Life Cycle Reliability and Safety Engineering
https://doi.org/10.1007/s41872-024-00276-4

ORIGINAL RESEARCH

Qualitative prioritization of accident risks in the mining industry

Kleopatra Petroutsatou[1] · Fani Antoniou[2] · Emmanouil Spyridon Markoulatos[3]

Received: 27 January 2024 / Accepted: 27 August 2024

Abstract

The mining industry is one of the industries that present a high degree of risk due to the unique working environment. This paper aims to rank risks related to the health and safety of workers in the mining industry by using a multi-criteria decision-making method. For the risk assessment, the fuzzy analytic hierarchy process (FAHP), which is based on the theory of fuzzy logic and can be used to deal with uncertain situations, was applied. An active underground mining project was selected as a case study, where, by observing the progress of the production process, the associated risks to health and safety were identified and recorded. Through the application of the FAHP, the risks identified in the case study and verified in the literature were ranked in order of importance based on the opinions of experts. The results of the risk assessment may guide all the stakeholders, i.e., project managers, workers, and public authorities, in the implementation of appropriate control measures to reduce or eliminate risk in this type of project.

Keywords Decision-making · Fuzzy analytic hierarchy process · Multi-criteria analysis · Risk analysis · Risk assessment · Underground mining project

1 Introduction

The mining industry is one of the industries with a high degree of risk, resulting in many fatal accidents and serious injuries (Gul et al. 2019). The increased risk that characterizes it is due to its peculiarities regarding the working environment, the mechanical equipment used, the temporary location of its installation, and its general dynamics. The mining industry is constantly developing its underground production equipment and working environment but has not yet achieved zero fatalities.

Based on the latest reports published in the European Union in 2017, over 9800 occupational accidents and 48 deaths of workers employed in the mining industry were recorded (ILO 2018). In Greece, the mining and quarrying industry is blamed for 2.1% of all accidents. From the latest activity reports submitted for the year 2017, combined with the data of the Safety Auditors of Northern and Southern Greece for the same period, it appears that ninety-four (94) industrial accidents occurred, two of which were fatal. Out of the total of 94 accidents recorded, 80 took place in mines, thus demonstrating the higher degree of risk involved in underground operations compared to surface operations (Greek Ministry of Environment 2018).

The mining industry worldwide is an economic catalyst, contributing to economic recovery and social progress of local communities (Wang et al. 2016). In Greece, the mining industry is an important economic activity, supplying mineral raw materials to vital sectors of the national economy and contributing positively to employment. To maintain high growth rates, companies operating in the industry should be committed to systematic risk management, identifying, and assessing risks, and making continuous efforts to reduce them to a tolerable level. Moreover, the damages due to accidents also include the development of a negative reputation apart from reduced productivity while increasing direct/indirect operating costs that result in firms losing

✉ Kleopatra Petroutsatou
kpetrout@civil.auth.gr

Fani Antoniou
fanton@ihu.gr

Emmanouil Spyridon Markoulatos
mmarkoulatos@outlook.com

[1] Department of Civil Engineering, Aristotle University of Thessaloniki, Campus GR, 541 24 Thessaloniki, Greece

[2] Environmental Engineering Department, International Hellenic University, Thessaloniki, Greece

[3] Hellenic Open University, Patras, Greece

Published online: 17 September 2024

competitiveness, making them economically vulnerable (Wang et al. 2016; Koulinas et al. 2019).

It is also well known that occupational accidents, in addition to the economic and social impacts on the victims and firms, also impact society. Most of the financial burden of an occupational accident is borne by the state. It includes the costs of health care, rehabilitation, and social benefits such as compensation for absence from work and early retirement due to disability or death. The impact of occupational accidents on society relates to the temporary or permanent lack of workers from the production process, the increase in mortality beyond the expected level, and the increase in the population of vulnerable groups requiring social protection and financial support (Targoutsidis 2008).

As stipulated by the current Greek legislation, every company that employs more than one worker must have a written occupational risk assessment, through which the study and assessment of occupational risks are carried out. However, it is not always clear in which order the identified risks should be addressed. Risk management is about making decisions on the mitigation or elimination of risks on an ongoing basis by comparing them with each other, thus constituting a Multi-Criteria Decision-Making (MCDM) problem. Health and safety decision-makers are interested in achieving the best possible risk mitigation measures with the lowest possible costs, quickly, and with the least possible human resources. Therefore, ranking risks in order of importance is a critical process for better risk management.

The determination of accident-contributing risks, hazards, factors, and/or causes in the construction industry has been widely investigated. According to Liang et al. (2020), at least 35% of published construction safety management research that has been published in the last 30 years aims to (a) analyze accident statistics, (b) identify and evaluate their causes, and (c) assess the risk of their occurrence. Interestingly, Meng et al. (2020) in their recent bibliographic review found that the application of game theory is on the rise in the research of safety in both construction and underground mining projects. Nevertheless, in most cases, statistical methods are applied to prioritize risks, factors, or causes. These include frequencies, correlation analysis, factor analysis, decision trees, and the relative importance index (RII). For example, recently, Winge and Albrechtsen (2018), Betsis et al. (2019), and Chen (2020) used actual accident data and correlation analysis to prioritize construction site risks in Malaysia, Greece, and China. On the other hand, Zhang et al. (2020) applied grey relational analysis to accident data from 571 construction accidents in China. Numerous researchers in the past 5 years have based their prioritization of construction site risks on opinions of experts based on questionnaire surveys and used the calculated frequencies or relative importance indices (RII) (Tayeh et al. 2020; Antoniou and Merkouri 2021)as well as, correlation analysis (Tayeh et al. 2020; Yap and Lee 2020)and factor analysis (Asilian-Mahabadi et al. 2020; Tayeh et al. 2020; Mosly 2022) to rank them in terms of importance. Very few such studies were found employing MCDM, particularly in relation to safety risks in construction. One earlier study by Amiri et al. (2016) employed decision trees to analyze a database of construction accidents throughout Iran between 2007 and 2011. More recently, Soltanzadeh et al. (2022) used FAHP for the risk assessment of 37 risk sources in a significant construction project in Iran based on expert opinion. On the other hand, several works have been found that apply MCDMs and group decision-making methods to prioritize and/or assess construction management decision criteria, delay factors, financial risks, and other ranking decision-making problems. For example, the Technique for Order Preference by Similarity to Ideal Situation (TOPSIS), the Delphi Method, the Preference Ranking Organization METHod for Enrichment Evaluations (PROMETHEE), and the Analytic Hierarchy Process (AHP) have been consistently used for such problems (Aretoulis et al. 2020; Antoniou 2021; Kalogeraki and Antoniou 2021; Petroutsatou et al. 2021, 2022; Petroutsatou and Kantilierakis 2023).

The AHP is a multi-criteria decision-making method developed by Saaty in the early 1980s that has been used significantly since and is still in wide use today. A simple search in Scopus (TITLE-ABS-KEY (ahp OR "analytical hierarchy process") returned 43.043 documents from 1980 to 2022. As seen in the figure, the trend through time is still on the rise, with a record of 4.667 documents published in 2022. The most significant percentage of these documents refer to the Engineering subject area (21.0%).

The method was created to contribute to the decision-making process characterized by many interrelated and sometimes conflicting factors (Saaty 1980). Its main innovation was the ability to systematically address many non-measurable and subjective criteria alongside measurable and objective criteria because it allows the integration of subjective evaluations by producing a common numerical basis for the solution using a specifically defined scale of 1–9. It is a measurement methodology that derives priority scores for a given set of items, i.e., criteria, alternatives, risks, etc. It requires the construction of a three or more-level hierarchy and a decision-maker to make judgments on pairs of elements (pairwise comparisons) to derive both the criteria weights and priority scores for each alternative against each criterion. The resulting scores at each level are then synthesized throughout to derive global priority scores for each alternative (Shapiro and Koissi 2017).

The process has been widely applied in the construction sector. Specifically, after a literature review it was found that it has been used to (a) select the optimal alternative based on multiple selection criteria, (b) determine selection criteria weights for use in other MCDM methods or (c) to rank classified lists of elements (risks, factors, criteria) according to their perceived importance or impact for prioritization purposes.

Numerous studies in the construction sector have examined the use of AHP for optimal alternative selection. Examples include the use of the AHP for equipment selection (Shapira and Goldenberg 2005; Petroutsatou et al. 2021, 2022), selection of construction contractors and subcontractors (Mustafa and Ryan 1990; Topcu 2004; Abudayyeh et al. 2007), project procurement system (Al Khalil 2002; Mahdi and Alreshaid 2005), selection of design firms (Cheung et al. 2002).

Using the first stage of the AHP to determine weights of selection criteria and then applying other MCDMs to make optimal choices between alternatives is also quite common. For example, it has been used with the Multi-Attribute Utility Theory (MAUT), the PROMETHEE, or the TOPSIS and other MCDMs for project procurement systems, contract type, and contractor selection problems (Antoniou et al. 2016; Antoniou and Aretoulis 2018; Salman 2022) and choice of disagreement resolution methodology (Chan et al. 2006). Finally, the research by Taylan et al. (2014) calculated selection criteria weights using fuzzy AHP and then applied TOPSIS for project selection based on risk assessment. Recently, it has been used to calculate weights to be inputted into an Artificial Neural Network (ANN) designed to predict major risks and construction project quality (Lin et al. 2022). Finally, El-Tourkey et al. (2022) applied AHP to calculate selection criteria weights and used MAUT for building construction's mobile crane selection.

The AHP, owing to its procedure that forces the decision-maker to make pairwise comparisons between elements per level, can be utilized successfully for prioritization purposes. This has been done by Li and Wen (2022) for prioritization of construction risks, by Wakchaure and Jha (2012) to prioritize bridge elements for maintenance, and by Cooksey et al. (2011) to rank good practice indicators for asset management. More recently, it has been used to prioritize the challenges of implementing modular integrated construction (Wai et al. 2023) and for ranking the importance of sustainability performance indicators (Rajabi et al. 2022). It is this method of application of the AHP that will be applied in this research that aims to prioritize a classified list of underground mining safety risks.

Although the AHP considers subjective judgment, it does not support the inherent uncertainty in human judgment Kutlu and Ekmekçioğlu (2012). To face this dilemma, many researchers turned to the fuzzy analytic hierarchy process (FAHP). Van Laarhoven and Pedrycz (1983) presented the first related work on FAHP in 1983, which compared fuzzy ratios described by triangular membership functions. In another variant, Buckley (1985) determined fuzzy priorities by applying trapezoidal membership functions. Chang (1996)introduces a new approach to the fuzzy analytic prioritization process by proposing the use of triangular fuzzy numbers and the application of the extended analysis method (Demirel et al. 2008; Kutlu and Ekmekçioğlu 2012).

This research aims to identify the risks related to health and safety of workers in the mining industry and to prioritize them based on the importance of addressing them according to expert opinion. The FAHP will be applied as it aims to prioritize underground mining safety risks by considering the views of three experts while supporting uncertainty in their judgement. The prioritization of risks guides health and safety managers to better allocate resources for mitigation or examination of the identified risks.

2 Literature review of risks in underground mining projects

In addition to the risks identified during the visit to the underground operation under consideration, an extensive literature review on the hazards occurring in underground operations was carried out to enrich further the list of identified hazards with sources of risk that were not perceived during the visit to the project under consideration. The methodology followed for the review was implemented in two phases. In the first phase, searches were carried out in scientific research databases (Scopus, Science Direct, Springer) to identify research related to the identification of risks in underground mining operations since 2010. The searches were performed based on keywords and their combinations, such as risk identification, underground mining projects, mining equipment, human factors, and human errors. In the second phase, a content analysis was carried out to eliminate irrelevant articles. Consequently, the number of selected sources for detailed review and identification of risks was limited to 17 scientific journal articles (Table 1).

After studying the articles in Table 1 in detail, it was found that eight of them identified risks during the construction processes in mining and quarrying sites. Specifically, Utembe et al. (2015), working on the identification of chemical hazards found in mining, report that the production of large amounts of dust during operations, which consists mainly of silica in crystalline form, can cause many respiratory diseases, such as upper respiratory tract irritation, silicosis, pulmonary tuberculosis and occupational asthma. They also stress that due to the exposure of workers to high levels of diesel particulate matter, in addition to causing cardiovascular dysfunction and eye and nose irritation, they may experience neuroinflammation and neurodegenerative diseases.

Tripathy and Ala (2018), in their effort to establish a baseline of identifiable risk sources in an underground mining project, collected statistics and audit reports from

Table 1 Articles related to the identification of risks in underground mining projects

References	Year	Scope of article
Badri et al. (2013)	2013	Managing safety in underground mining activities and building a knowledge base of risks in underground gold mining
Bahn 2013)	2013	Risk identification and risk management in underground mining operations
Smith et al. (2016)	2016	Identification of the risks involved in small-scale gold mining operations
Utembe et al. (2015)	2015	Identification of health risks in mining
Tong et al. (2019)	2019	Study of factors influencing unsafe behaviours associated with causing explosions in coal mines
Mahdevari et al. (2014)	2014	Assessment of health and safety risks associated with coal mining
Khanzode et al. (2011)	2011	Assessment and monitoring of risks in coal mines
Debia et al. (2017)	2017	Assessment of exposure to diesel emissions of workers in gold mines
Tripathy and Ala 2018)	2018	Identification of hazards encountered in underground lignite mining
Domínguez et al. (2019)	2019	Assessment of risks in underground mining and risk mitigation measures
Galvin 2016)	2016	Hazards encountered in underground mining operations
Dhillon 2009)	2009	Hazards arising from the use of mechanical equipment
Patterson and Shappell 2010)	2010	Analysis of unsafe behaviour of workers in the mining sector
Lenné et al. (2012)	2012	Analysis of factors related to human errors and unsafe behaviour
Liu et al. (2018)	2018	Analysis of human factors associated with accidents in coal mines
Yaghini et al. (2018)	2018	Human errors and unsafe behaviours in the mining industry
Saleh and Cummings 2011)	2011	Risks associated with the blasting process

7000 accidents between 2001 and 2014 in India. They identified a series of significant risks associated with the misuse of mechanical equipment, the blasting process, the ventilation systems and flooding of the galleries. Similarly, research by Khanzode et al. (2011) also ranks low lighting, the presence of groundwater, and poor maintenance of mechanical equipment as possible causes of accidents in underground mining projects.

Bahn (2013) documents a list of risks created with the input of 77 underground mining workers. The identified risks were classified into four risk groups: prominent, insignificant, emerging, and non-obvious risks. The risks identified by the workers included mechanical failures leading to loss of hydraulic fluid pressure, faulty equipment, poor operator education and training, water ingress (flooding), human behavior, lack of communication and failure to follow safety procedures.

Mahdevari et al. (2014), after collecting information on three underground mining operations, identified 86 potential health and safety hazards for workers. The identified hazards included releases of gaseous pollutants such as H_2S, CO, CO_2 and NO, disruption of ventilation systems, vibrations caused by mechanical equipment throughout the body and missing procedures to deal with non-activation of explosives. Other hazards due to organizational factors include the non-use of personal protective equipment (PPE), lack of fire-fighting equipment, unauthorized entry into the explosion area, inadequate personnel training, and insufficient supervision.

(Liu et al. 2018) collected statistics on 362 serious underground mining accidents in China from 2000 to 2016 that are intertwined with human factors. Their results showed that supervision deficiencies are the main reason for major coal mine accidents, including failure to implement existing regulations, failure to identify problems related to the selection of personnel, lack of machinery maintenance, inefficient training procedures and inadequate supervision of operations. In addition, they found that the poor mental state of workers, including those operating machinery, is a precursor to unsafe behavior that manifests itself as mental fatigue, low alertness, and lack of concentration. Although human error is of great importance, psychosocial factors are often overlooked in the risk assessment process. The physical working environment is also a precursor to unsafe behavior due to the unfavorable conditions prevailing in underground works. Regarding dangerous behaviors of workers, the most common reasons are violation of regulations and wrong decisions.

Lenné et al. (2012), in their effort to better understand the systemic factors involved in mining accidents, examined 263 major accidental events in Australia during 2007–2008, which they analyzed using the Human Factors Analysis and Classification System (HFACS). In terms of the hazards arising from the production process, these are mainly due to the presence of project machinery working at height and the presence of electricity networks. They determined that in accidents caused by human error, 90% are related to unsafe acts. The most common dangerous actions of workers involved failure to identify the risks involved in completing a task, incorrect use of work equipment and failure to use PPE. Restricted underground access, low lighting levels, adverse weather conditions and an unfavorable mental state were found to be precursors of unsafe behaviors. Regarding errors due to inadequate supervision, these are mainly due to a lack of communication or coordination between crews, insufficient preparation, and time pressure.

3 Methodology

A three-stage methodology was applied to identify and rank the risks encountered in the mining industry. Firstly, the production process of an actual underground mining project was monitored, and potential health and safety risks were identified and recorded in a risk list after on-site visits and interviews with the site and safety engineers. This list was enriched by hazards found in the literature review (Sect. 2). The final list was divided into five categories: physical, environmental, chemical, organizational and human risks, forming the risks' hierarchical structure.

Secondly, by applying a knowledge mining technique (Antoniou et al. 2013), three experts employed in the mining project rated the importance of the risk categories and risks that make up the hierarchical structure using linguistic variables. Finally, by applying the FAHP, the risk categories and risks were ranked in ascending order according to their importance. This approach determines and discusses the risks that should be avoided or mitigated to pave the strategy plan of companies involved in this industry (ISO 31000:2018).

3.1 The AHP

The main feature of the AHP is its inherent capability of systematically dealing with many non-quantifiable attributes, as well as with tangible and objective factors. The AHP allows for the incorporation of subjective judgments and user intuition into the decision-making process by producing a common formal and numeric basis for solutions. The process follows the following steps:

Step 1: Hierarchical problem structuring, which includes the decomposition of the problem and the creation of a hierarchy.
Step 2: Pairwise comparisons and creation of decision tables.
Step 3: Calculation of weights or priority values for each element in each decision matrix and consistency checks.
Step 4: Aggregation of resulting weights and priority values to evaluate rank alternatives.

Essentially, the AHP implements pairwise comparisons to enhance objectivity and produces one or more decision matrices per level. Each element is compared in terms of importance using the scale shown in Table 2.

The eigenvector of each decision matrix is the priority vector of the elements compared, which represents their relative weights regarding the element located one level higher in the hierarchy. The average of the normalized column method is used to calculate w_i, the relative weight of the element in row i (which is an element of the eigenvector w), for a reciprocal nXn matrix, is as follows:

$$w_i = \frac{1}{n} \times \sum_{j=1}^{n} \frac{a_{ij}}{\sum_{k=1}^{n} a_{kj}} \tag{1}$$

where a_{ij} = element is in row i and column j of the decision matrix.

The consistency of the obtained matrices is evaluated by calculating the consistency ratio (CR) as defined by Saaty (1980). The CR is a tool for controlling the consistency of pairwise comparisons. Since one of the advantages of AHP is its ability to allow subjective judgment, and with intuition playing an essential role in the selection of the best alternative, absolute consistency in the pairwise comparison procedure should not be expected. The CR enables one to control the extent of inconsistency to a maximum desirable level for each decision matrix and the entire hierarchy. Based on

Table 2 Intensity of importance scale

Intensity of importance	Definition
1	Equal
3	Moderate
5	Strong
7	Very Strong
9	Extreme
2, 4, 6, 8	Intermediate values between adjacent scale values
Reciprocals of above nonzero values	If activity i has one of the above ratings when compared to activity j, then j has the reciprocal value when compared with i

numerous empirical studies, Saaty (1980), stated that for tolerable inconsistency, the CR must be less than or equal to 0.10 irrespective of the nature of the problem; if this condition is not fulfilled, a revision of the comparisons is recommended. As a result, the consistency of each comparison matrix is calculated by:

$$CR = Consistency\,Index\,(II)/Random\,index\,(RI) \tag{2}$$

where $II = (\lambda_{max} - n)/(n - 1)$, with n the number of elements in the matrix, RI = the Random consistency index of a randomly generated reciprocal matrix and λ_{max} = the maximum eigenvalue of the comparison matrix.

3.2 The fuzzy analytic hierarchy process

When processing real-world problems, it is assumed that uncertain and imprecise data will have to be used. Therefore, there are better solutions than conventional approaches. An effective method to deal with uncertainty is the theory of fuzzy logic. Although humans are comparatively effective in qualitative prediction, they do not achieve quantitative predictions. Fuzzy linguistic models allow for the translation of verbal expressions into numerical values, thus quantitatively addressing the imprecision in expressing the meaning of each criterion (Kaya et al. 2012). Therefore, in decision-making problems, using imprecise information with qualitative characteristics, such as language variables, can only be exploited through a combination of the MCDM and fuzzy logic (Jakiel and Fabianowski 2015).

The FAHP incorporates fuzzy set theory into the AHP to select the optimal MCDM problem alternative. It differs from the AHP due to the introduction of linguistic variables in the process. That is, the comparison of elements is performed using linguistic variables (for example, significant, very significant, negligible, etc.) expressed by fuzzy membership functions (Chan and Wang 2013) instead of deterministic values. This reduces the ambiguity involved in the selection and degree of comparison of elements (risk categories and risks, in this case), thus accounting for the subjectivity of the judgments.

The primary approach of the FAHP is based on the use of triangular fuzzy numbers during pairwise comparisons to calculate the weights of the risk categories and the global priorities of each risk. The fuzzy weights must be defuzzified to prioritize the risks. In this method, the qualitative criteria (risks) are expressed in terms of weights defined by the experts. The local priorities calculated for each criterion (risk) are summed up into global priority scores by applying the principle of hierarchical composition.

When more than one decision-maker is involved in the evaluation process, the different risk matrices are combined to create a synthetic pairwise comparison matrix. The geometric mean method is the most popular approach for constructing synthetic matrices. Their values are converted from fuzzy to crisp, and the process continues according to the AHP (Chan and Wang 2013). The process is performed in four steps:

Step 1: First, pairwise comparison tables are created, considering all elements (risk categories and risks) and the opinion of each expert involved. In this step, those involved in decision-making are asked to compare the elements in each level against each other in verbal terms based on how important element is compared to another in terms of the objective. The verbal preferences are then converted into triangular fuzzy numbers. The following decision matrix is then generated:

$$\tilde{A} = \begin{bmatrix} 1 & \cdots & \widetilde{\alpha_{1,n}} \\ \vdots & \ddots & \vdots \\ \widetilde{\alpha_{n,1}} & \cdots & 1 \end{bmatrix} \tag{3}$$

where: $\tilde{a}_{ij} = 1/\tilde{\alpha}_{ji}$ and

$$\tilde{\alpha}_{ij} = \begin{cases} \check{1}\,\check{3}\,\check{5}\,\check{7}\,\check{9} & when\ i\ is\ relatively\ more\ important\ than\ j \\ 1 & if\ they\ are\ of\ equal\ importance\ i = j \\ \frac{1}{\tilde{1}}\,\frac{1}{\tilde{3}}\,\frac{1}{\tilde{5}}\,\frac{1}{\tilde{7}}\,\frac{1}{\tilde{9}} & when\ i\ is\ relatively\ less\ important\ than\ j \end{cases} \tag{4}$$

Step 2: Since the evaluation of the elements (risk category and risks) by more than one expert will lead to the creation of different comparison tables, it is necessary to create an aggregated table. The elements that will make up the aggregate table are calculated using the geometric mean method proposed by Buckley (1985) based on the number of E experts involved in the process.

$$\tilde{a}_{ij} = \left(\tilde{a}_{ij}^{1} \otimes \tilde{a}_{ij}^{2} \otimes \cdots \otimes \tilde{a}_{ij}^{E}\right)^{1/E} \tag{5}$$

Step 3: The fuzzy geometrical means ($\tilde{r}_j$) και the fuzzy criteria (risk) weights ($\tilde{w}_j$) are calculated using the following equations:

$$\tilde{r}_i = (\widetilde{a_{i1}} \otimes \widetilde{a_{i2}} \otimes \ldots \widetilde{a_{in}})^{1/n} \tag{6}$$

$$\tilde{w}_i = \tilde{r}_i \otimes (\tilde{r}_1 \oplus \ldots \tilde{r}_n)^{-1} \tag{7}$$

Step 4: Since the weights are expressed in verbal variables, the next step is to defuzzify them to form the ranking. Assuming that the fuzzy weights of each element can be expressed as:

$$\tilde{w}_i = \left(Lw_i, Mw_i, Uw_i\right) \tag{8}$$

where Lw_i, Mw_i, Uw_i are the lowest, mean, and highest fuzzy weight values for element i. The values of the defuzzified weights are given by:

$$w_i = \frac{\left[\left(Uw_i - Lw_i\right) + \left(Mw_i - Lw_i\right)\right]}{3} + Lw_i \tag{9}$$

Many approaches to FAHP are found in the literature. Buckley (1985) proposed fuzzy priorities of comparison ratios whose membership functions were trapezoidal. Chang (1996) proposed a new approach to the FAHP by introducing the use of triangular fuzzy numbers for pairwise comparisons and the use of the Extended Analysis (EA) method for the synthetic extent values of pairwise comparisons. His approach is one of the most popular FAHP approaches with wide use in risk assessment in the mining industry.

The successful application of the FAHP depends on the consistency with which the decision-maker's judgments are expressed. This problem is exacerbated when a group of experts carries out the decision-making. Therefore, the decisions of experts should be checked to avoid accepting judgments if they show a high degree of inconsistency. The consistency check must be carried out, as a pairwise comparison table showing a high degree of inconsistency may lead to incorrect results. To check the consistency of fuzzy comparison matrices, Gogus and Boucher (1998) suggest splitting them into two matrices and calculating the consistency ratio of each matrix according to the method proposed by Saaty (1980). The calculation of the consistency ratio is performed as follows:

Step 1: Since the judgments are expressed in fuzzy triangular numbers of the form $A_i = (l_i, m_i, u_i)$, each fuzzy comparison table is divided into two independent tables. The first table consists of the mean numbers of the linguistic variable against which each element has been assessed ($A_m = [a_{ijm}]$), while the second is generated by the geometric mean of the upper and lower bounds of the linguistic variable, i.e.:

$$\mathrm{A}_g = \left[\sqrt{a_{ijm}a_{ijl}}\right] \tag{10}$$

Step 2: The weight vectors for each comparison matrix are calculated using Saaty's (1980) method from the equations:

$$w_i^m = \frac{1}{n}\sum_{j=1}^{n}\frac{a_{ijm}}{\sum_{i=1}^{n}\sqrt{a_{ijm}}} \tag{11}$$

$$w_i^g = \frac{1}{n}\sum_{j=1}^{n}\frac{\sqrt{a_{iju}\times a_{ijl}}}{\sum_{i=1}^{n}\sqrt{a_{iju}a_{ijl}}} \tag{12}$$

Step 3: The largest eigenvalue λ_{max} of each matrix is calculated from the equations:

$$\lambda_{max}^m = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{n} a_{ijm}\left(\frac{W_i^m}{W_i^m}\right) \tag{13}$$

$$\lambda_{max}^m = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{n} \sqrt{a_{ijm}\times a_{ijl}}\left(\frac{W_i^g}{W_i^g}\right) \tag{14}$$

Step 4: The Consistency Index (CI) is calculated for each table according to the equations:

$$CI^m = \frac{\left(\lambda_{max}^m - n\right)}{n-1} \tag{15}$$

$$CI^g = \frac{\left(\lambda_{max}^g - n\right)}{n-1} \tag{16}$$

Step 5: The Consistency Ratio (CR) of each table is calculated according to relations (14) and (15). It is calculated by dividing the consistency ratio by the Random consistency index (RI) defined for each table as given by Gogus and Boucher (1998)

$$CR^m = \frac{CI^m}{RI^m} \tag{17}$$

$$CR^m = \frac{CI^g}{RI^g} \tag{18}$$

The matrix under consideration is considered to contain consistent judgments if the two consistency ratios are equal to or less than 0.1. In case the consistency ratios have values greater than 0.1, the decision makers are asked to repeat the process of comparing the elements (risk categories and risks) (Fig. 1).

4 Case study application of FAHP

4.1 Development of the risk registry

The mining industry is one of the most hazardous workplaces. Accident prevention should be based on identifying the risks that have a significant role in safety management so that they can be used as drivers to reduce accidents and improve prevention methods. Identifying all risks is a critical process because it must ensure that no risk is omitted from the risk assessment process. The observation of the

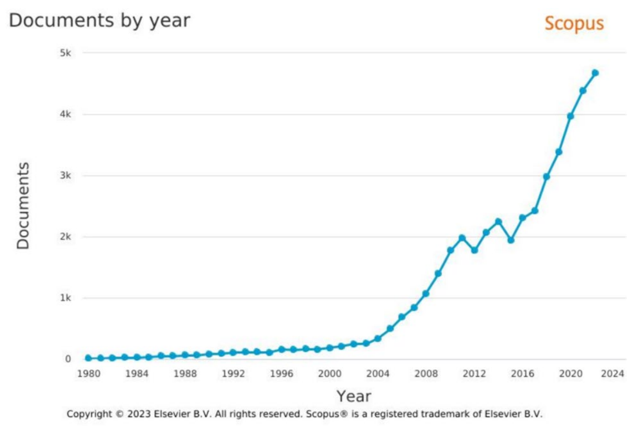

Fig. 1 AHP documents published yearly in Scopus

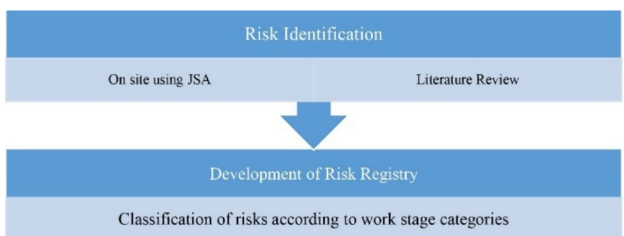

Fig. 2 Risk identification and classification process

working environment and the recording of the production process, including the technological, the material and the chemical means, should be conducted. Expert assessments, results and reports from on-site inspections and audits can additionally be used.

The risk identification process aims to establish a comprehensive Risk Registry with all the potential risks that may have an impact on the achievement of the workplace objectives and, consequently, on the health and safety of the organization's workers. This phase also aims to identify the nature and extent of all possible consequences and to understand the likelihood and the impact of their occurrence. The use of accident statistics, occupational diseases and the study of accidents that have occurred in the past in related activities provide helpful information at this phase. The process of identifying sources of risk can be carried out with the help of tools such as checklists, risk indices, a Hazard and Operability study (HAZOP), Job Safety Analysis (JSA) and Failure Mode and Effects Analysis (FMEA) (Aven 2008) (Fig. 2).

The sources of risks occurring in underground mining projects were investigated and identified. Three information-gathering techniques were followed in conjunction with the job safety analysis (JSA) technique (Aven 2008). Data collection methods applied were on-site observation of the progress of the operations of the project under study, review of literature and collection of questionnaires from project personnel. Through the literature review, the Risk Registry was enriched, and risk prevention and response procedures and statistical reports of accidents related to the mining industry were recorded. Furthermore, to obtain factual data on the root causes of the hazards, a visit to an active underground mining project was carried out for a month, and several on-site interviews were conducted to consolidate the risk list based on the JSA approach.

A JSA is a method of systematic prevention of risks arising from a job, which aims to identify the risks or potential accidents associated with each stage of the job and, consequently, to identify measures to be taken to eliminate, or if this is not possible, to control the risks identified (Albrechtsen et al. 2019). The implementation of the method was carried out in two stages:

- The underground mining process was decomposed and separated into individual work stages according to their order of execution—the monitoring of the production process of the considered project assisted in the effective separation of the tasks.
- The possible accidental events and hazardous conditions that may endanger the health and physical integrity of workers are identified.

Applying the process of risk identification mentioned above, the risk registry presented in Table 3 was developed, recording the identified hazards based on the production stage where they might occur. Based on the risk registry, the risk analysis regarding the qualitative prioritization of risks will be performed.

As expected, the primary sources of risks are:

- Risks arising from the presence of electricity.
- Risks related to the use of mining machinery.
- Risks regarding the separation of rocks from the roof of the excavation face.
- Risks from slipping and falling from height.
- Risks arising from the placement and use of explosives.
- Risks arising from poor air quality.

4.2 Application of the FAHP methodology

After the risk identification phase, for risk qualitative risk analysis, the FAHP is applied, using expert comparative judgments of risks. This prioritization of risks includes the likelihood and consequence of the risk if it happens (ISO31000/2018). The approach adopted is that proposed by Buckley (1985) in his paper due to the weaknesses of other researchers' approaches. Understanding that different groups involved in the project have different objectives and expectations regarding risk management, they are expected

Table 3 Risk registry

Production stage	Potential risks to health and safety	Who is affected
Marking of position of blast holes	Slip hazard	Blasthole marker
	Risk of falling from a height	Blasthole marker
	Risk of overturning a basket vehicle	All bystanders
	Extreme exposure to noise	All bystanders
	Extreme exposure to dust	All bystanders
	Extreme exposure to vibration	Basket carrier operator
	Extreme exposure to exhaust fumes	All bystanders
Drilling of blast holes	Risk of electric shock	All bystanders
	Risk of a nearby worker's body part becoming entangled with the moving parts of the drilling machine	Auxiliary staff
	Slip hazard	Auxiliary staff
	Risk of ejection of machine moving parts-foreign bodies	Auxiliary staff
	Risk of overturning of the drilling machinery	All bystanders
	Risk of mechanical failure of the drilling system	All bystanders
	Risk of unstable rock falls	All bystanders
	Risk of unintentional explosions	All bystanders
	Risk of burns	Auxiliary staff
	Extreme exposure to noise	All bystanders
	Extreme exposure to dust	All bystanders
	Extreme exposure to vibration	Blasthole drill rig operator
	Extreme exposure to exhaust fumes	All bystanders
Priming of explosives	Risk of ejection of debris	Primers
	Slip hazard	Primers
	Risk of explosion during transport of explosives	All bystanders
	Risk of falling from a height	Primers
	Risk of overturning of a basket vehicle	All bystanders
	Risk of premature explosion	All bystanders
	Danger due to lack of communication	All bystanders
	Risk of mechanical failure	All in the danger zone
	Extreme exposure to noise	All bystanders
	Extreme exposure to vibration	Basket carrier operator
	Extreme exposure to exhaust fumes	All bystanders
Blasting	Risk of ejection of rock debris	All in the danger zone
	Risk of entrapment by detached rock masses	All in the danger zone
	Risk due to poor communication	All in the danger zone
	Extreme exposure to noise	All in the danger zone
	Extreme exposure to dust	All in the danger zone
	Extreme exposure to air pollutants	All in the danger zone
Loading and transport of geomaterials	Risk of mechanical failure	All in the danger zone
	Risk of entrapment by rockmasses	Auxiliary personnel
	Risk of crushing a worker	Auxiliary personnel
	Risk of collision during movement of vehicles	All bystanders
	Risk of unstable rock falls	All bystanders
	Risk of electric shock	Loader operator
	The danger of loader tipping over	All bystanders
	Extreme exposure to noise	All bystanders
	Extreme exposure to dust	All bystanders
	Extreme exposure to vibration	Loader and truck operators
	Extreme exposure to exhaust fumes	All bystanders

Table 3 (continued)

Production stage	Potential risks to health and safety	Who is affected
Debris removal operations	Risk of mechanical failure	All in the danger zone
	Risk of unstable rock falls	All in the danger zone
	Extreme exposure to noise	All bystanders
	Extreme exposure to dust	All bystanders
	Extreme exposure to vibration	Basket and bogger operator
	Extreme exposure to exhaust fumes	All bystanders
	Slip hazard	Mine workers
	Risk of falling from a height	Mine workers
	Risk of entanglement of adjacent workers with the moving parts of the excavator	Mine workers, excavator operator
	Risk of the excavator overturning	All bystanders
	Risk of overturning a basket vehicle	All bystanders
Gallery support works	Risk of electric shock	All in the danger zone
	Risk of an adjacent worker's body part becoming entangled with the moving parts of the drilling machinery	Auxiliary staff
	Risk of slipping	Auxiliary staff
	Risk of ejection of moving parts-foreign bodies	Auxiliary staff
	Risk of overturning of drilling machinery	All bystanders
	Risk of mechanical failure	All in the danger zone
	Risk of falling unstable rocks	All bystanders
	Risk of burns	Auxiliary personnel
	Extreme exposure to noise	All bystanders
	Extreme exposure to dust	All bystanders
	Extreme exposure to vibration	Blasthole drill rig operator
	Extreme exposure to exhaust fumes	All bystanders
Extension works of air, water, ventilation, and electricity networks	Risk of electric shock	Maintenance staff
	Risk of falling from a height	Maintenance staff
	Risk of entanglement of adjacent workers with the moving parts of the basket vehicle	All bystanders
	Risk of tipping of the basket carrier	All bystanders
	Extreme exposure to noise	All bystanders
	Extreme exposure to dust	All bystanders
	Extreme exposure to vibration	Maintenance staff
	Extreme exposure to exhaust gases	All bystanders

to approach the risk assessment process providing different perspectives.

For this reason, three decision-makers (DMs) from different positions in the project under consideration were selected to take part in the evaluation of the risk categories (criteria) and risks (sub-criteria). Table 4 shows the DMs 1–3 and their area of employment in the project under study. Applying the methodology of the FAHP, it is attempted to consider the subjectivity of the DMs' judgments and to reduce the uncertainty and ambiguity of the process. DMs from different backgrounds may express different opinions on the importance of the risks under consideration, leading to

Table 4 The employment position and years of experience of the participants

ID	Position	Years of experience
DM-1	Safety engineer	8
DM-2	Production engineer	17
DM-3	Foreman	20

inaccurate results in the decision-making process. To avoid this, pairwise comparisons between experts will be consolidated to include the subjective judgment of all participants in the process.

4.2.1 Defining the hierarchical structure

Considering the findings of the risk identification process and the extant literature review on the risks encountered in underground mining projects (Table 1), 24 risks (sub-criteria) were obtained (Table 5). Then, the hierarchical structure of the problem was developed, consisting of three levels, as shown in Fig. 3. Due to the nature of the problem under consideration, the hierarchical structure does not include a 4th level, which concerns alternative solutions, because the FAHP is being applied for prioritization or risks, not for the choice of an optimal alternative. At the left of the diagram, the main objective is placed, i.e., the risk prioritization, as part of the quantitative risk analysis of the risk assessment process. To the right, level 2 includes the risk categories, followed by level 3 of the hierarchy, which lists the risks per category. The five categories encompass physical risks, environmental risks, chemical risks, organizational risks, and human risks.

4.2.2 Pairwise comparison

The experts selected as DMs made pairwise comparisons between risk categories and then between risks within each category. Their judgments reflect the contribution of each risk category (criterion) and risk (sub-criterion) (how important a_i is relative to a_j) to the occurrence of risk. The comparison tables generated by the subjective judgment of

Table 5 The risks per category and their coding

Physical risks	C1
Slip hazard	SC1.1
Risk of falling from a height	SC1.2
Risk of entanglement of a worker's body part with the moving parts of machinery/moving project machinery	SC1.3
Risk of mechanical failure during execution of work	SC1.4
Risk of overturning of project machinery	SC1.5
Extreme exposure to vibrations	SC1.6
Risk of unstable rock falls-ejection of debris	SC1.7
Risk of unintentional explosions	SC1.8
Environmental risks	C2
Extreme exposure to noise	SC2.1
Risk of electric shock	SC2.2
Adverse environmental conditions (high temperature-humidity, low light)	SC2.3
Flooding	SC2.4
Chemical risks	C3
Extreme exposure to dust	SC3.1
Extreme exposure to exhaust fumes and blasting by-products	SC3.2
Inadequate ventilation system (insufficient capacity-malfunction)	SC3.3
Organizational risks	C4
Unskilled-Untrained Workers	SC4.1
Insufficient machinery and equipment maintenance	SC4.2
Lack of communication-coordination of work	SC4.3
Inadequate fire protection system	SC4.4
Non-use of PPE	SC4.5
Human risks	C5
Non-compliance with safety regulations	SC5.1
Mental fatigue, high stress and lack of concentration	SC5.2
Traffic violations (non-compliance with speed limits and unsafe parking of machinery)	SC5.3
Wrong decisions during the execution of tasks	SC5.4

Fig. 3 Illustration of the risk hierarchical structure

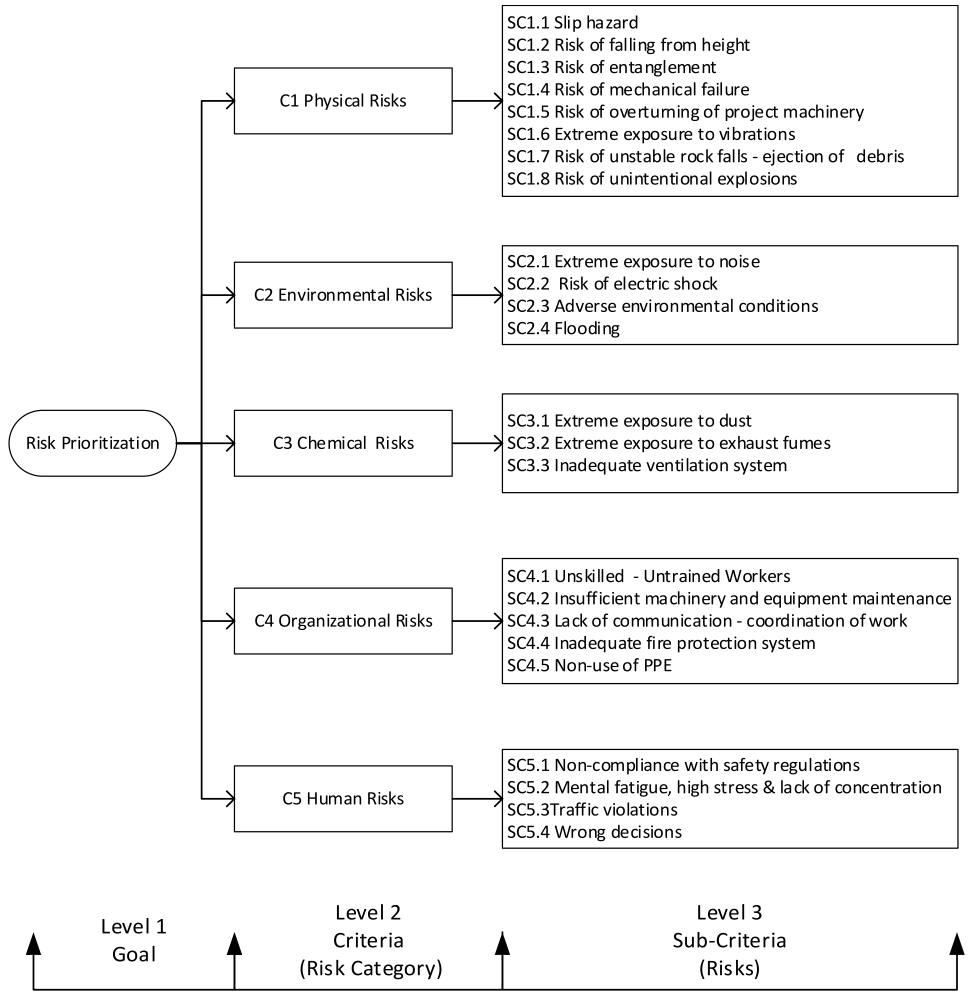

Table 6 Correspondence of linguistic variables to fuzzy numbers

Linguistic variable	Code	Fuzzy numbers
Absolutely unimportant	AU	(1/9, 1/7, 1/5)
Significantly unimportant	SU	(1/7, 1/5, 1/3)
Weakly unimportant	WU	(1/5, 1/3, 1)
Equally important	EI	(1, 1, 1)
Weakly more important	WI	(1, 3, 5)
Significantly more Important	SI	(3, 5, 7)
Absolutely more Important	AI	(5, 7, 9)

the three experts are then consolidated to create a synthetic comparison table.

The experts were asked to rate the risk categories (criteria) and risks (sub-criteria) using six linguistic variables to facilitate the process as they express human reasoning to a greater extent than numbers. Using the linguistic scale, they ranked the risks from “equally important” to “absolutely more important” based on their weight in the occurrence of the risk. The linguistic scale proposed by Liu and Tsai (2012) was adopted, which is presented in Table 6, showing the linguistic variables in correspondence with the fuzzy triangular numbers that express them. Liu and Tsai (2012) approach was preferred over others because, in addition to the linguistic variables of superiority, it also includes variables expressing the degree of non-significance, thus making it easier for experts during the comparison process.

For example, if "Risk of unstable rock falls (SC1.7)" is considered by the DM as absolutely more critical compared to "Extreme exposure to vibration (SC1.6)" (because when unstable rock fall in underground mines, the number of people affected is large, and the risk is judged to be severe compared to those exposed to vibration) then "Risk of unstable rock fall (SC1.7)" will be assigned a fuzzy number (5, 7, 9) and "Extreme exposure to vibration (SC1.6)" will be given the corresponding inverse fuzzy number (1/9, 1/7, 1/5). If the two being compared are considered by the DM to be of equal importance, then they are given a fuzzy number (1, 1, 1).

Participants in the process compared all risk categories (criteria) in pairs and rated them in terms of importance on the linguistic scale, as shown in Table 6. Thus, from each DM, a 5X5 comparison table was obtained. Having completed the process of comparing the risk categories (criteria), the participants proceeded to compare the risks (sub-criteria). The risks (sub-criteria) comprising each criterion (risk category) are compared pairwise with each other and are scored according to their importance with the corresponding linguistic variable. As a result, six comparison tables were obtained from each DM, i.e. an 8X8 comparison table for the risks in category C1, a 4X4 comparison table for the risks in category C2, a 3X3 comparison table for the risks in category C3, a 5X5 comparison table for the risks in category C4 and a 4X4 comparison table for the risks in category C5 (Please see Appendix).

4.2.3 Consistency check

A consistency check is performed for all comparison tables by calculating the consistency ratio of each judgment according to the method proposed by Gogus and Boucher (1998) and applying Eqs. (13)–(18).

Table 7 gives the maximum eigenvalues (λmmax and λgmax), consistency indices (CIm and CIg) and consistency ratios (CRm and CRg) for each comparison table completed by the participants. Most comparison tables show consistency ratios of less than 0.1. Since the comparisons are expressed in triangular fuzzy numbers, it is challenging to avoid inconsistency in some of the comparison tables (Wang et al. 2016). Because most of the tables show consistency, it is assumed that the results obtained are valid.

4.2.4 Determination of fuzzy weights and defuzzification

Since more than one DM is involved in the process, risk category (criteria) comparison tables are consolidated into an aggregate table containing the judgments of all participants. Similarly, the same approach is followed for the risk (sub-criteria) comparison tables for each risk category. At this point, the linguistic variables are converted into triangular fuzzy numbers. The geometric mean method is used to generate the synthetic decision tables by applying Eq. (11) for each fuzzy membership function (L, M, U). Using the fuzzy membership functions of the aggregate matrices, the fuzzy geometric means ($\widetilde{r_i}$) and fuzzy weights ($\widetilde{w_i}$) of the criteria (risk category) and risks (sub-criteria) are calculated. Applying Eq. (6) to the risk categories (criteria), we obtain

Table 7 Maximum eigenvalues, consistency indices and consistency ratios for each comparison table (See also Appendix)

DM-1	λmmax	CIm	RIm	CRM	λgmax	CIg	RIg	CRg
C	5.2009	0.0502	1.0720	**0.0468**	5.0999	0.0250	0.3597	**0.0695**
SC1	13.0068	0.7153	1.3410	**0.5334**	11.9612	0.5659	0.4164	**1.3590**
SC2	4.0739	0.0246	0.7937	**0.0310**	4.0226	0.0075	0.2627	**0.0286**
SC3	3.0655	0.0328	0.4890	**0.0670**	3.0200	0.0100	0.1796	**0.0558**
SC4	5.1978	0.0495	1.0720	**0.0461**	5.1430	0.0357	0.3597	**0.0994**
SC5	4.0328	0.0109	0.7937	**0.0138**	4.0150	0.0050	0.2627	**0.0190**
DM-2	λmmax	CIm	RIm	CRM	λgmax	CIg	RIg	CRg
C	6.3513	0.3378	1.0720	**0.3151**	5.9247	0.2312	0.3597	**0.6427**
SC1	15.0416	1.0059	1.3410	**0.7501**	13.5891	0.7984	0.4164	**1.9175**
SC2	4.1222	0.0407	0.7937	**0.0513**	4.0617	0.0206	0.2627	**0.0783**
SC3	3.0655	0.0328	0.4890	**0.0670**	3.0200	0.0100	0.1796	**0.0558**
SC4	5.1487	0.0372	1.0720	**0.0347**	5.1095	0.0274	0.3597	**0.0761**
SC5	4.1159	0.0386	0.7937	**0.0487**	4.0742	0.0247	0.2627	**0.0941**
DM-3	λmmax	CIm	RIm	CRM	λgmax	CIg	RIg	CRg
C	7.2235	0.5559	1.0720	**0.5186**	6.9106	0.4776	0.3597	**1.3279**
SC1	11.4368	0.4910	1.3410	**0.3661**	10.1633	0.3090	0.4164	**0.7422**
SC2	4.1247	0.0416	0.7937	**0.0524**	4.0621	0.0207	0.2627	**0.0788**
SC3	3.0000	0.0000	0.4890	**0.0000**	3.0000	0.0000	0.1796	**0.0000**
SC4	5.0419	0.0105	1.0720	**0.0098**	5.0830	0.0208	0.3597	**0.0577**
SC5	4.1222	0.0407	0.7937	**0.0513**	4.0616	0.0205	0.2627	**0.0782**

CRM and CRg are important for the consisency and the validation of the method (in bold)

$$\widetilde{r_i} = \left(\widetilde{a_{i1}} \otimes \widetilde{a_{i2}} \otimes \cdots \widetilde{a_{in}}\right)^{\frac{1}{n}} \rightarrow$$
$$\left(\widetilde{r_1}\right) = (1.517, 2.254, 2.904)$$
$$\left(\widetilde{r_2}\right) = (0.344, 0.477, 0.734)$$
$$\left(\widetilde{r_3}\right) = (0.327, 0.514, 0.859)$$
$$\left(\widetilde{r_4}\right) = (0.863, 1.267, 1.829)$$
$$\left(\widetilde{r_5}\right) = (0.988, 1.477, 2.253)$$

Subsequently, the fuzzy weights ($\widetilde{w_i}$) of each criterion (risk category) C1 to C5 and all risks (sub-criteria) can be calculated by applying Eq. (7):

$$\widetilde{w_i} = \widetilde{r_i} \otimes \left(\widetilde{r_1} \oplus \ldots \widetilde{r_n}\right)^{-1}$$

By applying the center of gravity method, the non-fuzzy values of the fuzzy weights can be determined so that it is then possible to rank the risk categories (criteria) and risks (sub-criteria) according to their perceived severity. Since the fuzzy weights of the risk categories (criteria)/risks (sub-criteria) are expressed in the form (L, M, U), Eq. (9) will be used to decompose the fuzzy weights resulting in the defuzzified weights.

$$w_1 = 0.424$$
$$w_2 = 0.100$$
$$w_3 = 0.112$$
$$w_4 = 0.255$$
$$w_5 = 0.306$$

Subsequently, the local defuzzified weights (normalized) are calculated from the relation:

$$n_i = \frac{w_{i,i}}{\sum_n^i wi}$$

The normalized weights of the five criteria (risk categories) are calculated as follows:

$$n_1 = 0.354$$
$$n_2 = 0.084$$
$$n_3 = 0.094$$
$$n_4 = 0.213$$
$$n_5 = 0.256$$

Next, the defuzzified weights of the risks (sub-criteria) and their corresponding normalized local weights are also calculated in the same manner. Finally, the global priorities of the risks (sub-criteria) are determined, which will ultimately lead to the prioritization of the identified risks. The global priority of each risk (sub-criterion) is calculated by multiplying its local weight by the local weight of the risk category (criteria) it belongs to. The global priorities are presented in Table 8.

Finally, the ranking of the criteria (categories) and risks (sub-criteria) according to their perceived experts' significance (Table 9, Fig. 4) is done by ranking the calculated aggregate global priorities in descending order.

5 Discussion of results

The pairwise comparison of the risk categories (criteria) and risks (sub-criteria) that make up the hierarchical structure was carried out by three employees of the project under review. The selected participants are employed in different jobs and have other cognitive backgrounds. Therefore, they express different perspectives in assessing the importance of the identified risks.

Table 8 Priorities of the Risk Categories and Risks

Criteria/sub-criteria	Normalized local priorities	Global priorities
	ni	ngi
C1		0.354
SC1.1	0.035	0.012
SC1.2	0.126	0.045
SC1.3	0.111	0.039
SC1.4	0.046	0.016
SC1.5	0.132	0.047
SC1.6	0.032	0.011
SC1.7	0.215	0.076
SC1.8	0.304	0.107
C2		0.084
SC2.1	0.071	0.006
SC2.2	0.576	0.048
SC2.3	0.136	0.011
SC2.4	0.217	0.018
C3		0.094
SC3.1	0.102	0.010
SC3.2	0.346	0.032
SC3.3	0.551	0.052
C4		0.213
SC4.1	0.209	0.045
SC4.2	0.259	0.055
SC4.3	0.084	0.018
SC4.4	0.248	0.053
SC4.5	0.199	0.042
C5		0.256
SC5.1	0.590	0.151
SC5.2	0.127	0.033
SC5.3	0.159	0.041
SC5.4	0.124	0.032

Table 9 Ranking of risks in order of importance

Risks (sub-criteria)	Code	ngi	Rank
Non-compliance with safety regulations	SC5.1	0.151	1
Risk of unintentional explosions	SC1.8	0.107	2
Risk of unstable rock falls-ejection of debris	SC1.7	0.076	3
Insufficient machinery and equipment maintenance	SC4.2	0.055	4
Inadequate fire protection system	SC4.4	0.053	5
Inadequate ventilation	SC3.3	0.052	6
Risk of electric shock	SC2.2	0.048	7
Risk of overturning of project machinery	SC1.5	0.047	8
Risk of falling from height	SC1.2	0.045	9
Unskilled-Untrained Workers	SC4.1	0.045	9
Non-use of PPE	SC4.5	0.042	11
Traffic violations	SC5.3	0.041	12
Risk of entanglement	SC1.3	0.039	13
Mental fatigue, high stress and lack of concentration	SC5.2	0.033	14
Exposure to exhaust fumes and blasting by-products	SC3.2	0.032	15
Wrong decisions	SC5.4	0.032	15
Flooding	SC2.4	0.018	17
Lack of communication-coordination of work	SC4.3	0.018	17
Risk of mechanical failure	SC1.4	0.016	19
Slip hazard	SC1.1	0.012	20
Adverse environmental conditions	SC2.3	0.011	21
Body exposure to vibrations	SC1.6	0.011	21
Exposure to dust	SC3.1	0.010	23
Exposure to noise	SC2.1	0.006	24
Non-compliance with safety regulations	SC5.1	0.151	1
Risk of unintentional explosions	SC1.8	0.107	2
Risk of unstable rock falls-ejection of debris	SC1.7	0.076	3
Insufficient machinery and equipment maintenance	SC4.2	0.055	4

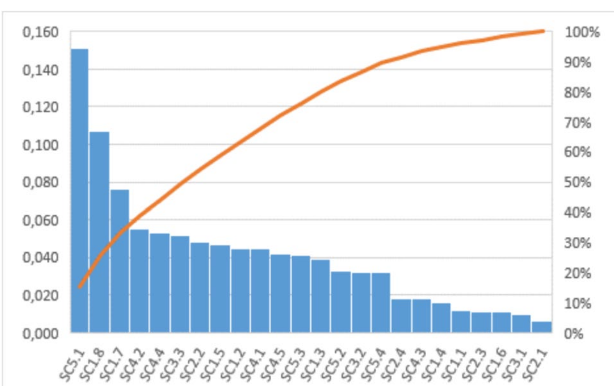

Fig. 4 Pareto Diagram of health and safety risk priorities for underground mining according to global priorities

DM-1, when comparing the risk categories (criteria), ranked the “Organizational risks (C4)” category as the most important of all, followed by “Physical risks (C1)”, “Human risks (C5)” and “Chemical risks (C3)” and ranked the “Environmental risks (C2)” category last. In contrast, DM-2 ranked the “Physical risks (C1)” category as the most important of all. The ranking order was completed by the “Organizational (C4), Human (C5), Chemical (C3) and Environmental (C2) risks” categories respectively. DM-3 rated “Human risks (C5) as the most important of all followed by the “Physical (C1), Environmental (C2), Organizational (C4) and Chemical (C3) risks categories in rank order.

In terms of their judgments on the risks per category, DM-1 considered the “risk of electric shock” (SC2.2) as the most critical hazard and ranked the following in descending order of importance:

- SC3.3 Inadequate ventilation system
- SC4.4 Inadequate fire protection system
- SC4.2 Insufficient machinery and equipment maintenance.
- SC3.2 Extreme exposure to exhaust fumes and blasting by-products,
- SC1.8 Risk of unintentional explosions.

According to DM-2, the "risk of electric shock (SC2.2)" is the most serious and followed by:

- SC3.3 Inadequate ventilation system
- SC5.1 Non-compliance with safety regulations
- SC4.2 Insufficient machinery and equipment maintenance
- SC1.8 Risk of unintentional explosions
- SC4.4 Inadequate fire protection system.

DM-3, unlike the other two, judged "non-compliance with safety regulations (SC5.1)" to be the most critical risk, with the other five most important risks being:

- SC2.4 Flooding
- SC2.2 Risk of electric shock
- SC3.2 Extreme exposure to exhaust fumes and blasting by-products
- SC3.3 Inadequate ventilation system
- SC4.5 Non-use of PPE.

However, according to the final ranking presented in Table 8 and obtained from the aggregate of the judgments of all participants, the aggregate order of importance of the risk categories (criteria) consists of "Physical risks (C1)" in first place, followed by Human (C5), Organizational (C4), Chemical (C3) and Environmental (C2) risks. The position occupied by the chemical and environmental risks is likely since their effects are primarily not immediately apparent. In contrast, participants, in addition to physical risks, considered the contribution of human risks and work organization to the increase in risk to be significant. This judgment is in line with the evidence from studies on the influence of organization and human behavior on accident events that have shown that the minimization of human error can lead to a significant reduction of accident events (Patterson and Shappell 2010; Kumar et al. 2020; Antoniou and Merkouri 2021; Antoniou and Agrafioti 2023).

In terms of the risks, the highest-ranking risk was "non-compliance with safety regulations (SC5.1)," followed by the "risk of unintentional explosions (SC1.8)", the "risk of unstable rock falls—ejection of debris (SC1.7)" and "insufficient machinery and equipment maintenance (SC4.2)". Accidents associated with placing and activating explosives are considered particularly serious because of the consequences they may cause and the large number of workers they may affect. Bearing in mind the Pareto principle (Ayyub 2014), the diagram in Fig. 4 depicts the 10 risks that produce a significant overall effect for which prevention measures should be focused on to minimize the risk of worksite accidents, these are:

- SC5.1 Non-compliance with safety regulations,
- SC1.8 Risk of unintentional explosions,
- SC1.7 Risk of unstable rock falls—ejection of debris,
- SC4.2 Insufficient machinery and equipment maintenance,
- SC4.4 Inadequate fire protection system,
- SC3.3 Inadequate ventilation,
- SC2.2 Risk of electric shock,
- SC1.5 Risk of overturning of project machinery,
- SC1.2 Risk of falling from a height,
- SC4.1 Unskilled—Untrained Workers.

According to the statistical reports of the National Social Security Agency (NSSA 2019) on the nature of accidents recorded in 2017 in the mining industry, the highest percentage of accidents involved falls from height and collapses, followed by being struck by moving objects, followed by being crushed between objects, falls from height or the same level and exposure to high temperatures. Comparing the above with the proposed risk response list, we observe that the results of processing the participants' judgments using the FAHP are consistent with those recorded by the NSSA for 2017.

6 Conclusions

The prioritization of risks according to the order in which they are addressed provides a roadmap for reducing or eliminating significant risks and for the optimal management of available resources. While the AHP has been widely used in risk assessment it fails to control the subjective judgments' ambiguity. Therefore this research employs the FAHP methodology, which is based on the theory of fuzzy logic, to deal with the uncertain situations in mining works and to manage the imprecision, ambiguity and subjectivity with which participants' preferences are expressed allowing the extraction valid results (Emrouznejad and Ho 2017; Tyagi et al. 2018).

An active underground mining project was selected as a case study, where the associated health and safety risks were identified and recorded by monitoring the progress of the production process. Aiming at a complete inventory of the risks encountered in underground mining projects and the need for additional research on specific risk groups, an extensive literature review was carried out, the results of which further enriched the risk list and constituted the input data for the process. Three experts from different employment backgrounds compared risks with each other in pairs, rating their importance using triangular fuzzy language variables. Applying the FAHP approach (Buckley 1985), the global weights of the priorities were calculated, and the risks and their categories were ranked according to their importance.

The results of the FAHP indicate the priority in which the risks considered should be addressed and, by extension, the order in which control actions and/or mitigation measures should be taken. Ideally, the risks with the highest probability of occurrence and with the potential to cause harm should be addressed first, followed by those with the lowest probability of occurrence and potential to cause harm.

The risk assessment results provide guidance for implementing appropriate control measures to reduce or eliminate risk. A limitation of the approach taken may be that the risk investigation was carried out exclusively for mining front extension and ore removal operations. Maintenance work on the mechanical equipment was not considered in the risk identification process. The risks arising from heavy machinery (e.g. drill rigs) maintenance operations in conjunction with making the decision to replace risky equipment by considering the balance between cost of repair and cost of replacement, as examined using regression analysis by Al-Chalabi (2022) could be considered in a future investigation.

The approach adopted was intended to address the subjectivity and ambiguity that characterizes the judgments of decision-makers. The experts who took part in prioritizing the identified risks ranked them in terms of their importance relative to the others. They expressed their subjective judgment by giving a linguistic variable for both risk parameters, the probability of occurrence and the severity of the consequences of each risk. The application of the FAHP to rank the risks and combining it with quantitative analysis techniques (such as, for example, the FMEA technique) for the final determination of risk would be a fascinating case for future research in the context of risk assessment. Finally, it is envisaged that the FAHP methodology proposed for ranking site-specific risks in combination with MetaMining (Liu et al. 2023) that uses digital twinning concepts to simulate underground mining accident risks and the Internet of Things to set off alarms in time (Tan et al. 2020) can become a significant accident mitigation tool.

Appendix

Risk comparison tables and geometric means and fuzzy weights of criteria and sub criteria

(1) Risk category comparison tables for each DM

DM-1

	C1	C2	C3	C4	C5
C1	EI	SI	WI	EI	EI
C2	SU	EI	WU	SU	SU
C3	WU	WI	EI	SU	WU
C4	EI	SI	SI	EI	WI
C5	EI	SI	WI	WU	EI

DM-2

	C1	C2	C3	C4	C5
C1	EI	AI	SI	WI	SI
C2	AU	EI	WU	SU	SU
C3	SU	WI	EI	WI	SU
C4	WU	SI	WU	EI	WI
C5	SU	SI	SI	WU	EI

DM-3

	C1	C2	C3	C4	C5
C1	EI	SI	SI	SI	SU
C2	SU	EI	SI	EI	WI
C3	SU	SU	EI	AU	SU
C4	SU	EI	AI	EI	SU
C5	SI	WU	SI	SI	EI

(2) Risk comparison tables per category by DM-1

	SC1.1	SC1.2	SC1.3	SC1.4	SC1.5	SC1.6	SC1.7	SC1.8
SC1.1	EI	AU	AU	WU	AU	SI	AU	AU
SC1.2	AI	EI	WI	SI	WI	SI	SU	SU
SC1.3	AI	WU	EI	AI	WU	AI	EI	WU
SC1.4	WI	SU	AU	EI	SU	SI	SU	SU
SC1.5	AI	WU	WI	SI	EI	AU	WU	SU
SC1.6	SU	SU	AU	SU	AI	EI	AU	AU
SC1.7	AI	SI	EI	SI	WI	AI	EI	EI
SC1.8	AI	SI	WI	SI	SI	AI	EI	EI

	SC2.1	SC2.2	SC2.3	SC2.4
SC2.1	EI	AU	WU	WU
SC2.2	AI	EI	SI	SI
SC2.3	WI	SU	EI	EI
SC2.4	WI	SU	EI	EI

	SC3.1	SC3.2	SC3.3
SC3.1	EI	SU	AU
SC3.2	SI	EI	WU
SC3.3	AI	WI	EI

	SC4.1	SC4.2	SC4.3	SC4.4	SC4.5
SC4.1	EI	WU	WI	SU	WI
SC4.2	WI	EI	SI	EI	WI
SC4.3	WU	SU	EI	SU	EI
SC4.4	SI	EI	SI	EI	SI
SC4.5	WU	WU	EI	SU	EI

	SC5.1	SC5.2	SC5.3	SC5.4
SC5.1	EI	SI	WI	AI

	SC5.1	SC5.2	SC5.3	SC5.4
SC5.2	SU	EI	WU	EI
SC5.3	WU	WI	EI	WI
SC5.4	AU	EI	WU	EI

(3) Risk comparison tables per category by DM-2

	SC1.1	SC1.2	SC1.3	SC1.4	SC1.5	SC1.6	SC1.7	SC1.8
SC1.1	**EI**	SU	SU	WI	AU	SI	AU	AU
SC1.2	SI	**EI**	WU	SI	SU	AI	SU	SU
SC1.3	SI	WI	**EI**	SI	WU	AI	WU	SU
SC1.4	WU	SU	SU	**EI**	SU	SI	SU	SU
SC1.5	AI	SI	WI	SI	**EI**	AU	WI	WU
SC1.6	SU	AU	AU	SU	AI	**EI**	AU	AU
SC1.7	AI	SI	WI	SI	WU	AI	**EI**	WU
SC1.8	AI	SI	SI	SI	WI	AI	WI	**EI**

	SC2.1	SC2.2	SC2.3	SC2.4
SC2.1	**EI**	AU	WU	WU
SC2.2	AI	**EI**	SI	SI
SC2.3	WI	SU	**EI**	EI
SC2.4	WI	SU	EI	**EI**

	SC3.1	SC3.2	SC3.3
SC3.1	EI	SU	AU
SC3.2	SI	EI	SU
SC3.3	AI	SI	EI

	SC4.1	SC4.2	SC4.3	SC4.4	SC4.5
SC4.1	EI	SU	WI	WU	EI
SC4.2	SI	EI	AI	EI	WI
SC4.3	WU	AU	EI	SU	SU
SC4.4	WI	EI	SI	EI	WI
SC4.5	EI	WU	SI	WU	EI

	SC5.1	SC5.2	SC5.3	SC5.4
SC5.1	EI	SI	SI	WI
SC5.2	SU	EI	WU	WU
SC5.3	SU	WI	EI	EI
SC5.4	WU	WI	EI	EI

(4) Risk comparison tables per category by DM-3

	SC1.1	SC1.2	SC1.3	SC1.4	SC1.5	SC1.6	SC1.7	SC1.8
SC1.1	EI	EI	AU	WU	SU	SU	WU	SU
SC1.2	EI	EI	SI	SI	WI	SI	EI	SU
SC1.3	AI	SU	EI	EI	EI	WI	SU	SU
SC1.4	WI	SU	EI	EI	SU	SI	AU	AU
SC1.5	SI	WU	EI	SI	EI	AI	WU	WI
SC1.6	SI	SU	WI	SU	AU	EI	SU	AU
SC1.7	WI	EI	SI	AI	WI	SI	EI	WU
SC1.8	SI	SI	SI	AI	WU	AI	WI	EI

	SC2.1	SC2.2	SC2.3	SC2.4
SC2.1	EI	AU	WU	AU
SC2.2	AI	EI	SI	EI
SC2.3	WI	SU	EI	AU
SC2.4	AI	EI	AI	EI

	SC3.1	SC3.2	SC3.3
SC3.1	EI	WU	WU
SC3.2	SI	EI	EI
SC3.3	SI	EI	EI

	SC4.1	SC4.2	SC4.3	SC4.4	SC4.5
SC4.1	EI	WI	WI	SI	EI
SC4.2	WU	EI	EI	EI	SU
SC4.3	WU	EI	EI	EI	SU
SC4.4	SU	EI	EI	EI	SU
SC4.5	EI	SI	SI	SI	EI

	SC5.1	SC5.2	SC5.3	SC5.4
SC5.1	EI	SI	AI	SI
SC5.2	SU	EI	WI	WI
SC5.3	AU	WU	EI	EI
SC5.4	SU	WU	EI	EI

(5) Geometric mean and relative fuzzy weights

Criteria	Geometric mean of fuzzy comparison value			Relative Fuzzy weight of each Criteria		
	ri			wi		
	L	M	U	L	M	U
C1	1,517	2,254	2,904	0,177	0,376	0,719
C2	0,344	0,477	0,734	0,040	0,080	0,182
C3	0,327	0,514	0,859	0,038	0,086	0,213
C4	0,863	1,267	1,829	0,101	0,212	0,453
C5	0,988	1,477	2,253	0,115	0,247	0,558

(6) Geometric mean and relative fuzzy weights

Subcriteria	Geometric mean of fuzzy comparison value			Relative Fuzzy weight of each Criteria		
	ri			wi		
	L	M	U	L	M	U
SC1.1	0,262	0,360	0,547	0,017	0,033	0,078
SC1.2	0,906	1,378	1,968	0,058	0,127	0,281
SC1.3	0,792	1,143	1,770	0,050	0,106	0,252
SC1.4	0,334	0,480	0,721	0,021	0,044	0,103
SC1.5	0,844	1,355	2,156	0,054	0,125	0,308
SC1.6	0,257	0,339	0,494	0,016	0,031	0,070
SC1.7	1,505	2,348	3,362	0,096	0,217	0,479
SC1.8	2,111	3,412	4,699	0,134	0,316	0,670

(7) Geometric mean and relative fuzzy weights

Subcriteria	Geometric mean of fuzzy comparison value			Relative Fuzzy weight of each Criteria		
	ri			wi		
	L	M	U	L	M	U
SC2.1	0,246	0,331	0,585	0,035	0,059	0,141
SC2.2	2,466	3,271	3,979	0,349	0,586	0,959
SC2.3	0,512	0,748	0,994	0,072	0,134	0,239
SC2.4	0,926	1,235	1,505	0,131	0,221	0,363

(8) Geometric mean and relative fuzzy weights

Subcriteria	Geometric mean of fuzzy comparison value			Relative Fuzzy weight of each Criteria		
	ri			wi		
	L	M	U	L	M	U
SC3.1	0,278	0,356	0,548	0,054	0,092	0,211
SC3.2	0,893	1,266	1,843	0,172	0,329	0,708
SC3.3	1,430	2,222	2,786	0,276	0,578	1,071

(9) Geometric mean and relative fuzzy weights

Subcriteria	Geometric mean of fuzzy comparison value			Relative Fuzzy weight of each Criteria		
	ri			wi		
	L	M	U	L	M	U
SC4.1	0,670	1,119	1,682	0,088	0,205	0,441
SC4.2	1,017	1,467	1,924	0,133	0,269	0,504
SC4.3	0,327	0,412	0,670	0,043	0,075	0,176
SC4.4	1,034	1,435	1,799	0,135	0,263	0,472
SC4.5	0,766	1,029	1,562	0,100	0,188	0,409

(10) Geometric mean and relative fuzzy weights

Subcriteria	Geometric mean of fuzzy comparison value			Relative Fuzzy weight of each Criteria		
	ri			wi		
	L	M	U	L	M	U
SC5.1	2,067	3,248	4,243	0,281	0,614	1,215
SC5.2	0,411	0,610	0,994	0,056	0,115	0,284
SC5.3	0,541	0,815	1,193	0,074	0,154	0,342
SC5.4	0,473	0,619	0,913	0,064	0,117	0,261

Acknowledgements The authors would like to thank all the anonymous experts, engineers working in the mining industry for the valuable contributions in this research. Without their constructive comments this work would not have been accomplished.

Funding This research received no external funding.

Data availability All data used is confidential in nature and may olny be provided with restrictions.

Declarations

Conflict of interest The authors declare no conflict of interest.

References

Abudayyeh O, Asce M, Saad et al (2007) Hybrid prequalification-based, innovative contracting model using AHP. J Manag Eng 23:88–96. https://doi.org/10.1061/ASCE0742-597X200723:288

Al Khalil MI (2002) Selecting the appropriate project delivery method using AHP. Int J Project Manag 20:469–474

Albrechtsen E, Solberg I, Svensli E (2019) The application and benefits of job safety analysis. Saf Sci 113:425–437. https://doi.org/10.1016/j.ssci.2018.12.007

Al-Chalabi H (2022) Development of an economic replacement time model for mining equipment: a case study. Life Cycle Reliab Saf Eng 11:203–217. https://doi.org/10.1007/s41872-022-00188-1

Amiri M, Ardeshir A, Fazel Zarandi MH, Soltanaghaei E (2016) Pattern extraction for high-risk accidents in the construction industry: a data-mining approach. Int J Inj Contr Saf Promot 23:264–276. https://doi.org/10.1080/17457300.2015.1032979

Antoniou F (2021) Delay risk assessment models for road projects. Systems. https://doi.org/10.3390/systems9030070

Antoniou F, Agrafioti NF (2023) Meta-analysis of studies on accident contributing factors in the Greek construction industry. Sustainability 15:2357. https://doi.org/10.3390/su15032357

Antoniou F, Aretoulis GN (2018) Comparative analysis of multi-criteria decision making methods in choosing contract type for highway construction in Greece. Int J Manag Decis Mak. https://doi.org/10.1504/IJMDM.2018.088821

Antoniou F, Merkouri M (2021) Accident factors per construction type and stage: a synthesis of scientific research and professional experience. Int J Inj Contr Saf Promot 28:439–453. https://doi.org/10.1080/17457300.2021.1930061

Antoniou F, Aretoulis GN, Konstantinidis DK, Kalfakakou GP (2013) An empirical study of researchers' and practitioners' views on compensating major highway project contractors. Int J Manag Decis Mak 12:351–375. https://doi.org/10.1504/IJMDM.2013.056883

Antoniou F, Konstantinidis D, Aretoulis GN (2016) Application of the multi attribute utility theory for the selection of project procurement system for Greek highway projects. Int J Manag Decis Mak 15:83–112. https://doi.org/10.1504/IJMDM.2016.077761

Aretoulis GN, Papathanasiou J, Antoniou F (2020) PROMETHEE-based ranking of project managers based on the five personality traits. Kybernetes 49:1083–1102. https://doi.org/10.1108/K-10-2018-0551

Asilian-Mahabadi H, Khosravi Y, Hassanzadeh-Rangi N et al (2020) Factors affecting unsafe behavior in construction projects: development and validation of a new questionnaire. Int J Occup Saf Ergon 26:219–226. https://doi.org/10.1080/10803548.2017.1408243

Aven T (2008) Risk management. In: Handbook of performability engineering. Springer, London, pp 719–742

Ayyub BM (2014) Risk analysis in engineering and economics, 2nd edn. CRC Press, Taylor and Francis Group, Boca Raton, London

Badri A, Nadeau S, Gbodossou A (2013) A new practical approach to risk management for underground mining project in Quebec. J Loss Prev Process Ind 26:1145–1158. https://doi.org/10.1016/j.jlp.2013.04.014

Bahn S (2013) Workplace hazard identification and management: the case of an underground mining operation. Saf Sci 57:129–137. https://doi.org/10.1016/j.ssci.2013.01.010

Betsis S, Kalogirou M, Aretoulis G, Pertzinidou M (2019) Work accidents correlation analysis for construction projects in northern Greece 2003–2007: a retrospective study. Safety. https://doi.org/10.3390/safety5020033

Buckley JJ (1985) Fuzzy hierarchical analysis. Fuzzy Sets Syst 17:233–247. https://doi.org/10.1016/0165-0114(85)90090-9

Chan HK, Wang X (2013) Hierarchical model in decision making. In: Fuzzy hierarchical model for risk assessment. Springer, London, pp 25–43

Chan EH, Suen HC, Chan CK (2006) MAUT-based dispute resolution selection model prototype for international construction projects. J Constr Eng Manag 132:444–451. https://doi.org/10.1061/(asce)0733-9364(2006)132:5(444)

Chang D-Y (1996) Applications of the extent analysis method on fuzzy AHP. Eur J Oper Res 95:649–655. https://doi.org/10.1016/0377-2217(95)00300-2

Chen Y (2020) The development and validation of a human factors analysis and classification system for the construction industry. Int J Occup Saf Ergon. https://doi.org/10.1080/10803548.2020.1787623

Cheung FKT, Kuen JLF, Skitmore M (2002) Multi-criteria evaluation model for the selection of architectural consultants. Constr Manag Econ 20:569–580. https://doi.org/10.1080/01446190210159818

Cooksey SR, Jeong HS, Chae MJ (2011) Asset management assessment model for state departments of transportation. J Manag Eng 27:159–169. https://doi.org/10.1061/(asce)me.1943-5479.0000055

Debia M, Couture C, Njanga P-E et al (2017) Diesel engine exhaust exposures in two underground mines. Int J Min Sci Technol 27:641–645. https://doi.org/10.1016/j.ijmst.2017.05.011

Demirel T, Demirel NÇ, Kahraman C (2008) Fuzzy analytic hierarchy process and its application, pp 53–83

Dhillon BS (2009) Mining equipment safety: a review, analysis methods and improvement strategies. Int J Min Reclam Environ 23:168–179. https://doi.org/10.1080/17480930902916239

Domínguez CR, Martínez IV, Piñón Peña PM, Rodríguez Ochoa A (2019) Analysis and evaluation of risks in underground mining using the decision matrix risk-assessment (DMRA) technique, in Guanajuato, Mexico. J Sustain Min 18:52–59. https://doi.org/10.1016/j.jsm.2019.01.001

El-Tourkey M, Alshibani A, Mohammed A et al (2022) An integrated decision support system for mobile crane selection. Expert Syst Appl 189:116053. https://doi.org/10.1016/j.eswa.2021.116053

Emrouznejad A, Ho W (2017) Analytic hierarchy process and fuzzy set theory. In: Fuzzy analytic hierarchy process. Chapman and Hall/CRC, CRC Press, Boca Raton, London, pp 1–10

Galvin JM (2016) Operational hazards. In: Ground engineering—principles and practices for underground coal mining. Springer, Cham, pp 477–523

Gogus O, Boucher TO (1998) Strong transitivity, rationality and weak monotonicity in fuzzy pairwise comparisons. Fuzzy Sets Syst 94:133–144. https://doi.org/10.1016/S0165-0114(96)00184-4

Greek Ministry of Environment E and CC-Y (2018) Report on the mining and quarrying activities in Greece

Gul M, Ak MF, Guneri AF (2019) Pythagorean fuzzy VIKOR-based approach for safety risk assessment in mine industry. J Safety Res 69:135–153. https://doi.org/10.1016/j.jsr.2019.03.005

ILO (2018) Accidents at work—statistics by economic activity—statistics explained. In: Retrieved July 05, 2020. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Accidents_at_work_-_statistics_by_economic_activity

Jakiel P, Fabianowski D (2015) FAHP model used for assessment of highway RC bridge structural and technological arrangements. Expert Syst Appl 42:4054–4061. https://doi.org/10.1016/j.eswa.2014.12.039

Kalogeraki M, Antoniou F (2021) Improving risk assessment for transporting dangerous goods through European road tunnels: a Delphi study. Systems. https://doi.org/10.3390/systems9040080

Kaya İ, Kahraman C, Çebi S (2012) Computational intelligence techniques for risk management in decision making, pp 9–38

Khanzode VV, Maiti J, Ray PK (2011) A methodology for evaluation and monitoring of recurring hazards in underground coal mining. Saf Sci 49:1172–1179. https://doi.org/10.1016/j.ssci.2011.03.009

Koulinas GK, Marhavilas PK, Demesouka OE et al (2019) Risk analysis and assessment in the worksites using the fuzzy-analytical hierarchy process and a quantitative technique—a case study for the Greek construction sector. Saf Sci 112:96–104. https://doi.org/10.1016/j.ssci.2018.10.017

Kumar P, Gupta S, Gunda YR (2020) Estimation of human error rate in underground coal mines through retrospective analysis of mining accident reports and some error reduction strategies. Saf Sci 123:104555. https://doi.org/10.1016/j.ssci.2019.104555

Kutlu AC, Ekmekçioğlu M (2012) Fuzzy failure modes and effects analysis by using fuzzy TOPSIS-based fuzzy AHP. Expert Syst Appl 39:61–67. https://doi.org/10.1016/j.eswa.2011.06.044

Lenné MG, Salmon PM, Liu CC, Trotter M (2012) A systems approach to accident causation in mining: an application of the HFACS method. Accid Anal Prev 48:111–117. https://doi.org/10.1016/j.aap.2011.05.026

Li J, Wen YY (2022) Association analysis of human error causes of electric shock construction accidents in China. Arch Civ Eng 68:427–443. https://doi.org/10.24425/ace.2022.140651

Liang H, Zhang S, Su Y (2020) The structure and emerging trends of construction safety management research: a bibliometric review. Int J Occup Saf Ergon 26:469–488. https://doi.org/10.1080/10803548.2018.1444565

Lin CL, Fan CL, Chen BK (2022) Hybrid analytic hierarchy process—artificial neural network model for predicting the major risks and quality of Taiwanese construction projects. Appl Sci (Switzerland). https://doi.org/10.3390/app12157790

Liu H-T, Tsai Y (2012) A fuzzy risk assessment approach for occupational hazards in the construction industry. Saf Sci 50:1067–1078. https://doi.org/10.1016/j.ssci.2011.11.021

Liu R, Cheng W, Yu Y, Xu Q (2018) Human factors analysis of major coal mine accidents in China based on the HFACS-CM model and AHP method. Int J Ind Ergon 68:270–279. https://doi.org/10.1016/j.ergon.2018.08.009

Liu K, Chen L, Li L et al (2023) MetaMining: mining in the Metaverse. IEEE Trans Syst Man Cybern Syst 53:3858–3867. https://doi.org/10.1109/TSMC.2022.3233588

Mahdevari S, Shahriar K, Esfahanipour A (2014) Human health and safety risks management in underground coal mines using fuzzy TOPSIS. Sci Total Environ 488–489:85–99. https://doi.org/10.1016/j.scitotenv.2014.04.076

Mahdi IM, Alreshaid K (2005) Decision support system for selecting the proper project delivery method using analytical hierarchy process (AHP). Int J Project Manag 23:564–572. https://doi.org/10.1016/j.ijproman.2005.05.007

Meng Q, Tan S, Li Z et al (2020) A review of game theory application research in safety management. IEEE Access 8:107301–107313. https://doi.org/10.1109/ACCESS.2020.2999963

Mosly I (2022) Factors influencing safety performance in the construction industry of Saudi Arabia: an exploratory factor analysis. Int J Occup Saf Ergon 28:901–908. https://doi.org/10.1080/10803548.2020.1838774

Mustafa MA, Ryan TC (1990) Decision support for bid evaluation. Project Management 8:230–235

National Social Security Agency (2019) Worker accident reports (yearly). In: Retrieved July 05, 2020, https://www.efka.gov.gr/sites/default/files/2020-02/etisio_2017.pdf

Patterson JM, Shappell SA (2010) Operator error and system deficiencies: Analysis of 508 mining incidents and accidents from Queensland, Australia using HFACS. Accid Anal Prev 42:1379–1385. https://doi.org/10.1016/j.aap.2010.02.018

Petroutsatou K, Kantilierakis D (2023) Productivity analysis and associated risks in steel structures. Buildings 13:905. https://doi.org/10.3390/buildings13040905

Petroutsatou K, Maravas A, Saramourtsis A (2021) A life cycle model for estimating road tunnel cost. Tunnel Undergr Space Technol. https://doi.org/10.1016/j.tust.2021.103858

Petroutsatou K, Ladopoulos I, Tsakelidou K (2022) Scientometric analysis and AHP for hierarchizing criteria affecting construction equipment operators' performance. Sustainability 14:6836. https://doi.org/10.3390/su14116836

Rajabi S, El-Sayegh S, Romdhane L (2022) Identification and assessment of sustainability performance indicators for construction projects. Environ Sustain Indic. https://doi.org/10.1016/j.indic.2022.100193

Saaty TL (1980) The analytic hierarchy process. McGraw Hill, New York

Saleh JH, Cummings AM (2011) Safety in the mining industry and the unfinished legacy of mining accidents: safety levers and defense-in-depth for addressing mining hazards. Saf Sci 49:764–777. https://doi.org/10.1016/j.ssci.2011.02.017

Salman A (2022) Selection of construction bidders using the analytical hierarchy process and Friedman theory. Front Built Environ. https://doi.org/10.3389/fbuil.2021.815022

Shapira A, Goldenberg M (2005) AHP-based equipment selection model for construction projects. J Constr Eng Manag 131:1263–1273. https://doi.org/10.1061/(ASCE)0733-9364(2005)131:12(1263)

Shapiro AF, Koissi MC (2017) Fuzzy logic modifications of the analytic hierarchy process. Insur Math Econ 75:189–202

Smith NM, Ali S, Bofinger C, Collins N (2016) Human health and safety in artisanal and small-scale mining: an integrated approach to risk mitigation. J Clean Prod 129:43–52. https://doi.org/10.1016/j.jclepro.2016.04.124

Soltanzadeh A, Mahdinia M, Omidi Oskouei A et al (2022) Analyzing health, safety, and environmental risks of construction projects using the fuzzy analytic hierarchy process: a field study based on a project management body of knowledge. Sustainability (Switzerland). https://doi.org/10.3390/su142416555

Tan A, Wang S, Xin N et al (2020) A multi-channel transmission scheme in green internet of things for underground mining safety warning. IEEE Access 8:775–788. https://doi.org/10.1109/ACCESS.2019.2959659

Targoutsidis A (2008) Economics of occupational health and safety in EL.IN.Y.A.E (**in Greek**). http://www.elinyae.gr/ekdoseis/biblia/oikonomia-tis-ygeias-kai-tis-asfaleias-tis-ergasias. Accessed 17 Nov 2022

Tayeh BA, Salem TJ, Abu Aisheh YI, Alaloul WS (2020) Risk factors affecting the performance of construction projects in Gaza strip. Open Civ Eng J 14:94–104. https://doi.org/10.2174/1874149502014010094

Taylan O, Bafail AO, Abdulaal RMS, Kabli MR (2014) Construction projects selection and risk assessment by fuzzy AHP and fuzzy TOPSIS methodologies. Appl Soft Comput 17:105–116. https://doi.org/10.1016/j.asoc.2014.01.003

Tong R, Yang Y, Ma X et al (2019) Risk assessment of miners' unsafe behaviors: a case study of gas explosion accidents in coal mine, China. Int J Environ Res Public Health 16:1765. https://doi.org/10.3390/ijerph16101765

Topcu YI (2004) A decision model proposal for construction contractor selection in Turkey. Build Environ 39:469–481. https://doi.org/10.1016/j.buildenv.2003.09.009

Tripathy DP, Ala CK (2018) Identification of safety hazards in Indian underground coal mines. J Sustain Min 17:175–183. https://doi.org/10.1016/j.jsm.2018.07.005

Tyagi S, Chambers T, Yang K (2018) Enhanced fuzzy-analytic hierarchy process. Soft Comput 22:4431–4443. https://doi.org/10.1007/s00500-017-2639-y

Utembe W, Faustman E, Matatiele P, Gulumian M (2015) Hazards identified and the need for health risk assessment in the South African mining industry. Hum Exp Toxicol 34:1212–1221. https://doi.org/10.1177/0960327115600370

Van Laarhoven PJM, Pedrycz W (1983) A fuzzy extension of Saaty's priority theory. Fuzzy Sets Sys V 229–241(11):229–241

Wai CT, Yi PW, Olanrewaju OI et al (2023) A critical analysis of benefits and challenges of implementing modular integrated construction. Int J Constr Manag 23:656–668. https://doi.org/10.1080/15623599.2021.1907525

Wakchaure SS, Jha KN (2012) Determination of bridge health index using analytical hierarchy process. Constr Manag Econ 30:133–149. https://doi.org/10.1080/01446193.2012.658075

Wang Q, Wang H, Qi Z (2016) An application of nonlinear fuzzy analytic hierarchy process in safety evaluation of coal mine. Saf Sci 86:78–87. https://doi.org/10.1016/j.ssci.2016.02.012

Winge S, Albrechtsen E (2018) Accident types and barrier failures in the construction industry. Saf Sci 105:158–166. https://doi.org/10.1016/j.ssci.2018.02.006

Yaghini A, Pourrahimian Y, Hall RA (2018) Human factors and human error in the mining industry: a review and lessons from other industries. CIM J. https://doi.org/10.15834/cimj.2018.5

Yap JBH, Lee WK (2020) Analysing the underlying factors affecting safety performance in building construction. Prod Plan Control 31:1061–1076. https://doi.org/10.1080/09537287.2019.1695292

Zhang W, Zhu S, Zhang X, Zhao T (2020) Identification of critical causes of construction accidents in China using a model based on system thinking and case analysis. Saf Sci 121:606–618. https://doi.org/10.1016/j.ssci.2019.04.038