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Safety Assessment of Emergency Training for Industrial Accident Scenarios Based on Analytic Hierarchy Process and Gray-Fuzzy Comprehensive Assessment

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ABSTRACT To evaluate the safety of emergency training for industrial accident scenarios, an approach combining analytic hierarchy process (AHP) and gray-fuzzy evaluation is proposed. According to the characteristics of industrial emergency training scenarios, a safety evaluation index system for this training is constructed from four aspects: human, machine, environment, and management. The index weight is established using the AHP and the evaluation model is established base of the gray-fuzzy evaluation method. Based on the combination of the two methods, the quantitative results on training safety was obtained and the most important factor that have the greatest impact on training safety was found. Using this new assessment method, the safety of an industrial accident training scenario for a domestic emergency training facility are assessed, the defects in its emergency capacity are determined, and measures and suggestions are recommended to provide scientific and effective basis for improving emergency capacity.

INDEX TERMS Emergency training, industrial accidents, safety assessment, AHP, gray fuzzy evaluation.

NOMENCLATURE

T	The target layer
Pi	First-level indicators
Mi	Secondary-level indicators
Ni	Tertiary-level indicators
M_i	Weight of the secondary-level indicators relative to the upper level
N_i	Weight of the tertiary-level indicators relative to the upper level
W_{Pi}	Weight of the first-level index
W_{Mi}	Weight of the secondary-level indicators relative to the target level
W_{Ni}	Weight of the tertiary-level indicators relative to the target level
K	Tertiary-level indicators set
V	The gray category set
C	The evaluation level set
D	The safety risk assessment sample matrix
d_{ij}	Element of matrix D
n_{ij}	The sum of gray statistics number
r_{ij}	The gray assessment weight vector of evaluation
f	Albino weight function
B	Gray-fuzzy judgment matrix
Q	The results of secondary-level fuzzy judgment
Z	The result of the evaluation object
F	The comprehensive evaluation value

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I. INTRODUCTION

With the national attention focused on emergency management and the development of the emergency industry, to improve the emergency rescue ability of firefighters and meet the needs of national fire combat simulation training, a variety of disaster emergency simulation training scenarios should be implemented. These should include industrial accident scenes that simulate the combustion and explosion of hazardous chemicals. During training, the combustion and leakage of hazardous chemicals should be simulated, which entails certain risks. Therefore, safety assessments should be conducted on training facilities and the training process.

Currently, the constructed industrial accident simulation training scenarios mainly simulate leakage, fire and poisoning accidents at chemical industrial parks. Some Chinese scholars studied the risk assessment of chemical industry parks. Li [1] used the fire and explosion risk index evaluation method to quantitatively assess the safety of fire and explosion accidents in the liquefied petroleum gas (LPG) storage tank area; Zhou *et al.* [2] used the improved Kent scoring method to evaluate the risk of a public pipe gallery in a chemical industry park. Liang *et al.* [3]. studied and analyzed various problems in the risk and hidden danger management of special equipment in China's chemical industry parks. Pang and Lu [4] proposed a toxic operation classification method and a method for estimating the diffusion radius of liquid ammonia leakage to evaluate the potential danger and harm of a site using liquid ammonia.

In terms of safety and emergency response, Zhang and Yang examined the emergency response ability of a chemical industry park [5], [6]. Ge evaluated emergency management ability by combining the analytic hierarchy process (AHP) and gray theory [7]. Chen used triangle fuzzy number theory and fuzzy comprehensive evaluation theory to comprehensively evaluate the emergency rescue ability during chemical industry park accidents [8]. Miao proposed a multi-level fuzzy comprehensive evaluation model based on AHP and the fuzzy mathematical method for coal mining enterprises' emergency responses [9].

For more approach, Mohammadfam *et al.* [10] put forward a decision-making approach, ANP-TOPSIS, for assessing and improving the effectiveness of occupational health and safety management systems and identifying the influential factors and their effects on OHSMS effectiveness. Li *et al.* [11] proposed a two-stage solution methodology by combining multi-objective optimization using the q-DEA with an integrated decision-making technique FCM-GRP. Wu *et al.* [12] proposed a multiple attribute group decision making method based on the extended hesitant Pythagorean fuzzy VIKOR under the HPFSs environment. Them also proposed an integrated methodology to address MCGDM problems based on the best-worst method (BWM) [13] and the VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) technique in an interval type-2 fuzzy environment [14].

The key process in risk assessment technology is to construct an assessment matrix. The aim of this process is to obtain the weight of each risk factor and comprehensively evaluate complex fuzzy information. Specific methods to achieve this include: package AHP [15]–[17], fuzzy AHP (FAHP) [18], gray relational analysis (GRA) [19], [20], artificial neural network (ANN) [21]–[23], Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) [24], [25], and the gray-fuzzy evaluation method (FCA) [26]. Each of the above methods has its own advantages and disadvantages. The AHP proposed by Saaty in the 1970s is a well-known method for decision-making in many fields, including engineering [27]–[29], to help decision makers identify the most important factors.

Compared with these studies, although many studies have been conducted to assess the emergency capacity of industrial parks, no complete index system and assessment method exists for the safety assessment of emergency training in industrial environments. By the combination of AHP and grey fuzzy comprehensive evaluation, index weight analysis and quantitative safety assessment of emergency rescue training safety in industrial accident scenarios can be carried out, then the training safety level can be obtained, and safety recommendations can be provided accordingly.

For uncertain fuzzy information, the gray clustering method can be used to quantitatively classify factors into correct categories by establishing a whitening function. The combined application of the fuzzy mathematics method and the gray clustering method in structure evaluation is both objective and quantitative [30]–[32]. Therefore, we combined the AHP with the gray-fuzzy evaluation model to assess the safety of the emergency training system for industrial accident scenarios. The purpose was to obtain more objective and reasonable assessment results and provide an effective basis for improving the emergency training.

Here, we studied the characteristics of industrial accident emergency training scenarios to establish an industrial accident scenario rescue training safety evaluation index system. Combining the AHP and gray-fuzzy evaluation, we identified the factors that have a more of an impact on the safety of emergency training for industrial accident scenarios. The weights of each factor were established, a safety evaluation model was constructed, and an example was used to verify the rationality of the model.

The main contributions of this work are the following threefold:

(1) A safety evaluation index system: To evaluate the training safety in industrial accident scenarios, a safety evaluation index system is established.

(2) A safety assessment approach: Using AHP combined with gray fuzzy comprehensive evaluation, the safety evaluation of the industrial accident emergency rescue training base was carried out, and suggestions for improvement were provided based on the evaluation results.

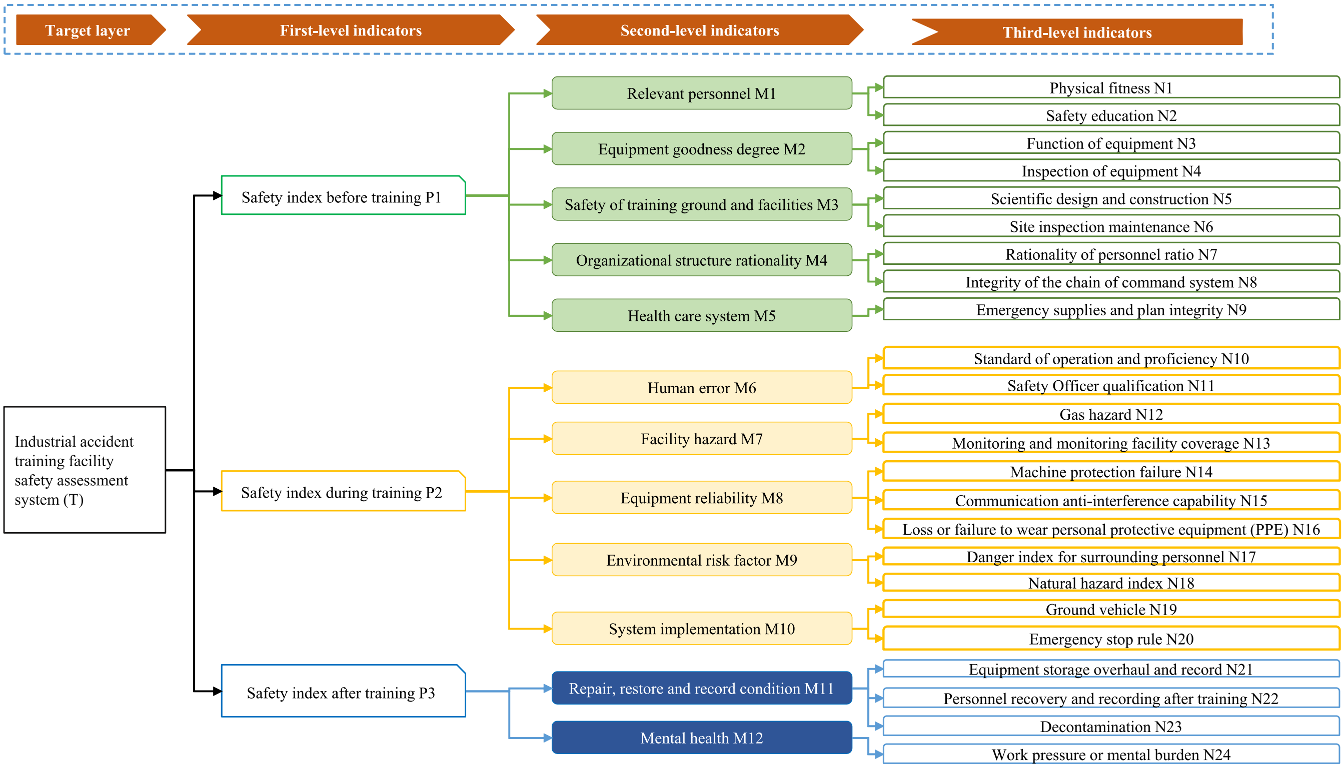

FIGURE 1. Safety assessment index system of emergency training for industrial accident scenarios.

(3) A novel safety assessment model: With the safety index system and the assessment approach, a novel safety assessment model aims at emergency rescue training safety of industrial accident scenario is proposed.

II. CONSTRUCTION OF SAFETY ASSESSMENT INDEX SYSTEM FOR INDUSTRIAL ACCIDENT TRAINING

A. INFLUENCING FACTORS OF EMERGENCY EVACUATION CAPACITY BY FAULT TREE ANALYSIS

The purpose of a safety assessment is to identify and weigh threats and vulnerabilities to obtain the overall safety level of the assessment object [33]. Specifically, these assessments are based on the idea to qualitatively or quantitatively analyze the risk factors in the system and the hazards that cause accidents [34]. The safety assessment system for training scenarios is a large and complex multi-factor system. Due to its numerous influencing factors, various factors may interact with each other, resulting in high uncertainty and a series of related problems. A training scenario is often composed of multiple systems, which considerably decrease the safety of training. To construct a reasonable safety evaluation index system for industrial accident scenarios, through field investigation, expert interviews, safety engineering, and human–machine–environment–management theoretical analysis, we divided the index system into the following four levels: the target layer (T), the first-level indicator layer (P), the secondary-level indicator layer (M), and the tertiary indicator layer (N), as shown in Figure 1.

III. ESTABLISHMENT OF GRAY-FUZZY COMPREHENSIVE SAFETY ASSESSMENT MODEL

The basic principle of gray-fuzzy evaluation is evaluating the risk factors that cannot be quantified or are difficult to quantify by relying on the membership degree in fuzzy mathematics and the gray level in gray theory [35]. Based on the industrial accident scenario index system, the weight of the evaluation index for each level was determined using the AHP. In the evaluation of each indicator, fuzzy comments such as "safe", "relatively safe", "general", "relatively dangerous", and "dangerous" were used for evaluation. Then, the gray-fuzzy evaluation method was adopted to quantitatively express the gray, fuzzy, and factors difficult to quantify in the evaluation process to increase the accuracy of the evaluation result. The flow diagram of the proposed assessment is presented in Figure 2.

A. DETERMINATION OF INDEX WEIGHT BASED ON AHP

An expert questionnaire was administered to obtain data statistics. The importance of each first-level (P1, P2, P3), secondary-level (M1, M2..., M11, M12), and tertiary-level (N1, N2,..., N22, N23) index was scored, and the weight of each set of indicators relative to the superior indicators using AHP was calculated.

The weight of each level of index relative to the target layer is the product of the weight of each level. The weight of the first-level index is denoted W_{Pi}; the weights of the secondary- and tertiary-level indexes relative to the upper level are denoted M_i and N_i, respectively; and the weight

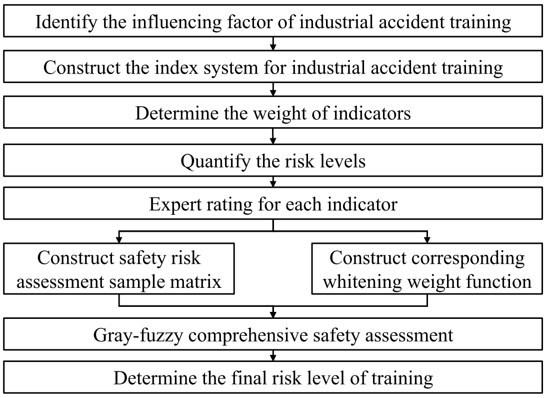

FIGURE 2. Process of the proposed approach.

of the secondary- and tertiary-level indexes relative to the target layer are denoted W_{Mi} and W_{Ni}, respectively Then, the relational expressions are shown:

$$W_{Mi} = W_{Pi} \cdot M_i \tag{1}$$

$$W_{Ni} = W_{Mi} \cdot N_i \tag{2}$$

B. SAFETY ASSESSMENT BASED ON GRAY-FUZZY EVALUATION METHOD

1) SET THE FACTOR SET AND COMMENT SET, AND DETERMINE THE RATING STANDARD OF RISK ASSESSMENT INDICATORS

Set the factor set and the rating set, and assume the risk rating set:

$$K = \{k_1, k_2, \ldots, k_s\}$$
$$V = \{v_1, v_2, \ldots, v_l\}$$
$$C = (c_1, c_2, \ldots, c_l)$$

Quantify the risk levels and assign them separately. In the study, 10 experts were selected to score the indicators, and the score interval was [0,10]. The gray category was divided into five grades: dangerous, relatively dangerous, general, relatively safe, and safe. The score of each grade is $C = \{1, 3, 5, 7, 9\}$, and the intermediate value is taken.

2) ESTABLISH THE EVALUATION SAMPLE MATRIX

With m experts, the tertiary-level index K_{ij} is graded, and the grade given by the nth expert to the index K_{ij} is d_{ij}^n (n = 1, 2,..., m). Then, the safety risk assessment sample matrix D of industrial accident fire training scenario is constructed as:

$$D = \begin{bmatrix} d_{11}^1 & d_{11}^2 & \cdots & d_{11}^m \\ d_{12}^1 & d_{12}^2 & \cdots & d_{12}^m \\ \vdots & \vdots & \vdots & \vdots \\ d_{ij}^1 & d_{ij}^2 & \cdots & d_{ij}^m \end{bmatrix} \tag{3}$$

3) DETERMINE THE WHITENING WEIGHT FUNCTION

According to the grading grade, the gray number of the evaluation gray class is set to 5, and the corresponding whitening weight function is as follows:

(1) The albino weight function f_1 with a grade of "danger" is:

$$f(d_{ij}^n) = \begin{cases} 0, & d_{ij}^n \notin [0,3] \\ 1, & d_{ij}^n \in [0,1] \\ \dfrac{3-d_{ij}^n}{3-1}, & d_{ij}^n \in [1,3] \end{cases} \tag{4}$$

(2) The albino weight function f_2 with a grade of "more dangerous" is:

$$f(d_{ij}^n) = \begin{cases} \dfrac{d_{ij}^n-1}{3}, & d_{ij}^n \in [1,3] \\ \dfrac{5-d_{ij}^n}{2}, & d_{ij}^n \in [3,5] \\ 0, & d_{ij}^n \notin [1,5] \end{cases} \tag{5}$$

(3) The whitening weight function f_3 with the grade of "general" is:

$$f(d_{ij}^n) = \begin{cases} \dfrac{d_{ij}^n-3}{3}, & d_{ij}^n \in [3,5] \\ \dfrac{7-d_{ij}^n}{2}, & d_{ij}^n \in [5,7] \\ 0, & d_{ij}^n \notin [3,7] \end{cases} \tag{6}$$

(4) The albino weight function f_4 with a grade of "relatively safe" is:

$$f(d_{ij}^n) = \begin{cases} \dfrac{d_{ij}^n-5}{3}, & d_{ij}^n \in [5,7] \\ \dfrac{9-d_{ij}^n}{2}, & d_{ij}^n \in [7,9] \\ 0, & d_{ij}^n \notin [5,9] \end{cases} \tag{7}$$

(5) The whitening weight function f_5 with the grade of "safe" is:

$$f(d_{ij}^n) = \begin{cases} \dfrac{d_{ij}^n-7}{3}, & d_{ij}^n \in [7,9] \\ 1 & d_{ij}^n \in [9,+\infty] \\ 0, & d_{ij}^n \notin [7,+\infty] \end{cases} \tag{8}$$

The gray statistics method can be used to calculate the gray statistics number for the evaluation index K_{ij} belonging to the evaluation gray category e (e = 1, 2, 3, 4, 5). Then, the sum of gray statistics number n_{ij} can be obtained by summarizing the evaluation index K_{ij}. The calculation formulas are shown in Equations (9) and (10):

$$n_{ij}^{e} = \sum_{n=1}^{m} f_e\left(d_{ij}^n\right) \tag{9}$$

$$n_{ij} = \sum_{e=1}^{5} n_{ij}^e \tag{10}$$

4) GRAY EVALUATION WEIGHT AND GRAY-FUZZY WEIGHT MATRIX CALCULATION

For the evaluation index K_{ij}, the gray evaluation weight belonging to the evaluation gray category e is denoted as r_{ij}^e, and the calculation is shown in Equation (11):

$$r_{ij}^{e} = \frac{n_{ij}^{e}}{n_{ij}} \tag{11}$$

Then, the gray assessment weight vector of evaluation index K_{ij} for each gray class is:

$$r_{ij} = \left(r_{ij}^{1}, r_{ij}^{2}, r_{ij}^{3}, r_{ij}^{4}, r_{ij}^{5}\right) \tag{12}$$

representing the fuzzy membership degree of the risk index subset K_{ij} relative to the assessment grade set V.

Then, K_{ij} is comprehensively calculated to obtain the gray assessment weight matrix relative to each gray class, namely the gray fuzzy membership weight matrix, denoted as R_i. The calculation is shown in Equation (13):

$$R_i = \begin{pmatrix} r_{i1} \\ r_{i2} \\ \vdots \\ r_{in} \end{pmatrix} = \begin{pmatrix} r_{i1}^{1} & r_{i1}^{2} & \cdots & r_{i1}^{5} \\ r_{i2}^{1} & r_{i2}^{2} & \cdots & r_{i2}^{5} \\ \vdots & \vdots & \ddots & \vdots \\ r_{in}^{1} & r_{in}^{2} & \cdots & r_{in}^{5} \end{pmatrix} \tag{13}$$

5) CALCULATE THE GRAY-FUZZY JUDGMENT MATRIX OF THE INDICATORS AT ALL LEVELS

The first-level and the secondary-level fuzzy evaluations are conducted for each grade of the evaluation object. The gray fuzzy evaluation set is obtained, and the gray fuzzy judgment matrix is constructed for calculation. The result of first-level fuzzy evaluation is denoted as B_i, and the calculation is shown in Equation (14). The result of secondary-level fuzzy evaluation is denoted as Q_s.

$$\begin{aligned} B_i &= (b_{i1}, b_{i2}, \cdots, b_{i5}) \\ &= W_i \cdot R_i \\ &= (w_{i1}, w_{i2}, \cdots, w_{in}) \begin{pmatrix} r_{i1}^{1} & r_{i1}^{2} & \cdots & r_{i1}^{5} \\ r_{i2}^{1} & r_{i2}^{2} & \cdots & r_{i2}^{5} \\ \vdots & \vdots & \ddots & \vdots \\ r_{in}^{1} & r_{in}^{2} & \cdots & r_{in}^{5} \end{pmatrix} \end{aligned} \tag{14}$$

Then, B_i is synthesized and constructed into a new gray-fuzzy judgment matrix B_s. On this basis, secondary-level fuzzy judgment is performed, and the results are denoted as Q_s. The calculation is:

$$\begin{aligned} Q_s &= (Q_1, Q_2, \ldots, Q_S) \\ &= W_s \cdot B_s \\ &= (w_1, w_2, \ldots, w_s) \cdot \begin{pmatrix} B_1 \\ B_2 \\ \vdots \\ B_S \end{pmatrix} \end{aligned} \tag{15}$$

6) CALCULATE THE COMPREHENSIVE EVALUATION VALUE OF THE INDICATOR SET

By synthesizing Q_s, the index K contained in the evaluation object can be obtained. The gray evaluation weight matrix of each evaluation gray class is denoted Q_i. The calculation is:

$$Q = \begin{pmatrix} Q_1 \\ Q_2 \\ \vdots \\ Q_l \end{pmatrix} \tag{16}$$

The gray-fuzzy comprehensive evaluation is conducted for the evaluation object, and the result is denoted Z. The calculation is shown in Equation (17):

$$Z = W \cdot Q = (w_1, w_2, \ldots, w_l) \begin{pmatrix} Q_1 \\ Q_2 \\ \vdots \\ Q_l \end{pmatrix} \tag{17}$$

7) CALCULATE THE COMPREHENSIVE ASSESSMENT VALUE OF RISKS

Different values are assigned according to different levels of evaluation gray class. Since the assignment vector of the evaluation level set C is

$$C = (c_1, c_2, \ldots, c_m) \tag{18}$$

the comprehensive evaluation value F of safety risk of the evaluation object can be obtained as:

$$F = Z \cdot C^{T} \tag{19}$$

According to the above steps, the system can be evaluated comprehensively.

IV. CASE ANALYSIS

Using the established model, an industrial accident scenario in a domestic emergency training facility was selected as an example, and its safety was assessed to determine its safety index. In this study, we use Matlab for programming and calculation on the Windows platform.

A. DETERMINE THE INDEX WEIGHT

In this evaluation, 10 experts' questionnaires were selected for statistics calculation. Then the importance scores of the first-level indexes (P1, P2, P3), secondary-level indexes (M1, M2..., M11, M12), and tertiary-level indexes (N1, N2, ..., N22, N23) were obtained. Next, the judgment matrix was constructed, and the index weight was calculated through the AHP, where λ_{max} is the maximum eigenvalue, C.I. is the consistency index, and C.R. is the consistency ratio.

1) FIRST-LEVEL AND SECONDARY-LEVEL INDEXES

The scoring results and weights of the existing first-level and secondary-level indicators are shown in Table 1 to Table 4.

TABLE 1. Significance score and weight of first-level indicators.

T - P	P1
P1	1
P2	5
P3	1
$\lambda_{max} = 3$	

TABLE 2. Relative importance of secondary indicators under P1.

P1 - M	M1	M2	M3	M4	M5	M_i
M1	1	1/3	1/3	3	1/2	0.1293
M2	3	1	1/2	3	1	0.2417
M3	3	2	1	2	1	0.3002
M4	1/3	1/3	1/2	1	1/3	0.0832
M5	2	1	1	3	1	0.2456
λ_{max} = 5.2754			C.I. = 0.0688, C.R. = 0.0615 < 0.1			

TABLE 3. Relative importance of secondary indexes under P2.

P2 -M	M6	M7	M8	M9	M10	Mi
M6	1	2	3	5	3	0.3902
M7	1/2	1	2	5	3	0.2773
M8	1/3	1/2	1	3	1/2	0.1178
M9	1/5	1/5	1/3	1	1/5	0.0487
M10	1/3	1/3	2	5	1	0.1660
λ_{max} = 5.2272			C.I. = 0.0568, C.R. = 0.0507 < 0.1			

TABLE 4. Relative importance of secondary indexes under P3.

P3 - M	M11	M12	Index weight M_i
M11	1	1/2	0.6667
M12	2	1	0.3333

2) TERTIARY-LEVEL INDEX

To determine the tertiary level indicators, the collected results were processed. Finally, the weights of the tertiary-level indexes corresponding to each secondary-level index were obtained. Since M5 and M12 only correspond to one tertiary-level index, the weights of N9 and N24 were 1 relative to M5 and M12, respectively. The weights of other indexes are shown in Table 5 to Table 14.

TABLE 5. Weight of tertiary-level indicators under M1.

	N1	N2	N_i
N1	1	2	0.3333
N2	1/2	1	0.6667

TABLE 6. Weight of tertiary-level indicators under M2.

	N3	N4	N_i
N3	1	2	0.3333
N4	1/2	1	0.6667

3) THE WEIGHT OF EACH INDICATOR RELATIVE TO THE TARGET LAYER

The weight values of all levels of indicators were calculated according to Section 3. A. The final index weights are shown in Table 15.

According to Table 15, the weight ratio of the M6, M7, M10, and M11 indexes is more than or close to 0.1; the human error weight in M6 reached 0.27, the highest of the indexes. These high-weight indicators should receive attention because they are important for promoting the overall safety of training facilities. Although the weight of the other indicators was relatively low, they will also impact the overall security, which should not be ignored.

TABLE 7. Weight of tertiary-level indicators under M3.

	N5	N6	N_i
N5	1	4	0.2000
N6	1/4	1	0.8000

TABLE 8. Weight of the tertiary-level indicators under M4.

	N7	N8	N_i
N7	1	3	0.2500
N8	1/3	1	0.7500

TABLE 9. Weight of tertiary-level indicators under M5.

	N10	N11	N_i
N10	1	1	0.5000
N11	1	1	0.5000

TABLE 10. Weight of the tertiary-level indicators under M6.

	N12	N13	N_i
N12	1	1	0.5000
N13	1	1	0.5000

TABLE 11. Weight of the tertiary-level indicators under M7.

	N14	N15	N16	N_i
N14	1	3	1/2	0.3196
N15	1/3	1	1/4	0.1220
N16	2	4	1	0.5584
λ_{max} = 3.0183			C.I. = 0.0091, C.R. = 0.0176 < 0.1	

TABLE 12. Weight of the tertiary-level indicators under M8.

	N17	N18	N_i
N17	1	1/4	0.8000
N18	4	1	0.2000

TABLE 13. Weight of tertiary-level indicators under M9.

	N19	N20	N_i
N19	1	1/5	0.1667
N20	5	1	0.8333

B. GRAY-FUZZY EVALUATION

1) ESTABLISH THE EVALUATION SAMPLE MATRIX

In this evaluation, 10 experts scored 24 indicators, and the scoring results are shown in Table 16.

The scoring results are converted into a matrix to obtain the sample evaluation matrix D.

TABLE 14. Weight of tertiary-level indicators under M11.

	N21	N22	N23	N_i
N21	1	1/3	1/4	0.1120
N22	3	1	1/2	0.3196
N23	4	2	1	0.5584
$\lambda_{max} = 3.0183$		C.I. = 0.0091, C.R. = 0.0176 < 0.1		

TABLE 15. Index weights of all levels of indicators.

First-level indicators	W_{Pi}	Secondary-level indicators	M_i	W_{Mi}	Tertiary-level indicators	N_i	W_{Ni}
P1	0.1429	M1	0.1293	0.0185	N1	0.3333	0.0062
					N2	0.6667	0.0123
		M2	0.2417	0.0345	N3	0.3333	0.0115
					N4	0.6667	0.023
		M3	0.3002	0.0429	N5	0.2	0.0086
					N6	0.8	0.0343
		M4	0.0832	0.0119	N7	0.25	0.003
					N8	0.75	0.0089
		M5	0.2456	0.0204	N9	1	0.0351
P2	0.7143	M6	0.3902	0.2787	N10	0.5	0.1394
					N11	0.5	0.1394
		M7	0.2773	0.1981	N12	0.5	0.099
					N13	0.5	0.099
		M8	0.1178	0.0841	N14	0.3196	0.0269
					N15	0.122	0.0103
					N16	0.5584	0.047
		M9	0.0487	0.0347	N17	0.8	0.0278
					N18	0.2	0.007
		M10	0.166	0.1184	N19	0.1667	0.0198
					N20	0.8333	0.0988
P3	0.1429	M11	0.6667	0.0953	N21	0.122	0.0116
					N22	0.3196	0.0304
					N23	0.5584	0.0532
		M12	0.3333	0.0476	N24	1	0.0476

2) CALCULATE THE GRAY STATISTICS

The element d_{ij} in the sample evaluation matrix was substituted into the whitening weight function. According to Equations (9) and (10), the gray statistics of each evaluation gray category n_{ij}^e and the total gray statistics n_{ij} were obtained. Taking the index N1 as an example, the calculation is:

TABLE 16. Expert scoring results.

Index \ Expert	1	2	3	4	5	6	7	8	9	10
N1	9	4	2	5	1	4	9	6	1	8
N2	9	7	9	2	1	5	1	4	4	4
N3	7	7	3	6	5	9	6	5	7	1
N4	1	7	3	1	9	1	10	3	1	5
N5	3	4	8	10	5	10	5	6	7	8
N6	10	8	6	4	10	7	10	6	3	4
N7	7	4	6	4	8	4	3	4	4	2
N8	3	1	7	7	3	1	1	2	6	4
N9	10	8	1	7	1	7	9	10	5	1
N10	6	1	5	4	3	7	5	2	9	9
N11	10	10	1	7	7	9	4	9	1	4
N12	4	6	7	5	3	5	8	4	7	6
N13	4	9	9	6	4	1	1	4	4	10
N14	10	7	3	6	1	9	5	6	6	6
N15	10	1	6	2	1	10	6	9	6	8
N16	7	1	4	3	8	3	8	3	3	7
N17	7	10	9	9	1	8	4	8	9	9
N18	5	4	3	10	4	7	5	2	9	5
N19	7	7	9	3	2	8	10	6	4	7
N20	8	2	1	2	6	7	5	10	6	3
N21	10	7	6	9	10	5	2	6	3	10
N22	5	7	9	7	8	3	4	10	10	4
N23	5	10	4	7	5	4	4	6	8	6
N24	5	3	5	6	10	7	9	3	6	5

$$\begin{aligned} n_{N1}^{1} &= \sum_{n=1}^{10} f_1(d_{11}) = f_1(d_{11}) + f_1(d_{12}) \\ &\quad + f_1(d_{13}) + \cdots + f_1(d_{110}) \\ &= f_1(9) + f_1(4) + f_1(2) + f_1(5) + f_1(1) \\ &\quad + f_1(4) + f_1(9) + f_1(6) + f_1(1) + f_1(8) \\ &= 0 + 0 + 0.5000 + 1 + 0 + 0 + 0 + 0 + 1 + 0 \\ &= 2.5000 \end{aligned} \tag{20}$$

Similarly, $n_{N1}^2 = 1.5000$, $n_{N1}^3 = 2.5000$, $n_{N1}^4 = 1.0000$, and $n_{N1}^5 = 2.5000$. Therefore, the total gray statistics of N1 belonging to each evaluation gray category is:

$$n_{N1} = n_{N1}^1 + n_{N1}^2 + n_{N1}^3 + n_{N1}^4 + n_{N1}^5 = 10 \tag{21}$$

Similarly, the gray statistics and the total gray statistics of the remaining indicators can be calculated as shown in Table 17.

3) CALCULATE THE GRAY WEIGHT VECTOR AND WEIGHT MATRIX

For any index, the gray evaluation weight is:

$$r_{ij}^e = \frac{n_{ij}^e}{n_{ij}} \tag{22}$$

and the weight vector is

$$r_{ij} = \left(r_{ij}^1, r_{ij}^2, r_{ij}^3, r_{ij}^4, r_{ij}^5\right) \tag{23}$$

TABLE 17. Gray statistics for evaluation indicators and total gray statistics.

	n_{ij}^1	n_{ij}^2	n_{ij}^3	n_{ij}^4	n_{ij}^5	n_{ij}
N1	2.5000	1.5000	2.5000	1.0000	2.5000	10.0000
N2	2.5000	2.0000	2.5000	1.0000	2.0000	10.0000
N3	1.0000	1.0000	3.0000	4.0000	1.0000	10.0000
N4	4.0000	2.0000	1.0000	1.0000	2.0000	10.0000
N5	0.0000	1.5000	3.0000	2.5000	3.0000	10.0000
N6	0.0000	2.0000	2.0000	2.5000	3.5000	10.0000
N7	0.5000	4.0000	3.0000	2.0000	0.5000	10.0000
N8	3.5000	3.0000	1.0000	2.5000	0.0000	10.0000
N9	3.0000	0.0000	1.0000	2.5000	3.5000	10.0000
N10	1.5000	2.0000	3.0000	1.5000	2.0000	10.0000
N11	2.0000	1.0000	1.0000	2.0000	4.0000	10.0000
N12	0.0000	2.0000	4.0000	3.5000	0.5000	10.0000
N13	2.0000	2.0000	2.5000	0.5000	3.0000	10.0000
N14	1.0000	1.0000	3.0000	3.0000	2.0000	10.0000
N15	2.5000	0.5000	1.5000	2.0000	3.5000	10.0000
N16	1.0000	4.5000	0.5000	3.0000	1.0000	10.0000
N17	1.0000	0.5000	0.5000	2.0000	6.0000	10.0000
N18	0.5000	2.5000	4.0000	1.0000	2.0000	10.0000
N19	0.5000	2.0000	1.0000	4.0000	2.5000	10.0000
N20	2.0000	2.0000	2.0000	2.5000	1.5000	10.0000
N21	0.5000	1.5000	2.0000	2.0000	4.0000	10.0000
N22	0.0000	2.0000	2.0000	2.5000	3.5000	10.0000
N23	0.0000	1.5000	4.5000	2.5000	1.5000	10.0000
N24	0.0000	2.0000	4.0000	2.0000	2.0000	10.0000

According to Table 17, the weights of index N1 are:

$$
\begin{aligned}
r_{N1}^1 &= \frac{n_{N1}^1}{n_{N1}} = 0.2500 \\
r_{N1}^2 &= \frac{n_{N1}^2}{n_{N1}} = 0.1500 \\
r_{N1}^3 &= \frac{n_{N1}^3}{n_{N1}} = 0.2500 \\
r_{N1}^4 &= \frac{n_{N1}^4}{n_{N1}} = 0.1000 \\
r_{N1}^5 &= \frac{n_{N1}^5}{n_{N1}} = 0.2500
\end{aligned} \tag{24}
$$

Therefore, the gray weight vector r_{N1} of index N1 is as follows: $r_{N1} = (0.2500, 0.1500, 0.2500, 0.1000, 0.2500)$. Similarly, the gray weight vector of other indexes can be obtained, and the fuzzy weight matrix B can be formed, as shown in Table 18.

4) GRAY-FUZZY COMPREHENSIVE EVALUATION

The gray evaluation weight matrix $Q_{Mi} = N_i \cdot R_{Ni}$ of the secondary-level index is calculated as:

$$
\begin{pmatrix} Q_{M1} \\ Q_{M2} \\ Q_{M3} \\ Q_{M4} \\ Q_{M5} \end{pmatrix}
= \begin{pmatrix}
0.2500 & 0.1833 & 0.2500 & 0.1000 & 0.2167 \\
0.3000 & 0.1667 & 0.1667 & 0.2000 & 0.1667 \\
0.0000 & 0.1900 & 0.2200 & 0.2500 & 0.3400 \\
0.2750 & 0.3250 & 0.1500 & 0.2375 & 0.0125 \\
0.3000 & 0.0000 & 0.1000 & 0.2500 & 0.3500
\end{pmatrix} \tag{25}
$$

TABLE 18. Fuzzy weight matrix R.

First-level indicators	Secondary-level indicators	Tertiary-level indicators	r_{ij}^1	r_{ij}^2	r_{ij}^3	r_{ij}^4	r_{ij}^5
P1	M1	N1	0.2500	0.1500	0.2500	0.1000	0.2500
		N2	0.2500	0.2000	0.2500	0.1000	0.2000
	M2	N3	0.1000	0.1000	0.3000	0.4000	0.1000
		N4	0.4000	0.2000	0.1000	0.1000	0.2000
	M3	N5	0.0000	0.1500	0.3000	0.2500	0.3000
		N6	0.0000	0.2000	0.2000	0.2500	0.3500
	M4	N7	0.0500	0.4000	0.3000	0.2000	0.0500
		N8	0.3500	0.3000	0.1000	0.2500	0.0000
	M5	N9	0.3000	0.0000	0.1000	0.2500	0.3500
P2	M6	N10	0.1500	0.2000	0.3000	0.1500	0.2000
		N11	0.2000	0.1000	0.1000	0.2000	0.4000
	M7	N12	0.0000	0.2000	0.4000	0.3500	0.0500
		N13	0.2000	0.2000	0.2500	0.0500	0.3000
	M8	N14	0.1000	0.1000	0.3000	0.3000	0.2000
		N15	0.2500	0.0500	0.1500	0.2000	0.3500
		N16	0.1000	0.4500	0.0500	0.3000	0.1000
	M9	N17	0.1000	0.0500	0.0500	0.2000	0.6000
		N18	0.0500	0.2500	0.4000	0.1000	0.2000
	M10	N19	0.0500	0.2000	0.1000	0.4000	0.2500
		N20	0.2000	0.2000	0.2000	0.2500	0.1500
P3	M11	N21	0.0500	0.1500	0.2000	0.2000	0.4000
		N22	0.0000	0.2000	0.2000	0.2500	0.3500
		N23	0.0000	0.1500	0.4500	0.2500	0.1500
	M2	N24	0.0000	0.2000	0.4000	0.2000	0.2000

$$
\begin{pmatrix} Q_{M6} \\ Q_{M7} \\ Q_{M8} \\ Q_{M9} \\ Q_{M10} \end{pmatrix}
= \begin{pmatrix}
0.1750 & 0.1500 & 0.2000 & 0.1750 & 0.3000 \\
0.1000 & 0.2000 & 0.3250 & 0.2000 & 0.1750 \\
0.1183 & 0.2893 & 0.1421 & 0.2878 & 0.1625 \\
0.0900 & 0.0900 & 0.1200 & 0.1800 & 0.5200 \\
0.1750 & 0.2000 & 0.1833 & 0.2750 & 0.1667
\end{pmatrix} \tag{26}
$$

$$\begin{pmatrix} Q_{M11} \\ Q_{M12} \end{pmatrix} = \begin{pmatrix} 0.0061 & 0.1660 & 0.3396 & 0.2439 & 0.2444 \\ 0.0000 & 0.2000 & 0.4000 & 0.2000 & 0.2000 \end{pmatrix} \tag{27}$$

Therefore, gray evaluation weight matrices of the three first-level indicators are:

$$\begin{aligned} Q_{P1} &= (M_1, M_2, M_3, M_4, M_5) \cdot \begin{pmatrix} Q_{M1} \\ Q_{M2} \\ Q_{M3} \\ Q_{M4} \\ Q_{M5} \end{pmatrix} \\ &= (0.1293, 0.2417, 0.3002, 0.0832, 0.2456) \\ &\quad \cdot \begin{pmatrix} 0.2500 & 0.1833 & 0.2500 & 0.1000 & 0.2167 \\ 0.3000 & 0.1667 & 0.1667 & 0.2000 & 0.1667 \\ 0.0000 & 0.1900 & 0.2200 & 0.2500 & 0.3400 \\ 0.2750 & 0.3250 & 0.1500 & 0.2375 & 0.0125 \\ 0.3000 & 0.0000 & 0.1000 & 0.2500 & 0.3500 \end{pmatrix} \\ &= (0.2014, 0.1481, 0.1757, 0.2175, 0.2574) \end{aligned} \tag{28}$$

Similarly,

$$\begin{aligned} Q_{P2} &= (M_6, M_7, M_8, M_9, M_{10}) \cdot \begin{pmatrix} Q_{M6} \\ Q_{M7} \\ Q_{M8} \\ Q_{M9} \\ Q_{M10} \end{pmatrix} \\ &= (0.1434, 0.1857, 0.2212, 0.2121, 0.2377) \\ Q_{P3} &= (M_{11}, M_{12}) \cdot \begin{pmatrix} Q_{M11} \\ Q_{M12} \end{pmatrix} \\ &= (0.0041, 0.1773, 0.3597, 0.2293, 0.2296) \end{aligned} \tag{29}$$

$$Q = \begin{pmatrix} Q_{P1} \\ Q_{P2} \\ Q_{P3} \end{pmatrix} = \begin{pmatrix} 0.2014 & 0.1481 & 0.1757 & 0.2175 & 0.2574 \\ 0.1434 & 0.1857 & 0.2212 & 0.2121 & 0.2377 \\ 0.0041 & 0.1773 & 0.3597 & 0.2293 & 0.2296 \end{pmatrix} \tag{30}$$

The fuzzy comprehensive evaluation matrix is:

$$\begin{aligned} Z &= W_{Pi} \cdot Q \\ &= (0.1429, 0.7143, 0.1429) \\ &\quad \cdot \begin{pmatrix} 0.2014 & 0.1481 & 0.1757 & 0.2175 & 0.2574 \\ 0.1434 & 0.1857 & 0.2212 & 0.2121 & 0.2377 \\ 0.0041 & 0.1773 & 0.3597 & 0.2293 & 0.2296 \end{pmatrix} \\ &= (0.1318, 0.1791, 0.2345, 0.2153, 0.2394) \end{aligned} \tag{31}$$

As can be seen from the above formula, the industrial accident fire training scenario has risk levels of 13.19%, 17.91%, 23.45%, 21.53%, and 23.94%, respectively.

Finally, the comprehensive evaluation value of the industrial accident training base is:

$$\begin{aligned} F = Z \cdot C^T &= (0.1318, 0.1791, 0.2345, 0.2153, 0.2394) \\ &\quad \cdot (1, 3, 5, 7, 9)^T = 5.5033 \end{aligned} \tag{32}$$

Similarly, three first-level indicators were obtained, including a safety score before training of F_{P1} of 5.3627 on average, a safety score during training (F_{P2}) of 5.4301 on average, and a safety score after training (F_{P3}) of 6.0061 on average.

The secondary index score matrix $F_{Mi} = Q_{Mi} \cdot (1, 3, 5, 7, 9)$, T = (4.7000, 4.5333, 6.4800, 3.7750, 5.7000, 5.5500, 5.5500, 5.3000, 5.1736, 6.9000, 5.1167, 6.1091, 5.8000). The safety levels from F_{M1} to F_{M12} are: relatively dangerous, relatively dangerous, general, relatively dangerous, general, general, general, general, general, general, general, and general. Among them, indicators such as M1, M2, and M4 are all at the relatively dangerous level, so they need to be improved. The specific results are as follows:

(1) For the relevant personnel (M1), detailed health checks should be conducted on participants. For trainees who do not meet the training standards, measures such as training degradation or training prohibition should be implemented. Participants should be assessed for their technical level and mastery of safety procedures. Those who fail the assessment should be provided with technical and safety education. Only those who pass the technical and safety professional assessment should participate in the training.

(2) For the equipment degree (M2), reasonable training equipment and apparatus should be selected and purchased to ensure the matching of equipment and courses. Pre-training equipment inspection and out-of-warehouse procedures should be strictly implemented. Training equipment that does not meet the standards, has defects, or is outdated should be sent for repair or recycled to prevent training accidents.

(3) For the organization structure rationality (M4), the ratio of organizers to trainees should be guaranteed to not be too low to maintain a complete chain of command. Thus, adequate supervision and protection could be provided during training to reduce unnecessary errors during training. When an emergency occurs, the ability to evacuate or rescue the first time will be sufficient.

V. CONCLUSION

In this study, a comprehensive AHP-gray-fuzzy assessment model was constructed for an emergency training facility for industrial accident scenarios, and we conducted a safety assessment. The specific conclusions are as follows:

(1) Emergency training was divided into three levels: before, during, and after training. Combined with human–machine–environment–management theory, we analyzed the risk factors in each stage, and we constructed at safety assessment index system for emergency training for industrial accidents.

(2) Using AHP, the weight of each index was determined. For the higher-weighted indexes, we should focus on improving safety, including human error (M6); facility hazard (M7); system implementation (M10); repair, restore, and record condition (M11), etc. These high-weight indicators are crucial for promoting the overall safety training facilities. Notably, the influence of low-weight indexes on training safety should not be ignored.

(3) For the industrial emergency training facility, gray-fuzzy evaluation was adopted to assess safety. According to the assessment results, indicators with low scores should be improved, such as M1 for related personnel, M2 for equipment goodness degree, and M4 for organizational structure rationality, which all received classification as ''relatively dangerous'' and still considerable room for improvement. The facility should take relevant measures to improve the safety of the above indicators.

(4) This method combines AHP and gray-fuzzy evaluation so that it is possible to get quantitative results and find the most influential factor on training safety. In future research, it could be considered to be applied to training safety assessment in other scenarios, and the indicator system needs to be adjusted accordingly.

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