Advances in Differential Equations and Control Processes 2026, 33(2), 4235.
doi: https://doi.org/10.59400/adecp4235

Article

A data-driven approach to coal mine safety performance using swarm intelligence and ensemble learning

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CITATION

Liu Y, Li J, Teng T, et al. A data-driven approach to coal mine safety performance using swarm intelligence and ensemble learning. Advances in Differential Equations and Control Processes. 2026; 33(2): 4235. https://doi.org/10.59400/adecp4235

ARTICLE INFO

Received: 5 April 2026
Revised: 21 May 2026
Accepted: 26 May 2026
Available online: 5 June 2026

Abstract: At present, there are some shortcomings in the dynamic adaptability and subjectivity of coal mine safety performance evaluation, and it is difficult to realize the short-term safety performance evaluation with full staff participation. In this study, based on the Analytic Network Process-Technique for Order Preference by Similarity to an Ideal Solution (ANP-TOPSIS), a coal mine safety performance evaluation index system was constructed, and the evaluation index was optimized by a particle swarm optimization algorithm to improve the accuracy of dynamic index weight allocation. Emotional processing analysis technology is introduced, and the survey evaluation form is designed to quantify the subjective emotional tendency. Statistical methods such as the intra-group correlation coefficient, consistency test and regression model are used to improve the reliability of expert scoring data and quantitatively analyze individual subjective differences. Using the random forest classification method, combined with the term frequency-inverse document frequency (TF-IDF) to vectorize the text data, a bottom-up dynamic evaluation method of employee safety performance based on machine learning is established. The random forest model achieved an average F1-score of 0.929, with all six safety dimensions scoring above 0.8. The example shows that the short-process long-period safety performance evaluation based on ANP-TOPSIS-PSO, and a random forest model can accurately describe the coal mine safety appearance and provide scientific decision support for improving the coal mine safety performance level.

Keywords: coal mine safety performance; random forest; ANP-TOPSIS; particle swarm optimization; assessment

1. Introduction

Safety performance refers to the measurable results achieved through controlling and eliminating risks based on safety production policies and predetermined safety management objectives [1]. In the implementation process of coal mine safety performance evaluation, a top-down implementation strategy is usually adopted, and its execution effect depends on the support of senior management and professionals. Due to the high-risk nature of the coal mining industry itself and the potentially catastrophic consequences of accidents, safety performance is not only a management tool but also the lifeline for the survival and development of coal mining enterprises.

At the level of influencing factors, studies have revealed the critical roles of organizational management and human elements. Research by Ghahramani et al. [2], Khalid et al. [3], and Hadjimanolis et al. [4], among others, has clarified the profound impact of safety management systems, safety culture, and work attitudes on safety performance. Cheng et al. [5] introduced the Objectives and Key Results (OKR) method into coal mine safety performance management, while Li [6] discussed the construction of a safety production management system based on the concept of risk pre-control. Regarding human factors, Xiao et al. [7] analyzed the direct and indirect effects of psychological states on drivers' safety performance, and Sang and Li [8] revealed the mechanism through which team relationship conflict affects miners' safety performance via a cross-level study. In terms of evaluation methods and model development, various modern mathematical methods and intelligent technologies have been widely applied. Liu et al. [9] utilized BP neural networks to evaluate coal mine safety management performance. Qian Meng et al. established a coal mine safety evaluation model with higher accuracy based on particle swarm optimization - support vector machine (PSO-SVM) [10]. Wang et al. [11] enriched theoretical research on safety evaluation models for backfill mining mines using the entropy weight-attribute mathematical theory. Di Gravio et al. [12], Singh and Misra [13], and So et al. [14] conducted safety performance evaluations in specific sectors using methods such as the Aerospace Performance Factor (APF), Dominance-based Rough Set Approach (DRSA), and weighted ranking surveys, respectively. Li et al. [15] indirectly identified factors for improving safety performance through text mining and Bayesian network techniques applied to accident cases. Focusing on the high-risk coal mining industry specifically, Liu et al. [16, 17] investigated the construction of dual-prevention mechanisms, risk classification management and control, and hidden danger investigation and treatment in non-coal mines and heating enterprises. Yao et al. [18] studied the development of a standardized management system for coal mine ventilation safety production based on game combination weighting and the rank-sum ratio method. Liu et al. [19] proposed a comprehensive risk evaluation method for coordinated coal-water mining based on the Analytic Network Process (ANP). These studies have established a foundational framework, yet they reveal persistent gaps in dynamic adaptability, comprehensive staff involvement, and real-time assessment, motivating the present research to develop an integrated model leveraging swarm intelligence optimization and machine learning for dynamic safety evaluation.

This paper realizes an efficient bottom-up full-process safety performance evaluation by constructing a machine learning evaluation model for coal mine safety performance based on random forests. While improving evaluation efficiency, it can realize the periodicity of safety performance evaluation and reduce evaluation costs. This method provides a new approach for safety performance evaluation in the coal mining industry, solving the subjectivity and lag of performance evaluation to a certain extent. It offers strong guarantees for the safe production and sustainable development of coal mining enterprises and provides a feasible idea for safety performance evaluation in other industries.

2. Materials and methods

2.1. Determination of evaluation indicators for coal mine safety performance

Based on relevant laws and regulations, including the Regulations on Coal Mine Safety Production and the Basic Requirements and Scoring Methods for the Coal Mine Safety Production Standardization Management System [20], as well as a literature review [21–23], this study performed semantic merging and dimensionality reduction on the original safety performance-related indicators of coal mines [24–26]. The initially identified factors influencing safety performance were then integrated [27–31] to establish a coal mine safety performance evaluation index system, as shown in **Figure 1**.

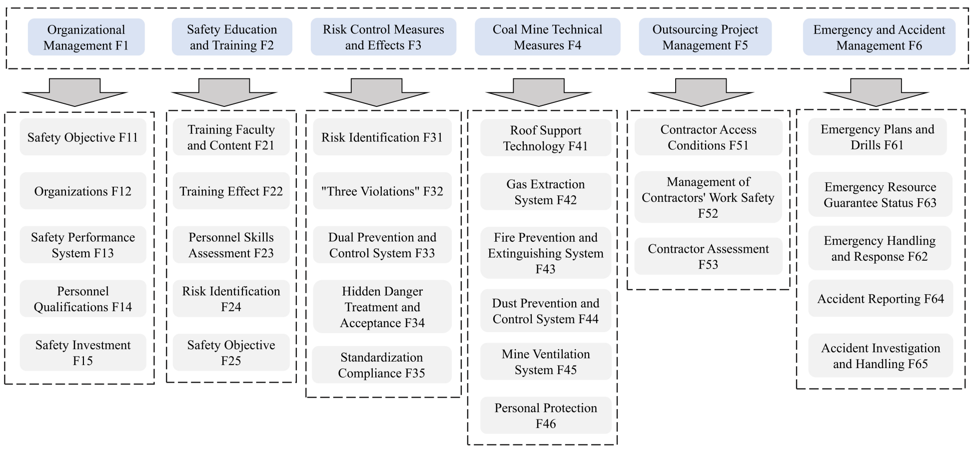

Figure 1. Coal Mine Safety Performance Industrial Index System.

2.2. ANP-TOPSIS-PSO method for determining the baseline weights of coal mine safety indicators

2.2.1. Determining the benchmark weights of coal mine indicators by ANP-TOPSIS

The Analytic Network Process (ANP) is a decision-making method suitable for non-independent hierarchical structures [32]. It considers the correlations between factors, introduces a feedback mechanism, and addresses the mutual influence relationships among internal factors of the system, thereby overcoming the limitations of the Analytic Hierarchy Process (AHP). The Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) is an efficient means to solve multi-attribute polynomial decision-making problems [33]. The combination of ANP and TOPSIS can target decision-making problem structures with dependence and feedback and determine weights, with the process as follows:

(1) Establish a standardized matrix

Collect the data needed to calculate the values of each indicator to form an original decision matrix, and make the original decision matrix have the same trend to obtain matrix A, that is:

$$A = \begin{bmatrix} a_{11} & a_{1\mathrm{j}} & \cdots & a_{1\mathrm{n}} \\ a_{\mathrm{i}1} & a_{\mathrm{ij}} & \cdots & a_{\mathrm{in}} \\ \vdots & \vdots & \cdots & \vdots \\ a_{\mathrm{m}1} & a_{\mathrm{mj}} & \cdots & a_{\mathrm{mn}} \end{bmatrix} \tag{1}$$

In Equation (1), m is the number of evaluation schemes; n is the number of secondary evaluation indicators.

$$\begin{cases} a_{ij} = \frac{a'_{ij}}{\max a'_{ij}} \text{ Positive indicator} \\ a_{ij} = \frac{\min a'_{ij}}{a'_{ij}} \text{ Negative indicator} \end{cases} \tag{2}$$

In Equation (2), $\max a'_{ij}$ is the maximum value of the scores for the *j*-th indicator; $\min a'_{ij}$ is the minimum value of the scores for the *j*-th indicator. Perform normalization processing on the original data matrix, that is:

$$b_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}} \tag{3}$$

In Equation (3), b_{ij} represents the score data under each indicator obtained after normalization processing.

(2) Construct the weighted standardized matrix

The weights of each indicator are obtained by using ANP, and the weighted standardized matrix *C* is obtained by multiplying the weights by the standardized matrix *B*.

$$C = \begin{bmatrix} b_{11}z_1 & b_{1j}z_1 & \cdots & b_{1\mathrm{n}}z_1 \\ b_{\mathrm{i}1}z_i & b_{\mathrm{ij}}z_i & \cdots & b_{\mathrm{in}}z_i \\ \vdots & \vdots & \cdots & \vdots \\ b_{\mathrm{m}1}z_n & b_{\mathrm{mj}}z_n & \cdots & b_{\mathrm{mn}}z_n \end{bmatrix} \tag{4}$$

$$C^+ = \{(\max c_{ij} | j \in J), i = 1, ..., m\} = \{c_1^+, ..., c_n^+\} \tag{5}$$

$$C^- = \{(\min c_{ij} | j \in J), \ i = 1, ..., m\} = \{c_1^-, ..., c_n^-\} \tag{6}$$

In Equations (5) and (6), C^+ is the positive ideal solution, C^- is the negative ideal solution, and *J* is the set of indicators.

(3) Calculate the Euclidean distance and relative closeness

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \left(c_{ij} - c_j^+\right)^2} \tag{7}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} \left(c_{ij} - c_j^-\right)^2} \tag{8}$$

$$E_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{9}$$

In Equations (7)–(9), D_i^+ represents the distance from scheme i to the positive ideal scheme; D_i^- represents the distance from scheme i to the negative ideal scheme; and E_i represents the relative closeness. The advantages and disadvantages of schemes can be judged by ranking the closeness. The larger the value, the better the evaluation object.

18 experts were invited to score the importance of each indicator to obtain the standard weights. The expert members cover fields such as safety, mining, machinery, and emergency rescue, including safety performers, technical experts, safety researchers, etc., who are closely related to the production of underground coal mines. The expert information is shown in **Table 1**.

Table 1. Expert information.

Serial number	Professional field	Number of people	Explanation
1	Safety Management	9	Including safety directors, safety management personnel, safety engineers, etc., most of whom have more than 10 years of mine-related work experience. Technical personnel and operators with more than 10 years of work experience. Technical personnel and engineers with more than 10 years of work experience. Mine rescue personnel with more than 10 years of work experience.
2	mining	3	Including safety directors, safety management personnel, safety engineers, etc., most of whom have more than 10 years of mine-related work experience. Technical personnel and operators with more than 10 years of work experience. Technical personnel and engineers with more than 10 years of work experience. Mine rescue personnel with more than 10 years of work experience.
3	Mechanical, electrical	3	Including safety directors, safety management personnel, safety engineers, etc., most of whom have more than 10 years of mine-related work experience. Technical personnel and operators with more than 10 years of work experience. Technical personnel and engineers with more than 10 years of work experience. Mine rescue personnel with more than 10 years of work experience.
4	Emergency rescue	3	Including safety directors, safety management personnel, safety engineers, etc., most of whom have more than 10 years of mine-related work experience. Technical personnel and operators with more than 10 years of work experience. Technical personnel and engineers with more than 10 years of work experience. Mine rescue personnel with more than 10 years of work experience.

The 1–9 scaling method in the Analytic Hierarchy Process (AHP) is adopted to conduct expert questionnaires for data collection. The data required for each indicator value is calculated, and then the original decision matrix is constructed. Based on the expert group decision-making, the weights of each secondary indicator and primary indicator in the coal mine safety performance evaluation index system are determined.

2.2.2. Optimization of coal mine index weights based on the PSO algorithm

When evaluating coal mine safety performance, the implementation of safety performance is based on the status of the project and the predetermined safety management goals. Therefore, it is necessary to adopt different index weights to adapt to its characteristics and changes according to specific circumstances. Based on the index weight system, the Particle Swarm Optimization (PSO) algorithm is used to optimize the coal mine index weights under different coal mine working conditions. PSO is a swarm intelligence-based optimization algorithm that finds the optimal solution by simulating the movement of individuals in a group within the search space [34]. Its speed and position update formulas are as follows:

$$v_{i,d}^{(t+1)} = \omega v_{i,d}^{(t)} + c_1 r_1 (p_{i,d}^{\text{best}} - x_{i,d}^{(t)}) + c_2 r_2 (g_d^{\text{best}} - x_{i,d}^{(t)}) \tag{10}$$

$$x_{i,d}^{(t+1)} = x_{i,d}^{(t)} + v_{i,d}^{(t+1)} \tag{11}$$

In Equations (10) and (11), $v_{i,d}^{(t+1)}$ and $x_{i,d}^{(t+1)}$ represent the velocity and position of particle *i* in the *d*-th dimension at the *t*-th generation, respectively; $p_{i,d}^{\text{best}}$ is the historical optimal position of particle *i*; g_d^{best} is the historical optimal position of the entire population; ω is the inertia weight; c_1 and c_2 are learning factors; and r_1 and r_2 are random numbers uniformly distributed within [1]. The PSO takes the minimum fitting error between ANP-TOPSIS weights and historical weights as the optimization objective, and the fitness function is defined as follows:

$$\text{Fitness} = \frac{1}{m} \sum_{i=1}^{m} (S_i - \widehat{S}_i)^2 \tag{12}$$

The particle swarm optimization (PSO) algorithm is employed to dynamically optimize the indicator weights. The key parameters are set as follows: the number of particles is 100 the maximum number of iterations is 100, the inertia weight ω decreases linearly from 0.9 to 0.4, the learning factors c_1 = 0.7624 and c_2 = 1.2709. The convergence condition is defined as the fitness value remains unchanged for 20 consecutive iterations.

2.3. Construct a coal mine safety performance evaluation model based on random forest

2.3.1. Random forest model design

A random forest consists of many unrelated decision trees. It uses supervised learning to map all inputs to corresponding outputs and makes simple judgments on the outputs to achieve the purpose of classification [34]. Its core control formula is as follows [35]:

Classification Task Control Equation:

$$\widehat{y} = \text{mode}(\{h_1(x), h_2(x), \ ..., \ h_m(x)\}) \tag{13}$$

Regression Task Control Equation:

$$\widehat{y} = \frac{1}{m} \sum_{i-1}^{m} h_i(x) \tag{14}$$

In Equations (13) and (14), $h_i(x)$ represents the prediction result of the *i*-th tree for sample x, and “mode” denotes the mode.

$$f(x) = \text{majority vote of } \{f_t(x)\}_{t=1}^{T} \tag{15}$$

In Equation (15), $f_i(x)$ is the voting result of the *i*-th decision tree. By counting the prediction results of all base learners, the result that appears most frequently is selected as the prediction of the entire random forest $f(x)$ model for x [36,37].

The random forest (RF) model is constructed for the dynamic classification and quantitative evaluation of coal mine safety performance. The hyperparameters are set as: the number of decision trees $(\text{n\_estimators} = 100)$, the maximum depth of the decision tree $(\text{max\_depth} = 50)$, the minimum number of samples required for node splitting $(\text{min\_samples\_split} = 2)$. The original dataset is divided into a training set, and test set according to the ratio of 8:2. A 5-fold cross-validation strategy is adopted in the training process to avoid overfitting and ensure the stability of the model.

This paper constructs indicators through the ANP-TOPSIS method and optimizes them using the PSO algorithm to build a safety performance evaluation model, based on which machine learning training is conducted. By collecting safety data, inspection records, and employee feedback information, text vectorization technology and keyword extraction algorithms are used to perform feature extraction on text data and generate high-quality feature vectors. A subjective coefficient is adopted to correct individual subjective biases, and a classifier is built based on keyword features to classify and quantify employees' text, ultimately achieving efficient coal mine safety performance evaluation. The coal mine safety performance evaluation process based on ANP-TOPSIS-PSO and Random Forest is shown in **Figure 2**.

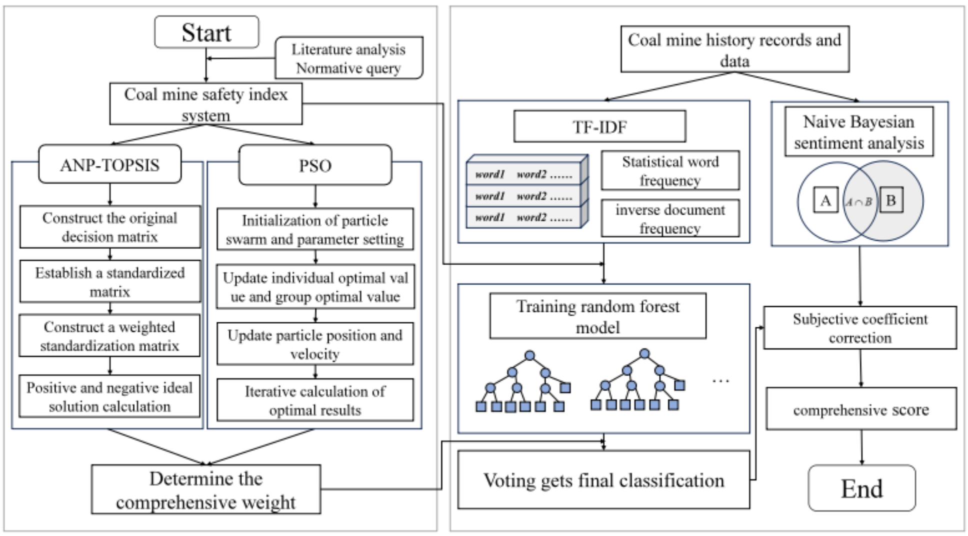

Figure 2. Coal mine safety performance evaluation process based on ANP-TOPSIS-PSO and random forest.

In the integrated model and indicator construction module shown in **Figure 2**, ANP is adopted to address the non-independent correlations among indicators, and is combined with TOPSIS to determine the baseline weights, thereby ensuring the systematicness of the indicator system and the rationality of initial weight assignment. The PSO algorithm adaptively optimizes the baseline weights in accordance with the on-site production conditions, risk distribution and management status of coal mines, which enhances the dynamic adaptability of the weight system. The comprehensive safety performance score relies on the random forest to establish a bottom-up dynamic evaluation model based on the optimized weights. The above combination gives full play to the respective advantages of each method: ANP-TOPSIS guarantees structural rationality, PSO realizes dynamic optimization, and Random forests can efficiently classify and mine multi-source data.

2.3.2. Cleaning of collected raw data and quantitative correction of employees' subjective biases

The training samples of the model are derived from collected safety cases, accident reports, laws and regulations, etc. To ensure data accuracy and availability, cleaning work is carried out on the sample sources. The Harbin Institute of Technology Stop Word List [38] is used to eliminate stop words and special characters, to remove noise in the data and form high-quality feature vectors. The cleaning process is shown in **Figure 3**. The operational data of the model comes from coal mine employees, so it is crucial to fully consider individual differences and cognitive biases. A survey form is designed for the model to collect data and quantify subjective biases, as shown in **Table 2**.

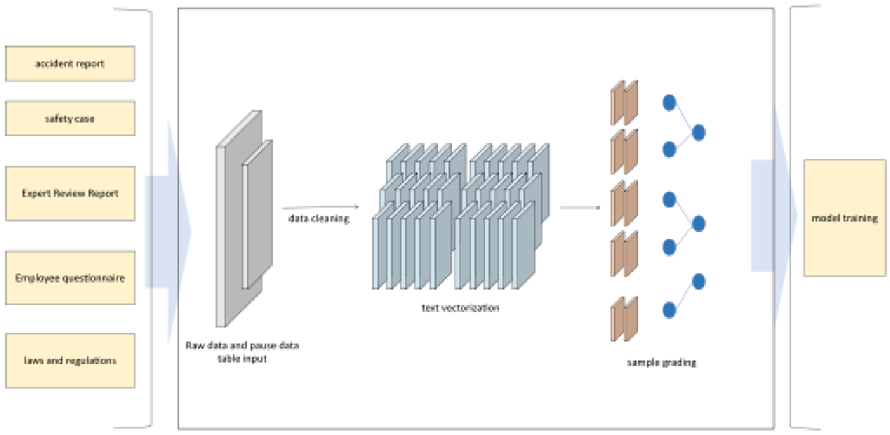

Figure 3. Cleaning process of raw data collected.

Table 2. Quantitative questionnaire of subjective deviation of employees.

Employee information (anonymous)	Job title	Age	Gender	Professional title	Evaluator 1	Evaluator 2	Evaluator 3	Score of mutual evaluation within the group
-	-	-	-	-	-	-	-	-
-	-	-	-	-	-	-	-	-
Note:	Three evaluators scored 5 objectives, with a scoring range of 1 to 5.						Filling Time: Investigator:	- -

To ensure that the obtained employee evaluation data is highly reliable and consistent, the Intraclass Correlation Coefficient (ICC), F-test statistics, and Kappa coefficient(κ) are calculated to conduct reliability analysis on the scoring data. The specific calculation formulas are as follows:

$$\mathrm{ICC} = \frac{\mathrm{MS}_{\text{subject}} - \mathrm{MS}_{\text{error}}}{\mathrm{MS}_{\text{subject}} + \mathrm{MS}_{\text{error}}} \tag{16}$$

$$F = \frac{\mathrm{MS}_{\text{between}}}{\mathrm{MS}_{\text{within}}} \tag{17}$$

$$\kappa = \frac{p_{\text{obs}} - p_{\text{exp}}}{1 - p_{\text{exp}}} \tag{18}$$

In Equations (16)–(18), $\mathrm{MS}_{\text{subject}}$ is the mean square value of the evaluated object, $\mathrm{MS}_{\text{error}}$ is the mean square value of the error, $\mathrm{MS}_{\text{within}}$ is the mean square value between groups, and $\mathrm{MS}_{\text{within}}$ is the mean square value within groups. p_{obs} is the observed proportion of agreement, and p_{exp} is the expected proportion of agreement.

To measure the integrity of the evaluated individuals, it is necessary to calculate the score standard deviation to assess the degree of closeness of the scores for each evaluated object.

$$SD = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{19}$$

In Equation (19), x_i is the score given by each evaluator, $\bar{x}$ is the average score of the evaluated object, and n is the number of evaluators. When selecting evaluators, the impact of group conflicts on miners' safety performance is considered [38]. Superiors who have direct or indirect working relationships are chosen, and at the same time, evaluators should possess certain professional qualities and impartiality.

Quantify the impact of evaluator characteristics on scores using a regression model. Take scores as the dependent variable and evaluator characteristics as independent variables and establish a regression model to analyze how evaluator characteristics affect scoring results.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon \tag{20}$$

In Equation (20), y is the individual bias coefficient, $x_1, x_2, x_3 ... x_n$ are the evaluator characteristics, $\beta_1, \beta_2, \beta_3, ...\beta_n$ are the regression coefficients, and ε is the error term. Comprehensive analysis is conducted on the data under the same indicator system, and a source subjective coefficient is assigned to individual texts for correction. Each cluster is calculated using the following formula:

$$s = \frac{\sum_{i=1}^{n}(s_i \partial_j + 1) \times 50}{n} \tag{21}$$

In Equation (21), ∂_j is the subjective coefficient of the sample provider, s_i is the sample evaluation score, and n is the total number of samples. Adding 1 is to convert the negative evaluation score into a non-negative interval, and multiplying by 50 is to normalize the score to the common 0–100 scoring interval. This transformation ensures the rationality and readability of the subjective evaluation score, and the processed score conforms to the normal distribution after verification.

2.3.3. Vectorization technology for coal mine text data

The core of building a machine learning model lies in the quantitative conversion of text. According to the specific needs of the coal mine safety performance evaluation model, the Term Frequency-Inverse Document Frequency (TF-IDF) algorithm is adopted to realize text vectorization [39]. Its core calculation formula is as follows:

$$TF(t,d) = \frac{f_{t,d}}{\Sigma_{t' \in d} f_{t',d}} \tag{22}$$

$$IDF(t,D) = \log\left(\frac{N}{|\{d \in D : t \in d\}|}\right)_{\omega} \tag{23}$$

In Equations (22) and (23), TF(t, d) represents the number of times word t appears in document d, N represents the total number of documents in document set D, and $|\{d \in D : t \in d\}|$ represents the number of documents containing word t.

The Uniform Manifold Approximation and Projection (UMAP) technology is used for dimensionality reduction of the data, mapping high-dimensional text data to points in a three-dimensional space, as shown in **Figure 4**. This is to intuitively display the similar relationship between texts and verify the effect of sample vectorization.

$$L = -\sum_{i,j} p_{ij} \log q_{ij} \tag{24}$$

In Equation (24), L is the loss value, p_{ij} represents the similarity between point i and point j in the high-dimensional space, and q_{ij} represents the similarity between point i and point j in the low-dimensional space.

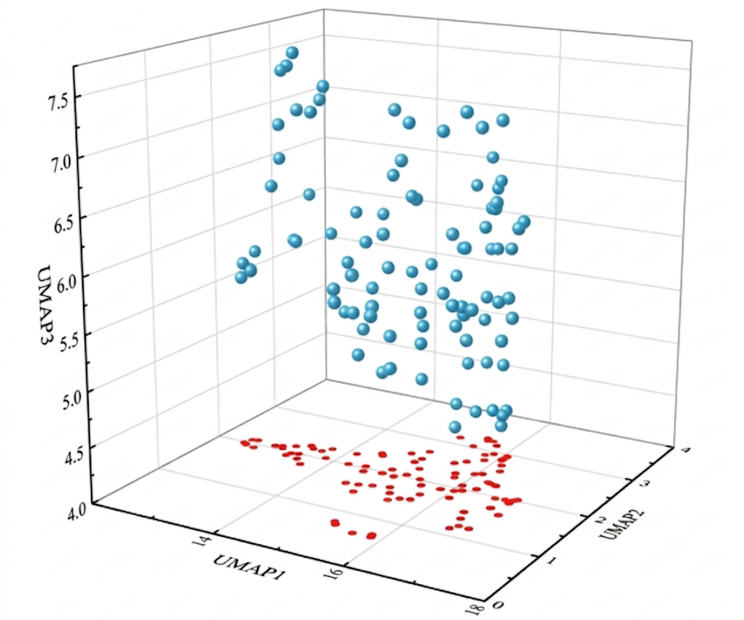

Figure 4. Mapping relationship diagram.

After completing the classification task, the Naive Bayes algorithm is used for sentiment analysis to explore the sentiment tendency in the text content. The derived probability calculation equation for sentiment analysis is as follows:

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)} \tag{25}$$

$$P(S_i|W) = \frac{P(W_1|S_i)P(W_2|S_i)\cdots P(W_n|S_i) \cdot P(S_i)}{P(W_1)P(W_2)\cdots P(W_n)} \tag{26}$$

In Equations (25) and (26), W_i is the word segmentation result of the training sample, S_i corresponds to two emotions, P and N, $P(W_i)$ is the frequency of occurrence of the corresponding word, and $P(W_i|S_i)$ is the probability of occurrence of the word in negative scenarios.

3. Results and discussion

3.1. Background of the engineering case

A coal mine in Wuhai, Inner Mongolia Autonomous Region, has a mine field area of 4.046 km^2, with mining elevations ranging from +950 m to +1,250 m. The retained resource reserves in the mining area are 25.7437 million t, and the ore types include 1/3 coking coal, coking coal, and fat coal. The mine is a low gas mine; the coal seam spontaneous combustion tendency is classified as type II spontaneous combustion coal seam; the coal dust is explosive; and the hydrogeological type is medium. The coal mine has established a sound and strict safety management system, attaching great importance to employees' safety training and education, and regularly organizing all employees to participate in safety knowledge training. It has built a normalized safety hazard investigation mechanism, set up a professional hazard investigation team, and conducted comprehensive and detailed inspections of underground operation areas, ground production facilities, etc., daily.

3.2. Based on PSO to optimize the weight of coal mine indicators

Collect the mine's past accident reports and safety performance indicators and implement the Particle Swarm Optimization (PSO) algorithm to optimize the weight configuration, obtaining the optimization results of coal mine indicator weights, as shown in **Table 3**. In each iteration process, the quality of the current weight configuration is evaluated according to the fitness function, and the position and velocity of particles are updated. Through continuous iteration, the particle swarm gradually converges to the global optimal solution, and the convergence curve is shown in **Figure 5**.

Table 3. Comparison table of index weights before and after PSO optimization.

First-level indicator	Weight before optimization	Weight after optimization	Secondary indicator	Normalized weight before optimization	Weight before optimization	Normalized weight after optimization	Weight after optimization
Organizational Management F1	0.1762	0.180	Safety Objective F11	0.062	0.011	0.086	0.016
			Organizations F12	0.262	0.046	0.169	0.030
			Safety Performance System F13	0.160	0.028	0.159	0.029
			Personnel Qualifications F14	0.097	0.017	0.272	0.049
			Safety Investment F15	0.418	0.074	0.314	0.057
Safety Education and Training F2	0.131	0.133	Training Faculty and Content F21	0.297	0.039	0.206	0.028
			Training Effect F22	0.540	0.071	0.438	0.058
			Personnel Skills Assessment F23	0.163	0.021	0.356	0.047
Risk Control Measures and Effects F3	0.199	0.231	Risk Identification F31	0.319	0.064	0.148	0.034
			"Three Violations" F32	0.109	0.022	0.231	0.053
			Dual Prevention and Control System F33	0.184	0.037	0.121	0.028
			Hidden Danger Treatment and Acceptance F34	0.319	0.064	0.247	0.057
			Standardization Compliance F35	0.068	0.014	0.253	0.058
Coal Mine Technical Measures F4	0.232	0.219	Roof Support Technology F41	0.388	0.090	0.253	0.055
			Gas Extraction System F42	0.252	0.058	0.195	0.043
			Fire Prevention and Extinguishing System F43	0.153	0.035	0.064	0.014
			Dust Prevention and Control System F44	0.043	0.010	0.147	0.032
			Mine Ventilation System F45	0.067	0.016	0.226	0.050
			Personal Protection F46	0.101	0.024	0.116	0.025

Table 3. *Cont.*

First-level indicator	Weight before optimization	Weight after optimization	Secondary indicator	Normalized weight before optimization	Weight before optimization	Normalized weight after optimization	Weight after optimization
Outsourcing Project Management F5	0.109	0.050	Contractor Access Conditions F51	0.297	0.032	0.248	0.012
			Management of Contractors' Work Safety F52	0.539	0.059	0.406	0.020
			Contractor Assessment F53	0.163	0.018	0.347	0.017
Emergency and Accident Management F6	0.154	0.186	Emergency Plans and Drills F61	0.262	0.040	0.220	0.041
			Emergency Handling and Response F62	0.160	0.025	0.236	0.044
			Emergency Resource Guarantee Status F63	0.419	0.064	0.168	0.031
			Accident Reporting F64	0.097	0.015	0.199	0.037
			Accident Investigation and Handling F65	0.062	0.010	0.178	0.033

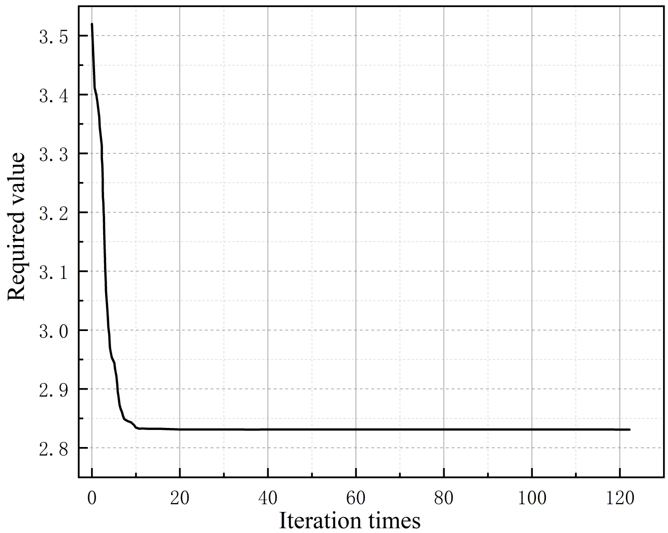

Figure 5. Convergent curve.

The comparison before and after optimization is shown in **Figure 6**. It can be seen from the figure that the optimized safety performance evaluation model has shown significant improvements and a shift in focus compared with the pre-optimized one. The weight focus has shifted from Roof Support Technology F41 and Management of Contractors' Work Safety F52 to Standardization Compliance F35 and Mine Ventilation System F45.

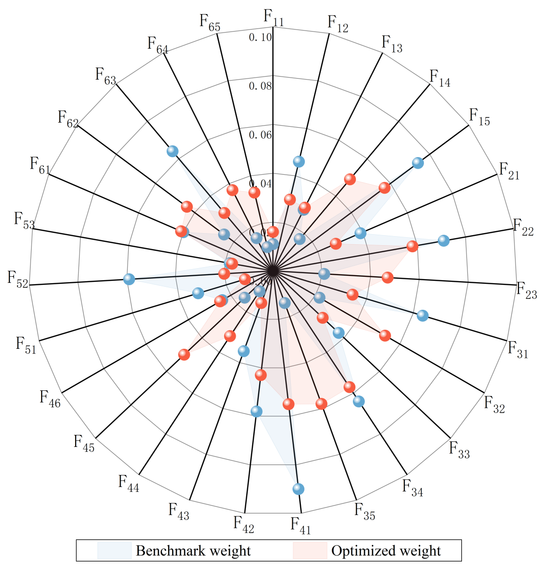

Figure 6. Weight optimization radar chart.

As indicated in **Table 3**, notable adjustments occur in certain indicator weights following PSO optimization; for instance, the weight of Management of Contractors' Work Safety F52 decreases from 0.059 to 0.020. Such revisions do not suggest instability in the initial ANP-TOPSIS weights, which are derived from expert scoring and embody professional experience and subjective judgment under normative frameworks. The PSO algorithm takes the minimum fitting error between ANP-TOPSIS benchmark weights and historical operational weights as its optimization objective, and performs adaptive weight reconfiguration in line with the mine's actual production conditions, risk distribution characteristics, and on-site management status. The divergence between the pre-optimization and post-optimization weights validates the value of combining expert knowledge with data-driven field information, thereby strengthening the dynamic adaptability and engineering rationality of the weight system for coal mine safety performance evaluation.

3.3. Training features of the random forest model and feature recognition of coal mine employees

3.3.1. Training features of the random forest model and quantification results of subjective bias

Historical coal mine safety performance records and web-based accident case data were collected, manually annotated and categorized in compliance with relevant laws and regulations. The collected unstructured text data were preprocessed using the Harbin Institute of Technology stopword list, followed by Chinese word segmentation based on a domain dictionary. The TF-IDF algorithm (parameter settings: $\text{ngram}_{\text{range}} = (1, 4)$, $\text{max}_{\text{features}} = 500$) was adopted to transform text into numerical feature vectors. The textual sentiment polarity score was incorporated as an auxiliary feature and concatenated with the TF-IDF vector. The fused feature set was then imported into the random forest regression model to generate continuous evaluation scores and indicator classification.

On the premise of ensuring the accuracy and availability of preprocessed text data, word frequency statistics are performed on the data, and the Pearson correlation coefficient is calculated to conduct sample correlation analysis. Its calculation formula is as follows:

$$r = \frac{cov(X, Y)}{\sigma_X \sigma_Y} \tag{27}$$

In Equation (27), $cov(X, Y)$ is the covariance, and σ_X, σ_Y are the standard deviations of X and Y respectively. The Pearson correlation coefficient can measure the strength and direction of the linear correlation between two variables, and the results are shown in **Figure 7**.

Figure 7 shows that there are significant differences among the indicators and that the predetermined goals can be achieved. The ROC curves and AUC values for each subcategory as well as the micro-average are shown in **Figure 8**.

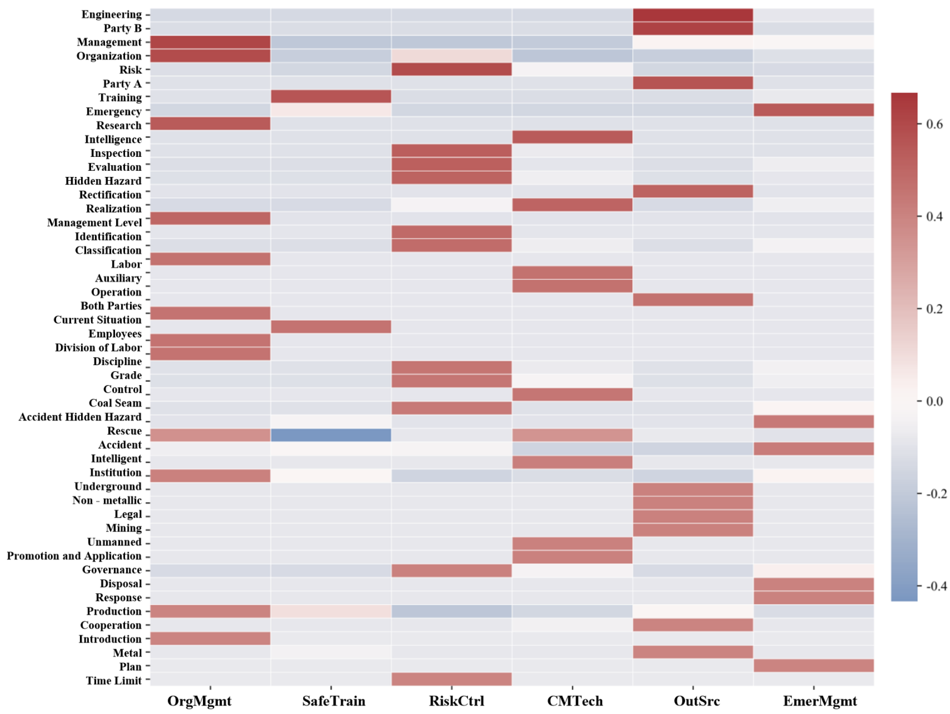

Figure 7. Correlation matrix of training set features and labels.

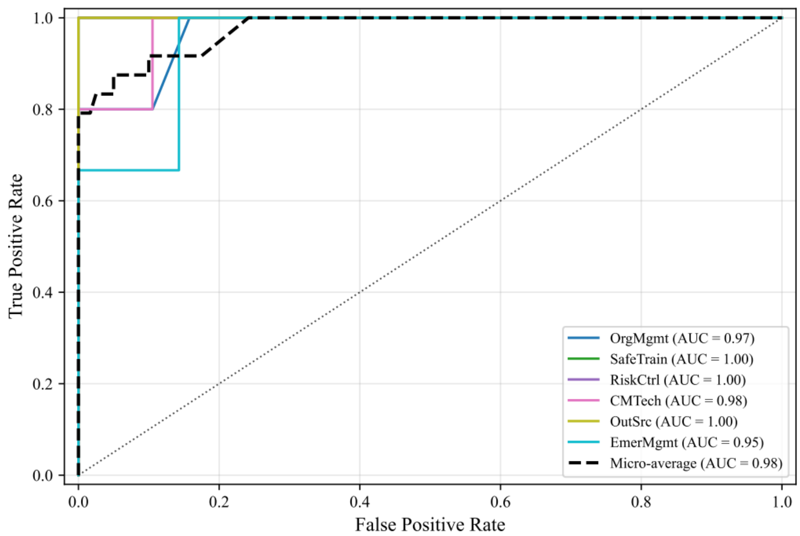

Figure 8. ROC curves and AUC values of the test set for each safety dimension.

Figure 8 shows SafeTrain, RiskCtrl, and OutSrc achieve an AUC of 1.00. The CMTech and OrgMgmt subcategories yield AUC values of 0.98 and 0.97, respectively, while EmerMgmt achieves an AUC of 0.95. The micro-average AUC reaches 0.98, confirming the model's high discriminative ability at the global level.

In **Figure 9**, the label correlation matrix reflects the intrinsic relationships among the six evaluation dimensions of coal mine safety performance. The correlation coefficients between dimensions are moderate, with no strong negative correlations observed. For the classification task, all F1-scores exceed 0.8, and the average F1-score reaches 0.929.

Figure 9. Training Set Label Correlation Matrix.

The random forest model was used to quantify employees' text data into values ranging from −1 to 1 and classify them into corresponding clusters. This not only reflects the intensity of the tendency but also indicates the direction of emotional tendency (−1 represents completely negative, and 1 represents completely positive). Taking the tunneling team as an example, a total of 131 valid texts were collected, and the distribution of data quantified by the trained model is shown in **Figure 10**.

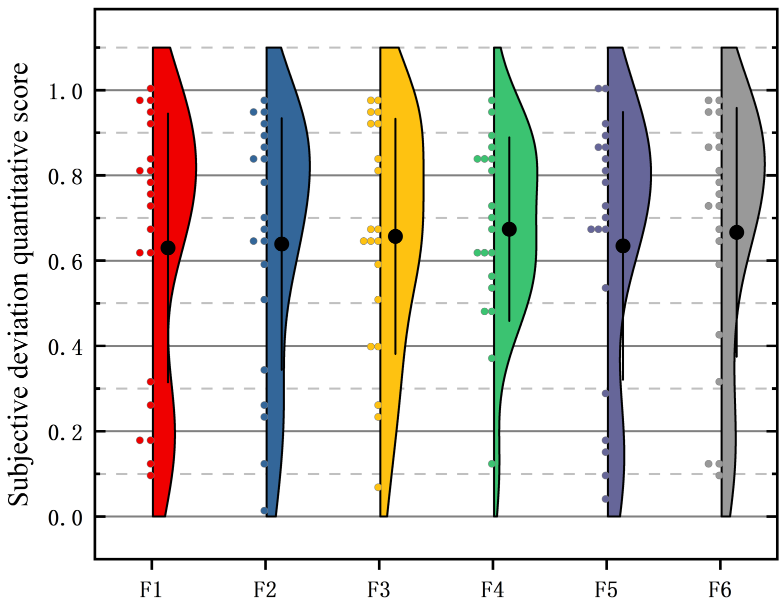

Figure 10. Employee emotional score distribution map.

It can be seen from **Figure 10** that the tunneling team has a relatively high degree of recognition for the enterprise. Their feedback on outsourcing management is relatively neutral; however, they have the highest recognition in terms of organizational management, risk control measures and effects, as well as emergency and accident management.

3.3.2. Interpretability analysis based on the SHAP model

To improve model transparency, this section adopts the SHAP (Shapley Additive Explanations) method to conduct interpretability analysis on the optimal model. Based on the Shapley value in game theory, SHAP can fairly quantify the contribution of each feature to the results and provide interpretations at both global and local levels. The results are shown in the following figures.

From **Figure 11**, features such as "Responsibilities", "Content", "Emergency Response", and "Disposal Process" exhibit the widest distribution of SHAP values, indicating that they are the core factors influencing emergency management performance. For samples with high feature values (red dots), the corresponding SHAP values are generally positive, suggesting that clear division of responsibilities, comprehensive plan content, and standardized disposal processes can significantly improve the model's positive evaluation of safety performance. In contrast, the SHAP values of samples with low feature values (blue dots) are concentrated around 0, indicating a weak impact on the evaluation results.

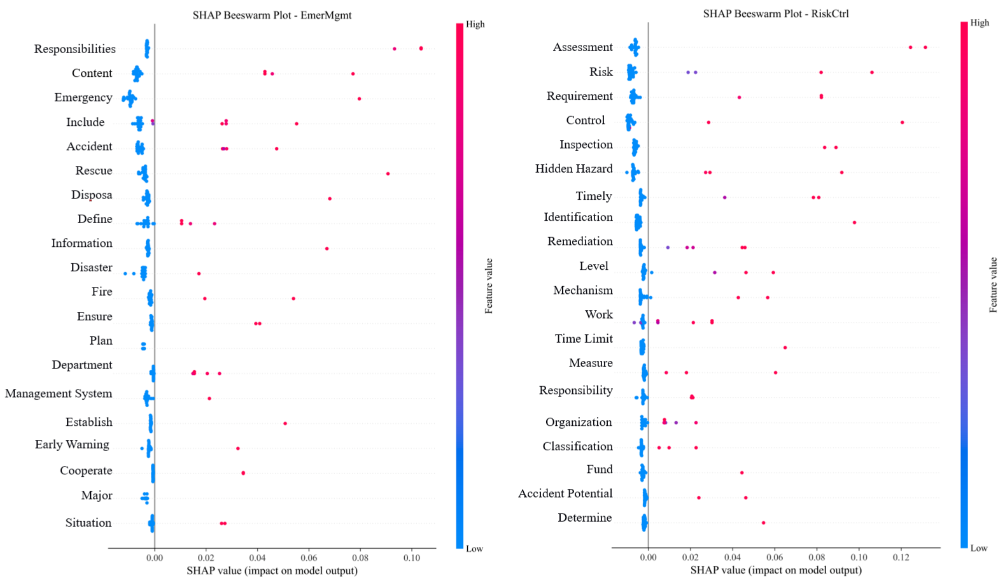

Figure 11. SHAP beeswarm plots of RiskCtrl and EmerMgmt dimensions.

The results presented in **Figure 12** indicate that within the safety training dimension, Assessment, Safety, and Training are the core features influencing the model's output. Samples with high feature values (red dots) exhibit significantly positive SHAP values, demonstrating that a sound safety assessment system, routine safety training, and clear safety specifications play a key positive driving role in safety performance evaluation. In contrast, with regard to coal mine technical measures, Intelligence, Realization, and Underground contribute the most prominently to the model.

From **Figure 13**, in the organizational management dimension, Organization, Management, and Responsibility are the core influencing features. Samples with high feature values (red dots) exhibit significantly positive SHAP values, indicating that a sound organizational structure, clear management authority and responsibility, and effective accountability mechanisms act as key drivers for improving safety performance. In contrast, within the external collaboration dimension, Party A, Engineering, and Remediation contribute the most prominently, demonstrating that the management of external partners, standardized engineering construction practices, and closed-loop rectification of hazards exert a decisive impact on safety performance. Overall, features in both dimensions follow a high-value positive driving pattern: the safety-enabling effects become significant only when the levels of management and collaboration reach a certain threshold.

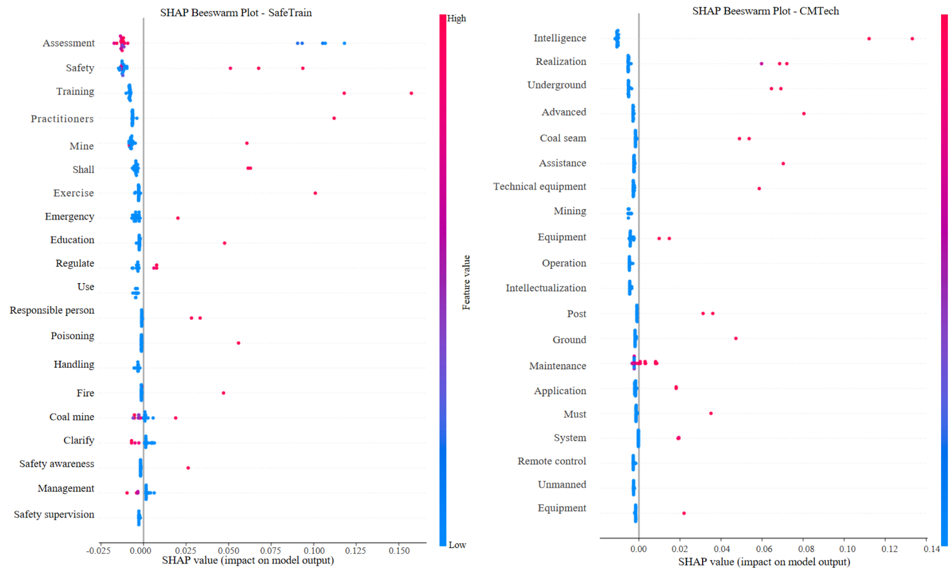

Figure 12. SHAP beeswarm plots of SafeTrain and CMTech dimensions.

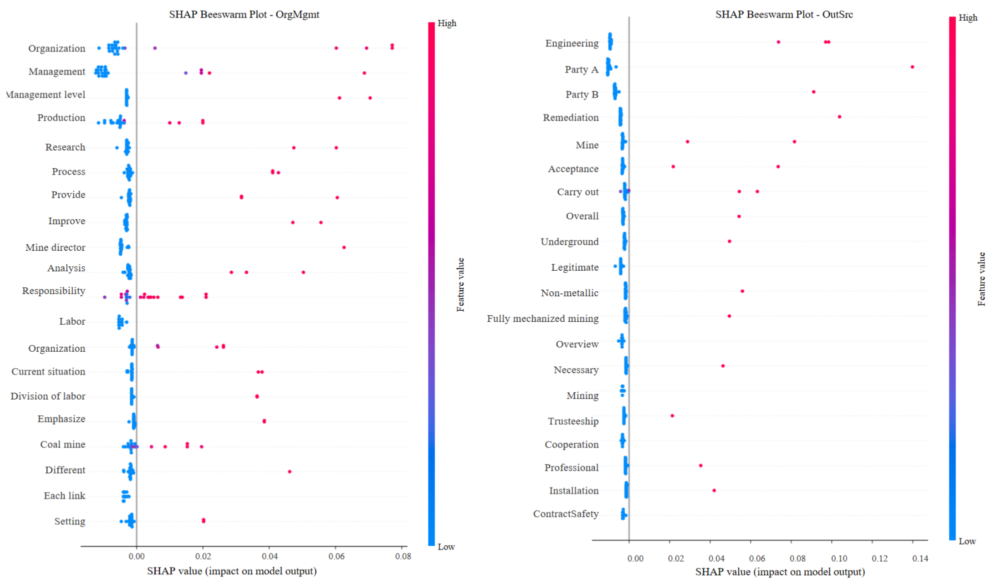

Figure 13. SHAP beeswarm plots of OrgMgmt and OutSrc dimensions.

3.3.3. Baseline model comparison and ablation study

To further validate the effectiveness and superiority of the proposed classification framework, we conducted a baseline model comparison and an ablation study using the collected dataset.

(1) Baseline Model Comparison

We compared the micro-average Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) values of the proposed Random Forest (RF) model against three commonly used machine learning baselines: Support Vector Machine (SVM), Logistic Regression, and Naive Bayes. The comparison results are shown in **Figure 14**.

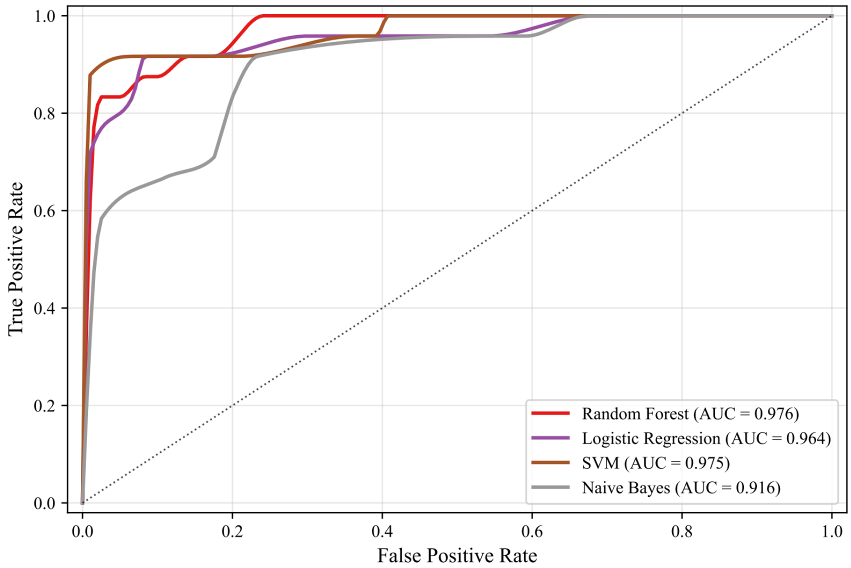

Figure 14. Micro-average ROC Curves Comparison.

As illustrated in the ROC comparison, the proposed Random Forest model achieves the highest performance with an AUC of 0.976. SVM follows closely with an AUC of 0.975, while Logistic Regression and Naive Bayes exhibit lower performance, achieving AUC values of 0.964 and 0.916, respectively. The superior AUC of the Random Forest model underscores the advantages of ensemble learning in handling the high-dimensional and complex non-linear features inherent in coal mine safety text data, ensuring higher reliability in multi-class performance evaluation tasks.

(2) Ablation Study

To quantitatively analyze the contribution of each core module in the proposed hybrid approach, ablation experiments are conducted. Model performance is assessed utilizing macro F1-score and macro accuracy. Four comparative experimental settings are established as follows:

Without an optimal threshold module (TF-IDF + RF): The optimal threshold strategy is discarded, and classification is performed with default probability thresholds only.

Without TF-IDF feature extraction (CountVec + RF + OptThr): TF-IDF is substituted by conventional count vectorization for feature representation.

Random forest replacement (TF-IDF + SingleTree + OptThr): The random forest ensemble classifier is replaced with a single decision tree.

Proposed method (TF-IDF + RF + OptThr): The intact integrated framework adopted in this work and the experimental results are shown in **Figure 15**.

The ablation results presented in **Figure 15** clearly demonstrate that the complete proposed model significantly outperforms all variants, achieving a Macro F1 score of 0.920 and a Macro Accuracy of 0.972.

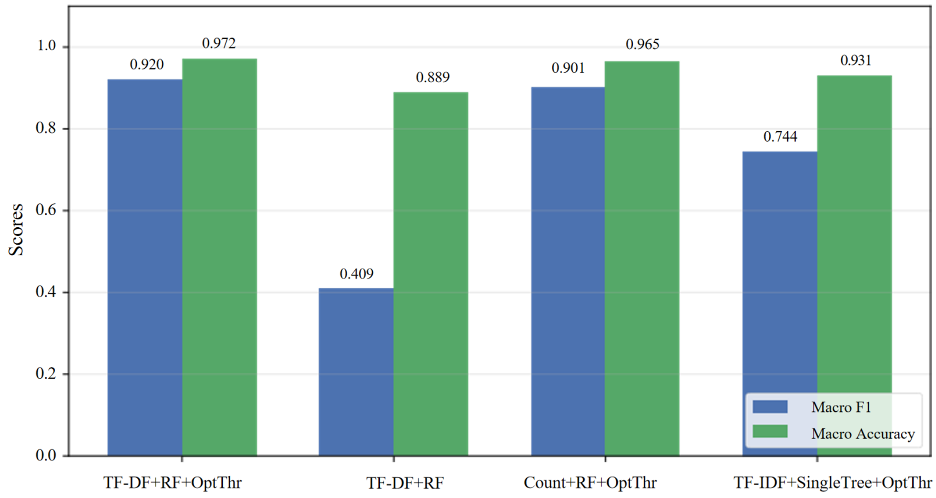

Figure 15. Results of the ablation study.

Remarkably, eliminating the optimal threshold module leads to a sharp decline in macro F1-score to 0.409, while macro accuracy remains at a relatively high level of 0.889. Such pronounced performance deterioration demonstrates that the optimal threshold strategy serves as a core component to mitigate class imbalance and facilitate accurate identification of minority risk samples.

In addition, substituting random forest with a single decision tree lowers the macro F1-score to 0.744, verifying that ensemble learning effectively suppresses overfitting and sustains favorable generalization performance. A marginal performance decline is observed when count vectorization replaces TF-IDF, with the macro F1-score falling to 0.901. This result indicates that TF-IDF can achieve refined feature characterization via reasonable weight assignment for domain-specific safety vocabulary.

3.3.4. Coal mine employees' characteristics

Taking the Electrical and Mechanical Department of this mine as an example for analysis, there are 76 employees in the department, with personnel distributed across various positions and professional titles, and their ages range from 20 to 60 years old. A designed questionnaire was used to invite three direct superior leaders to evaluate the employees as assessors. The intraclass correlation coefficient (ICC) calculated using the formula shown in Section 2.3.2 is 0.698, indicating that the data have good consistency. A further analysis of the κ value among different groups of assessors found no obvious deviation, and the results of the assessor correlation analysis are shown in **Figure 16**.

Calculations of rater bias were conducted for employees of the Electrical and Mechanical Department to reflect the degree of deviation between individual raters' scores and the overall evaluation trend. Regression analysis was used to quantify the impact of these characteristics on the scores, and this impact was combined with scoring bias to obtain a more comprehensive indicator of rater subjectivity. The results are shown in **Figure 17**.

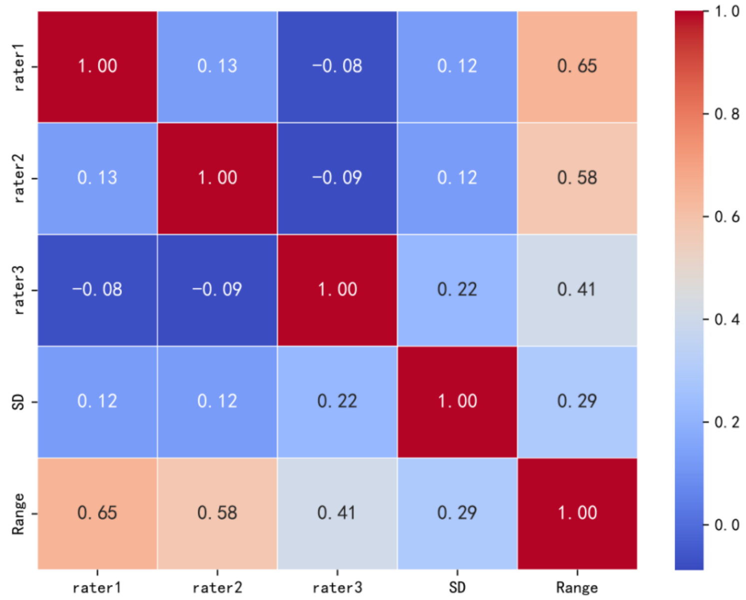

Figure 16. Thermal correlation diagram between evaluators.

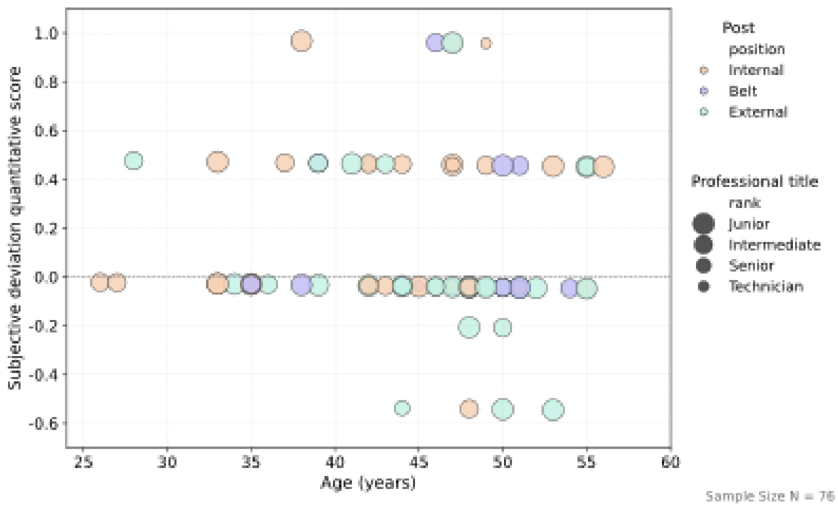

Figure 17. Quantitative score of subjective deviation of the electromechanical team.

From the distribution shown in **Figure 17**, there is no obvious linear correlation between age and subjective evaluation scores. Employees of various positions and professional titles are distributed across different age groups, with some high scores concentrated in the 35–50 age range, reflecting that coal mine employees in this age group have a higher degree of recognition of the enterprise. As age increases, the rate of promotion in job grades accelerates. However, most junior workers have low recognition due to limited experience, so it is recommended to carry out targeted "mentorship (passing on experience, providing guidance, and offering assistance)" and practical operation training. Overall, there is no absolute difference in subjective scores across professional titles, which reflects the weak correlation between the professional title system of the Electrical and Mechanical Department and age as well as subjective evaluations.

3.4. Short-term safety performance evaluation, rectification and improvement of coal mines

3.4.1. Coal mine safety performance evaluation

After cleaning the daily work summaries, the cleaned texts are imported into the trained random forest model, which can automatically identify the corresponding indicators and weights, realizing qualitative and quantitative analysis of the texts. The subjective tendency coefficients of the employees who provided the texts are used to correct the results of the quantitative analysis to improve operational accuracy. Taking all employees as the research sample, text data and questionnaire surveys are collected. By applying these to the aforementioned model parameters, the daily safety performance scores of mine within a certain month can be calculated, as shown in **Figure 18**.

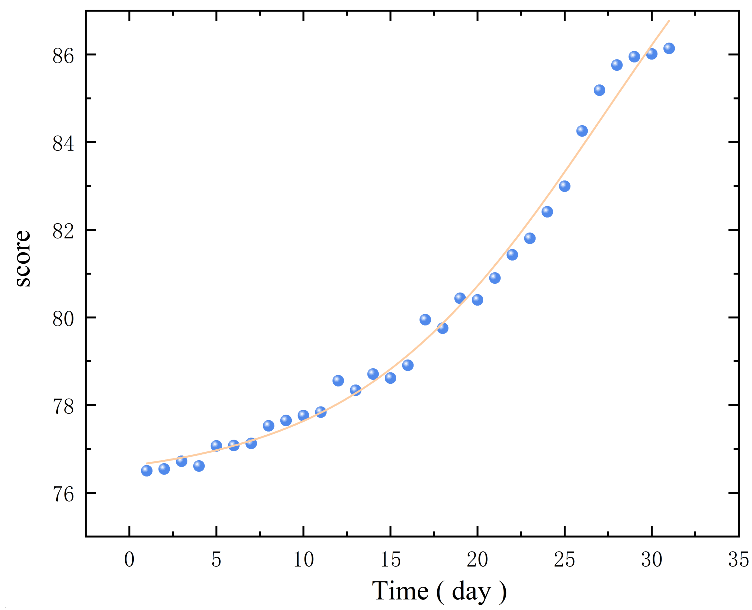

Figure 18. Daily safety performance score of a month in a coal mine.

It can be seen from **Figure 18** that the daily safety performance scores of the coal mine in a certain month showed an overall fluctuating upward trend. At the initial stage, the data fluctuated between 76.5 and 77.07, staying at a relatively low level with a small fluctuation range. In the middle stage, the data gradually rose from 77.08 to 78.91. Although there were small fluctuations up and down during this period, the upward trend was obvious. In the later stage, the data increased from 78.91 to 86.14, and the fluctuation range decreased, tending to be stable, and finally remained at a relatively high level. After one month of project follow-up, the overall safety performance of the coal mine increased by 12.6%.

3.4.2. Coal mine safety hazard identification, rectification and improvement

In practice, the identification of potential safety hazards relies on the analytic hierarchy process (AHP) and the safety checklist method executed by field personnel, while the proposed model processes these documented records to dynamically evaluate and track the hidden danger conditions on a daily basis. Taking the 11th day as an example, based on the information provided by employees and specific evaluation indicators, the water seepage hazard in the goaf is retroactively identified, as shown in **Table 4**.

Table 4. Hidden danger identification source traceability table.

Example	Evaluation coefficient	Subjective bias	First-level indicator	First-level indicator weight	Secondary indicator	Secondary indicator weight	Subjective tendency coefficient
Water leakage was found in the goaf, with a risk of water hazards (Employee A)	−0.94	0.96	Risk Control Measures and Effects F3	0.231	Risk Identification F31	0.034	0.84
I did not attend this month's safety training (Employee B)	0.25	0.46	Safety Education and Training	0.133	Training Effect	0.206	0.62

The statistical analysis of key safety performance nodes and their ranking results is shown in **Table 5**. These nodes will be incorporated into the safety checklist as priority inspection areas to ultimately achieve an overall improvement in the coal miner's safety performance level.

Table 5. Key inspection system sorting table.

Subsystem	Factor indicator	Importance ranking
Safety Education and Training	Training Faculty and Content	1
Risk Control Measures and Effects	Risk Identification	2
	"Three Types of Violation Behaviors"	3
Coal Mine Technical Measures	Roof Support Technology	4
	Dust Prevention and Control System	5

4. Discussion

The ANP-TOPSIS-PSO-Random-Forest model constructed in this study realizes innovation in three dimensions. First, the model overcomes the inherent limitation of static weight allocation in traditional coal mine safety performance assessment models by integrating the network hierarchy of ANP, the relative distance evaluation logic of TOPSIS, and the group intelligence optimization algorithm of PSO. It is found that the centrality of weights has shifted from "roof support technology" and "contractor management" to "standardization compliance" and "ventilation system". "This indicates that the PSO algorithm was able to reconfigure the weighting priorities over the course of 100 iterations while maintaining the convergence stability of the algorithm.

Second, by combining TF-IDF vectorization technology with the random forest classification algorithm, the model establishes a novel bottom-up evaluation mechanism, thereby shortening the safety performance assessment cycle.

Despite the above advantages, several limitations warrant consideration. The dataset originates from a geological setting characterized by low gas content and moderate water influx; therefore, additional validation is required to assess the generalizability of the proposed model to mines with high gas content or those prone to dynamic geological phenomena.

5. Conclusion

This study demonstrates that the proposed machine learning framework provides a dynamic, data-driven solution for coal mine safety performance assessment. By integrating the structural integrity analysis of ANP-TOPSIS, adaptive weight adjustment using PSO, and high-dimensional pattern recognition via random forest, the framework shortens the safety performance assessment cycle while maintaining diagnostic accuracy. The random forest model achieved an average F1-score of 0.929. Future research will focus on conducting multi-mine collaborative learning experiments to validate the framework's transferability under heterogeneous geological conditions.

Author contributions: YL was responsible for the overall conception, design and writing of the paper; JL provided algorithm support and model reconstruction, TT collected relevant literature information; WY assisted in writing the thesis; HW participated in the translation of the thesis; DC assisted in the on-site test; FG offered suggestions and strategies to improve the manuscript; FJ recorded the experimental data. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the National Natural Science Foundation of China (52464019,52504234), the Inner Mongolia Natural Science Foundation of China (2024LHMS05031), the Inner Mongolia Key Research and Development and Achievement Transformation Project (2025YFHH0034,2025YFSH0063), Sub-project of Science and Technology Program in Hainan District, Wuhai City, Inner Mongolia (NKDHX2025231, NKDHX2024238).

Institutional review board statement: Not applicable.

Informed consent statement: Not applicable.

Data availability statement: The data used in this study are available from the corresponding author upon reasonable request.

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

AI use statement: DeepSeek was used to enhance the manuscript's language and formatting. The authors confirm that all scientific content and conclusions are original and accurately reflect their work.

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