



OPEN Evaluating regulatory influences on coal mine accidents in China using a fuzzy multi-criteria decision-making approach

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Amidst the global surge in industrialization, frequent coal mine safety incidents pose significant risks to miners' lives and environmental stability. This study employs Fuzzy Multi-Criteria Decision-Making (FMCDM) to quantitatively analyze regulatory factors affecting coal mine safety in China from 2012 to 2022, identifying key elements that influence accident risks and regional policy disparities. By integrating Structural Equation Modeling (SEM), Fuzzy Decision-Making Trial and Evaluation Laboratory (FDEMATEL), and Gaussian Fuzzy Monte Carlo Analytic Network Process (GFMANP), a comprehensive risk assessment model is developed. This multifaceted approach addresses the limitations of traditional assessment methods, not only identifying the key regulatory factors impacting coal mine safety but also quantifying their influence and interrelationships. The findings reveal a strong correlation between design schemes and management systems (correlation coefficient 0.4931), emphasizing their interdependence and the importance of an integrated approach to safety management. In addition, the results show that technical documents and Southwest factors have the highest risk values (0.1506 and 0.2050, respectively), which provide a detailed risk assessment for different regions of China and are crucial for developing security strategies for different regions. Based on these findings, the recommendations include optimizing the synergy between design schemes and management systems, enhancing technical document management, and developing region-specific safety strategies to reduce the risks of coal mine accidents and improve safety management standards.

Keywords Coal mine accidents, Regulatory factors, Fuzzy multi-criteria decision-making (FMCDM), Risk assessment

Amid accelerating global industrialization, coal remains a cornerstone of the world's energy structure, providing a significant portion of energy needs. However, the frequent occurrence of coal mine safety and production accidents presents substantial threats to miners' lives and poses serious societal and environmental challenges. These concerns have rightfully made coal mine production safety a focal point for researchers, policymakers, and industry leaders alike.

Extensive research has dissected the factors contributing to coal mine accidents, identifying key areas such as unsafe human behavior, equipment, environment, and system failures. For instance, Li et al. categorized accident causes into four primary areas, highlighting that the strength of coal mine safety management in these domains determines accident probabilities¹. Further studies by Wang et al. and Shi et al. reinforce these findings, pointing to factors like regulations, safety environments, and management systems as critical to ensuring mine safety^{2,3}. Similarly, Chu & Muradian stated that the problems faced by coal mining globally in terms of accidents, occupational diseases, and environmental impacts are mainly caused by complex geological conditions, lack of technological implementation, human factors, lack of financial investment, and ineffective management of safety and environment⁴. The study by Wu et al. concluded that coal mine geological conditions, coal mining technology, safety training, and coal mine safety supervision force affect coal mine safety⁵.

Among these factors, the role of safety regulations cannot be overstated. Ineffective or hazardous regulations have been shown to contribute to accidents significantly. For example, Zhang et al. analyzed 320 accidents in Shandong Province, revealing a high prevalence of dangerous regulatory practices⁶. Complementary studies,

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such as those by Geng & Saleh and Niu et al., emphasize that strengthening regulatory frameworks and enforcement can substantially improve safety outcomes in the coal mining industry^{7,8}. X. Wang et al. used a vector autoregressive model (VAR) to analyze policy stringency, scope, technological content, and industrial objectives, highlighting the need for rigorous safety policies⁹. Chen et al. employed an unbiased grey Markov model to examine the impact of the coal mine safety regulatory system at different stages, finding significant effects on production safety¹⁰. Yinnan et al. used a nonlinear time-varying factor model to analyze spatial and temporal variation patterns, showing convergence in safety accidents and coal production across provinces in China, with geographic disparities¹¹. Zhu et al. confirmed that China's coal mine safety policy effectively reduces accidents and mortality rates, suggesting that strict safety policies can significantly improve coal mine safety¹². However, a comparative study by Q. Liu et al. points out that China's uniform prescriptive coal mine safety regulatory system is ineffective compared to Australia's risk management-based legislation¹³. This suggests that we must consider the specific conditions of different countries and regions when formulating safety policies.

Despite the rich body of qualitative research on coal mine safety regulatory factors, there is a notable lack of quantitative data to support these findings comprehensively. This study aims to bridge this gap by employing an innovative framework that integrates multiple quantitative analysis methods with fuzzy logic to address uncertainty and ambiguity in the decision-making process, and systematically quantifies and evaluates the risk of regulatory factors in coal mine accidents. Comprehensively understand the complex interaction between various factors and their impact on accident risk, reveal the deep connection behind the data, and provide scientific decision support for coal mine safety management.

Methods

To comprehensively analyze the factors influencing coal mine accident protocols, our research employs a multi-step approach that integrates several analytical methods. The research process commenced with the collection of a substantial amount of accident sample data and progressed through multiple stages of analysis, ultimately culminating in the Fuzzy Multi-Criteria Decision-Making (FMCDM) approach. Figure 1 visually illustrates this analytical framework.

We begin by compiling an extensive database of 567 recorded coal mine accidents, which serves as the foundation for our analysis. The regulatory factors associated with these accidents are identified and categorized to understand the context of the incidents. We then define the variables relevant to our research objectives and classify the accident factors using the 4M1E model (Man, Machine, Material, Method, and Environment). Structural Equation Modeling (SEM) is utilized to estimate regression and covariance coefficients, providing

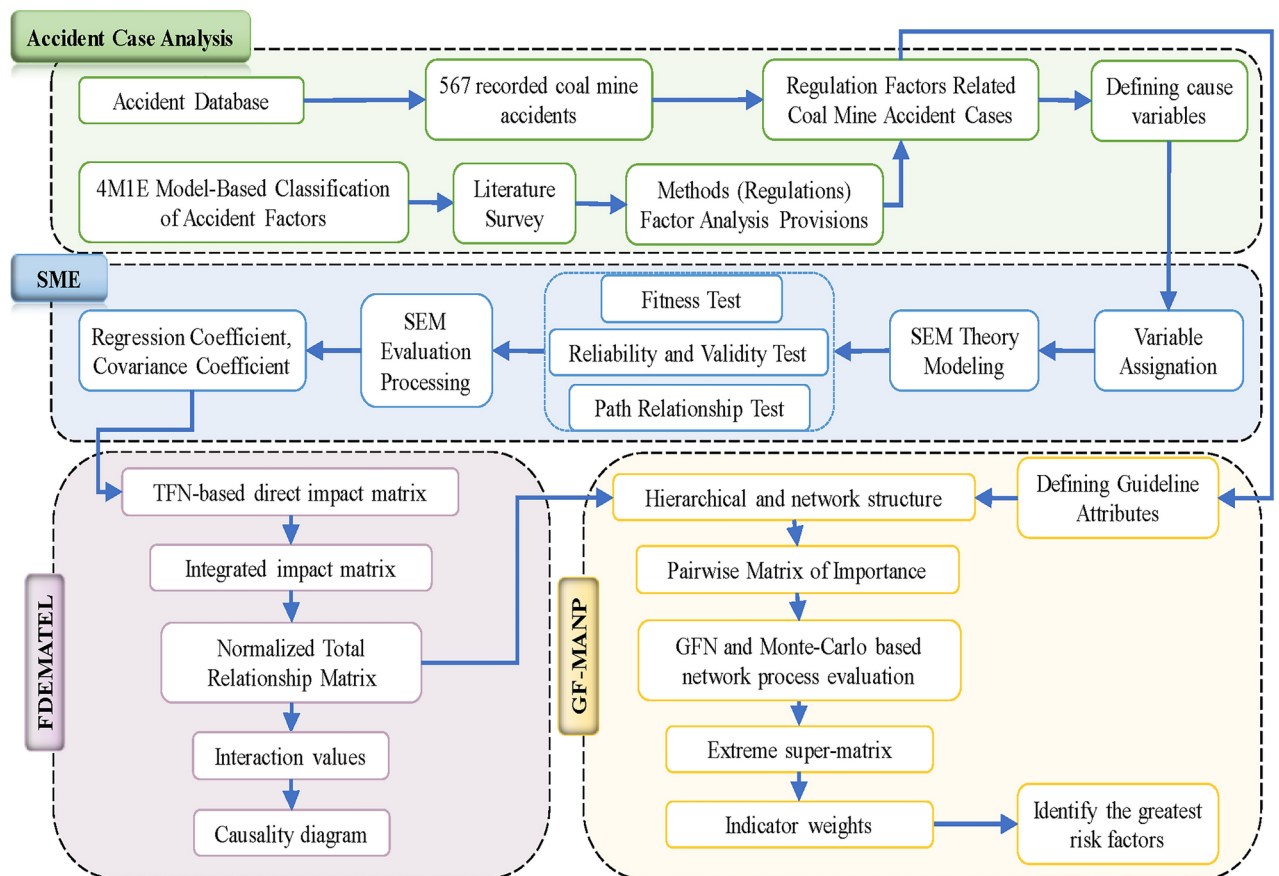


Fig. 1. Analytical framework of this study.

insights into the relationships between variables. This is followed by a series of model evaluations to ensure accuracy and reliability¹⁴. The Decision-Making Trial and Evaluation Laboratory (DEMATEL) method is applied to calculate the centrality and causality of each indicator, reflecting their relative importance and influence¹⁵. The Analytic Network Process (ANP) allows us to consider the relationships between multiple elements simultaneously and quantifies the study of non-quantitative events, addressing subjective inconsistencies¹⁶.

FMCD, as an extension of MCDA, is utilized to address the uncertainty and ambiguity inherent in the decision-making process by incorporating fuzzy logic¹⁷. By integrating SEM, fuzzy DEMATEL, and GFMANP, we can quantify and assess the risks associated with regulatory factors in coal mine accidents. This approach will provide a systematic and comprehensive understanding of the complex interactions among these factors and their influence on accident risk. This holistic approach seeks to uncover the underlying connections within the data, based on the intrinsic characteristics of accidents, and to provide scientific decision support for coal mine safety management.

Data sources

In this study, the period from 2012 to 2022 was selected as the research period, and a total of 567 coal mine accident case investigation reports were sorted and analyzed based on the data of coal mine accident investigation reports released by the websites of China's National and Provincial Mining Safety Supervision Bureaus in the previous years. The study found that 462 accidents, accounting for 81.48%, were related to regulatory factors.

Our analysis of statistical data from 2012 to 2022 reveals a significant trend in coal mine accidents influenced by regulatory factors, as illustrated in Fig. 2. From 2016 to 2019, there was a notable increase in the frequency of accidents, which we attribute to various external factors, including the introduction of new regulations and potential industry adjustments. This period of increase was followed by a decrease in accident rates post-2019, which may be associated with the global impact of COVID-19. The pandemic led to changes in production levels, safety measures, and regulatory enforcement, all of which could have contributed to the downward trend in accidents. Despite the overall decline, the proportion of accidents linked to regulatory factors has continued to rise over the last decade and is now stabilizing at a high level. This trend underscores the enduring impact of regulatory factors on coal mine accidents, even in the face of evolving external conditions and industry responses.

No coal mine accidents were recorded during this period in Beijing, Tianjin, Zhejiang, Shanghai, Guangdong, Hainan, Taiwan, Tibet, Hong Kong, and Macao. This is mainly because all coal mines in Guangdong and Zhejiang have been closed since 2007, while no statistics on coal mine production and related accidents are available for the Tibet Autonomous Region, Hainan Province, Hong Kong Special Administrative Region, Macao Special Administrative Region, and Taiwan. Therefore, the data collected in this study does not include the provinces as mentioned above. The study further analyses the provinces by dividing them into seven regions based on geographic location, natural environment, and other factors: Northeast China, North China, East China, Central China, South China, Southwest China, and Northwest China.

Fig. 3 shows the regional distribution map of the 24 coal-producing provinces in China affected by regulatory factors. The northeast region includes Heilongjiang, Jilin, and Liaoning. The north region includes the Inner Mongolia Autonomous Region, Shanxi, and Hebei. The east region includes Jiangsu, Shandong, Anhui, and Fujian. The central region includes Henan, Hubei, Hunan, and Jiangxi. The southern region includes Guangxi Zhuang Autonomous Region, Yunnan Province, Guizhou Province, Sichuan Province, and Chongqing

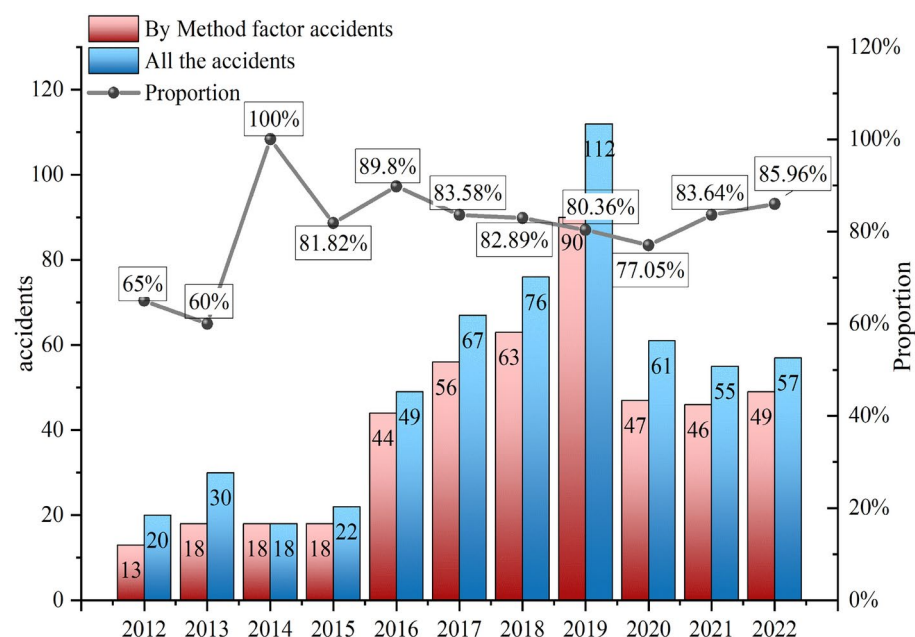


Fig. 2. Accident trend chart from 2012 to 2022.

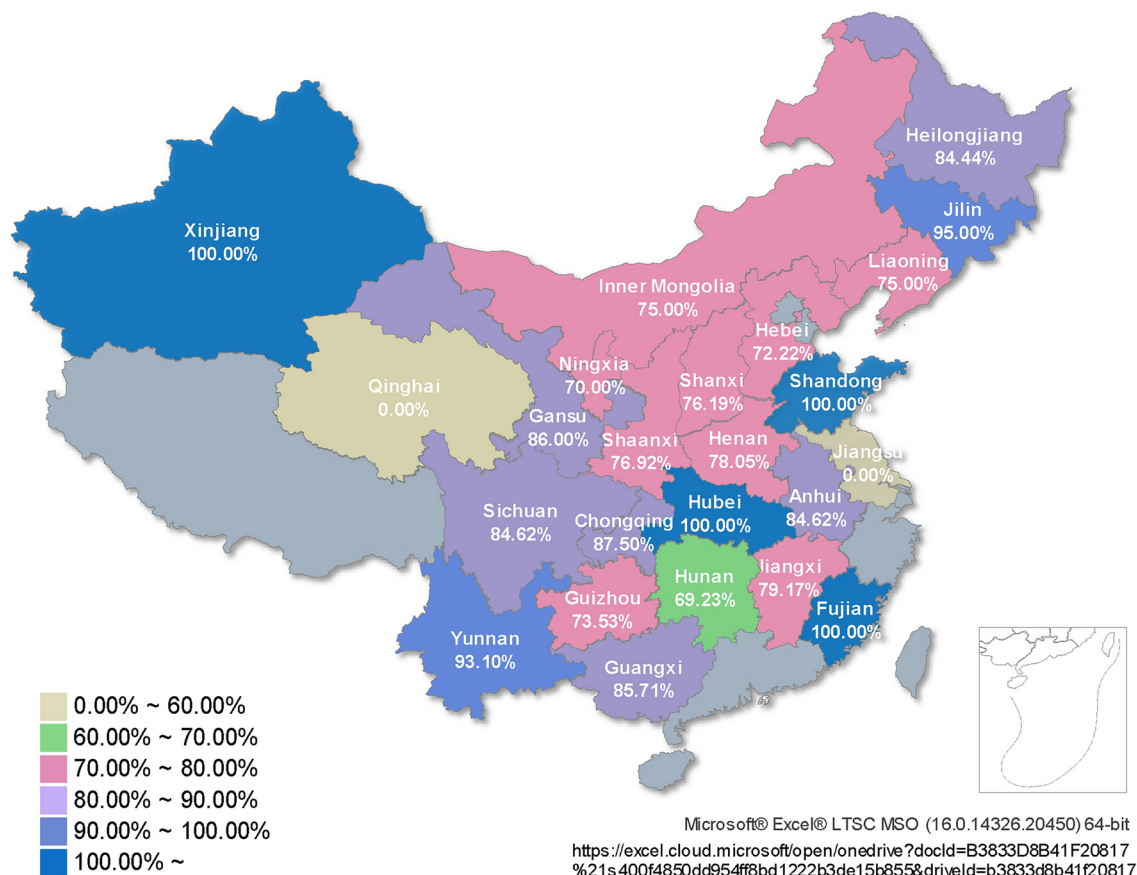


Fig. 3. Distribution of regulatory factors impact region.

Municipality. The northwest region includes Xinjiang Uygur Autonomous Region, Qinghai Province, Shaanxi Province, Gansu Province, and Ningxia Hui Autonomous Region.

As can be seen from the distribution map, the provinces in China where more coal production accidents occur due to the influence of regulatory factors are mainly concentrated in the Northeast and Northwest as well as in the Eastern and Southern regions. In contrast, the North-Central region has fewer accidents caused by the influence of regulatory factors. This distribution pattern reflects differences in safety supervision and the enforcement of regulations in different regions. Further analysis may reveal the extent to which specific regulations affect coal production safety in different regions and how improvements to these regulations can reduce accident rates.

Indicators selection

Before carrying out the fuzzy multi-criteria decision-making assessment, this study identifies the theoretical framework of regulatory factors affecting coal mine safety accidents by analyzing the existing literature, summarizing the opinions of industry experts, and selecting the critical indicator variables that are closely related to coal mine safety based on the literature review, including design schemes, management systems, technical documents, organizational measures, and process methods¹⁸. Figure 4 demonstrates the categorization of coal mine accident regulatory factors. These indicators are considered to be effective in capturing the impact of regulatory factors on accident rates.

In the coal mining industry, the safety of design schemes is of paramount importance. This involves not only the design of the mine structure but also the design of underground systems and dedicated work programs, among other things. A scientific design scheme can ensure the safety of production equipment and the working environment, thus reducing the risk of accidents caused by design flaws. Conversely, if the design scheme is not well considered or its safety is ignored, it may lead to frequent equipment failures or even cause significant safety accidents.

Coal mine safety management system includes but is not limited to the production safety responsibility system, production technology management system, equipment management system, operation permit system, safety inspection, and accident investigation system. The formulation of these systems not only needs to be clear on paper but, more importantly, strictly enforced in actual operation. Strict management systems can improve the safety awareness of operators, eliminate major risks and hidden dangers at the source, provide a solid guarantee for production safety, and effectively reduce the possibility of accidents.

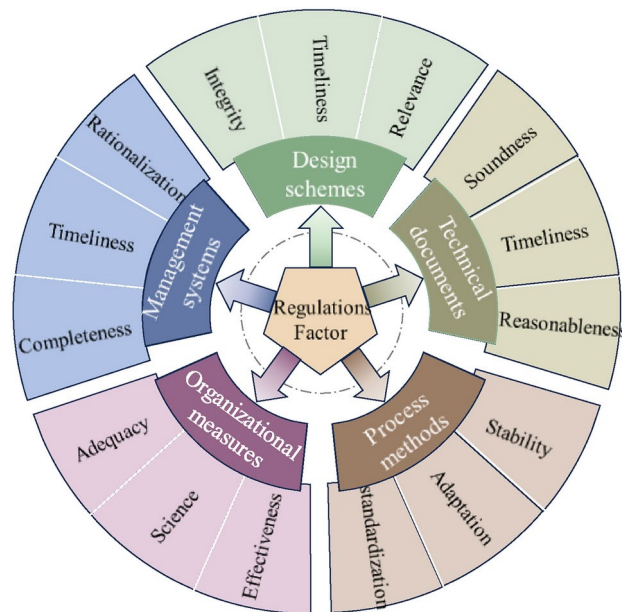


Fig. 4. Classification of regulatory factors influencing the coal mine accidents.

Technical documents contain detailed operating instructions, safety operating procedures, and emergency plans. These should be customized to the specific conditions of the mine, provide clear operating steps and countermeasures, and provide clear operating guidelines for operators to reduce the risk of safety accidents caused by misuse. Unclear or overly brief technical documents may lead to operator confusion during operations and increase the risk of accidents.

Comprehensive organizational measures include risk prevention and control, accident prevention, and continuous risk assessment and control measures. These measures ensure that every employee is fully aware of potential risks in their respective positions and takes appropriate preventive measures. Effective organizational measures act as a solid line of defense to safeguard the lives of employees and the integrity of production facilities. Suppose these measures are not formulated scientifically or are flawed. In that case, they may increase the risk of accidents and cause a lack of an effective response in the event of an accident, failing to control it promptly and causing further damage.

Process methods include coal mining, ventilation, support, and other operational construction methods. These methods must comply with the relevant laws and rules and be based on scientific principles to ensure that operations are reasonable and legal. Reasonable process methods can avoid safety hazards from the source, reduce the labor intensity of operators, and lower the risk of accidents. Unreasonable processes not only increase labor intensity but may also expose personnel to hazardous environments and raise the risk of accidents.

Fuzzy multi-criteria decision-making evaluation modeling

Fuzzy decision-making trial and evaluation laboratory

This section provides an overview of the FDEMATEL process, which is essential for understanding the direct and indirect effects of various factors.

(1) Establishment of the Assessment Language Scale.

The process begins by establishing a linguistic scale, which involves converting the direct relationship scale into a fuzzy scale using a triangular fuzzy number (TFN). This conversion of DEMATEL's relationship scale to a TFN is detailed in Appendix Table 11. Additionally, the degree of influence of each influencing factor is categorized into five distinct levels¹⁹. The triangular fuzzy number consists of a minimum value a , a median value m , and a maximum value r .

(2) Constructing a direct influence relationship matrix.

Next, corresponding to the six variables included in the SEM analysis ($m=6$), an initial direct influence matrix C_{ij} was built based on the interrelationships between the influencing factors. When $i = j$ is $c_{ij} = 0$.

According to the semantic conversion table, the values of the interactions are transformed into corresponding triangular fuzzy numbers to obtain the fuzzy direct influence matrix. The defuzzification solution is performed using the CFCS method to construct a direct influence relationship matrix based on the defuzzification of each relevant variable²⁰. Initially, the triangular fuzzy numbers are normalized. Defuzzification is a process that converts imprecise or uncertain data into a more precise and usable form. Its steps include standardizing and normalizing triangular fuzzy numbers, calculating clear values, and deriving a de-fuzzified clear direct influence relationship matrix T_{ij} based on the FDEMATEL relationship scale.

(3) Establishing a comprehensive influence matrix.

The resulting clear direct relationship matrix was normalized, and follow the unit matrix of the normalization direct relationship matrix to calculate the integrated impact relationship matrix Z_{ij} .

(4) Calculation of impact factors.

Influence Degree I and Influenced Degree D are calculated as the sum of all elements x in the respective row or column where a factor is located. Centrality C and Causality R are determined by the sum of Influence Degree and Influenced Degree and their difference, respectively. Factors with higher centrality C have greater influence and control over other factors. A causality R greater than 0 indicates that the factor is a dominant causal factor, mainly playing a driving or motivating role. In contrast, a causality R less than 0 indicates that other factors mainly influence the factor and is a passive consequential factor.

(5) Determining the threshold.

Define a threshold α based on the average interactions of the regulatory factors in the comprehensive influence relationship matrix²¹. This value ensures that only the most influential relationships are considered, focusing the analysis on the most relevant factors.

(6) Constructing the normalized total relationship matrix.

After excluding the elements of the comprehensive influence relationship matrix Z that are smaller than the threshold value, it is normalized according to the summation of the rows to construct the normalized total relationship matrix W . The elements of the normalized total relationship matrix will be used for the construction of the super-matrix in the GFMANP.

(7) Drawing causality diagram.

Causality is represented in a Cartesian coordinate system using centrality C as the horizontal coordinate and causality R as the vertical coordinate to identify key factors in the decision-making system²².

Gaussian Fuzzy Monte Carlo Analytic Network Process

The traditional fuzzy hierarchical analysis approach has some limitations in dealing with decision-making problems, especially in dealing with ambiguity and consistency. The choice of Gaussian Fuzzy Monte Carlo ANP (GFMANP) over other potential decision-making models, such as traditional ANP or Bayesian networks, is justified by its ability to handle the complexity of the decision-making process in the context of coal mine safety. GFMANP combines the strengths of ANP in managing interdependencies with the robustness of fuzzy logic and Monte Carlo simulations to deal with uncertainty and variability in data. This hybrid model provides a more nuanced and accurate representation of the decision-making process, which is crucial for the high-stakes environment of coal mine safety management.

Gaussian fuzzy numbers are a type of fuzzy number that employs the Gaussian function to represent the uncertainty of a variable. They are particularly useful in this study for modeling the uncertainty associated with the frequency and severity of coal mine accidents across different regions²³. By introducing Gaussian fuzzy numbers instead of the traditional triangular fuzzy numbers, these limitations can be overcome based on the advantages of the Gaussian distribution, which represents a true judgment of expert judgments and statistical data, thus improving the accuracy and realism of the decision-making process²⁴.

(1) Conversion of Gaussian fuzzy numbers.

According to the Saaty linguistic preference measure in Table 12 of the appendix, the triangular fuzzy number is expressed as (l_k, m_k, u_k) , l_k , m_k , and u_k are the possible minimum, median, and maximum values of each element, respectively. The rule $k = T[l_k, m_k, u_k] = G[x : \mu_i^k, \sigma_i^k]$ is followed to convert the triangular fuzzy number (TFN) into a Gaussian fuzzy number (GFN)²⁵, and the attributes and alternatives are evaluated by GFN.

(2) Monte Carlo simulation.

Monte Carlo simulation is a powerful and flexible numerical method for solving many problems with stochasticity and uncertainty that are difficult to deal with by traditional methods, and for improving the efficiency of decision-making²⁶. In fuzzy multi-criteria decision-making, it can be used to assess the combined performance of alternatives.

This article uses the Monte Carlo method to obtain Monte Carlo Gaussian fuzzy numbers by simulating the minimum value \bar{l}_k , the median value \bar{m}_k , and the maximum value \bar{u}_k of the random variable²⁰. The initial mean and standard deviation (μ_i^k and σ_i^k) obtained from the pairwise comparison table are used in the simulation process to obtain 1000 random variables in the range of 0 to 1, thus determining the random mean $\bar{X}_i^k = \text{random}(\mu_i^k)$ and standard deviation $s_i^k = \text{random}(\sigma_i^k)$ that conform to the Gaussian distribution.

(3) Relative weight calculation.

Before determining the evaluation model of coal mine accident regulatory factors, it is necessary to operate the fuzzy matrix between the constructed indicators to find out the relative weight of each indicator.

First, the relative importance of each factor in the pairwise comparison table is assessed using linguistic variables, which are represented by ternary numbers \bar{l} , \bar{m} , and \bar{u} . Gaussian fuzzy numbers are applied to construct the judgment matrix. Assuming that the degree of influence of attribute Q_i or alternative C_i on the j alternatives or attributes corresponding to it is the sub-criterion, the pairwise comparison judgment matrix is constructed. In the matrix \bar{P}_{ij} , $P_{ij} = (\bar{l}_{ij}, \bar{m}_{ij}, \bar{u}_{ij}) = (\bar{l}_i/\bar{u}_j, \bar{m}_i/\bar{m}_j, \bar{u}_i/\bar{l}_j)$, for any P_{ij} , P_{ji} ($i \neq j$) has: $\bar{l}_{ij} + \bar{u}_{ji} = \bar{m}_{ij} + \bar{m}_{ji} = \bar{u}_{ij} + \bar{l}_{ji}$.

Next, the elements in each matrix P_{ij} are normalized. The fuzzy weights of each attribute and alternative in the Gaussian fuzzy pairwise comparison matrix are calculated using geometric averaging²⁷, to obtain the fuzzy value of the i th attribute or alternative under the j th alternative or attribute.

The mean values and standard deviation values were recalculated.

Finally, the Gaussian fuzzy value of the i th attribute or alternative is de-fuzzified to obtain the clarity value Z_i . Determine the canonical geometric vector $W_{ij} = (Z_{i1}, Z_{i2}, \dots, Z_{in})^T$ with the attribute or scheme i as a sub-criterion i . If i has no effect on j , then $W_{ij} = 0$.

(4) Create a super-matrix.

To account for the network relationships during the GFMANP analysis²⁸, an unweighted super-matrix W was constructed based on the normalized interrelationship values obtained in the FDEMATEL evaluation and the de-fuzzified canonical weight matrices from the GFMANP assessment.

W_{ij} is normalized in the unweighted super-matrix but not in the overall unweighted super-matrix. Therefore, the clear values of the weights obtained from the hierarchical analysis were normalized and multiplied with the unweighted super-matrix to determine the weighted super-matrix \bar{W} . The limiting super-matrix $\bar{W}^k = \lim_{k \rightarrow \infty} \bar{W}^k$ is constructed by raising the limiting power of the weighted super-matrix until the elements in the rows of the super-matrix are equal to each other, reaching a stable value.

(5) Determination of the final significant value of GFMANP.

These limit values are used as unique column vectors of the matrix \bar{W}^k indicating the importance of the contributing factors for the final variable evaluation. Prioritization of final attributes and alternatives based on quantitative values of the importance of factors²⁹.

Results and discussion

Structural equation modelling analysis

Modelling

As a basis for the Fuzzy Decision-Making Trial and Evaluation Laboratory (FDEMATEL), this study uses Structural Equation Modeling (SEM) to quantify the interactive relationships between the regulatory factors of coal mine accidents and their indicator variables. SEM analysis was carried out using IBM SPSS Amos 24.0.0.0 (https://pan.baidu.com/s/136pSIFkIwI_ra26UZSWIJw?pwd=fp8t), which is popular for its functionality, user-friendliness, and intuitive graphical interface.

In the constructed model (Fig. 5), the rate of accidents due to regulatory factors is defined as the endogenous latent variable R, while the variables A, B, C, D, and E serve as exogenous latent variables explaining these regulatory influencing factors. Specifically, A1-3, B1-3, C1-3, D1-3, and E1-3 represent indicator variables related to design schemes, management systems, technical documents, organizational measures, and process methods, respectively. e4-e19 denote the measurement errors of the indicator variables, p4-p19 denote the path coefficient between the indicator variable and its corresponding latent variables, π represents the correlation between exogenous latent variables, and υ represents the effect of the exogenous latent variable on the endogenous latent variable R.

This method assumes that the relationships between variables are linear and that the data are normally distributed. It also presumes that the sample size is sufficiently large to yield stable parameter estimates. However, these assumptions may not always be valid, particularly in complex systems such as coal mine safety, where relationships can be non-linear and the data may not follow a normal distribution.

Model testing and modification

The fitness of the model was assessed by the following metrics: CMIN/DF, RMSEA, RMR, GFI, AGFI, IFI, TLI, and CFI. According to the results in Table 1, the value of CMIN/DF (chi-square degrees of freedom ratio) is 2.365, which is in the ideal range of 1–3; the value of RMSEA (root mean square of error) is 0.049, which is below the standard of excellence of 0.05; and the other indexes, such as GFI, AGFI, IFI, TLI and CFI, are all over the level of excellence of 0.9. These results indicate that the model has good fitness.

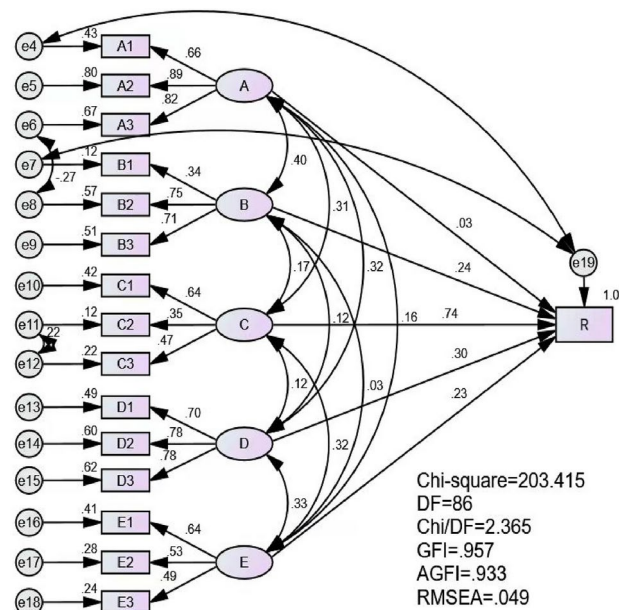


Fig. 5. SEM analysis model diagram of regulatory factors leading to coal mine accidents.

Detection indicators	CMIN/DF	RMSEA	RMR	GFI	AGFI	IFI	TLI	CFI
reference standard	1–3	<0.08	<0.08	>0.8	>0.8	>0.8	>0.8	>0.8
Actual results	2.365	0.049	0.010	0.957	0.933	0.960	0.944	0.960

Table 1. Model fit tests.

The structural equation model fitness results show that all parameters met the critical requirements for goodness of fit. Therefore, the results of SEM analysis can be used to assess cases of coal mine accidents caused by regulatory factors. The correlation coefficients and regression coefficients are represented by (π ; $\hat{\nu}$), and the relationships between the exogenous latent variables and their effects on the endogenous latent variable Y are as follows: $A \leftrightarrow B$, $\pi=0.40$; $A \leftrightarrow C$, $\pi=0.31$; $A \leftrightarrow D$, $\pi=0.32$; $A \leftrightarrow E$, $\pi=0.16$; $B \leftrightarrow C$, $\pi=0.17$; $B \leftrightarrow D$, $\pi=0.12$; $B \leftrightarrow E$, $\pi=0.03$; $C \leftrightarrow D$, $\pi=0.12$; $C \leftrightarrow E$, $\pi=0.32$; $D \leftrightarrow E$, $\pi=0.33$; $A \rightarrow R$, $\hat{\nu}=0.03$; $B \rightarrow R$, $\hat{\nu}=0.24$; $C \rightarrow R$, $\hat{\nu}=0.74$; $D \rightarrow R$, $\hat{\nu}=0.30$; $E \rightarrow R$, $\hat{\nu}=0.23$.

While the SEM model shows good fitness, potential biases due to the nature of the data should be considered. The data, sourced from reports of the safety and security department, might introduce biases related to underreporting or misclassification of incidents. Additionally, the subjective nature of expert input in constructing the fuzzy scales for FDEMATEL can affect the model's objectivity.

The SEM analysis shows that technical documents factor C has the most significant effect on the accident rate, with an impact coefficient $\hat{\nu}$ of 0.74, implying that the quality and availability of technical documents play a crucial role in accident prevention. This is because technical documents establish standardized procedures and guidelines to ensure consistency of operation by operators, in addition, they outline how to handle hazardous materials, operate and maintain machinery, and manage potential risks, as well as provide emergency response measures and further risk reduction in the event of an accident. Any deficiencies or inaccuracies in these documents could lead to a misunderstanding of safety protocols, resulting in a higher likelihood of accidents.

Management systems factor B, organizational measures factor D, and process methods factor E also had a significant but relatively small impact on accident rates, with impact coefficients $\hat{\nu}$ of 0.24, 0.30, and 0.23, respectively. This implies that while these factors are important, they may not be the primary drivers of accident rates. The relatively smaller impact could be attributed to the fact that these factors often rely on the foundational guidance provided by technical documents. For instance, a robust management system is essential, but its effectiveness is contingent upon the accuracy and applicability of technical documents that inform its policies.

Design schemes factor (A) has a minimal direct impact on accident rates, with an influence coefficient ($\hat{\nu}$) of 0.03. This might seem counterintuitive, as one would expect design flaws to lead to accidents directly. However, the low coefficient suggests that design issues often exacerbate other problems rather than causing accidents on their own. This could be because design schemes are often a static aspect at the outset of a project, while management systems and technical documents are dynamic and can mitigate risks associated with design flaws through ongoing oversight and adaptation.

In addition, according to the covariance coefficient between the exogenous latent variables, the highest correlation was found between design schemes factor A and management systems factor B, with a correlation coefficient of 0.40, indicating a strong positive correlation. The high correlation suggests that safety conditions considered during the design stage are closely linked to the successful establishment and implementation of management systems. This highlights the importance of a consistent approach to safety from the earliest stages of mine development through to operational management. Often, the design phase and the establishment of management systems take place simultaneously. The initial design must consider the practicalities of implementing a management system that can enforce safety standards. Conversely, a management system that is well-aligned with the design's intent can more effectively identify and address safety issues that may arise due to design limitations. This finding highlights the importance of the interdependence between design schemes and management systems in coal mine safety management to ensure safe and efficient production.

FDEMATEL analysis and evaluation

In the above study, structural equation modeling (SEM) was used to assess the correlation between the factors influencing coal mine accidents involving design schemes (A), management systems (B), technical documents (C), organizational measures (D), process methods (E), and the incidence of regulatory accidents (R). Next, the interrelationships between these variables were further explored using Fuzzy Decision Laboratory Analysis (FDEMATEL).

The correlation and regression coefficients derived from the SEM analysis were used to create a direct relationship matrix (Table 2) and express the assessed variables using triangular fuzzy numbers. This allowed for a quantitative association between the variables being assessed. Using MCDM Online Tools (<https://mcdm.adsa.bghhg23.xyz/>), the comprehensive impact matrix Z is calculated, as shown in Table 3.

A threshold value of 0.2077 was determined by the mean of the elements in the matrix Z. If the value of the effect between the factors is lower than this threshold, it is considered that there is no significant effect between them. Accordingly, the following conclusions were drawn:

- Variable A significantly affects variables R, A, B, C, D, and E;
- Variable B significantly affects variables R, A, B, and C;
- Variable C significantly affects variables R, A, B, and E;
- Variable D significantly affects variables R, A, and E;
- Variable E significantly affects variables R, A, C, and D.

	R	A	B	C	D	E
R	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A	0.1622	0.1825	0.6472	0.5361	0.7190	0.6157
B	0.1851	0.3053	0.1689	0.2894	0.0000	0.0000
C	0.3536	0.1930	0.1839	0.0000	0.0000	0.2563
D	0.1264	0.1469	0.0000	0.0000	0.0000	0.1280
E	0.1727	0.1723	0.0000	0.1745	0.2810	0.0000

Table 4. Normalized integrated impact matrix.

Indicator Factor	Influence Degree	Arrange in Order	Influenced Degree	Arrange in Order	Centrality	Arrange in Order	Causality	Arrange in Order
R	0.0000	6	1.9895	1	1.9895	5	-1.9895	6
A	1.9377	1	1.6149	2	3.5526	1	0.3228	4
B	1.5742	3	1.206	3	2.7802	2	0.3682	2
C	1.7257	2	1.0223	4	2.748	3	0.7035	1
D	0.9409	5	0.6894	6	1.6303	6	0.2514	5
E	1.2982	4	0.9545	5	2.2527	4	0.3437	3

Table 5. Combined impact relationship and ranking of regulatory indicators related to coal mine.

Using Eqs.9–12, the degrees of influence, influenced, centrality, and causality were calculated. Table 5 summarizes the combined impact relationships of the indicator factors, including specific values and their rankings.

The causal effect of the regulatory factor on accidents (R) is negative, indicating a consequential relationship. The causal relationships of design schemes (A), management systems (B), technical documents (C), organizational measures (D), and process methods (E) are all positive values, indicating that all these factors have an impact on the occurrence of accidents in coal mines related to regulatory factors.

Further analysis of the factors in the cause category reveals that design schemes (A), management systems (B), and technical documents (C) have the highest influence degree at 1.9377, 1.7257, and 1.5742, respectively. They also have the highest influence degree at 1.6149, 1.2060, and 1.0223, respectively. This suggests that these three factors are the most important in the analysis of the causes of coal mine accidents' caused by regulatory factors. They are also the most influenced by other factors. Among them, Indicator Factor A has the highest influence degree and is highly influential, emphasizing the importance of design schemes in coal mine safety management and the need for continuous optimization. Indicator Factor B ranked third in terms of influence and being influenced, highlighting the significant role of management systems in preventing coal mine accidents, particularly in the enforcement and oversight of regulations. Indicator factor C ranks second in terms of influence but has a relatively low influenced degree. This suggests that the accuracy and completeness of technical documents are crucial to coal mine safety. Factor C is relatively independent and less affected by other factors. Indicator factors D and E have a lower influence degree and susceptibility to influence, but they still play a unique role. This implies that the selection of organizational measures and the enhancement of process methods can somewhat contribute to reducing the risk of accidents. However, their significance is less pronounced than design schemes and management systems.

According to the centrality ranking, factor A in design schemes has the highest centrality, indicating its undeniable importance in the safety management of coal mine accident regulations. Organizational measures factor D has the lowest centrality but still exert some influence on the safety of daily operations.

Finally, by taking centrality as the horizontal coordinate and causality as the vertical coordinate, and with the average centrality of 2.4922 for division, a coordinate diagram illustrating a causal relationship is depicted as shown in Fig. 7. The graphical results show that among the factors affecting coal mine regulatory factors, the importance of design schemes, management systems, and technical documents is high. In contrast, the importance of organizational measures and process methods is relatively low.

After a comparative analysis of the influence relationship between the factors affecting coal mine accident regulations, the following conclusions can be drawn:

The design schemes factor ranks the highest in influencing degree and being influenced degree. This indicates that the design schemes factor is the most critical regulatory factor influencing coal mine accidents. Its absence and defects directly lead to the system being unable to be implemented fundamentally, technical documents not being able to guide the operation effectively, and the measures and methods not being able to solve the problems in the operation process. This emphasizes the importance of optimizing design schemes to prevent coal mine accidents. Any change in design schemes needs to be considered carefully.

Compared with the technical documents factor, the management systems factor exhibits a lower influence degree on regulatory factors and a relatively higher susceptibility to being influenced. This may reflect the lack of adaptability of management systems in response to updates in technical documents and its excessive reliance

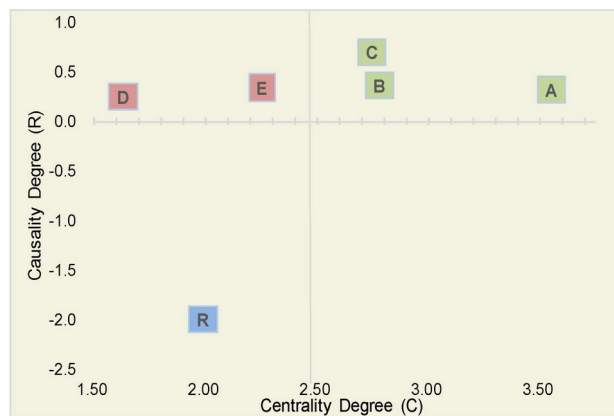


Fig. 7. Degree-of-center-cause cartesian coordinate diagrams.

on such information. If technical documents lack accuracy or timeliness, it may negatively impact management systems' effectiveness.

Organizational measures and process methods factors have low influence and are easily influenced among all the assessed factors. However, the direct impact of procedural methods on daily operational safety is more significant than organizational measures. Therefore, it is necessary to revisit and strengthen the strategy development and implementation process of organizational measures to enhance their role and effectiveness in the safety management systems.

Future policies should mandate comprehensive design reviews and integrate standardized design schemes from the outset. Subsequent research could investigate the development of adaptive management systems that respond in real-time to updates in technical documents and technological advancements. This exploration should include the incorporation of digital tools and automated monitoring to enhance the accuracy and timeliness of compliance with technical documents, ultimately improving the effectiveness of management systems. Furthermore, emphasis should be placed on how technological advancements, such as artificial intelligence (AI) and the Internet of Things (IoT), can strengthen the efficacy of methods and measures by providing real-time monitoring and predictive analytics for safety management.

GFMANP analysis and evaluation

This study defines the ultimate goal, assessment attributes, and alternatives through Structural Equation Modeling (SEM) analysis. In Gaussian Fuzzy Monte Carlo Analytic Network Process (GFMANP), various regions where coal mine accidents occur are utilized as assessment attributes. There are seven attributes, which are Northeast China (Q1), North China (Q2), East China (Q3), Central China (Q4), South China (Q5), Southwest China (Q6), and Northwest China (Q7). These regional attributes play a vital role in the assessment of GFMANP. The alternatives were then based on key causal factors from the study or endogenous potential variables from the SEM analysis, including design schemes (C1), management systems (C2), technical documents (C3), organizational measures (C4), and process methods (C5). The ultimate goal of the study is to quantify the regulatory factors that contribute to coal mine accidents.

Furthermore, the hierarchical and network structure of GFMANP was constructed based on the correlations and regressions identified in the SEM analysis and the interactions obtained in the FDEMATEL analysis. In the network layer, the arrows indicate the influence exerted by the first-end indicators on the end indicators. Figure 8 shows the hierarchical structure of the network of coal mine accident regulatory factors.

(1) Fuzzy pairwise comparisons.

Based on the importance of the identified attributes and alternatives, a fuzzy comparison matrix between the indicators was constructed and their relative weights were calculated. The significance of all assessment attributes and options is measured in terms of the frequency and severity of accidents in a given area in a given year, with the frequency being signaled by the number of accidents per year in different regions, and the severity being indicated by the number of accident fatalities and injuries.

(2) Monte Carlo simulation.

Before the calculation of the network structure, a pairwise judgment table was developed based on the importance levels of the attributes and alternatives. This table served as the foundation for evaluating the Gaussian fuzzy analysis network process. The mean μ_i^k and standard deviation σ_i^k of all-cause alternatives and regional attributes obtained in the pairwise judgment table are subjected to Monte Carlo simulation. This process helps in determining the minimum value (\underline{l}_k), median value (\overline{m}_k), and maximum value (\overline{u}_k) values of random variables following a Gaussian distribution. These values are then used to calculate the Monte Carlo Gaussian fuzzy numbers. Using the Northeast region (Q1) as a sub-norm example, a pairwise comparison matrix is established as shown in Table 6. The evaluation results of the alternatives with corresponding attributes are calculated based on the pairwise comparison matrix (Table 7).

(3) Weight vector matrix construction.

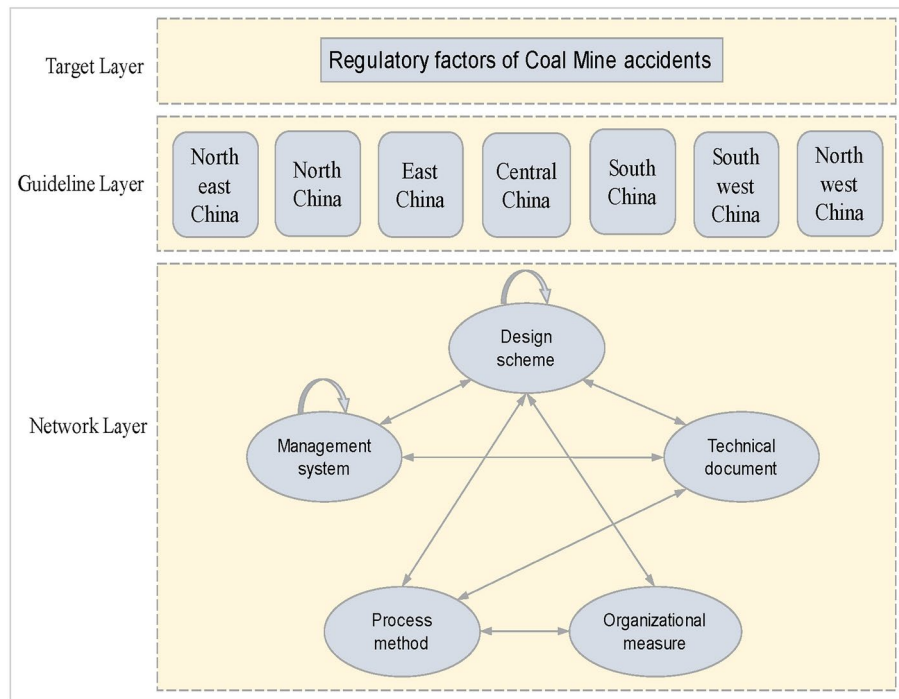


Fig. 8. Using GFMANP to assess the hierarchy and network structure of regulatory factors for coal mine accidents in different regions.

Q1	C1			C2			C3			C4			C5		
C1	1.00	1.00	1.00	0.89	1.00	1.13	0.29	0.32	0.37	0.61	0.69	0.78	0.42	0.48	0.54
C2	0.89	1.00	1.13	1.00	1.00	1.00	0.29	0.32	0.37	0.61	0.69	0.78	0.42	0.48	0.54
C3	2.73	3.08	3.47	2.73	3.08	3.47	1.00	1.00	1.00	1.88	2.12	2.39	1.31	1.48	1.67
C4	1.29	1.46	1.64	1.29	1.46	1.64	0.42	0.47	0.53	1.00	1.00	1.00	0.62	0.70	0.79
C5	1.84	2.08	2.36	1.84	2.08	2.36	0.60	0.68	0.76	1.27	1.43	1.62	1.00	1.00	1.00

Table 6. Fuzzy pairwise comparison matrix for indicators of coal mine regulatory factors. (Using Q1 in the Northeastern Region as a sub-criterion example).

	triangular fuzzy number			Gaussian fuzzy number	deblurred value
	l_i	m_i	u_i	$G[x : \bar{X}, \bar{s}]$	Z_i
C1	0.1097	0.1160	0.1228	$G[x : 0.1160, 0.1021]$	0.116232
C2	0.1097	0.1160	0.1228	$G[x : 0.1160, 0.1021]$	0.116232
C3	0.3368	0.3574	0.3780	$G[x : 0.3574, 0.3318]$	0.3573832
C4	0.1528	0.1688	0.1849	$G[x : 0.1688, 0.2585]$	0.1688359
C5	0.2210	0.2417	0.2625	$G[x : 0.2417, 0.3347]$	0.2417164

Table 7. Calculations results of Monte Carlo Gaussian Fuzzy for various indicators of coal mine regulatory factors. (Using Q1 in the Northeastern Region as a sub-criterion example).

Similarly, the Gaussian fuzzy results of the area attribute corresponding to the alternatives were calculated. The de-fuzzified values of the corresponding criteria were used to construct the weight vectors of the network structure for computing the parsed network structure in the super-matrix. The obtained clear weight vector matrix is shown in Tables 8–9.

(4) Extreme super-matrix calculation.

The unweighted super-matrix was constructed based on the normalized composite impact matrix of FDEMATEL and the weight vector of GFMANP. The super-matrix was weighted to obtain the final assessment values of the attributes and alternatives. The overall weights of the indicators were calculated using the software

W _q	Q1	Q2	Q3	Q4	Q5	Q6	Q7
C1	0.1162	0.0684	0.2290	0.2151	0.4831	0.1489	0.1558
C2	0.1162	0.0684	0.1583	0.2151	0.0000	0.0223	0.1047
C3	0.3574	0.4080	0.2290	0.2151	0.5242	0.6698	0.4800
C4	0.1688	0.0471	0.1584	0.1437	0.0000	0.0114	0.1047
C5	0.2417	0.4080	0.2290	0.2151	0.0000	0.1489	0.1558

Table 8. Clear weight vector matrix with each regional indicator of coal mine accidents as sub-criteria.

W _c	C1	C2	C3	C4	C5
Q1	0.0158	0.0758	0.0111	0.1673	0.0294
Q2	0.0229	0.1100	0.0314	0.1152	0.1214
Q3	0.0106	0.0352	0.0024	0.0543	0.0094
Q4	0.0158	0.0758	0.0036	0.0774	0.0141
Q5	0.0073	0.0000	0.0017	0.0000	0.0000
Q6	0.9128	0.6543	0.9404	0.5113	0.8140
Q7	0.0158	0.0509	0.0111	0.0774	0.0141

Table 9. Clear weight vector matrix with indicators of individual regulatory factors for coal mine accidents as sub-criteria.

	R	Q1	Q2	Q3	Q4	Q5	Q6	Q7	C1	C2	C3	C4	C5
R	0.2856	0.2856	0.2856	0.2856	0.2856	0.2856	0.2856	0.2856	0.2856	0.2856	0.2856	0.2856	0.2856
Q1	0.0140	0.0140	0.0140	0.0140	0.0140	0.0140	0.0140	0.0140	0.0140	0.0140	0.0140	0.0140	0.0140
Q2	0.0232	0.0232	0.0232	0.0232	0.0232	0.0232	0.0232	0.0232	0.0232	0.0232	0.0232	0.0232	0.0232
Q3	0.0064	0.0064	0.0064	0.0064	0.0064	0.0064	0.0064	0.0064	0.0064	0.0064	0.0064	0.0064	0.0064
Q4	0.0193	0.0193	0.0193	0.0193	0.0193	0.0193	0.0193	0.0193	0.0193	0.0193	0.0193	0.0193	0.0193
Q5	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005
Q6	0.2050	0.2050	0.2050	0.2050	0.2050	0.2050	0.2050	0.2050	0.2050	0.2050	0.2050	0.2050	0.2050
Q7	0.0174	0.0174	0.0174	0.0174	0.0174	0.0174	0.0174	0.0174	0.0174	0.0174	0.0174	0.0174	0.0174
C1	0.1136	0.1136	0.1136	0.1136	0.1136	0.1136	0.1136	0.1136	0.1136	0.1136	0.1136	0.1136	0.1136
C2	0.0634	0.0634	0.0634	0.0634	0.0634	0.0634	0.0634	0.0634	0.0634	0.0634	0.0634	0.0634	0.0634
C3	0.1505	0.1505	0.1505	0.1505	0.1505	0.1505	0.1505	0.1505	0.1505	0.1505	0.1505	0.1505	0.1505
C4	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322
C5	0.0688	0.0688	0.0688	0.0688	0.0688	0.0688	0.0688	0.0688	0.0688	0.0688	0.0688	0.0688	0.0688

Table 10. Limiting super-matrix.

yaanp 2.9.9957.25277, and the limiting super-matrix was established by performing 13 cycles on the weighted super-matrix as shown in (Table 10) (<https://pan.baidu.com/s/1Z59UtvBrRfouDEMEsE3sRQ?pwd=pi83>).

(5) Final assessment and interpretation.

Eventually, the values of each row in the finite super-matrix were used as a reference for the final GFMANP results. The final assessment summarized the most important accident regulatory factors, and the areas with the highest risk in terms of the regulatory factors of coal mine safety and production accidents were justified. The assessment results are shown in Fig. 9.

This study focuses on the regulatory risk factors of coal mine production. Through quantitative analysis methods, vital regulatory factors with significant impacts on coal mine safety were identified. This provides a scientific basis for developing effective prevention strategies.

The quantitative value of the significance of technical documents reached 0.1505, which is the highest among all assessed factors. This finding emphasizes the importance of technical documents in the coal mine safety management systems. Defects or errors in technical documents may lead to operational errors or neglect of safety measures, which may increase the probability of accidents. Therefore, coal mining enterprises should ensure the completeness, timeliness, and accuracy of technical documents as the basis for accident prevention.

The quantitative values of significance for design schemes, process methods, and management systems were 0.1136, 0.0688, and 0.0634, respectively. These data show that the rationality and safety of design schemes are critical to reducing the risk of accidents, the choice of process methods and the quality of their execution are directly related to the safety of daily operations, and management systems are the key link in ensuring that all safety procedures are followed. Coal mining companies should take measures in these areas, such as regularly

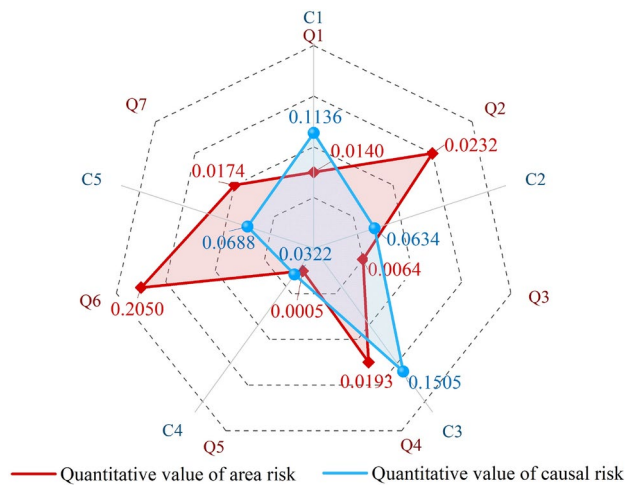


Fig. 9. Risks quantification results with various regional and regulatory causal factors of coal mine accidents.

reviewing design options, optimizing process flows, and strengthening the implementation of management systems.

When analyzed from the perspective of regional differences, the Southwest region has a significant quantitative value of 0.2050, notably higher than other regions. This may indicate that the region faces unique challenges regarding regulatory factors. This could be attributed to the region's complex terrain, which poses operational challenges, or potentially less stringent supervision and law enforcement. Additionally, the economic reliance on coal mining in Southwest China might lead to the prioritization of production over safety measures, resulting in a higher risk profile.

In comparison, the quantitative values of significance for East China and South China are 0.0064 and 0.0005, respectively. This suggests that Regulatory factors have not been a major contributor to accidents in these areas. Enhanced enforcement at coal mines, along with improved oversight across all levels of the organizational hierarchy, a more strategic allocation of safety resources, and a culture that prioritizes safety have all contributed to better regulatory performance in these regions. It shows that the regulatory framework is more effective and commitment to safety is stronger in East and South China.

For high-risk regions like Southwest China, with a significant quantitative value of 0.2050, our findings suggest a need for enhanced targeted safety supervision. Specific strategies such as stricter enforcement of safety standards, increased investment in safety technologies, and the development of region-specific safety protocols could mitigate risks. Additionally, implementing region-specific training programs for miners and management could also be effective.

These insights can guide the development of targeted safety strategies that consider regional nuances.

We found an interesting difference when comparing the results of the FDEMATEL model and the GFMANP model. In the FDEMATEL model, design schemes emerge as the most critical factor. Its absence or deficiency directly impacts the implementation, guidance, and problem-solving of the system. On the other hand, the GFMANP model highlights the technical documents factor with the highest quantitative value of significance, underscoring its central role. This distinction mainly arises from variations in the number and nature of accidents that occur in different regions. Problems with technical documents are particularly severe in specific regions, and these issues can result in serious injuries and fatalities as workers operate without the correct frame of reference. Therefore, although design schemes have the most significant influence degree, the inspection and management of technical documents should be given priority from the perspective of integrated risk management.

Based on the above analysis, we suggest that coal mining enterprises should take the following measures:

- Enhance synergy between design schemes and management systems: Ensure that design schemes are rational and closely integrated with management systems to prevent dysfunction. Establish a cross-departmental collaboration mechanism and conduct regular cross-functional meetings to enhance effective communication among designers, managers, and operators for discussing and resolving issues.
- Prioritize the management of technical documents: Focus on enhancing the management and updating of technical documents to guarantee their completeness, timeliness, and accuracy to minimize the risk of operational errors and accidents. Establishing a standardization and review process for technical documents is essential. For instance, setting up an update cycle and review frequency for technical documents can ensure their quality and reliability.
- Customized management of regional differences: Develop and implement targeted safety management strategies tailored to the specific conditions of different regions. Factors such as regional culture, rules, and geographical conditions are also taken into account to ensure that management measures are adapted to the local environment.

By implementing these strategies, coal mining enterprises can more effectively manage and reduce the risk of accidents at the regulatory level, thereby enhancing safety across the industry.

Overall, the analysis in this study reveals the core factors contributing to the regulatory risk in coal mine safety accidents. It is recommended that coal mining companies prioritize the management and updating of technical documents. However, they should not overlook the significance of design schemes, process methods, and management systems. In addition, developing targeted improvement measures based on the specific conditions of different regions will help elevate the safety standards of the entire industry.

Conclusions

In this paper, the key regulatory factors affecting coal mine safety and production accidents have been thoroughly analyzed and evaluated by adopting a fuzzy multi-criteria decision-making approach, which not only highlights the complex interactions among various regulatory factors but also identifies high-priority factors and region-specific risks that contribute to coal mine safety. The study mainly presents the following conclusions:

1. Design schemes and management systems are closely related; a scientific design scheme requires the support of an effective management system, and they rely on each other to ensure the safety of coal mines. For instance, the "Shenhua Coal Mine" has successfully integrated design solutions with management practices, leading to a notable reduction in accident rates over the past decade. This case exemplifies the potential benefits of aligning design and management strategies.
2. Design schemes, technical documents, management systems, organizational measures, and process methods interact significantly, with design schemes and management systems playing a crucial role that cannot be overlooked. A holistic approach that considers these factors is essential for mitigating risks.
3. Technical documents play a strategic role in risk management, and their accuracy and comprehensiveness are essential for ensuring coal mine safety. As demonstrated by the "Fuxin No. 1 Mine", where regular updates to technical documents have been linked to improved safety records.
4. Coal mine safety management in the Southwest region encounters unique challenges and necessitates safety strategies that are specifically tailored to the local environment and operating conditions. By examining the "Panzhihua Mine" in Sichuan, which has adapted national standards to local conditions, we can see the positive impact of region-specific safety strategies.

In summary, this research contributes to the field by applying fuzzy multi-criteria decision-making techniques to a complex real-world problem, by providing a robust methodological framework for identifying key factors and regional risks to coal mine safety. This sets a precedent for future research by advocating for more refined data analysis and exploring advanced analytical methods to further predict and prevent accidents.

While this study offers valuable insights, it also has limitations, such as a lack of detailed analysis for more granular factors. Future research could enhance this foundation by thoroughly developing and implementing more granular data collection methodologies, to capture and evaluate more detailed influences within regulatory factors. Undertaking comprehensive regional studies to create detailed safety profiles for each province. This would involve analyzing the unique geological, socio-economic, and operational conditions that affect mine safety to delving deeper into regional variations. Evaluating the efficacy of implementing the recommendations through case studies, before and after comparisons, and considering additional regulatory factors that could impact coal mine safety. Explore integrating new technologies, such as automation and remote sensing, into coal mine safety frameworks to enhance operational safety and accident prevention.

Data availability

All data generated or analysed during this study are included in this published article.

Appendix 1: detailed calculations of FDEMATEL and GFMANP

Triangular fuzzy semantic conversion table

The following table provides the conversion of the semantic scale to triangular fuzzy numbers (TFN) used in the Fuzzy Decision-Making Trial and Evaluation Laboratory (FDEMATEL) process (Tables 11, 12):

Semantic scale	Relationship scale	TFN
No impact	0	(0, 0, 0.25)
Very low impact	1	(0, 0.25, 0.50)
low impact	2	(0.25, 0.50, 0.75)
influential	3	(0.50, 0.75, 1.00)
High impact	4	(0.75, 1.00, 1.00)

Table 11. Triangular fuzzy semantic conversion table.

Semantic scale	Saaty scale	TFN	GFN
equivalence in importance	1	$T[l_1, m_1, u_1]$	$G[x : \mu_1^1, \sigma_1^1]$
Moderate importance	3	$T[l_3, m_3, u_3]$	$G[x : \mu_3^3, \sigma_3^3]$
High importance	5	$T[l_5, m_5, u_5]$	$G[x : \mu_5^5, \sigma_5^5]$
Very high importance	7	$T[l_7, m_7, u_7]$	$G[x : \mu_7^7, \sigma_7^7]$
Extremely high importance	9	$T[l_9, m_9, u_9]$	$G[x : \mu_9^9, \sigma_9^9]$

Table 12. TFN to GFN semantic conversion table.

Defuzzification and normalization equations

The defuzzification and normalization process involves the following equations:

1) Initial direct influence matrix construction:

$$C = c \begin{pmatrix} 0 & \dots & c_{1m} \\ \vdots & \ddots & \vdots \\ c_{m1} & \dots & 0 \end{pmatrix} = [c_{ij}]_{m \times m} \tag{1}$$

2) Normalization of triangular fuzzy numbers:

$$l'_{ij} = (l_{ij} - \min l_{ij}) / \Delta_{\min}^{\max} \tag{2}$$

$$m'_{ij} = (m_{ij} - \min m_{ij}) / \Delta_{\min}^{\max} \tag{3}$$

$$r'_{ij} = (r_{ij} - \min r_{ij}) / \Delta_{\min}^{\max} \tag{4}$$

where l'_{ij} , m'_{ij} and r'_{ij} denote the normalized minimum, median, and maximum values, respectively.

3) Standardization of maximum and minimum values:

$$u_{ij} = m'_{ij} / (1 + m'_{ij} - l'_{ij}) \tag{5}$$

$$v_{ij} = r'_{ij} / (1 + r'_{ij} - m'_{ij}) \tag{6}$$

where u_{ij} and v_{ij} denote the normalized standard values of the minimum and maximum values, respectively.

4) Calculation of clarity values for the direct relationship matrix:

$$t_{ij} = \min c_{ij} + \left[\frac{u_y^k(1 - u_y^k) + (v_y^k)^2}{1 - u_y^k + v_y^k} \right] \cdot \Delta_{\min}^{\max} \tag{7}$$

5) Clear direct influence relationship matrix:

$$T_{ij} = [t_{ij}]_{m \times m} \tag{8}$$

Comprehensive influence matrix establishment

1) Normalization direct influence relationship matrix:

$$X = k \cdot T = \frac{1}{\max_{1 \leq i \leq m} \sum_{j=1}^m t_{ij}} \times [t_{ij}]_{m \times m} \tag{9}$$

2) The comprehensive impact matrix is calculated using the unit matrix and the following equation:

$$Z = X(I - X)^{-1} = \begin{pmatrix} 0 & \dots & z_{1m} \\ \vdots & \ddots & \vdots \\ z_{m1} & \dots & 0 \end{pmatrix} = [z_{ij}]_{m \times m} \tag{10}$$

where I is the unit matrix.

Calculation of impact factors

Influence I – the sum of all elements in the row where a factor is located and indicates the value of the factor’s combined influence on all other factors. It is calculated as follows:

$$I = \sum_{j=1}^m z_{ij} \tag{11}$$

Being influenced D – the sum of the elements in the column in which a factor is located and indicates the

degree to which the factor is influenced by the combination of all other factors. It is calculated as follows

$$D = \sum_{i=1}^m z_{ij} \tag{12}$$

where z_{ij} denotes the influence value of element i on element j in the composite influence matrix Z . Centrality C – the sum of influence and being influenced and reflects the centrality and influence of a factor in the system. It is calculated as follows:

$$C = I + D \tag{13}$$

Causality R – the difference between the degree of influence and the degree of being influenced, revealing the causal relationship between factors. It is calculated as follows:

$$R = I - D \tag{14}$$

where C represents the degree of centrality of factor i , and R is the degree of causality of factor i .

Threshold determination

The threshold α is determined by the average value of the interactions among the elements of matrix Z :

$$\alpha = \frac{\sum_{i=1}^m \sum_{j=1}^m [z_{ij}]}{M} \tag{15}$$

where α is the threshold value of the matrix Z and M represents the total number of regulatory factor elements in matrix Z .

Normalized total relationship matrix

$$W = \frac{1}{\sum_{i=1}^m z_{ij}} \times [z_{ij}]_{m \times m} \tag{16}$$

The matrix W is constructed after excluding elements of Z below the threshold α and normalizing by row summation.

Gaussian fuzzy numbers conversion

The conversion of triangular fuzzy numbers (TFN) to Gaussian fuzzy numbers (GFN) is based on the Saaty linguistic preference measure, as detailed in Table 12.

1) Conversion between TFN and GFN:

$$l_k = \mu_i^k - (Z_{\frac{\alpha}{2}}) \frac{\sigma_i^k}{\sqrt{n}} \tag{17}$$

$$m_k = \mu_i^k \tag{18}$$

$$u_k = \mu_i^k + (Z_{\frac{\alpha}{2}}) \frac{\sigma_i^k}{\sqrt{n}} \tag{19}$$

2) Gaussian fuzzy number membership function

$$f(x | \mu_i, \sigma_i) = \frac{1}{\sigma_i \sqrt{2\pi}} \exp\left(-\frac{(x - \mu_i)^2}{2\sigma_i^2}\right) \tag{20}$$

2) Mean and standard deviation in line with independent Gaussian distribution:

$$\mu_i = \frac{1}{n} \sum_{m=1}^n x_m = \frac{x_1 + x_2 + \dots + x_n}{n} \tag{21}$$

$$\sigma_i = \sqrt{\sum_{m=1}^n \frac{(x_m - \mu_i)^2}{n - 1}} \tag{22}$$

where k is a measure of linguistic preference on the Saaty scale. i is the corresponding year. μ_i and σ_i represent the mean and standard deviation of the importance in i -year, respectively. $Z_{\frac{\alpha}{2}}$ denotes the critical value within the 95% confidence interval, usually 1.960. And n denotes the amount of data provided.

Monte Carlo simulation

The Monte Carlo method is employed to simulate the minimum, median, and maximum values of a random variable. This simulation technique can also be used to calculate the mean and standard deviation of a random variable that follows a Gaussian distribution.

Calculation of mean and standard deviation of random variables:

$$\bar{X} = \frac{1}{n} \left(\sum_{i=1}^N x_i \right) = \frac{x_1 + x_2 + \dots + x_n}{n} \quad (23)$$

$$s = \sqrt{\frac{\sum_{i=1}^N (x_i - \bar{x})^2}{n - 1}} \quad (24)$$

where \bar{X} represents the mean of the random variable, and s is the standard deviation of the random variable.

Relative weight calculation

The relative weight calculation involves constructing a judgment matrix and solving for the weight vector using geometric averaging. The defuzzification process is applied to obtain the clarity value.

1) Judgement matrix construction:

$$\tilde{P}_{ij} = \begin{bmatrix} (1, 1, 1) & P_{12} & \dots & P_{1j} \\ 1/P_{12} & (1, 1, 1) & \dots & P_{2j} \\ \dots & \dots & \ddots & \dots \\ 1/P_{1j} & 1/P_{2j} & \dots & (1, 1, 1) \end{bmatrix} \quad (25)$$

2) Fuzzy weight calculation:

$$\hat{l}_{ij} = \frac{\bar{l}_{ij}}{\sum_{i=1}^n \bar{l}_{ij}}; \hat{m}_{ij} = \frac{\bar{m}_{ij}}{\sum_{i=1}^n \bar{m}_{ij}}; \hat{u}_{ij} = \frac{\bar{u}_{ij}}{\sum_{i=1}^n \bar{u}_{ij}} \quad (i = 1, 2, \dots, n) \quad (26)$$

$$\tilde{w}_{ij} = [l_i = \left(\prod_{j=1}^n \hat{l}_{ij} \right)^{\frac{1}{n}}; m_i = \left(\prod_{j=1}^n \hat{m}_{ij} \right)^{\frac{1}{n}}; u_i = \left(\prod_{j=1}^n \hat{u}_{ij} \right)^{\frac{1}{n}}] \quad (27)$$

where l_i , m_i and u_i are the geometric means of the smallest, medium, and largest elements of the judgment matrix on the i row, respectively. \tilde{w}_{ij} denotes the fuzzy value of the i th criterion.

2) Calculation of mean and standard deviation of Gaussian fuzzy weight vector:

$$\tilde{X}_i = m_i \quad (28)$$

$$\tilde{s}_i = \frac{(\tilde{X} - l_i)\sqrt{n}}{(Z_{\frac{\alpha}{2}})} \quad (29)$$

3) Calculation of defuzzification clear value of Gaussian fuzzy value.

The Gaussian fuzzy value of the i th attribute or alternative is de-fuzzified using Eq. 30 to obtain the clarity value Z_i .

$$Z_i = \frac{\int_{l_i}^{u_i} x f_{\tilde{w}_{ij}}(x) dx}{\int_{l_i}^{u_i} f_{\tilde{w}_{ij}}(x) dx} = \frac{\int_{l_i}^{u_i} \frac{x}{\sqrt{2\pi\tilde{s}_i^2}} \exp\left(-\frac{(x-\tilde{X}_i)^2}{2\tilde{s}_i^2}\right) dx}{\int_{l_i}^{u_i} \frac{1}{\sqrt{2\pi\tilde{s}_i^2}} \exp\left(-\frac{(x-\tilde{X}_i)^2}{2\tilde{s}_i^2}\right) dx} \quad (30)$$

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Author contributions

YY was responsible for the detailed data curation, development of the analysis framework, methodology crafting, visualization creation, and for leading the original manuscript drafting and editing for clarity and impact. CL was pivotal in the study's conceptualization, overseeing formal analysis, securing funding, and providing overall supervision to the team. QY contributed to the formal analysis, offered supervision, and played a role in the manuscript's review and editing. CW ensured the accuracy of the study's methods through the methodology and validation processes. ML enriched the manuscript with visualizations and was involved in the writing review and editing process. All authors reviewed the manuscript.

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Declarations

Competing interests

The authors declare no competing interests.

Additional information

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