, the distance between classes is calculated, and the nearest classes are merged into a large class. Merging continues until a class is synthesized.

(2) Aggregation prospect values

According to the majority principle, the more decision experts in an aggregation, the greater the weight given to the aggregation; on the contrary, the weight given to the aggregation is smaller. The weight of aggregation R^f is ${\omega_f}^{XE} = n_f/m$. The weights of the decision experts in each aggregation are not equal, so the expert weights are calculated according to the contributions of decision experts to the aggregation similarity. ${\omega_{fq}}^{XE}$ ($0 < q < n_f$) is the weight of the q-th decision-making expert in the aggregation R^f:

$$\omega_{fq}^{XE} = \frac{\sum_{j2=1}^{n_f}\left(1 - d_V^{jq,j2}\right)}{\sum_{j1=1}^{n_f}\sum_{j2=1}^{n_f}\left(1 - d_V^{j1,j2}\right)} \tag{13}$$

The aggregation prospect values are obtained by using prospect values and decision expert weights, and then the aggregation prospect value matrix is obtained.

(3) Group prospect values

According to the aggregation prospect values and aggregation weights, the group prospect values are obtained, and then the group prospect value matrix is obtained.

3.4. Determination of Attribute Weights

In the existing research, attribute weights are often assumed or obtained by subjective or objective weighting methods. They only focus on the relative distance of attributes, ignoring the impact of attributes on the final alternative. The values of weight play a key role in the ranking and selection of alternatives. In the actual EDM process, the greater the difference of utility values between different the alternatives under the same attribute, the greater the role of this attribute in the ranking of alternatives, the weight given to this attribute is bigger. At the same time, the decision experts hope that the assessments of the alternative are optimal under each attribute, which is obviously difficult to achieve, but the gap between assessments of the alternative and assessments of the ideal alternative under each attribute can be as small as possible. The closer the distance between the alternative and the ideal alternative is, the better the alternative is. This paper constructs a relative entropy model under the condition that the attribute weights are completely unknown to determine the optimal attribute weights, as shown in Formula (14). On the one hand, it is hoped that the gap between the alternative and the ideal alternative is minimized; on the other hand, it is hoped that the difference between alternatives under various attributes can be maximized.

$$\begin{cases} minH(w) = \delta_1 \sum\limits_{i1=1}^{n}\sum\limits_{l=1}^{p} v_{li1} w_l \log\frac{v_{li1}}{v_l^*} - \delta_2 \sum\limits_{i2=1}^{n}\sum\limits_{i1=1}^{n}\sum\limits_{l=1}^{p} v_{li1} w_l \log\frac{v_{li1}}{v_{li2}} \\ \qquad s.t. \sum\limits_{l}^{p} w_l^2 = 1 \end{cases} \tag{14}$$

where $v_l^* = \max\limits_{0<i1<n}\{v_{li1}\}$. δ_1 and δ_2 refer to the relative importance of the objective function, $\delta_1 + \delta_2 = 1$.

The formula is calculated by using Lagrange theorem, and the optimal attribute weights are obtained:

$$w_l = \frac{\delta_1 \sum_{i1=1}^{n} v_{li1}\log\frac{v_{li1}}{v_l^*} - \delta_2 \sum_{i2=1}^{n}\sum_{i1=1}^{n} v_{li1} w_l \log\frac{v_{li1}}{v_{li2}}}{\sqrt{\sum_{l=1}^{p}\left(\delta_1 \sum_{i1=1}^{n} v_{li1}\log\frac{v_{li1}}{v_l^*} - \delta_2 \sum_{i2=1}^{n}\sum_{i1=1}^{n} v_{li1} w_l \log\frac{v_{li1}}{v_{li2}}\right)^2}} \tag{15}$$

The weights are normalized, and the optimal weights are obtained:

$$w_l = \frac{\delta_1 \sum_{i1=1}^{n} v_{li1}\log\frac{v_{li1}}{v_l^*} - \delta_2 \sum_{i2=1}^{n}\sum_{i1=1}^{n} v_{li1} w_l \log\frac{v_{li1}}{v_{li2}}}{\sum_{l=1}^{p}\left(\delta_1 \sum_{i1=1}^{n} v_{li1}\log\frac{v_{li1}}{v_l^*} - \delta_2 \sum_{i2=1}^{n}\sum_{i1=1}^{n} v_{li1} w_l \log\frac{v_{li1}}{v_{li2}}\right)} \tag{16}$$

3.5. Ranking of Alternatives

According to the attribute weights and group prospect values, the overall prospect values are obtained, and the overall prospect values are sorted to obtain the optimal alternative.

4. Case Study of Group Decision Making Method Considering Scenarios and Unknown Attribute Weights

4.1. Definition Framework

This paper takes the release of radioactive substances under the PWR5 accident source item of Daya Bay Nuclear Power Station [39–43] as an example to make a decision on large group emergency response. Specific accident parameters include: this event is the accident source of PWR5, the wind direction at the time of the event is easterly, and the wind speed is 1.8m/s. Based on the calculation of the estimated dose of the nuclear accident and the statistics of the number of the public within 40km around, there are four options for research:

- Concealing and distributing iodine tablets to the public within a 25 km radius, with a total of 117,000 people taking iodine tablets and concealing.
- Evacuate the public within 11km, conceal the public within 11–25 km, and distribute iodine tablets. The evacuated population will reach 10,000, and the number of people hiding and taking iodine will reach 10,000.
- The public within 25 km shall be concealed and iodine tablets shall be distributed to the public in all affected areas. The number of people hiding will reach 120,000, and the number of people evacuating will reach 700,000.
- Take concealment measures first, provide iodine tablets, and implement concealment when the smoke plume passes by; after the smoke plume passes, evacuate the public within 20 km. The number of evacuees will reach 74,000 and the number of iodine users will reach 800,000.

The three possible scenarios of the EE are optimistic, moderate, and pessimistic, corresponding to scenarios s_1, s_2, and s_3, respectively. The multi-attribute theory is used to build the attribute tree to get 6 attributes: the maximum avoidable individual dose c_1 (unit: mSv), the avoidable collective dose c_2 (unit: 10^4 mSv), the economic cost c_3 (unit: 10^6 yuan), the positive social psychosocial impact c_4 (range: 0–100), the negative social psychosocial impact c_5 (range: 0–100), and the political impact c_6 (range: 0–100). Among them, the maximum avoidable individual dose c_1, avoidable collective dose c_2, economic cost c_3, and political influence c_6 belong to objective attributes, while positive psychosocial influence c_4 and negative psychosocial influence c_5 belong to subjective attributes.

The minimum number of people for large group emergency decision-making is limited to 11. Assuming that there are 11 experts participating in the decision-making, the accuracy rate of all experts participating in the decision-making on the research and judgment of the nuclear accident scenarios, and the alternative assessments given by the decision-making experts on the spot, are collected from the rehearsal database during the actual decision-making. However, due to the constraints of conditions and the confidentiality of the nuclear accident data, this example is mainly to explore the feasibility and effectiveness of the decision-making method, so the solution process of the group conditional probabilities of scenario was omitted, and the numerical values of the scenario group conditional probabilities were given directly. Laboratory personnel are mainly responsible for nuclear power emergency management research, machine fault monitoring, and human factor accident analysis, and have a relevant knowledge foundation and research on nuclear power emergency response decision-making, so the relevant laboratory personnel were asked to give the alternative assessments under different scenarios and multiple attributes, as shown in Table A1.

4.2. Case Study

Step 1: the initial condition probabilities were clustered to get the aggregations of the conditional probability, and Formula (5) was used to calculate the expert weights. The initial condition probabilities and the expert weights were combined to get the aggregation condition probabilities, and the aggregation condition probability weights, and the aggregation condition probabilities were combined to get the group conditional probabilities, as shown in Table 1.

Table 1. Group conditional probabilities of the scenario.

$p^G(s_d' \mid s_t)$	s_1	s_2	s_3
s_1'	0.7	0.2	0.1
s_2'	0.2	0.7	0.2
s_3'	0.1	0.1	0.7

Step 2: it was assumed that the decision-making experts give priori probabilities of the occurrence of these scenarios according to historical experience as P = {0.5, 0.3, 0.2}, thus, Formula (3) was used to obtain posterior probabilities, as shown in Table 2.

Table 2. Posteriori probabilities of scenario.

$p^G(s_t \mid s_d')$	s_1'	s_2'	s_3'
s_1	0.8140	0.2857	0.2272
s_2	0.1395	0.6000	0.1363
s_3	0.0465	0.1142	0.6363

Assuming that the decision-making experts determine that the current scenario is s_2', the posterior probabilities of the three scenarios are $P^G(s_t \mid s_d')$ = {0.2857, 0.6000, 0.1142}.

Step 3: among the six attributes of decision-making, the maximum avoidable individual dose c_1, the avoidable collective dose c_2, and the positive social psychosocial impact c_4 are benefit type, while the economic cost c_3, the negative social psychological impact c_5, and the political impact c_6 are cost type. Therefore, Formulas (7) and (8) were used to standardize the number of assessment intervals provided by decision-making experts, as shown in Table A2.

In the initial stage of the nuclear accident emergency, the reference point was set as 0 to obtain the difference values of alternative assessments, and the value function in prospect theory and the random probability density function of assessment were combined to obtain the perceived utility, as shown in Table A3.

Step 4: the perceived utility values and the posterior probabilities of scenario obtained in Step 2 were aggregated to obtain the prospect values, as shown in Table A4.

Step 5: the prospect values were clustered by using the clustering algorithm based on the Euclidean distance, and four aggregations were obtained: $R^1 = \{e_3, e_5\}$, $R^2 = \{e_8, e_9\}$, $R^3 = \{e_1, e_2, e_4, e_7, e_{10}\}$, and $R^4 = \{e_6, e_{11}\}$. The Euclidean distance was used to calculate the contributions of decision experts to the aggregation similarity, and the expert weights were obtained, as shown in Table 3.

Table 3. Expert weights.

Aggregations	Experts	Alternatives/Attributes	c_1	c_2	c_3	c_4	c_5	c_6
R^1	e_3	x_1	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
		x_2	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
		x_3	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
		x_4	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
	e_5	x_1	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
		x_2	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
		x_3	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
		x_4	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
R^2	e_8	x_1	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
		x_2	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
		x_3	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
		x_4	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
	e_9	x_1	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
		x_2	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
		x_3	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
		x_4	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
R^3	e_1	x_1	0.2001	0.2000	0.2000	0.2002	0.2003	0.2004
		x_2	0.2001	0.2002	0.2002	0.2009	0.2003	0.2004
		x_3	0.2001	0.2002	0.2000	0.2006	0.2004	0.2002
		x_4	0.2004	0.2002	0.2005	0.2003	0.2003	0.2000
	e_2	x_1	0.2001	0.2000	0.2000	0.2001	0.2002	0.2004
		x_2	0.2001	0.2002	0.2001	0.2007	0.2001	0.2004
		x_3	0.2001	0.2002	0.2001	0.2000	0.2004	0.2003
		x_4	0.2004	0.2002	0.2005	0.2002	0.2000	0.2000
	e_4	x_1	0.1998	0.2000	0.2000	0.1993	0.2002	0.1992
		x_2	0.1998	0.1982	0.2002	0.1965	0.2003	0.1988
		x_3	0.1998	0.1994	0.2000	0.1998	0.2004	0.2001
		x_4	0.1999	0.1993	0.1979	0.2003	0.2003	0.2001
	e_7	x_1	0.2001	0.2000	0.1999	0.2002	0.2003	0.2002
		x_2	0.2001	0.2008	0.1994	0.2010	0.2003	0.2002
		x_3	0.2001	0.2001	0.1999	0.2005	0.2004	0.2003
		x_4	0.1994	0.1999	0.2005	0.1989	0.2003	0.1999
	e_{10}	x_1	0.1999	0.2000	0.2000	0.2002	0.1991	0.1997
		x_2	0.1999	0.2007	0.2002	0.2008	0.1992	0.2002
		x_3	0.1999	0.2001	0.1999	0.1991	0.1983	0.1991
		x_4	0.2000	0.2003	0.2005	0.2003	0.1990	0.2000
R^4	e_6	x_1	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
		x_2	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
		x_3	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
		x_4	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
	e_{11}	x_1	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
		x_2	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
		x_3	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
		x_4	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000

The aggregated prospect values were obtained by aggregating the prospect values and expert weights, as shown in Table 4.

Table 4. Aggregated prospect values.

Aggregations	Alternatives/Attributes	c_1	c_2	c_3	c_4	c_5	c_6
R^1	x_1	0.2093	0.0896	0.9985	0.8277	0.7410	0.7782
	x_2	0.2093	0.6750	0.8231	0.4271	0.2619	0.7765
	x_3	0.2093	0.9388	0.9955	0.3066	0.4586	0.7752
	x_4	0.8632	0.8536	0.0428	0.2087	0.7447	0.1909
R^2	x_1	0.2135	0.0932	0.9984	0.8359	0.7650	0.7497
	x_2	0.2135	0.6711	0.8294	0.4678	0.2802	0.7497
	x_3	0.2135	0.9360	0.9947	0.3742	0.4464	0.7906
	x_4	0.8585	0.7701	0.0426	0.2039	0.7182	0.1964
R^3	x_1	0.2025	0.0941	0.9978	0.8299	0.7734	0.7580
	x_2	0.2025	0.6696	0.8298	0.4326	0.2724	0.7558
	x_3	0.2025	0.9397	0.9943	0.3236	0.4322	0.7805
	x_4	0.8537	0.7952	0.0388	0.2078	0.7282	0.1960
R^4	x_1	0.2036	0.0995	0.9978	0.8323	0.7562	0.7523
	x_2	0.2036	0.6652	0.8302	0.4629	0.2788	0.7523
	x_3	0.2036	0.9341	0.9947	0.3234	0.3645	0.7898
	x_4	0.8500	0.8029	0.0432	0.2052	0.7230	0.1943

The aggregation weights are {2/11, 2/11, 5/11, 2/11} based on the ratio of the number of people in the aggregation to the total number of people. The aggregation prospect values and aggregation weights were used to obtain the group prospect values, as shown in Table 5.

Table 5. Group prospect values.

Alternatives/Attributes	c_1	c_2	c_3	c_4	c_5	c_6
x_1	0.2060	0.0941	0.9980	0.8310	0.7628	0.7591
x_2	0.2060	0.6700	0.8286	0.4435	0.2731	0.7578
x_3	0.2060	0.9379	0.9947	0.3296	0.4273	0.7830
x_4	0.8556	0.8026	0.0410	0.2068	0.7284	0.1948

Step 6: the constructed relative entropy model was used to calculate the attribute weights. This paper adopts the neutral principle, taking $\delta_1 = \delta_2 = 0.5$, and the optimal attribute weights were obtained: $w_1 = 0.1457$, $w_2 = 0.2109$, $w_3 = 0.3512$, $w_4 = 0.1083$, $w_5 = 0.0772$, and $w_6 = 0.1064$.

Step 7: according to the attribute weights and group prospect values, the overall prospect values were obtained: ${V_1}^G = 0.6302$, ${V_2}^G = 0.6122$, ${V_3}^G = 0.7293$, and ${V_4}^G = 0.4078$, which were used to sort the alternatives, so the optimal alternative is alternative 3.

In order to investigate the sensitivity of the LGEDM method, a sensitivity analysis was conducted for the scenario. Assuming that the current scenario determined by the experts is changed from $s_{2'}$ to $s_{3'}$, the posterior probabilities of the three scenarios are $P^G(s_t \mid s_d{}')$ = {0.2272, 0.1363, 0.6363}. The perceived utility values and the posterior probabilities of scenario were aggregated to obtain the prospect values. The aggregations were obtained by clustering the prospect values: $R^1 = \{e_3, e_4, e_5\}$, $R^2 = \{e_1, e_2, e_6, e_7, e_8, e_9\}$, and $R^3 = \{e_{10}, e_{11}\}$, and aggregated prospect values were obtained by aggregating expert weights and prospect values. The group prospect values were obtained by aggregating aggregated weights and aggregated prospect values. The attribute weights were obtained by using the constructed relative entropy model: $w_1 = 0.1796$, $w_2 = 0.2668$, $w_3 = 0.4307$, $w_4 = 0.0250$, $w_5 = 0.5180$, and $w_6 = 0.0462$. The overall prospect values were obtained by aggregating the attribute weights and group prospect values: ${V_1}^G = 0.5399$, ${V_2}^G = 0.6480$, ${V_3}^G = 0.7853$, and ${V_4}^G = 0.4867$. Therefore, when the scenario is $s_{3'}$, the final optimal alternative is alternative 3. Assuming that the current scenario determined by the experts is changed from $s_{2'}$ to $s_{1'}$, the posterior probabilities of the three scenarios are $P^G(s_t \mid s_d{}')$ = {0.8140, 0.1395, 0.0465}.

The perceived utility values and the posterior probabilities of scenario were aggregated to obtain the prospect values. The aggregations were obtained by clustering the prospect values: $R^1 = \{e_3, e_4, e_5\}$, $R^2 = \{e_1, e_2, e_6, e_8, e_9, e_{10}\}$, and $R^3 = \{e_6\}$, $R^4 = \{e_{11}\}$, and aggregated prospect values were obtained by aggregating expert weights and prospect values. The group prospect values were obtained by aggregating aggregated weights and aggregated prospect values. The attribute weights were obtained by using the constructed relative entropy model: $w_1 = 0.1185$, $w_2 = 0.1705$, $w_3 = 0.2825$, $w_4 = 0.1406$, $w_5 = 0.1336$, and $w_6 = 0.1542$. The overall prospect values were obtained by aggregating the attribute weights and group prospect values: ${V_1}^G = 0.7083$, ${V_2}^G = 0.5748$, ${V_3}^G = 0.6504$, and ${V_4}^G = 0.3477$. Therefore, when the scenario is $s_{1'}$, the final optimal alternative is alternative 1.

5. Conclusions and Future Works

In order to improve the accuracy of scenario probability, Bayesian theorem has been introduced into LGEDM method. In the existing research, the calculation of attribute weights only considers the difference between alternatives. In order to obtain the best attribute weights, a relative entropy model has been constructed, taking into account the difference between alternatives, and the difference between alternatives and the ideal solution. In LGEDM, the expert weights are mostly the average value of experts' assessments, but in actual decision-making, the expert weights are not the same. In order to solve this problem, the Euclidean distance has been used to measure the contributions of experts to the aggregation similarity, and the contribution degree has been used to obtain the expert weights. Furthermore, a case study has been provided to illustrate the feasibility of the LGEDM method.

In the proposed method, the decision-making preference information type of experts is interval value. However, in the real world, due to the lack of their own experience, ability, and knowledge, experts may have some hesitation when giving their own assessment and use the hesitation fuzzy language information type for assessment. The proposed method is only applicable to interval value decision-making emergency problems, which is also a limitation of this study. The research in the near future should consider the multi-attribute decision making problem of interval hesitant fuzzy numbers. Studying the linguistic information type of hesitant fuzzy numbers will make this method more widely used.

Author Contributions: Conceptualization, P.W.; methodology, P.W.; validation, P.W. and J.C.; writing—original draft preparation, P.W.; writing—review and editing, J.C.; supervision, J.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Research Foundation of Education Bureau of Hunan Province, China (grant No. 19A443) and Hunan Philosophy and Social Science Foundation Project (grant No. 14JD51).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: This study would like to express our gratitude to the laboratory experts who provided the case validation data.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Experts' assessments.

Scenario		s_1											
Alternatives/Attributes		c_1		c_2		c_3		c_4		c_5		c_6	
		$a_{li}{}^{jtL}$	$a_{li}{}^{jtU}$	$a_{li}{}^{jtL}$	$a_{li}{}^{jtU}$	$a_{li}{}^{jtL}$	$a_{li}{}^{jtU}$	$a_{li}{}^{jtL}$	$a_{li}{}^{jtU}$	$a_{li}{}^{jtL}$	$a_{li}{}^{jtU}$	$a_{li}{}^{jtL}$	$a_{li}{}^{jtU}$
e_1	x_1	1000	1100	80	90	1.6	2.6	80	90	0	10	0	5
	x_2	1000	1100	120	130	22.0	23.0	10	20	90	100	0	5
	x_3	1000	1100	150	160	2.2	3.2	10	20	80	90	20	30
	x_4	1200	1300	130	140	160.0	170.0	0	10	50	60	80	90
e_2	x_1	1000	1100	80	90	1.7	2.7	81	91	0	9	0	5
	x_2	1000	1100	120	130	23.0	24.0	10	20	91	100	0	5
	x_3	1000	1100	150	160	2.1	3.1	10	20	80	90	21	31
	x_4	1200	1300	128	138	160.0	170.1	0	10	49	59	80	90
e_3	x_1	990	1090	80	90	1.7	2.7	78	88	0	15	0	6
	x_2	990	1090	122	132	22.0	24.0	9	19	90	100	0	6
	x_3	990	1090	148	158	2.1	3.1	9	19	79	89	22	35
	x_4	1188	1280	128	138	160.0	170.1	0	10	48	58	81	91
e_4	x_1	1000	1100	80	90	1.7	1.8	82	90	0	9	0	5
	x_2	1000	1100	122	132	22.0	23.0	10	19	90	100	0	5
	x_3	1000	1100	150	160	2.3	3.3	10	19	80	90	22	32
	x_4	1210	1290	130	140	162.0	172.0	0	9	51	61	80	90
e_5	x_1	990	1100	80	89	1.7	2.7	78	88	0	15	0	5
	x_2	990	1100	122	132	22.0	24.0	10	20	90	100	0	5
	x_3	990	1100	148	158	2.0	3.0	10	20	80	88	22	35
	x_4	1200	1300	128	138	160.0	170.0	0	10	49	59	81	91
e_6	x_1	1000	1100	83	93	1.8	2.0	80	89	0	10	0	4
	x_2	1000	1100	118	128	21.0	22.0	10	20	88	98	0	4
	x_3	1000	1100	148	158	2.2	3.2	9	19	79	89	20	30
	x_4	1189	1289	127	137	158.0	168.0	0	9	50	60	80	90
e_7	x_1	1000	1090	80	90	1.5	2.0	80	90	0	10	1	4
	x_2	1000	1090	120	130	21.0	22.0	10	20	90	100	1	5
	x_3	1000	1090	148	158	2.1	3.1	10	20	80	90	22	32
	x_4	1188	1290	123	136	158.0	168.0	1	5	50	60	82	92
e_8	x_1	990	1090	80	90	1.7	2.0	80	90	0	10	0	4
	x_2	990	1090	121	131	22.0	23.0	11	21	90	99	0	4
	x_3	990	1090	148	158	2.3	3.3	11	21	80	90	16	26
	x_4	1200	1300	125	135	162.0	172.0	1	11	50	60	78	88
e_9	x_1	990	1090	80	90	1.6	2.0	80	90	0	10	0	4
	x_2	990	1090	121	131	22.0	23.0	11	21	90	99	0	4
	x_3	990	1090	148	158	2.2	3.2	11	21	80	90	16	26
	x_4	1198	1298	125	135	160.0	170.0	0	10	50	60	78	88
e_{10}	x_1	990	1100	80	90	1.6	2.6	80	90	0	10	0	4
	x_2	990	1100	120	130	22.0	23.0	10	20	90	99	0	4
	x_3	990	1100	150	160	2.0	3.0	10	20	80	90	16	26
	x_4	1200	1300	128	138	160.0	170.0	0	10	50	60	78	88
e_{11}	x_1	995	1095	82	92	1.6	2.6	88	98	0	10	0	4
	x_2	995	1095	119	129	22.0	24.9	10	19	90	100	0	4
	x_3	995	1095	146	156	2.1	3.1	10	19	80	90	15	25
	x_4	1200	1290	130	140	158.0	168.0	0	8	50	60	80	89

Table A1. *Cont.*

Scenario		s_2											
Alternatives/Attributes		c_1		c_2		c_3		c_4		c_5		c_6	
		$a_{li}{}^{jtL}$	$a_{li}{}^{jtU}$	$a_{li}{}^{jtL}$	$a_{li}{}^{jtU}$	$a_{li}{}^{jtL}$	$a_{li}{}^{jtU}$	$a_{li}{}^{jtL}$	$a_{li}{}^{jtU}$	$a_{li}{}^{jtL}$	$a_{li}{}^{jtU}$	$a_{li}{}^{jtL}$	$a_{li}{}^{jtU}$
e_1	x_1	900	1000	60	70	3.1	4.1	70	80	35	45	40	50
	x_2	900	1000	100	110	38.0	48.0	50	60	50	60	40	50
	x_3	900	1000	120	130	3.8	4.8	40	50	45	55	30	40
	x_4	1100	1200	110	120	170.0	180.0	35	45	35	45	80	90
e_2	x_1	900	1000	60	70	3.1	4.1	70	80	35	45	40	50
	x_2	900	1000	100	110	38.4	48.4	50	60	50	60	40	50
	x_3	900	1000	120	130	3.9	4.9	42	52	45	55	30	40
	x_4	1100	1200	110	120	170.0	180.1	36	46	35	45	80	90
e_3	x_1	890	990	60	70	3.2	3.5	70	80	35	45	40	46
	x_2	890	990	101	111	38.0	49.0	49	59	50	60	40	47
	x_3	890	990	120	130	3.7	4.7	39	49	43	53	31	41
	x_4	1088	1180	118	128	170.1	180.1	35	45	33	43	80	89
e_4	x_1	900	1000	60	70	3.2	4.2	71	80	35	45	41	50
	x_2	900	1000	102	112	38.0	47.0	50	55	50	60	41	50
	x_3	900	1000	120	129	3.9	4.9	42	52	45	55	32	42
	x_4	1110	1210	110	120	172.0	173.0	36	46	35	45	82	92
e_5	x_1	890	990	60	69	3.2	3.5	70	80	35	45	40	46
	x_2	890	990	100	110	40.0	51.8	49	59	50	60	40	47
	x_3	890	990	120	130	3.6	4.6	39	49	43	53	31	41
	x_4	1100	1180	117	127	168.0	178.0	35	45	33	43	80	89
e_6	x_1	900	1000	63	73	3.3	4.3	70	79	36	46	41	51
	x_2	900	1000	100	110	37.0	47.0	50	60	49	59	41	51
	x_3	900	1000	118	128	4.0	5.0	39	49	47	57	32	42
	x_4	1100	1200	109	119	169.0	179.0	34	44	36	46	80	90
e_7	x_1	900	1000	60	70	3.0	3.5	70	80	35	45	41	49
	x_2	900	1000	100	110	36.0	46.0	50	60	50	60	42	50
	x_3	900	1000	118	128	3.9	4.9	40	50	45	55	31	41
	x_4	1088	1190	109	119	168.0	178.0	35	45	35	45	78	88
e_8	x_1	880	1000	60	70	3.2	4.2	71	80	35	45	40	49
	x_2	880	1000	100	112	38.0	48.8	51	60	48	58	40	49
	x_3	880	1000	120	130	3.9	4.9	42	52	43	53	29	39
	x_4	1100	1200	108	118	172.0	182.0	31	41	35	45	78	88
e_9	x_1	880	1000	60	70	3.1	3.5	71	80	35	45	40	49
	x_2	880	1000	100	112	38.0	48.8	51	60	48	58	40	49
	x_3	880	1000	120	130	3.8	4.4	42	52	43	53	29	39
	x_4	1100	1200	108	118	170.0	180.0	34	44	35	45	78	88
e_{10}	x_1	890	1000	60	70	3.1	4.1	70	80	35	45	40	49
	x_2	890	1000	100	110	38.0	48.0	52	57	48	58	40	49
	x_3	890	1000	117	127	3.6	4.6	39	49	43	53	29	39
	x_4	1120	1220	108	118	169.0	179.0	35	45	35	45	78	88
e_{11}	x_1	890	990	62	72	3.1	4.1	68	78	35	45	40	50
	x_2	890	990	100	111	38.0	49.0	50	60	48	58	40	50
	x_3	890	990	115	125	3.7	4.7	39	49	46	56	28	38
	x_4	1090	1190	108	118	170.0	180.0	33	43	34	44	80	90

Table A1. *Cont.*

Scenario		s_3											
Alternatives/Attributes		c_1		c_2		c_3		c_4		c_5		c_6	
		$a_{li}{}^{jtL}$	$a_{li}{}^{jtU}$	$a_{li}{}^{jtL}$	$a_{li}{}^{jtU}$	$a_{li}{}^{jtL}$	$a_{li}{}^{jtU}$	$a_{li}{}^{jtL}$	$a_{li}{}^{jtU}$	$a_{li}{}^{jtL}$	$a_{li}{}^{jtU}$	$a_{li}{}^{jtL}$	$a_{li}{}^{jtU}$
e_1	x_1	800	900	40	50	23.9	24.9	40	50	85	95	80	90
	x_2	800	900	80	90	50.0	60.0	70	80	10	20	80	90
	x_3	800	900	100	110	24.1	25.1	75	85	10	20	80	90
	x_4	1000	1100	100	110	190.0	200.0	75	85	20	30	20	30
e_2	x_1	800	900	40	50	23.5	24.3	42	52	85	95	80	90
	x_2	800	900	80	90	50.0	60.0	70	80	10	20	80	90
	x_3	800	900	100	110	23.8	24.8	75	85	10	20	80	90
	x_4	1000	1100	100	110	190.0	200.1	76	86	20	30	20	30
e_3	x_1	790	890	38	48	24.0	25.0	39	49	83	100	80	90
	x_2	790	890	82	92	50.0	61.0	69	79	10	20	80	87
	x_3	790	890	100	110	24.1	25.1	76	86	10	20	80	85
	x_4	988	1088	100	110	191.0	200.1	75	85	19	29	19	29
e_4	x_1	800	900	40	50	24.0	25.0	40	50	86	96	81	91
	x_2	800	900	82	92	50.0	59.0	70	79	10	20	81	91
	x_3	800	900	100	105	24.2	25.2	76	86	10	20	81	91
	x_4	1010	1110	100	102	192.0	202.0	76	86	20	28	20	29
e_5	x_1	788	900	38	48	24.0	25.0	39	49	83	100	80	90
	x_2	788	900	82	92	50.0	61.0	69	79	10	20	80	87
	x_3	788	900	100	110	24.1	25.1	76	86	10	20	80	85
	x_4	1000	1100	100	110	191.0	200.1	75	85	19	29	19	29
e_6	x_1	800	900	41	51	24.1	25.1	40	49	86	96	81	91
	x_2	800	900	80	90	49.0	59.0	71	81	10	21	81	91
	x_3	800	900	100	110	24.5	25.5	76	86	12	22	81	91
	x_4	989	1089	100	110	189.0	199.0	75	85	20	30	19	29
e_7	x_1	800	900	40	50	23.8	24.8	40	50	85	95	81	91
	x_2	800	900	80	90	48.0	58.0	70	80	10	20	81	91
	x_3	800	900	100	110	24.8	25.8	75	85	10	20	81	91
	x_4	988	1090	100	110	188.0	198.0	75	85	20	30	22	32
e_8	x_1	790	890	40	50	24.0	25.0	41	50	85	95	80	90
	x_2	790	890	81	91	50.0	60.8	71	80	9	19	80	90
	x_3	790	890	100	110	24.2	25.2	76	86	9	19	80	90
	x_4	998	1098	102	112	192.0	202.0	75	85	20	30	20	30
e_9	x_1	790	890	40	50	23.9	24.9	41	50	85	95	80	90
	x_2	790	890	81	91	50.0	60.8	71	80	9	19	80	90
	x_3	790	890	100	110	24.1	24.9	76	86	9	19	80	90
	x_4	998	1098	102	112	190.0	199.0	75	85	20	30	20	30
e_{10}	x_1	790	890	40	50	23.9	24.9	39	49	85	95	80	90
	x_2	790	890	80	90	50.0	61.9	72	82	9	19	80	90
	x_3	790	890	100	110	23.9	24.8	74	84	9	19	80	90
	x_4	998	1098	100	110	189.0	199.0	74	84	20	30	20	30
e_{11}	x_1	800	900	43	53	23.9	24.9	41	51	86	96	80	90
	x_2	800	900	79	89	50.0	61.9	71	81	11	21	80	90
	x_3	800	900	100	110	24.0	25.0	74	84	11	21	78	88
	x_4	1000	1100	100	110	190.0	200.0	74	84	19	29	19	29

Table A2. Standardized assessment matrix.

Scenario		s_1											
Alternatives/Attributes		c_1		c_2		c_3		c_4		c_5		c_6	
		${a_{li}}^{jtL}$	${a_{li}}^{jtU}$	${a_{li}}^{jtL}$	${a_{li}}^{jtU}$	${a_{li}}^{jtL}$	${a_{li}}^{jtU}$	${a_{li}}^{jtL}$	${a_{li}}^{jtU}$	${a_{li}}^{jtL}$	${a_{li}}^{jtU}$	${a_{li}}^{jtL}$	${a_{li}}^{jtU}$
e_1	x_1	0.0000	0.3333	0.0000	0.1250	0.9941	1.0000	0.8889	1.0000	0.9000	1.0000	0.9444	1.0000
	x_2	0.0000	0.3333	0.5000	0.6250	0.8729	0.8789	0.1111	0.2222	0.0000	0.1000	0.9444	1.0000
	x_3	0.0000	0.3333	0.8750	1.0000	0.9905	0.9964	0.1111	0.2222	0.1000	0.2000	0.6667	0.7778
	x_4	0.6667	1.0000	0.6250	0.7500	0.0000	0.0594	0.0000	0.1111	0.4000	0.5000	0.0000	0.1111
e_2	x_1	0.0000	0.3333	0.0000	0.1250	0.9941	1.0000	0.8901	1.0000	0.9100	1.0000	0.9444	1.0000
	x_2	0.0000	0.3333	0.5000	0.6250	0.8676	0.8735	0.1099	0.2198	0.0000	0.0900	0.9444	1.0000
	x_3	0.0000	0.3333	0.8750	1.0000	0.9917	0.9976	0.1099	0.2198	0.1000	0.2000	0.6556	0.7667
	x_4	0.6667	1.0000	0.6000	0.7250	0.0000	0.0600	0.0000	0.1099	0.4100	0.5100	0.0000	0.1111
e_3	x_1	0.0000	0.3448	0.0000	0.1282	0.9941	1.0000	0.8864	1.0000	0.8500	1.0000	0.9341	1.0000
	x_2	0.0000	0.3448	0.5385	0.6667	0.8676	0.8795	0.1023	0.2159	0.0000	0.1000	0.9341	1.0000
	x_3	0.0000	0.3448	0.8718	1.0000	0.9917	0.9976	0.1023	0.2159	0.1100	0.2100	0.6154	0.7582
	x_4	0.6828	1.0000	0.6154	0.7436	0.0000	0.0600	0.0000	0.1136	0.4200	0.5200	0.0000	0.1099
e_4	x_1	0.0000	0.3448	0.0000	0.1250	0.9994	1.0000	0.9111	1.0000	0.9100	1.0000	0.9444	1.0000
	x_2	0.0000	0.3448	0.5250	0.6500	0.8749	0.8808	0.1111	0.2111	0.0000	0.1000	0.9444	1.0000
	x_3	0.0000	0.3448	0.8750	1.0000	0.9906	0.9965	0.1111	0.2111	0.1000	0.2000	0.6444	0.7556
	x_4	0.7241	1.0000	0.6250	0.7500	0.0000	0.0587	0.0000	0.1000	0.3900	0.4900	0.0000	0.1111
e_5	x_1	0.0000	0.3548	0.0000	0.1154	0.9941	1.0000	0.8864	1.0000	0.8500	1.0000	0.9451	1.0000
	x_2	0.0000	0.3548	0.5385	0.6667	0.8675	0.8794	0.1136	0.2273	0.0000	0.1000	0.9451	1.0000
	x_3	0.0000	0.3548	0.8718	1.0000	0.9923	0.9982	0.1136	0.2273	0.1200	0.2000	0.6154	0.7582
	x_4	0.6774	1.0000	0.6154	0.7436	0.0000	0.0594	0.0000	0.1136	0.4100	0.5100	0.0000	0.1099
e_6	x_1	0.0000	0.3460	0.0000	0.1333	0.9988	1.0000	0.8989	1.0000	0.8980	1.0000	0.9556	1.0000
	x_2	0.0000	0.3460	0.4667	0.6000	0.8785	0.8845	0.1124	0.2247	0.0000	0.1020	0.9556	1.0000
	x_3	0.0000	0.3460	0.8667	1.0000	0.9916	0.9976	0.1011	0.2135	0.0918	0.1939	0.6667	0.7778
	x_4	0.6540	1.0000	0.5867	0.7200	0.0000	0.0602	0.0000	0.1011	0.3878	0.4898	0.0000	0.1111
e_7	x_1	0.0000	0.3103	0.0000	0.1282	0.9970	1.0000	0.8876	1.0000	0.9000	1.0000	0.9670	1.0000
	x_2	0.0000	0.3103	0.5128	0.6410	0.8769	0.8829	0.1011	0.2135	0.0000	0.1000	0.9560	1.0000
	x_3	0.0000	0.3103	0.8718	1.0000	0.9904	0.9964	0.1011	0.2135	0.1000	0.2000	0.6593	0.7692
	x_4	0.6483	1.0000	0.5513	0.7179	0.0000	0.0601	0.0000	0.0449	0.4000	0.5000	0.0000	0.1099
e_8	x_1	0.0000	0.3226	0.0000	0.1282	0.9982	1.0000	0.8876	1.0000	0.8990	1.0000	0.9545	1.0000
	x_2	0.0000	0.3226	0.5256	0.6538	0.8749	0.8808	0.1124	0.2247	0.0000	0.0909	0.9545	1.0000
	x_3	0.0000	0.3226	0.8718	1.0000	0.9906	0.9965	0.1124	0.2247	0.0909	0.1919	0.7045	0.8182
	x_4	0.6774	1.0000	0.5769	0.7051	0.0000	0.0587	0.0000	0.1124	0.3939	0.4949	0.0000	0.1136
e_9	x_1	0.0000	0.3247	0.0000	0.1282	0.9976	1.0000	0.8889	1.0000	0.8990	1.0000	0.9545	1.0000
	x_2	0.0000	0.3247	0.5256	0.6538	0.8729	0.8789	0.1222	0.2333	0.0000	0.0909	0.9545	1.0000
	x_3	0.0000	0.3247	0.8718	1.0000	0.9905	0.9964	0.1222	0.2333	0.0909	0.1919	0.7045	0.8182
	x_4	0.6753	1.0000	0.5769	0.7051	0.0000	0.0594	0.0000	0.1111	0.3939	0.4949	0.0000	0.1136
e_{10}	x_1	0.0000	0.3548	0.0000	0.1250	0.9941	1.0000	0.8889	1.0000	0.8990	1.0000	0.9545	1.0000
	x_2	0.0000	0.3548	0.5000	0.6250	0.8729	0.8789	0.1111	0.2222	0.0000	0.0909	0.9545	1.0000
	x_3	0.0000	0.3548	0.8750	1.0000	0.9917	0.9976	0.1111	0.2222	0.0909	0.1919	0.7045	0.8182
	x_4	0.6774	1.0000	0.6000	0.7250	0.0000	0.0594	0.0000	0.1111	0.3939	0.4949	0.0000	0.1136
e_{11}	x_1	0.0000	0.3333	0.0000	0.1351	0.9940	1.0000	0.8980	1.0000	0.9000	1.0000	0.9551	1.0000
	x_2	0.0000	0.3333	0.5000	0.6351	0.8600	0.8774	0.1020	0.1939	0.0000	0.1000	0.9551	1.0000
	x_3	0.0000	0.3333	0.8649	1.0000	0.9910	0.9970	0.1020	0.1939	0.1000	0.2000	0.7191	0.8315
	x_4	0.6833	0.9833	0.6486	0.7838	0.0000	0.0601	0.0000	0.0816	0.4000	0.5000	0.0000	0.1011

Table A2. *Cont.*

Scenario		s_2											
Alternatives/Attributes		c_1		c_2		c_3		c_4		c_5		c_6	
		$a_{li}{}^{jtL}$	$a_{li}{}^{jtU}$	$a_{li}{}^{jtL}$	$a_{li}{}^{jtU}$	$a_{li}{}^{jtL}$	$a_{li}{}^{jtU}$	$a_{li}{}^{jtL}$	$a_{li}{}^{jtU}$	$a_{li}{}^{jtL}$	$a_{li}{}^{jtU}$	$a_{li}{}^{jtL}$	$a_{li}{}^{jtU}$
e_1	x_1	0.0000	0.3333	0.0000	0.1429	0.9943	1.0000	0.7778	1.0000	0.6000	1.0000	0.6667	0.8333
	x_2	0.0000	0.3333	0.5714	0.7143	0.7462	0.8027	0.3333	0.5556	0.0000	0.4000	0.6667	0.8333
	x_3	0.0000	0.3333	0.8571	1.0000	0.9904	0.9960	0.1111	0.3333	0.2000	0.6000	0.8333	1.0000
	x_4	0.6667	1.0000	0.7143	0.8571	0.0000	0.0565	0.0000	0.2222	0.6000	1.0000	0.0000	0.1667
e_2	x_1	0.0000	0.3333	0.0000	0.1429	0.9944	1.0000	0.7727	1.0000	0.6000	1.0000	0.6667	0.8333
	x_2	0.0000	0.3333	0.5714	0.7143	0.7441	0.8006	0.3182	0.5455	0.0000	0.4000	0.6667	0.8333
	x_3	0.0000	0.3333	0.8571	1.0000	0.9898	0.9955	0.1364	0.3636	0.2000	0.6000	0.8333	1.0000
	x_4	0.6667	1.0000	0.7143	0.8571	0.0000	0.0571	0.0000	0.2273	0.6000	1.0000	0.0000	0.1667
e_3	x_1	0.0000	0.3448	0.0000	0.1429	0.9983	1.0000	0.7778	1.0000	0.5556	0.9259	0.7414	0.8448
	x_2	0.0000	0.3448	0.5857	0.7286	0.7411	0.8033	0.3111	0.5333	0.0000	0.3704	0.7241	0.8448
	x_3	0.0000	0.3448	0.8571	1.0000	0.9915	0.9972	0.0889	0.3111	0.2593	0.6296	0.8276	1.0000
	x_4	0.6828	1.0000	0.8286	0.9714	0.0000	0.0565	0.0000	0.2222	0.6296	1.0000	0.0000	0.1552
e_4	x_1	0.0000	0.3226	0.0000	0.1449	0.9941	1.0000	0.7955	1.0000	0.6000	1.0000	0.7000	0.8500
	x_2	0.0000	0.3226	0.6087	0.7536	0.7420	0.7951	0.3182	0.4318	0.0000	0.4000	0.7000	0.8500
	x_3	0.0000	0.3226	0.8696	1.0000	0.9900	0.9959	0.1364	0.3636	0.2000	0.6000	0.8333	1.0000
	x_4	0.6774	1.0000	0.7246	0.8696	0.0000	0.0059	0.0000	0.2273	0.6000	1.0000	0.0000	0.1667
e_5	x_1	0.0000	0.3448	0.0000	0.1286	0.9983	1.0000	0.7778	1.0000	0.5556	0.9259	0.7414	0.8448
	x_2	0.0000	0.3448	0.5714	0.7143	0.7220	0.7895	0.3111	0.5333	0.0000	0.3704	0.7241	0.8448
	x_3	0.0000	0.3448	0.8571	1.0000	0.9920	0.9977	0.0889	0.3111	0.2593	0.6296	0.8276	1.0000
	x_4	0.7241	1.0000	0.8143	0.9571	0.0000	0.0572	0.0000	0.2222	0.6296	1.0000	0.0000	0.1552
e_6	x_1	0.0000	0.3333	0.0000	0.1538	0.9943	1.0000	0.8000	1.0000	0.5652	1.0000	0.6724	0.8448
	x_2	0.0000	0.3333	0.5692	0.7231	0.7513	0.8082	0.3556	0.5778	0.0000	0.4348	0.6724	0.8448
	x_3	0.0000	0.3333	0.8462	1.0000	0.9903	0.9960	0.1111	0.3333	0.0870	0.5217	0.8276	1.0000
	x_4	0.6667	1.0000	0.7077	0.8615	0.0000	0.0569	0.0000	0.2222	0.5652	1.0000	0.0000	0.1724
e_7	x_1	0.0000	0.3448	0.0000	0.1471	0.9971	1.0000	0.7778	1.0000	0.6000	1.0000	0.6842	0.8246
	x_2	0.0000	0.3448	0.5882	0.7353	0.7543	0.8114	0.3333	0.5556	0.0000	0.4000	0.6667	0.8070
	x_3	0.0000	0.3448	0.8529	1.0000	0.9891	0.9949	0.1111	0.3333	0.2000	0.6000	0.8246	1.0000
	x_4	0.6483	1.0000	0.7206	0.8676	0.0000	0.0571	0.0000	0.2222	0.6000	1.0000	0.0000	0.1754
e_8	x_1	0.0000	0.3750	0.0000	0.1429	0.9944	1.0000	0.8163	1.0000	0.5652	1.0000	0.6610	0.8136
	x_2	0.0000	0.3750	0.5714	0.7429	0.7450	0.8054	0.4082	0.5918	0.0000	0.4348	0.6610	0.8136
	x_3	0.0000	0.3750	0.8571	1.0000	0.9905	0.9961	0.2245	0.4286	0.2174	0.6522	0.8305	1.0000
	x_4	0.6875	1.0000	0.6857	0.8286	0.0000	0.0559	0.0000	0.2041	0.5652	1.0000	0.0000	0.1695
e_9	x_1	0.0000	0.3750	0.0000	0.1429	0.9977	1.0000	0.8043	1.0000	0.5652	1.0000	0.6610	0.8136
	x_2	0.0000	0.3750	0.5714	0.7429	0.7417	0.8027	0.3696	0.5652	0.0000	0.4348	0.6610	0.8136
	x_3	0.0000	0.3750	0.8571	1.0000	0.9927	0.9960	0.1739	0.3913	0.2174	0.6522	0.8305	1.0000
	x_4	0.6875	1.0000	0.6857	0.8286	0.0000	0.0565	0.0000	0.2174	0.5652	1.0000	0.0000	0.1695
e_{10}	x_1	0.0000	0.3333	0.0000	0.1493	0.9943	1.0000	0.7778	1.0000	0.5652	1.0000	0.6610	0.8136
	x_2	0.0000	0.3333	0.5970	0.7463	0.7447	0.8016	0.3778	0.4889	0.0000	0.4348	0.6610	0.8136
	x_3	0.0000	0.3333	0.8507	1.0000	0.9915	0.9972	0.0889	0.3111	0.2174	0.6522	0.8305	1.0000
	x_4	0.6970	1.0000	0.7164	0.8657	0.0000	0.0569	0.0000	0.2222	0.5652	1.0000	0.0000	0.1695
e_{11}	x_1	0.0000	0.3333	0.0000	0.1587	0.9943	1.0000	0.7778	1.0000	0.5417	0.9583	0.6452	0.8065
	x_2	0.0000	0.3333	0.6032	0.7778	0.7405	0.8027	0.3778	0.6000	0.0000	0.4167	0.6452	0.8065
	x_3	0.0000	0.3333	0.8413	1.0000	0.9910	0.9966	0.1333	0.3556	0.0833	0.5000	0.8387	1.0000
	x_4	0.6667	1.0000	0.7302	0.8889	0.0000	0.0565	0.0000	0.2222	0.5833	1.0000	0.0000	0.1613

Table A2. *Cont.*

Alternatives/Attributes		c_1		c_1		c_1		c_1		c_1		c_1	
		a_{li}^{jtL}	a_{li}^{jtL}	a_{li}^{jtL}	a_{li}^{jtL}	a_{li}^{jtL}	a_{li}^{jtL}	a_{li}^{jtL}	a_{li}^{jtL}	a_{li}^{jtL}	a_{li}^{jtL}	a_{li}^{jtL}	a_{li}^{jtL}
e_1	x_2	0.0000	0.3333	0.5714	0.7143	0.7441	0.8006	0.3182	0.5455	0.0000	0.4000	0.6667	0.8333
	x_3	0.0000	0.3333	0.8571	1.0000	0.9898	0.9955	0.1364	0.3636	0.2000	0.6000	0.8333	1.0000
	x_4	0.6667	1.0000	0.7143	0.8571	0.0000	0.0571	0.0000	0.2273	0.6000	1.0000	0.0000	0.1667
	x_1	0.0000	0.3448	0.0000	0.1429	0.9983	1.0000	0.7778	1.0000	0.5556	0.9259	0.7414	0.8448
e_2	x_2	0.0000	0.3448	0.5857	0.7286	0.7411	0.8033	0.3111	0.5333	0.0000	0.3704	0.7241	0.8448
	x_3	0.0000	0.3448	0.8571	1.0000	0.9915	0.9972	0.0889	0.3111	0.2593	0.6296	0.8276	1.0000
	x_4	0.6828	1.0000	0.8286	0.9714	0.0000	0.0565	0.0000	0.2222	0.6296	1.0000	0.0000	0.1552
	x_4	0.6667	1.0000	0.8571	1.0000	0.0000	0.0572	0.7727	1.0000	0.7647	0.8824	0.8571	1.0000
e_3	x_1	0.0000	0.3356	0.0000	0.1389	0.9943	1.0000	0.0000	0.2128	0.0000	0.1889	0.0000	0.1408
	x_2	0.0000	0.3356	0.6111	0.7500	0.7899	0.8524	0.6383	0.8511	0.8889	1.0000	0.0423	0.1408
	x_3	0.0000	0.3356	0.8611	1.0000	0.9938	0.9994	0.7872	1.0000	0.8889	1.0000	0.0704	0.1408
	x_4	0.6644	1.0000	0.8611	1.0000	0.0000	0.0517	0.7660	0.9787	0.7889	0.9000	0.8592	1.0000
e_4	x_1	0.0000	0.3226	0.0000	0.1538	0.9944	1.0000	0.0000	0.2174	0.0000	0.1163	0.0000	0.1408
	x_2	0.0000	0.3226	0.6462	0.8000	0.8034	0.8539	0.6522	0.8478	0.8837	1.0000	0.0000	0.1408
	x_3	0.0000	0.3226	0.9231	1.0000	0.9933	0.9989	0.7826	1.0000	0.8837	1.0000	0.0000	0.1408
	x_4	0.6774	1.0000	0.9231	0.9538	0.0000	0.0562	0.7826	1.0000	0.7907	0.8889	0.8732	1.0000
e_5	x_1	0.0000	0.3590	0.0000	0.1389	0.9943	1.0000	0.0000	0.2128	0.0000	0.1889	0.0000	0.1408
	x_2	0.0000	0.3590	0.6111	0.7500	0.7899	0.8524	0.6383	0.8511	0.8889	1.0000	0.0423	0.1408
	x_3	0.0000	0.3590	0.8611	1.0000	0.9938	0.9994	0.7872	1.0000	0.8889	1.0000	0.0704	0.1408
	x_4	0.6795	1.0000	0.8611	1.0000	0.0000	0.0517	0.7660	0.9787	0.7889	0.9000	0.8592	1.0000
e_6	x_1	0.0000	0.3460	0.0000	0.1449	0.9943	1.0000	0.0000	0.1957	0.0000	0.1163	0.0000	0.1389
	x_2	0.0000	0.3460	0.5652	0.7101	0.8005	0.8576	0.6739	0.8913	0.8721	1.0000	0.0000	0.1389
	x_3	0.0000	0.3460	0.8551	1.0000	0.9920	0.9977	0.7826	1.0000	0.8605	0.9767	0.0000	0.1389
	x_4	0.6540	1.0000	0.8551	1.0000	0.0000	0.0572	0.7609	0.9783	0.7674	0.8837	0.8611	1.0000
e_7	x_1	0.0000	0.3448	0.0000	0.1429	0.9943	1.0000	0.0000	0.2222	0.0000	0.1176	0.0000	0.1449
	x_2	0.0000	0.3448	0.5714	0.7143	0.8037	0.8611	0.6667	0.8889	0.8824	1.0000	0.0000	0.1449
	x_3	0.0000	0.3448	0.8571	1.0000	0.9885	0.9943	0.7778	1.0000	0.8824	1.0000	0.0000	0.1449
	x_4	0.6483	1.0000	0.8571	1.0000	0.0000	0.0574	0.7778	1.0000	0.7647	0.8824	0.8551	1.0000
e_8	x_1	0.0000	0.3247	0.0000	0.1389	0.9944	1.0000	0.0000	0.2000	0.0000	0.1163	0.0000	0.1429
	x_2	0.0000	0.3247	0.5694	0.7083	0.7933	0.8539	0.6667	0.8667	0.8837	1.0000	0.0000	0.1429
	x_3	0.0000	0.3247	0.8333	0.9722	0.9933	0.9989	0.7778	1.0000	0.8837	1.0000	0.0000	0.1429
	x_4	0.6753	1.0000	0.8611	1.0000	0.0000	0.0562	0.7556	0.9778	0.7558	0.8721	0.8571	1.0000
e_9	x_1	0.0000	0.3247	0.0000	0.1389	0.9943	1.0000	0.0000	0.2000	0.0000	0.1163	0.0000	0.1429
	x_2	0.0000	0.3247	0.5694	0.7083	0.7893	0.8509	0.6667	0.8667	0.8837	1.0000	0.0000	0.1429
	x_3	0.0000	0.3247	0.8333	0.9722	0.9943	0.9989	0.7778	1.0000	0.8837	1.0000	0.0000	0.1429
	x_4	0.6753	1.0000	0.8611	1.0000	0.0000	0.0514	0.7556	0.9778	0.7558	0.8721	0.8571	1.0000
e_{10}	x_1	0.0000	0.3247	0.0000	0.1429	0.9943	1.0000	0.0000	0.2222	0.0000	0.1163	0.0000	0.1429
	x_2	0.0000	0.3247	0.5714	0.7143	0.7830	0.8509	0.7333	0.9556	0.8837	1.0000	0.0000	0.1429
	x_3	0.0000	0.3247	0.8571	1.0000	0.9949	1.0000	0.7778	1.0000	0.8837	1.0000	0.0000	0.1429
	x_4	0.6753	1.0000	0.8571	1.0000	0.0000	0.0571	0.7778	1.0000	0.7558	0.8721	0.8571	1.0000
e_{11}	x_1	0.0000	0.3333	0.0000	0.1493	0.9943	1.0000	0.0000	0.2326	0.0000	0.1176	0.0000	0.1408
	x_2	0.0000	0.3333	0.5373	0.6866	0.7842	0.8518	0.6977	0.9302	0.8824	1.0000	0.0000	0.1408
	x_3	0.0000	0.3333	0.8507	1.0000	0.9938	0.9994	0.7674	1.0000	0.8824	1.0000	0.0282	0.1690
	x_4	0.6667	1.0000	0.8507	1.0000	0.0000	0.0568	0.7674	1.0000	0.7882	0.9059	0.8592	1.0000

Table A3. Perceived Utility Matrix of Experts.

Scenario Alternatives/Attributes		s_1 c_1	c_2	c_3	c_4	c_5	c_6
e_1	x_1	0.2023	0.0853	0.9974	0.9509	0.9558	0.9755
	x_2	0.2023	0.6026	0.8899	0.2062	0.0701	0.9755
	x_3	0.2023	0.9447	0.9942	0.2062	0.1880	0.7509
	x_4	0.8512	0.7190	0.0443	0.0769	0.4951	0.0769
e_2	x_1	0.2023	0.0853	0.9974	0.9514	0.9603	0.9755
	x_2	0.2023	0.6026	0.8851	0.2042	0.0639	0.9755
	x_3	0.2023	0.9447	0.9953	0.2042	0.1880	0.7407
	x_4	0.8512	0.6959	0.0447	0.0762	0.5048	0.0769
e_3	x_1	0.2084	0.0873	0.9974	0.9498	0.9336	0.9709
	x_2	0.2084	0.6402	0.8878	0.1979	0.0701	0.9709
	x_3	0.2084	0.9433	0.9953	0.1979	0.1990	0.7183
	x_4	0.8585	0.7116	0.0447	0.0785	0.5145	0.0762
e_4	x_1	0.2084	0.0853	0.9997	0.9607	0.9603	0.9755
	x_2	0.2084	0.6261	0.8917	0.2002	0.0701	0.9755
	x_3	0.2084	0.9447	0.9943	0.2002	0.1880	0.7305
	x_4	0.8772	0.7190	0.0439	0.0701	0.4854	0.0769
e_5	x_1	0.2137	0.0795	0.9974	0.9498	0.9336	0.9758
	x_2	0.2137	0.6402	0.8877	0.2104	0.0701	0.9758
	x_3	0.2137	0.9433	0.9958	0.2104	0.1991	0.7183
	x_4	0.8560	0.7116	0.0443	0.0785	0.5048	0.0762
e_6	x_1	0.2091	0.0903	0.9995	0.9553	0.9549	0.9804
	x_2	0.2091	0.5750	0.8949	0.2083	0.0714	0.9804
	x_3	0.2091	0.9410	0.9952	0.1959	0.1800	0.7509
	x_4	0.8454	0.6874	0.0448	0.0708	0.4843	0.0769
e_7	x_1	0.1900	0.0873	0.9987	0.9503	0.9558	0.9855
	x_2	0.1900	0.6162	0.8935	0.1959	0.0701	0.9806
	x_3	0.1900	0.9433	0.9942	0.1959	0.1880	0.7436
	x_4	0.8428	0.6700	0.0448	0.0347	0.4951	0.0762
e_8	x_1	0.1965	0.0873	0.9992	0.9503	0.9554	0.9800
	x_2	0.1965	0.6282	0.8917	0.2083	0.0645	0.9800
	x_3	0.1965	0.9433	0.9943	0.2083	0.1784	0.7866
	x_4	0.8560	0.6760	0.0439	0.0777	0.4898	0.0785
e_9	x_1	0.1977	0.0873	0.9990	0.9509	0.9554	0.9800
	x_2	0.1977	0.6282	0.8899	0.2183	0.0645	0.9800
	x_3	0.1977	0.9433	0.9942	0.2183	0.1784	0.7866
	x_4	0.8551	0.6760	0.0443	0.0769	0.4898	0.0785
e_{10}	x_1	0.2137	0.0853	0.9974	0.9509	0.9554	0.9800
	x_2	0.2137	0.6026	0.8899	0.2062	0.0645	0.9800
	x_3	0.2137	0.9447	0.9953	0.2062	0.1784	0.7866
	x_4	0.8560	0.6959	0.0443	0.0769	0.4898	0.0785
e_{11}	x_1	0.2023	0.0914	0.9974	0.9549	0.9558	0.9802
	x_2	0.2023	0.6073	0.8835	0.1858	0.0701	0.9802
	x_3	0.2023	0.9402	0.9947	0.1858	0.1880	0.7993
	x_4	0.8513	0.7454	0.0448	0.0587	0.4951	0.0708

Table A3. *Cont.*

Scenario Alternatives/Attributes		s_2 c_1	c_2	c_3	c_4	c_5	c_6
e_1	x_1	0.2023	0.0960	0.9975	0.9013	0.8208	0.7762
	x_2	0.2023	0.6777	0.7986	0.4893	0.2375	0.7762
	x_3	0.2023	0.9368	0.9940	0.2650	0.4445	0.9262
	x_4	0.8512	0.8087	0.0424	0.1416	0.8208	0.1099
e_2	x_1	0.2023	0.0960	0.9975	0.8990	0.8208	0.7762
	x_2	0.2023	0.6777	0.7966	0.4770	0.2375	0.7762
	x_3	0.2023	0.9368	0.9935	0.2941	0.4445	0.9262
	x_4	0.8512	0.8087	0.0428	0.1444	0.8208	0.1099
e_3	x_1	0.2084	0.0960	0.9993	0.9013	0.7671	0.8154
	x_2	0.2084	0.6910	0.7965	0.4677	0.2219	0.8076
	x_3	0.2084	0.9368	0.9950	0.2412	0.4883	0.9236
	x_4	0.8585	0.9114	0.0424	0.1416	0.8343	0.1032
e_4	x_1	0.1965	0.0972	0.9974	0.9092	0.8208	0.7989
	x_2	0.1965	0.7131	0.7932	0.4217	0.2375	0.7989
	x_3	0.1965	0.9423	0.9938	0.2941	0.4445	0.9262
	x_4	0.8560	0.8190	0.0058	0.1444	0.8208	0.1099
e_5	x_1	0.2084	0.0875	0.9992	0.9013	0.7671	0.8154
	x_2	0.2084	0.6777	0.7815	0.4677	0.2219	0.8076
	x_3	0.2084	0.9368	0.9955	0.2412	0.4883	0.9236
	x_4	0.8772	0.8986	0.0429	0.1416	0.8343	0.1032
e_6	x_1	0.2023	0.1024	0.9975	0.9113	0.8049	0.7840
	x_2	0.2023	0.6807	0.8033	0.5108	0.2556	0.7840
	x_3	0.2023	0.9319	0.9940	0.2650	0.3477	0.9236
	x_4	0.8512	0.8077	0.0427	0.1416	0.8049	0.1132
e_7	x_1	0.2084	0.0985	0.9987	0.9013	0.8208	0.7802
	x_2	0.2084	0.6952	0.8062	0.4893	0.2375	0.7642
	x_3	0.2084	0.9349	0.9930	0.2650	0.4445	0.9222
	x_4	0.8428	0.8163	0.0429	0.1416	0.8208	0.1150
e_8	x_1	0.2244	0.0960	0.9975	0.9186	0.8049	0.7646
	x_2	0.2244	0.6909	0.7992	0.5430	0.2556	0.7646
	x_3	0.2244	0.9368	0.9941	0.3728	0.4783	0.9249
	x_4	0.8606	0.7827	0.0420	0.1314	0.8049	0.1116
e_9	x_1	0.2244	0.0960	0.9990	0.9132	0.8049	0.7646
	x_2	0.2244	0.6909	0.7965	0.5117	0.2556	0.7646
	x_3	0.2244	0.9368	0.9950	0.3280	0.4783	0.9249
	x_4	0.8606	0.7827	0.0424	0.1389	0.8049	0.1116
e_{10}	x_1	0.2023	0.0997	0.9975	0.9013	0.8049	0.7646
	x_2	0.2023	0.7043	0.7974	0.4789	0.2556	0.7646
	x_3	0.2023	0.9339	0.9950	0.2412	0.4783	0.9249
	x_4	0.8649	0.8135	0.0427	0.1416	0.8049	0.1116
e_{11}	x_1	0.2023	0.1053	0.9975	0.9013	0.7753	0.7541
	x_2	0.2023	0.7217	0.7960	0.5322	0.2462	0.7541
	x_3	0.2023	0.9297	0.9945	0.2884	0.3349	0.9286
	x_4	0.8512	0.8302	0.0424	0.1416	0.8132	0.1068

Table A3. *Cont.*

Scenario alternatives/attributes		s_3					
		c_1	c_2	c_3	c_4	c_5	c_6
e_1	x_1	0.2023	0.0960	0.9975	0.1416	0.0809	0.0960
	x_2	0.2023	0.6777	0.8428	0.8013	0.9480	0.0960
	x_3	0.2023	0.9368	0.9965	0.9013	0.9480	0.0960
	x_4	0.8512	0.9368	0.0426	0.9013	0.8429	0.9368
e_2	x_1	0.2023	0.0960	0.9980	0.1444	0.0809	0.0960
	x_2	0.2023	0.6777	0.8412	0.7760	0.9480	0.0960
	x_3	0.2023	0.9368	0.9960	0.8787	0.9480	0.0960
	x_4	0.8512	0.9368	0.0429	0.8990	0.8429	0.9368
e_3	x_1	0.2035	0.0936	0.9975	0.1363	0.1227	0.0948
	x_2	0.2035	0.7126	0.8408	0.7712	0.9509	0.1213
	x_3	0.2035	0.9385	0.9970	0.9055	0.9509	0.1381
	x_4	0.8501	0.9385	0.0392	0.8865	0.8617	0.9377
e_4	x_1	0.1965	0.1024	0.9975	0.1389	0.0801	0.0948
	x_2	0.1965	0.7516	0.8475	0.7761	0.9486	0.0948
	x_3	0.1965	0.9660	0.9965	0.9035	0.9486	0.0948
	x_4	0.8560	0.9456	0.0422	0.9035	0.8575	0.9439
e_5	x_1	0.2159	0.0936	0.9975	0.1363	0.1227	0.0948
	x_2	0.2159	0.7126	0.8408	0.7712	0.9509	0.1213
	x_3	0.2159	0.9385	0.9970	0.9055	0.9509	0.1381
	x_4	0.8570	0.9385	0.0392	0.8865	0.8617	0.9377
e_6	x_1	0.2091	0.0972	0.9975	0.1266	0.0801	0.0936
	x_2	0.2091	0.6729	0.8479	0.8057	0.9434	0.0936
	x_3	0.2091	0.9358	0.9955	0.9035	0.9279	0.0936
	x_4	0.8454	0.9358	0.0429	0.8840	0.8447	0.9385
e_7	x_1	0.2084	0.0960	0.9975	0.1416	0.0809	0.0972
	x_2	0.2084	0.6777	0.8509	0.8013	0.9480	0.0972
	x_3	0.2084	0.9368	0.9924	0.9013	0.9480	0.0972
	x_4	0.8428	0.9368	0.0430	0.9013	0.8429	0.9358
e_8	x_1	0.1977	0.0936	0.9975	0.1290	0.0801	0.0960
	x_2	0.1977	0.6740	0.8430	0.7913	0.9486	0.0960
	x_3	0.1977	0.9138	0.9965	0.9013	0.9486	0.0960
	x_4	0.8551	0.9385	0.0422	0.8814	0.8342	0.9368
e_9	x_1	0.1977	0.0936	0.9975	0.1290	0.0801	0.0960
	x_2	0.1977	0.6740	0.8398	0.7913	0.9486	0.0960
	x_3	0.1977	0.9138	0.9970	0.9013	0.9486	0.0960
	x_4	0.8551	0.9385	0.0390	0.8814	0.8342	0.9368
e_{10}	x_1	0.1977	0.0960	0.9975	0.1416	0.0801	0.0960
	x_2	0.1977	0.6777	0.8370	0.8615	0.9486	0.0960
	x_3	0.1977	0.9368	0.9977	0.9013	0.9486	0.0960
	x_4	0.8551	0.9368	0.0428	0.9013	0.8342	0.9368
e_{11}	x_1	0.2023	0.0997	0.9975	0.1474	0.0809	0.0948
	x_2	0.2023	0.6489	0.8379	0.8340	0.9480	0.0948
	x_3	0.2023	0.9339	0.9970	0.8967	0.9480	0.1289
	x_4	0.8512	0.9339	0.0426	0.8967	0.8640	0.9377

Table A4. Prospect values of experts.

Alternatives/Attributes		c_1	c_2	c_3	c_4	c_5	c_6
e_1	x_1	0.2023	0.0929	0.9975	0.8286	0.7748	0.7554
	x_2	0.2023	0.6562	0.8297	0.4441	0.2709	0.7554
	x_3	0.2023	0.9390	0.9944	0.3209	0.4287	0.7812
	x_4	0.8512	0.7977	0.0430	0.2099	0.7303	0.1950
e_2	x_1	0.2023	0.0929	0.9975	0.8278	0.7761	0.7554
	x_2	0.2023	0.6562	0.8270	0.4333	0.2691	0.7554
	x_3	0.2023	0.9390	0.9943	0.3353	0.4287	0.7783
	x_4	0.8512	0.7911	0.0434	0.2112	0.7330	0.1950
e_3	x_1	0.2079	0.0932	0.9985	0.8277	0.7410	0.7775
	x_2	0.2079	0.6789	0.8276	0.4253	0.2619	0.7758
	x_3	0.2079	0.9388	0.9953	0.3048	0.4585	0.7752
	x_4	0.8575	0.8574	0.0427	0.2087	0.7461	0.1909
e_4	x_1	0.1999	0.0944	0.9981	0.8359	0.7760	0.7689
	x_2	0.1999	0.6927	0.8276	0.3989	0.2709	0.7689
	x_3	0.1999	0.9457	0.9942	0.3369	0.4288	0.7752
	x_4	0.8621	0.8049	0.0208	0.2099	0.7292	0.1958
e_5	x_1	0.2108	0.0859	0.9985	0.8277	0.7410	0.7789
	x_2	0.2108	0.6710	0.8186	0.4288	0.2619	0.7772
	x_3	0.2108	0.9388	0.9957	0.3083	0.4586	0.7752
	x_4	0.8688	0.8497	0.0429	0.2087	0.7433	0.1909
e_6	x_1	0.2050	0.0984	0.9981	0.8342	0.7649	0.7612
	x_2	0.2050	0.6496	0.8346	0.4581	0.2816	0.7612
	x_3	0.2050	0.9349	0.9945	0.3182	0.3661	0.7794
	x_4	0.8489	0.7880	0.0433	0.2062	0.7178	0.1972
e_7	x_1	0.2031	0.0950	0.9986	0.8285	0.7748	0.7608
	x_2	0.2031	0.6706	0.8362	0.4412	0.2709	0.7498
	x_3	0.2031	0.9375	0.9932	0.3180	0.4287	0.7769
	x_4	0.8428	0.7883	0.0434	0.1979	0.7303	0.1977
e_8	x_1	0.2134	0.0932	0.9980	0.8374	0.7650	0.7497
	x_2	0.2134	0.6711	0.8306	0.4758	0.2802	0.7497
	x_3	0.2134	0.9360	0.9944	0.3862	0.4464	0.7906
	x_4	0.8587	0.7701	0.0426	0.2017	0.7182	0.1964
e_9	x_1	0.2137	0.0932	0.9988	0.8343	0.7650	0.7497
	x_2	0.2137	0.6711	0.8281	0.4598	0.2802	0.7497
	x_3	0.2137	0.9360	0.9950	0.3622	0.4464	0.7906
	x_4	0.8584	0.7701	0.0426	0.2060	0.7182	0.1964
e_{10}	x_1	0.2050	0.0952	0.9975	0.8286	0.7650	0.7497
	x_2	0.2050	0.6722	0.8284	0.4447	0.2802	0.7497
	x_3	0.2050	0.9373	0.9954	0.3067	0.4464	0.7906
	x_4	0.8612	0.7940	0.0432	0.2099	0.7182	0.1964
e_{11}	x_1	0.2023	0.1007	0.9975	0.8304	0.7475	0.7433
	x_2	0.2023	0.6807	0.8258	0.4677	0.2761	0.7433
	x_3	0.2023	0.9332	0.9949	0.3286	0.3630	0.8002
	x_4	0.8512	0.8178	0.0431	0.2042	0.7281	0.1915

References

1. Liu, B.S.; Zhao, X.; Li, Y. Review and Prospect of Studies on Emergency Management. *Procedia Eng.* **2016**, *145*, 1501–1508. [CrossRef]
2. Domeneghetti, B.; Benamrane, Y.; Wybo, J.L. Analyzing nuclear expertise support to population protection decision making process during nuclear emergencies. *Saf. Sci.* **2018**, *101*, 155–163. [CrossRef]
3. Lv, J.; Mao, Q.H.; Li, Q.W.; Yu, R.F. A group emergency decision-making method for epidemic prevention and control based on probabilistic hesitant fuzzy prospect set considering quality of information. *Int. J. Comput. Intell. Syst.* **2022**, *15*, 33. [CrossRef]

4. Fu, M.; Wang, L.F.; Zheng, B.Y.; Shao, H.Y. The optimal emergency decision-making method with incomplete probabilistic information. *Sci. Rep.* **2021**, *11*, 23400. [CrossRef]
5. Wang, Y.N.; Liang, Y.Z.; Sun, H. A Regret Theory-Based Decision-Making Method for Urban Rail Transit in Emergency Response of Rainstorm Disaster. *J. Adv. Transp.* **2020**, *2020*, 3235429. [CrossRef]
6. Ding, Q.Y.; Wang, Y.M.; Goh, M. TODIM Dynamic Emergency Decision-Making Method Based on Hybrid Weighted Distance Under Probabilistic Hesitant Fuzzy Information. *Int. J. Fuzzy Syst.* **2021**, *23*, 474–491. [CrossRef]
7. Xu, X.H.; Ma, Z.P.; Chen, X.H. Research on the relationship between large group conflict, risk perception and the quality of emergency decision-making: The moderating effect of decision-making hesitation. *J. Manag. Eng.* **2020**, *34*, 90–99.
8. Xu, X.H.; Ma, Z.P.; Chen, X.H. Research on the dynamic evolution of large group emergency decision-making quality based on big data analysis of public preference. *China Manag. Sci.* **2022**, *30*, 140–149.
9. Xu, X.H.; Chen, X.H. Research on a large group decision-making method with multiple attributes and multiple schemes. *J. Syst. Eng.* **2008**, *23*, 137–141.
10. Yin, X.P.; Xu, X.H.; Chen, X.H. Research on the Selection of Large Group Emergency Decision Making Strategies from the Risk Perspective. *Syst. Eng. Theory Pract.* **2021**, *41*, 678–690.
11. Xu, X.H.; Wang, L.L.; Chen, X.H.; Liu, B.S. Large group emergency decision-making method with linguistic risk appetites based on criteria mining. *Knowl.-Based Syst.* **2019**, *182*, 104849. [CrossRef]
12. Ding, X.F.; Zhu, L.X.; Lu, M.S.; Wang, Q.F.; Yi, Q. A Novel Linguistic Z-Number QUALIFLEX Method and Its Application to Large Group Emergency Decision Making. *Sci. Program.* **2020**, *2020*, 1631869. [CrossRef]
13. Xu, X.H.; Du, Z.J.; Chen, X.H. Consensus model for multi-criteria large-group emergency decision making considering non-cooperative behaviors and minority opinions. *Decis. Support Syst.* **2015**, *79*, 150–160. [CrossRef]
14. Xu, X.H.; Zhong, X.Y.; Chen, X.H.; Zhou, Y.J. A dynamical consensus method based on exit–delegation mechanism for large group emergency decision making. *Knowl.-Based Syst.* **2015**, *86*, 237–249. [CrossRef]
15. Xu, X.H.; Zhang, Q.H.; Chen, X.H. Consensus-based non-cooperative behaviors management in large-group emergency decision-making considering experts' trust relations and preference risks. *Knowl.-Based Syst.* **2020**, *190*, 105018. [CrossRef]
16. Ding, Q.Y.; Wang, Y.M.; Goh, M. An extended TODIM approach for group emergency decision making based on bidirectional projection with hesitant triangular fuzzy sets. *Comput. Ind. Eng.* **2020**, *151*, 106959. [CrossRef]
17. Xu, X.H.; Yu, Y.F. Preference information fusion method considering attribute correlation in large group emergency decision-making. *Control. Decis.* **2021**, *36*, 2537–2546.
18. Fullér, R.; Majlender, P. On obtaining minimal variability OWA operator weights. *Fuzzy Sets Syst.* **2003**, *136*, 203–215. [CrossRef]
19. Wang, Y.M.; Luo, Y.; Liu, X.W. Two new models for determining OWA operator weights. *Comput. Ind. Eng.* **2007**, *52*, 203–209. [CrossRef]
20. Yari, G.; Chaji, A.R. Maximum Bayesian entropy method for determining ordered weighted averaging operator weights. *Comput. Ind. Eng.* **2012**, *63*, 338–342. [CrossRef]
21. Xu, X.H.; Yang, Y.S. Large group risk dynamic emergency decision-making method based on cumulative prospect theory. *Control. Decis.* **2017**, *32*, 1957–1965.
22. Xu, X.; Pan, B.; Yang, Y. Large-group risk dynamic emergency decision method based on the dual influence of preference transfer and risk preference. *Soft Comput.* **2018**, *22*, 7479–7490. [CrossRef]
23. Wu, G.H.; Tong, J.J.; Zhang, L.G.; Yuan, D.P.; Xiao, Y.Q. Research on rapid source term estimation in nuclear accident emergency decision for pressurized water reactor based on Bayesian network. *Nucl. Eng. Technol.* **2021**, *53*, 2534–2546. [CrossRef]
24. Zhang, Y.; Guo, H.M.; Zhao, Z.; Chen, W.F.; Shen, Y. Research on staged dynamic decision-making method of earthquake emergency based on sequential game theory and Bayesian theory. *China Earthq.* **2022**, *38*, 260–269.
25. Huang, Y.N.; Shen, S.C.; Yang, S.W.; Kuang, Y.; Li, Y.X.; Li, S. Asymmetrical Property of the Subproportionality of Weighting Function in Prospect Theory: Is It Real and How Can It Be Achieved? *Symmetry* **2021**, *13*, 1928. [CrossRef]
26. Kahneman, D.; Tversky, A. Prospect theory: Ananalysis of decision under risk. *Econometrica* **1979**, *47*, 263–291. [CrossRef]
27. Cover, T.M.; Thomas, J.A. *Elements of Information Theory*; John Wiley and Sons: New York, NY, USA, 2006.
28. Zhao, M.; Qiu, W.H.; Liu, B.H. A ranking method for multiple attribute decision making based on relative entropy. *Control. Decis.* **2010**, *25*, 1098–1100.
29. Wang, L.; Wang, Y.M.; Martinez, L. A group decision method based on prospect theory for emergency scenarios. *Inf. Sci.* **2017**, *418*, 119–135. [CrossRef]
30. Zhang, Z.X.; Wang, L.; Rodríguez, R.M.; Wang, Y.M.; Martínez, L. A hesitant group emergency decision making method based on prospect theory. *Complex Intell. Syst.* **2017**, *3*, 177–187. [CrossRef]
31. Wang, L.; Labella, Á.; Rodríguez, R.M.; Wang, Y.-M.; Martínez, L. Managing Non-Homogeneous Information and Experts' Psychological Behavior in Group Emergency Decision Making. *Symmetry* **2017**, *9*, 234. [CrossRef]
32. Qie, Z.J.; Rong, L.L. A scenario modelling method for regional cascading disaster risk to support emergency decision making. *Int. J. Disaster Risk Reduct.* **2022**, *77*, 103102. [CrossRef]
33. Gupta, U.; Ranganathan, N. Multievent crisis management using noncooperative multistep games. *IEEE Trans. Comput.* **2007**, *56*, 577–589. [CrossRef]
34. Zhang, Z.X.; Wang, L.; Wang, Y.M. An Emergency Decision Making Method for Different Scenario Response Based on Game Theory and Prospect Theory. *Symmetry* **2018**, *10*, 476. [CrossRef]

35. Zhang, J.; Hegde, G.G.; Shang, J.; Qi, X. Evaluating Emergency Response Solutions for Sustainable Community Development by Using Fuzzy Multi-Criteria Group Decision Making Approaches: IVDHF-TOPSIS and IVDHF-VIKOR. *Sustainability* **2016**, *8*, 291. [CrossRef]
36. Liu, W.; Li, L. Emergency decision-making combining cumulative prospect theory and group decision-making. *Granul. Comput.* **2019**, *4*, 39–52. [CrossRef]
37. Xu, X.; Huang, Y.; Chen, K. Method for large group emergency decision making with complex preferences based on emergency similarity and interval consistency. *Nat. Hazards* **2019**, *97*, 45–64. [CrossRef]
38. Li, P.; Ji, Y.; Wu, Z.; Qu, S.J. A New Multi-Attribute Emergency Decision-Making Algorithm Based on Intuitionistic Fuzzy Cross-Entropy and Comprehensive Grey Correlation Analysis. *Entropy* **2020**, *22*, 768. [CrossRef]
39. Xu, Z.X.; Xi, S.R.; Qu, J.Y. Multi attribute utility analysis method for nuclear accident emergency decision-making. *J. Tsinghua Univ.* **2008**, *3*, 445–448.
40. Xie, T.; Wei, Y.Y.; Chen, W.F.; Huang, H.N. Parallel evolution and response decision method for public sentiment based on system dynamics. *Eur. J. Oper. Res.* **2020**, *287*, 1131–1148. [CrossRef]
41. Xie, T.; Li, C.D.; Wei, Y.Y.; Jiang, J.J.; Xie, R. Cross-domain integrating and reasoning spaces for offsite nuclear emergency response. *Saf. Sci.* **2016**, *85*, 99–116. [CrossRef]
42. Chen, J.H.; Zou, S.L. An Intelligent Condition Monitoring Approach for Spent Nuclear Fuel Shearing Machines Based on Noise Signals. *Appl. Sci.* **2018**, *8*, 838. [CrossRef]
43. Xu, S.L.; Dong, H.G.; Qin, Z.W.; Han, Y.C.; Gong, D.W.; Zou, S.L.; Wei, C.Y.; Zhao, F. Parallel processing of radiation measurements and radiation video optimization. *Opt. Express* **2022**, *30*, 46870–46887. [CrossRef] [PubMed]