



A novel index for resilience measure of critical infrastructure systems in underground coal mines based on the operating environment: Case-study

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Abstract

Given the inherent risks and disruptions in underground coal mining operations, strengthening the resilience of critical infrastructure has become a vital priority. This paper aims to evaluate the resilience of the underground coal mining environment using historical data and expert judgment. The study serves as a framework for optimising the utilisation of critical infrastructure to minimise operational disturbances. To achieve this, a practical methodology has been developed, incorporating nearly two and a half years of collected operational data, a hierarchical structure, and a systematic approach. Furthermore, a case study is conducted to demonstrate the real-world applicability of the proposed method. Finally, the resilience index is introduced as a straightforward summation of ranked impact factors, providing a clear metric for resilience assessment.

Keywords

resilience, mining, failure data, operating environment, expert judgment, novel index

Introduction

The mining industry plays a crucial role in the global economy, holding a significant share in international trade (Da Silva et al., 2021). Mining and its associated industries contribute positively to economic and social development by generating employment and wealth (Brücker, Preuße, 2020; Cruz et al., 2021). Among mineral resources, energy supply sources hold a particularly prominent position, as no industry can sustain itself without a reliable energy supply (Tu et al., 2021; Norouzi Masir et al., 2021). Given coal's essential role in producing steel, cement, lime, aluminum, and other industrial materials, energy remains a key driver of industrial growth (Kurama et al., 2009; Wu et al., 2012). However, coal mining systems are highly vulnerable to various threats and disruptions that directly impact production capacity (Masir, 2021). These disturbances often stem from system failures (Madni, Jackson, 2009), posing risks to employee safety, health, and security while causing substantial annual economic losses (Hossain et al., 2019). For decades, ensuring the stability and reliability of coal mines has been a fundamental priority in the development of mining infrastructure (Lim-Camacho et al., 2021).

For years, researchers have extensively studied resilience across various engineering industries. However, these studies have notable limitations. Most existing research has primarily focused on energy systems (Hossain et al., 2019; Sabouhi et al., 2019; Zeng et al., 2021), transportation networks (Cerè et al., 2019; Li et al., 2020), and water supply networks (Behzadian et al., 2014), along with quantitative analyses in mining and coal. Despite this, coal mining operations are inherently vulnerable to numerous disruptions, which remain insufficiently explored in the literature. Furthermore, most existing studies primarily present conceptual frameworks and evaluation approaches rather than practical applications. Likewise, methodologically, current resilience measurement approaches often lack sufficient data and fail to account for the work environment. Overlooking operational conditions in resilience analyses can significantly distort results, as environmental factors not only influence system behaviour but also disrupt decision-making processes.

Moreover, effective management decisions from a production perspective require a comprehensive understanding of the interplay between operational capacity, system behaviour, and environmental conditions. Another critical aspect often neglected in resilience calculations is the impact of key influencing factors, such as commitment, sense of ownership, monitoring and prediction, lessons learned, scheduling status, and employment conditions.

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To address these gaps, this paper calculates resilience by integrating environmental failure data and identifying key influencing factors. Specifically, the study assesses critical infrastructure resilience through a three-step process. Firstly, operational environment data is collected. Secondly, the key resilience factors of critical infrastructure and their hierarchical relationships are systematically identified using a multi-criteria decision-making (MCDM) approach, providing a theoretical foundation for understanding resilience impacts. Thirdly, a new resilience indicator for critical infrastructure is introduced, offering a structured framework for resilience assessment.

Literature review

Resilience, derived from the Latin 'resilire' (to bounce back), initially emerged in ecosystem studies and has since expanded into multiple disciplines (Hossain et al., 2019). It is generally categorised into four approaches: empirical, conceptual framework, simulation, and index-based methods (Rød, 2020). Empirical models analyse resilience quantitatively using failure behaviour and recovery curves, subdivided into deterministic and probabilistic frameworks (Bruneau et al., 2003; Youn et al., 2011). However, most empirical studies assume system homogeneity and overlook environmental influences. Conceptual frameworks qualitatively assess resilience, though their application in engineering systems remains limited (Komljenovic et al., 2020). Simulation-based methods model resilience behaviour via fuzzy models, Monte Carlo simulations, optimisation algorithms, and Bayesian networks (Tepes, Neumann, 2020; Tong et al., 2020). While widely used in critical infrastructure, they require extensive data and expertise, making them impractical for universal implementation (Karakoc et al., 2019; Ouyang, Wang, 2015). Conversely, index-based approaches provide a semi-quantitative assessment by aggregating predefined resilience metrics (Rehak et al., 2019; Guo et al., 2020). Studies have explored index models for community resilience (Kammouh et al., 2017; Renschler et al., 2019) and technical infrastructure (Storesund, et al., 2018; Guo et al., 2020), considering factors such as redundancy and response capacity. Given these methods, this study introduces a resilience index tailored to underground coal mining, integrating technical, economic, and organisational parameters with fuzzy methodologies to address uncertainties.

Methods

Resilience in systems is categorised into two main components: hard (technical performance) and soft (organisational and human factors in preparedness and recovery). Both aspects must be evaluated to ensure robust resilience. Reliability is a key measure of system preparedness (Youn et al., 2011; Rød et al., 2016), while maintainability (M), supportability (S), organisational resilience (OR), and economic resilience (ER) contribute to recovery (Yoon et al., 2017). Reliability ensures sustained performance under specific conditions (Yoon et al., 2017; Afrin, Yodo, 2019), and maintainability reflects the ability to restore operations within a given timeframe (Sarwar et al., 2018; Rød et al., 2016). Supportability refers to inherent system features enabling effective maintenance, divided into passive (spare parts, logistics) and active (workforce availability, diagnostics) elements (Sarwar et al., 2018; Hosseini, Barker, 2016). Organisational resilience helps maintain stability after disturbances (Omer et al., 2014), while economic resilience mitigates losses and supports sustainable growth (Wang et al., 2020; Rose, 2007).

This study introduces a resilience index based on these five fundamental aspects. In Step 1, reliability and maintainability are assessed using operational data. In Step 2, due to limited direct data, organisational resilience, economic resilience, and supportability are analysed using multi-criteria decision-making methods.

Steps to implement reliability and maintainability based on historical data

To quantify resilience, system constraints—such as repair feasibility, production capacity in different states, maintenance duration, and environmental conditions—must be defined. Reliability analysis involves collecting failure data, that is, time between failures (TBF) and time to failure (TTF) from various sources, alongside key covariates like maintenance type, shift schedules, and working conditions (Tortorella, 2015).

Various models assess the impact of these covariates on hazard rates. This study employs the proportional hazard model (PHM) for time-independent factors and the stratified Cox regression method (SCRM) for time-dependent influences. If the PH assumption holds, PHM is used; otherwise, SCRM is applied for data analysis.

$$R(t, z) = (R_0(t) \prod_{i=1}^n z_i^{\alpha_i}) \quad [1]$$

$$R_s(t, z) = (R_{0s}(t))^{\exp \sum_{i=1}^n z_i \alpha_i} \quad [2]$$

Where (t, z) are reliability functions; $z\alpha = \sum_{i=1}^n z_i \alpha_i$; α (column vector) shows the regression coefficient of the relevant n covariates, (z) (row vector) represents the impact of every variable on the hazard function, and $R_0(t)$ is baseline reliability. In Equation 2, $R_s(t, z)$ and $R_{0s}(t)$ show the hazard rate and baseline hazard in the i layer, respectively.

Finally, the baseline reliability function is determined. In general, when applying the baseline hazard rate, the risk factors do not affect the failure pattern; for this reason, the rate of baseline hazard is considered to be the same as the rate of hazard. This paper uses parametric models and stochastic processes to model the baseline hazard rate (Kumar, Klefsjö, 1994).

Historical data from the field, including TBF, must be gathered to determine baseline reliability. Then, to choose the best model to fit the TBFs data, the assumption of independent and identically distributed (iid) of the data must be determined. Using analytical or graphic methods can analyse the trend test (Barabady, Kumar, 2008). Hence, trend (Military handbook, Laplace, Anderson Darling, and Mann-Kendall) and autocorrelation (graphical method) tests must be done. If there is a trend in the data, the non-homogeneous Poisson process (NHPP) technique, such as the power law process (PLP), can be used for analysis. When there is no sign of trends in the database, and they are correlated, the homogeneous Poisson process (HPP), like the branch Poisson process (BPP), can be used. Otherwise, the classical statistics method, that is, the renewable process (RP), can analyse the collected data. In this research, to do trend tests, Minitab software was applied. According to this software, for each trend test, if its p -value value is more than a significant level (0.05), the null hypothesis of the test (the null hypothesis of all tests is the absence of the trend) is accepted; otherwise, the null hypothesis is not accepted, and the data has a trend. In the following, to do a series correlation test, the i th data of TBF is drawn in terms of $(i - 1)h$ data of TBF in a two-dimensional space. If the drawn points do not have a specific order and are distributed sparsely, then the data are not correlated; in other words, if the drawn data are located along a line, they will be correlated (Garmabaki et al., 2016).

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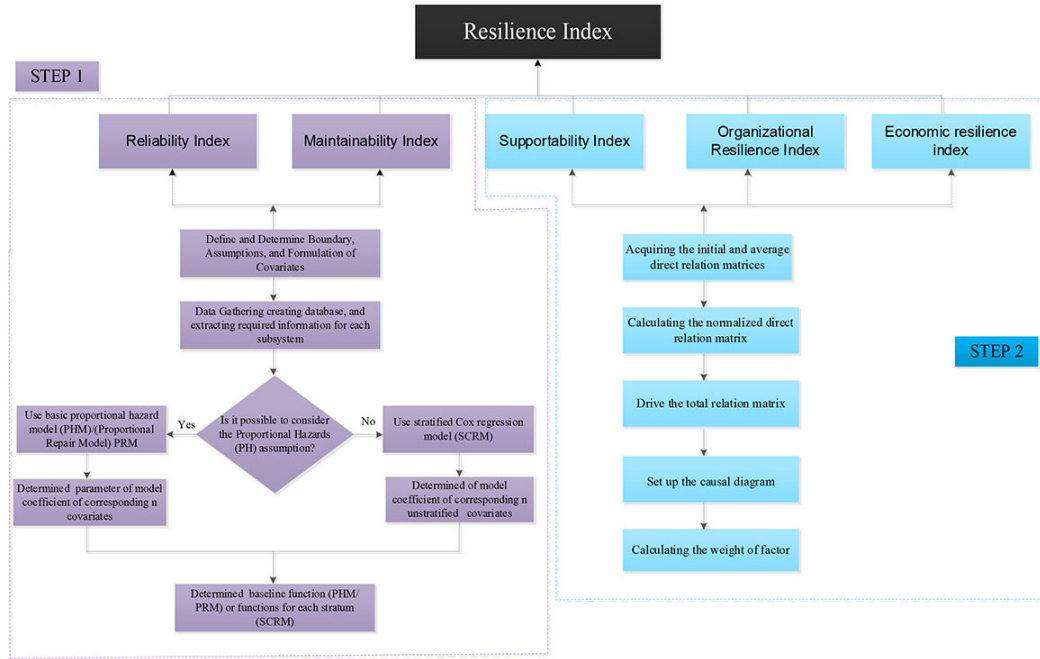


Figure 1—Process for calculating system resilience

Operating environment and covariates such as reliability affect system maintainability. In this index, the proportional repair model (PRM) and the SCRM are used to consider the impact of environmental situations in the repair estimation. PRM is an extended PHM used to predict the extent to which a part is repaired according to covariates. As can be seen in Figure 1, if the PH assumption is not rejected, the PRM is chosen; otherwise, if time-dependent covariates can be classified, it can be applied to the SCRM for data assessment. PRM and SCRM are calculated based on Equations 3 and 4, respectively (Barabadi et al., 2011):

$$M(t,w) = 1 - (1 - M_0(t))^{exp \sum_{j=1}^m \epsilon_j w_j} \quad [3]$$

$$M_g(t,w) = 1 - (1 - M_{0g}(t))^{exp \sum_{j=1}^m \epsilon_j w_j} \quad [4]$$

Where $M(t, w)$ represents the repair and maintainability function, ϵ denotes the regression coefficient of the corresponding covariates (w), and $M_0(t)$ defines the baseline repair rate and maintainability (the cumulative distribution function of time to repair, TTRs). In Equation 4, $M_{0g}(t)$ indicates the baseline maintainability in the g th stratum. Finally, the same procedure was applied to reliability to determine the baseline maintainability function, and TTR data were utilised for maintainability analysis.

The code developed in Python software was used to perform all the steps mentioned in the reliability and maintainability indices.

Steps to implement supportability and organisational resilience-based expert judgment

In this section, a questionnaire must first be designed to collect the necessary data to analyse organisational resilience and supportability. Questions should be asked to determine the underlying factors' current status at the hierarchy's lowest level. People selected for interviews and surveys, in addition to having adequate knowledge about infrastructure, must also have sufficient experience in interacting with infrastructure. In the next step, the feedback received must be quantified. After quantifying the opinions of experts using the MCDM approach, these opinions

should be merged to reach a consensus on the current status of the factor.

The calculation method is as follows: when the number of experts is equal to Z , the fuzzy number representing the opinion of expert z regarding the condition of the i th most effective base factor is defined as:

$$\tilde{p}_{iz} = (a_{iz}, b_{iz}, c_{iz})$$

where a_{iz} , b_{iz} , c_{iz} denote the lower, middle, and upper bounds of the expert's assessment of factor i .

The calculation method is as, when the number of experts is equal to Z . the fuzzy number from the point of view of z 's expert on the condition of i 's the most effective base factor is equal to $\tilde{p}_{iz} = (a_{iz}, b_{iz}, c_{iz})$ in the opinion of the most expert on the status of the first effective factor i , The output of aggregation of expert opinions on the current situation of the effective factor of i at the K level is obtained from Equation 5 (Zadeh, 1968).

$$(\tilde{p}_i)_K = (a_i, b_i, c_i) = \left(\min\{a_{iz}\}, \frac{\sum_{z=1}^Z b_{iz}}{Z}, \max\{c_{iz}\} \right) \quad [5]$$

Where, a_i , b_i , and c_i show the lower, the middle, and the upper bound, respectively, which is the current situation of the i effective base factor at the K 's level. Defuzzification is obtained from Equation 6. The output of Equation 5 is considered as the probabilities of the effective base factor of the i at the K level

$$(P_i)_K = \frac{(a_i + 2b_i + c_i)}{4} ; \quad 0 \leq P_i \leq 1 \quad [6]$$

The probabilities of the influential factor j at the $K-1$ level are also estimated using the weighted average of the probabilities of the base factors affecting that factor at the K -level level point as follows

$$(P)_{K-1} = \left(\sum_{i=1}^n P_i W_i \right)_K ; \quad \sum_{i=1}^n W_i = 1 \quad [7]$$

In Equation 7, P_j indicates the probabilities of the influential factor j at the $K-1$ level, and n represents the number of effective

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base factors connected to the influential factor j at the $K-1$ level. Also, W_i represents the normalised weight of the effective base factor of the i at the K level. The weight coefficients of different levels show the importance of influencing factors. To calculate the weight of impacting factors, the fuzzy decision-making trial, and evaluation laboratory (Fuzzy DEMATEL) method as an MCDM approach were used. The calculation steps are detailed in Appendix A (Gabus, Fontela, 1972).

Case study

Shields in underground coal mines play a vital role in ensuring safe and efficient extraction of coal seams within the longwall system. Designed to support controlled roof caving while simultaneously protecting miners, these critical infrastructure (CI) systems provide structural stability and operational reliability. In this study, the shield system of the Tabas Longwall coal mine in Iran is examined using the proposed methodology (Figure 2). The mining shield—FAZOS 10/28 Poz, 10/28Poz/BSN—is engineered to function in longwall faces with longitudinal inclinations exceeding 12° , incorporating additional stabilising devices for enhanced performance. The system operates seamlessly in seams with longitudinal inclinations up to 12° , stabilising devices up to 30° , and transverse inclinations ranging from $\pm 15^\circ$. Its backward advance functionality ensures continuous efficiency in longwall mining operations. This shield system is meticulously designed to automate key mining processes, including:

- Establishing roof support with initial load-bearing capacity.
- Maintaining continuous load-bearing stability for roof protection.



Figure 2—The location of the Tabas Longwall coal mine

- Releasing and advancing the support following each mining cycle.
- Adjusting the armored face conveyor (AFC) machine for optimal operation.
- Correcting canopy and support positions for improved structural integrity.
- Shielding the longwall front to ensure worker safety.
- Lifting the bases and stabilising the AFC for sustained performance.

A schematic representation of the shield system is presented in Figure 3, highlighting its core components, such as the canopy, wooden blocks, base, advancing ram, hydraulic legs, and other essential elements.

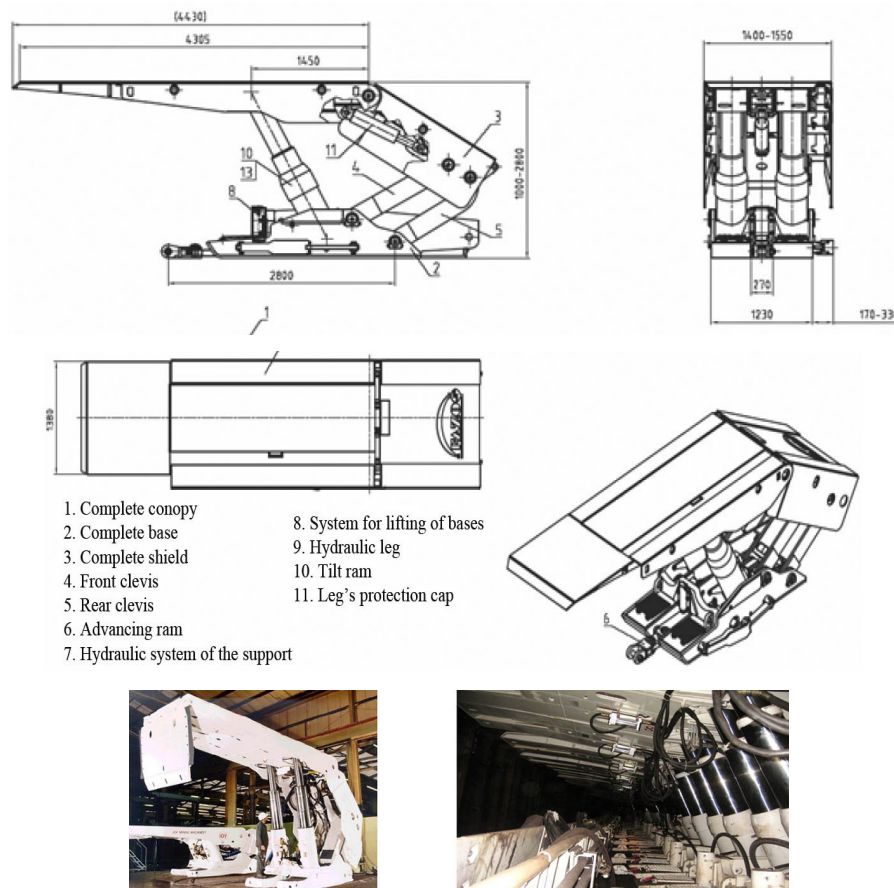


Figure 3—A schematic view of the mine shield system

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Resilience analysis of the shield system

Reliability, and maintainability indices

In the initial phase, data pertaining to the reliability and maintainability indices of the shield system must be systematically gathered. This dataset includes time-related parameters and covariates, which have been meticulously recorded over a period of approximately two and a half years. Table 1 presents the failure data of the shield system, while Table 2 provides details on the repair data, offering valuable insights into the system's overall performance and maintenance trends.

As illustrated in Table 2 and Table 3, respectively, the columns TBF and TTR provide insights into the shield system's performance across various environments. In the status column, a cell with a value of zero indicates a censored failure, whereas a value of one represents a confirmed shield failure. The remaining columns in the tables display covariates, which were collected through both quantitative and qualitative methods. For quantitative data, numerical values such as cut length (metres) and cut average (metres) were recorded. In contrast, qualitative data were gathered from multiple sources, including archived statistics, official documents, direct observations, and interviews with key personnel.

To accurately define the subsystem covariates, a comprehensive approach was taken—leveraging the expertise of managers and operators, conducting observations, analysing repair shop records

and reports, consulting maintenance teams, and incorporating field data. The categorised covariates are presented in Tables 3 and 4, detailing failure covariates and repair covariates, respectively.

The covariates of failure and repair operating environment of the shield system are statistically formulated, as shown in Table 5.

To evaluate the reliability and maintainability indices of the shield system, it is essential to consider the proportional hazards (PH) assumption and conduct the required tests outlined in Step 1 of Figure 1. Accordingly, all calculations were performed using custom-developed Python code to ensure precise analyses. The computed results for the reliability and maintainability indices of the shield system, based on the PH model, are systematically presented in Tables 6 and 7.

Table 1
The collected failure data of the shield system

Row	TBF (min)	Status	Shift	Working Place	Type of delay	Type of maintenance	Cut (m)	Cut average height (m)
1	50	0	3	1	1	1	1	2.1
3	140	1	1	1	1	1	3	2.1
3	50	1	2	1	1	1	3	2.1
4	60	1	1	1	1	1	0.5	2.1
5	50	1	2	1	1	1	0.5	2.1
6	120	1	1	1	1	1	2	2.1
.
.
.

Table 2
The collected repair data of the shield system

Row	TBF (min)	Status	Shift	Working Place	Type of delay	Personnel
1	290	0	3	1	1	3
3	380	1	1	1	1	3
3	410	1	2	1	1	3
4	380	1	1	1	1	3
5	310	1	2	1	1	3
6	290	1	1	1	1	3
.
.
.

Table 3
Classification and quantification of failure covariates for the shield system

Covariates	Classification (Qualification)
Shift	Morning (1)
	Midday (2)
	Night (3)
Working place	E0.face (1)
	E3.face (2)
Type of delay	Mineral (1)
	Mechanical (2)
	Electric (3)
Type of maintenance	Strap (1)
	Frame (2)

Table 4
Classification and quantification of repair covariates for the shield system

Covariates	Classification (Qualification)	Covariates	Classification (Qualification)
Shift	Morning (1)	Personnel	Captain (1)
	Midday (2)		Take care of the cable (2)
	Night (3)		Mineral (3)
Working place	E0.face (1)		Mechanical (4)
	E3.face (2)		Electric (5)
Type of delay	Mineral (1)		
	Mechanical (2)		
	Electric (3)		

Table 5
The covariates for the shield system failure and repair operating environment

Failure covariates	Repair covariates
Shift (z_1)	Shift (w_1)
Working place (z_2)	Working place shift (w_2)
Type of delay (z_3)	Type of delay shift (w_3)
Type of maintenance (z_4)	Personnel (w_4)
Cut (m) (z_5)	
Cut average height (m) (z_6)	

Table 6
Results rate proportional hazards model of reliability

covariates	coef	Exp (coef)	Se (coef)	coef lower 95%	coef upper 95%	Exp (coef) lower 95%	Exp (coef) upper 95%	Z	P	-log2 (p)
Shift	0.02	1.02	0.09	-0.15	0.18	0.86	1.20	0.18	0.86	0.22
Working place	-0.30	0.74	0.25	-0.79	0.19	0.46	1.21	-1.2	0.24	2.08
Type of delay	-0.06	0.94	0.20	-0.45	0.33	0.64	1.39	-0.3	0.76	0.39
Type of maintenance	0.00	1.00	0.00	0.00	0.00	1.00	1.00	0.63	0.53	0.92
Cut (m)	0.00	1.00	0.00	0.00	0.00	1.00	1.00	-0.03	0.98	0.03
Cut average height (cm)	0.01	1.01	0.01	-0.01	0.02	0.99	1.02	0.93	0.35	1.50

Table 7
Results rate proportional hazards model of maintainability

covariates	coef	Exp (coef)	se (coef)	coef lower 95%	coef upper 95%	Exp (coef) lower 95%	Exp (coef) upper 95%	Z	P	-log2(p)
Shift	0.10	1.11	0.08	-0.05	0.26	0.95	1.30	1.31	0.19	2.38
Working place	1.43	4.20	0.94	-0.41	3.28	0.66	2.60	1.52	0.13	2.97
Type of delay	0.03	1.03	0.24	-0.44	0.50	0.64	1.65	0.12	0.90	0.15
Personnel	0.00	1.00	0.00	0.00	0.00	1.00	1.00	0.46	0.64	0.64

The test statistic follows a Chi-square (1) distribution under the null hypothesis, where the covariate complies with the proportional hazards (PH) assumption. According to this hypothesis, the expected value of the test statistic is zero, and any deviation from zero may be statistically significant at predetermined significance levels, such as 0.01 or 0.05. If the p-value falls below these thresholds, the stratified Cox regression method (SCRM) should be employed instead. However, as indicated in Table 7, the p-values exceed both 0.05 and 0.01, confirming the validity of the proportional hazards model (PHM) for this analysis.

Following this confirmation, the actual reliability function for the shield system was derived using Equation 8. Ultimately, the resulting reliability curve for the shield system is depicted in Figure 4, providing valuable insights into its long-term operational performance.

$$R(t, z) = R_0(t) \exp(0.86z_1 + 0.24z_2 + 0.76z_3 + 0.53z_4 + 0.98z_5 + 0.35z_6) \quad [8]$$

As illustrated in Figure 4, the reliability of the shield system decreases to 50% after 29 hours of operation, factoring in the influence of environmental conditions. Furthermore, after 100 hours of continuous operation, the system's reliability declines to zero, indicating the need for maintenance or intervention to restore functionality.

As shown in Table 8, the p-values exceed 0.05 and 0.01, indicating that the PRM is accepted. Additionally, the

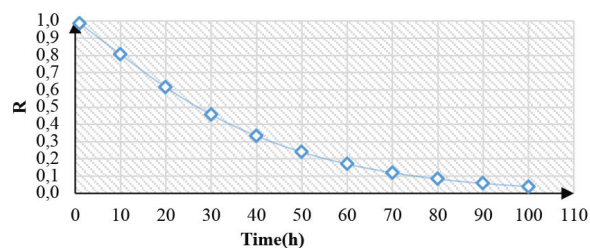


Figure 4—Shield system reliability

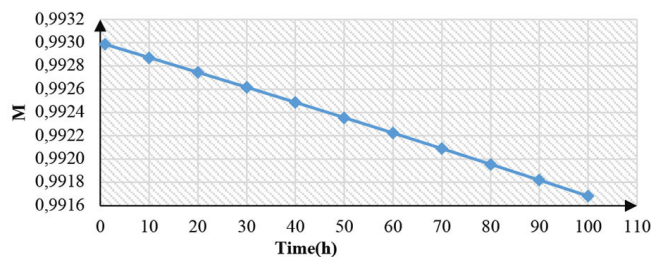


Figure 5—Shield system maintainability

maintainability value of the shield system was obtained using Equation 9. Finally, the maintainability curve of the shield system based on the operating environment, is illustrated in Figure 5.

$$M(t, w) = 1 - (1 - M_0(t)) \exp(0.19w_1 + 0.13w_2 + 0.9w_3 + 0.64w_4) \quad [9]$$

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As illustrated in Figure 6, the maintainability of the shield system has remained above 90% after 100 hours of operation, taking into account the effects of the operating environment. This stability highlights the system's resilience and reliability under various operational conditions.

Organisational resilience, supportability, and economic resilience indices

The concept of resilience plays a crucial role in enabling organisations to effectively respond to unanticipated events, particularly in volatile and uncertain environments (Mosoarca et al., 2019). The resilience of systems is influenced not only by the technology they incorporate but also by the organisations that manage those (Rehak et al., 2019). In this regard, considering the frequency of usage in previous studies, expert recommendations, and analytical assessments, the relevant factors of this index in underground coal mining were stratified (Appendix B) based on the following criteria: (a) Limited selection of impacting factors (b) Avoidance of redundant impacting factors (c) Preference for easily measurable parameters.

The organisational resilience index was structured around five key aspects: response and recovery (Luthans et al., 2015), absorption and reduction (Rehak et al., 2019), sense of ownership (Luthans et al., 2015), monitoring and prediction (Baroud et al., 2014), and commitment and resilience (Brown et al., 2017). If these aspects do not meet the desired standards within an organisation, both material and human resources may be ineffectively utilised in critical situations. Therefore, managers must take these influencing factors into account to enhance organisational resilience. To execute Step 2 of Figure 1 for analysing organisational resilience in underground coal mining based on the operating environment, questionnaires were distributed among personnel from 25 organisations, yielding 19 responses. Experts were then asked to evaluate the direct influence of row-based factors on column-based factors, as depicted in Table 1.

Subsequently, the Fuzzy DEMATEL method was employed to determine the weight of each factor. This was followed by calculating the probabilities of the impacting factors, resilience aspects, and overall organisational resilience. As illustrated in Figure 6, expert judgments indicate that response and recovery are the most critical aspects of resilience. However, nearly all aspects and influencing factors require improvement. Based on the findings, if the mine organisation experiences disruption (e.g., failure of the shield system), the probability of demonstrating resilience is 40.2%.

In alignment with the organisational resilience index rules, the aspects and influencing factors of the supportability index were carefully selected. Here, operational conditions (Hosseini, Barker, 2016; Sarwar et al., 2018; Tortorella, 2015) and system design (Tortorella, 2015) serve as the fundamental components of the supportability index (Appendix C). To establish the hierarchical structure of the shield system's supportability index, a comprehensive questionnaire consisting of 14 questions was developed to assess the state of key impacting factors. This questionnaire was completed by 14 preventive maintenance specialists and shield system operators. Subsequently, leveraging the outcomes of the survey, the probabilities of the primary influencing factors were determined. Additionally, using the Fuzzy DEMATEL technique, the weights of both aspects and individual impacting factors were calculated. Finally, in accordance with the proposed methodology, the probabilities of the supportability index and its generic aspects were computed. Figure 7 presents the calculation results, illustrating the weights and probabilities assigned to each parameter within the system. The analysis reveals that both aspects are equally significant and require improvements. Based on the findings, if the mine support section experiences disruptions—such as failures within the shield system—the probability of demonstrating resilience is estimated at 65.7%.

Building upon the principles established for organisational resilience and supportability indicators, the aspects and influencing factors of the economic resilience index were carefully selected.

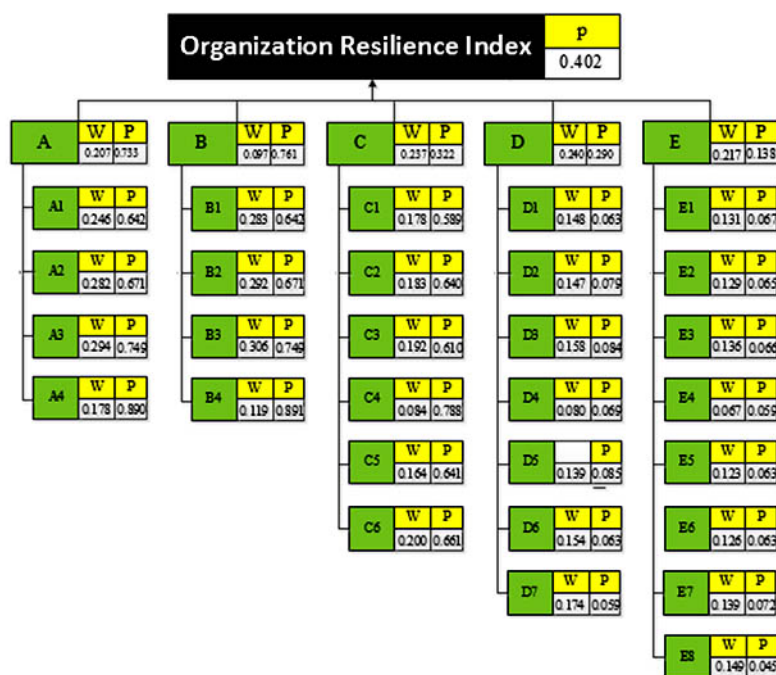


Figure 6—The results of the shield system organisational resilience index estimation

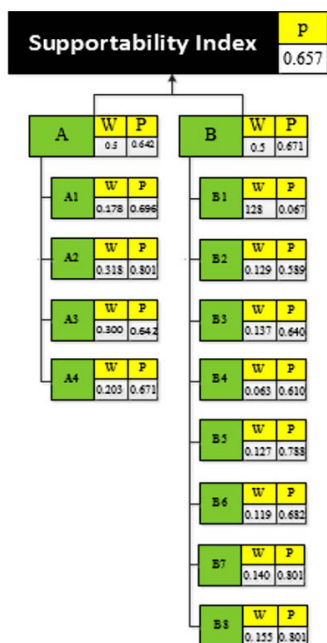


Figure 7—The results of the shield system supportability index estimation

As illustrated in Appendix D, fixed pricing (Da Silva et al., 2021; Czaplicka-Kolarz et al., 2015; Wu et al., 2018) and employment (Da Silva et al., 2021; Klank, 2011) serve as the fundamental components of this index. Following the methodology outlined in previous steps, a structured questionnaire consisting of 12 questions was developed to assess the primary influencing factors within the shield system. This questionnaire was completed by 18 experts from the economic sector relevant to the study. Using the responses obtained from the survey, the probabilities of the basic influencing factors were calculated. Additionally, the weights of the aspects and impacting factors were estimated through the fuzzy mathematical technique. Finally, applying the proposed methodology, the probabilities of the generic aspects and the overall economic resilience index were determined. Figure 8 presents the calculated economic resilience index results for the case study, depicting the weight and probability of each parameter within the system. The findings indicate that both aspects hold nearly equal significance and require improvement. Based on the results, if the mine's economic sector faces disruption—such as a failure in the shield system—the probability of exhibiting resilience is estimated at 49.7%.

Presentation of the main shield system resilience index

The estimated values for resilience concepts were utilised to calculate the resilience index (Ri), as presented in Table 8. This table distinguishes between reliability and maintainability indicators, which are assessed over time (up to 100 hours), and organisational resilience, support capability, and economic resilience, which are evaluated at fixed time intervals. To establish a structured resilience assessment, five classes were defined. The ideal class—representing the highest level of resiliency—is assigned 100% of the weight, while the lowest class receives 10% of the total weight. Consequently, the Ri is computed as the summation of index probabilities, as formulated in Equation 10. A higher Ri value signifies greater resilience, whereas lower values indicate a more vulnerable state. Using the Ri computational model, the minimum resiliency rating is 10, and the maximum possible is 100. In the case of the shield system within the Tabas underground coal mine, resilience levels



Figure 8—The results of the shield system economic resilience index estimation

were categorised into five distinct groups based on the Ri values, as detailed in Table 9.

$$Ri = \sum_{i=1}^5 \text{score}_R \tag{10}$$

According to Table 10 and Figure 9, the shield system demonstrates poor resilience, with its stability gradually declining over time. After 100 hours of operation, only 20%–30% of system failures are expected to be recoverable, allowing the water installation to resume normal functionality. Among the key indicators, reliability, maintainability, and supportability are in relatively good condition. However, organisational and economic resilience indexes exhibit major weaknesses, with most aspects and influencing factors falling below acceptable standards. Several contributing factors have led to this decline, including the absence

Table 8
Calculation of Ri for the shield system in the Tabas underground coal mine

Time (hr) (t)	R	M	S	OR	ER
1	0.98574	0.09930	0.657	0.402	0.497
10	0.80617	0.09929	0.657	0.402	0.497
20	0.61456	0.09927	0.657	0.402	0.497
30	0.45643	0.09926	0.657	0.402	0.497
40	0.33284	0.09925	0.657	0.402	0.497
50	0.23926	0.09924	0.657	0.402	0.497
60	0.16995	0.09922	0.657	0.402	0.497
70	0.11949	0.09921	0.657	0.402	0.497
80	0.08326	0.09920	0.657	0.402	0.497
90	0.05755	0.09918	0.657	0.402	0.497
100	0.03949	0.09917	0.657	0.402	0.497

Table 9
Classification of Ri

Ri	10-20	20-40	40-60	60-80	80-100
	very poor	Poor	fair	good	Excellent

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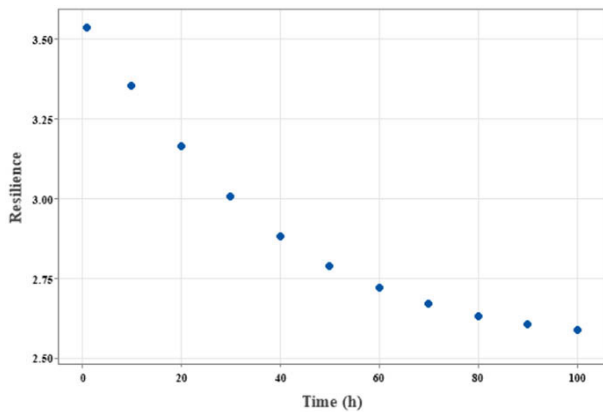


Figure 9—Shield system Ri curves

of coordinated and integrated policies, price intervention measures affecting the parts supply chain, weak economic diplomacy, and sanctions limiting access to essential replacement components.

To address these challenges, organisations must take proactive steps such as engaging mining personnel in company goal discussions, fostering a positive organisational atmosphere, and considering political and economic constraints. By implementing these strategies, the resilience of these indexes can be significantly improved.

Given the shield system's poor resilience, a series of corrective measures must be taken, including comprehensive training programmes, the employment of experienced professionals, and swift responses to spare parts maintenance and repair. Additionally, mine management should establish a specialised initiative to strengthen industry-academia collaboration, recognising that universities serve as critical foundations for developing skilled and specialised workforces. When academic expertise is effectively integrated into industrial production, it accelerates innovation, technological advancement, and economic growth.

Conclusion

This study introduced a novel resilience index (R_i) to assess resilience in underground coal mining, considering the impact of the operating environment. The analysis incorporated historical data and expert judgment, with data processing facilitated through a Python-based computational model. Additionally, the fuzzy set theory was applied to address potential uncertainties in expert evaluations. The proposed methodology accounts for multiple resilience indicators, including reliability, maintainability, supportability, organisational resilience, and economic resilience. To demonstrate its practical application, the model was implemented for the shield system in the Tabas Longwall coal mine, a vital component of underground mining operations.

Key findings from the study include:

- The operating environment significantly influences the shield system's resilience.
- The shield system's resilience declines over time.
- Organisational and economic resilience indicators exhibit weaker performance compared to reliability, maintainability, and supportability, leading to a substantial impact on overall resilience. Therefore, project managers should prioritise improvements in these two areas to enhance the shield system's stability within the production system.
- Between 20% and 30% of system failures are likely recoverable.
- Based on the R_i , the shield system in the Tabas underground coal mine is classified as having poor resilience.

These findings underscore the critical need for strategic interventions to improve resilience in underground mining operations. Strengthening organisational and economic resilience, along with proactive maintenance strategies, will be key to ensuring sustainable and reliable mining performance.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Obtaining average direct-relation matrices: utilizing fuzzy triangular number (TFN) (displayed in Table I and Figure 1), experts show the direct influence that parameter i exerts on parameter j . The TFN computes are $\tilde{z}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ that in first, second and third terms indicate the lower, middle, and upper bounds of TFN that shows the direct influence of parameter i on parameter j based upon the opinion of k^{th} expert. The average direct relation matrix can be estimated by averaging the h expert's value matrices as Equation 1:

Linguistic terms	Linguistic value
Very High Influence (VH)	(0.75, 1.0, 1.0)
High Influence (H)	(0.5, 0.75, 1.0)
Low Influence (L)	(0.25, 0.5, 0.75)
Very Low Influence (VL)	(0, 0.25, 0.5)
No Influence (NO)	(0, 0, 0.25)

$$\tilde{A} = \frac{(\tilde{Z}^1 \oplus \tilde{Z}^2 \oplus \dots \oplus \tilde{Z}^h)}{h} \quad [1]$$

Obtaining normalised direct-relation matrix. Based on the matrix, the normal direct-relation matrix can be obtained (Equation 2) as follows:

$$\tilde{X} = \frac{\tilde{A}}{r} \quad [2]$$

$$r = \max[\max_{1 \leq i \leq n} \sum_{j=1}^n u_{ij}, \max_{1 \leq j \leq n} \sum_{i=1}^n u_{ij}], \quad i, j = 1, 2, \dots, n. \quad [3]$$

Let $\tilde{x}_{ij} = (l'_{ij}, m'_{ij}, u'_{ij})$ be the elements of \tilde{X} and describe three crisp matrices, whose elements are obtained from \tilde{X} as follows:

$$X_l = \begin{bmatrix} 0 & l'_{12} & \dots & l'_{1n} \\ l'_{21} & 0 & \dots & l'_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ l'_{n1} & l'_{n2} & \dots & 0 \end{bmatrix}, \quad X_m = \begin{bmatrix} 0 & m'_{12} & \dots & m'_{1n} \\ m'_{21} & 0 & \dots & m'_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ m'_{n1} & m'_{n2} & \dots & 0 \end{bmatrix}, \quad X_u = \begin{bmatrix} 0 & u'_{12} & \dots & u'_{1n} \\ u'_{21} & 0 & \dots & u'_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ u'_{n1} & u'_{n2} & \dots & 0 \end{bmatrix} \quad [4]$$

Drive the total relation matrix. The total relation matrix \tilde{T} is calculated as follows (Equation 4), where the identity matrix is indicated as I .

$$\tilde{T} = \tilde{X} (I - \tilde{X})^{-1} \quad [4]$$

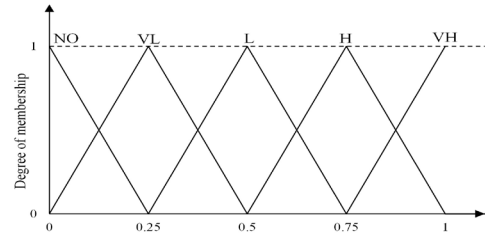


Figure 1—Linguistic variables

The elements of the matrix contain fuzzy triangular numbers as presented in the following Equation.5:

$$\tilde{T} = \begin{bmatrix} \tilde{t}_{11} & \tilde{t}_{12} & \dots & \tilde{t}_{1n} \\ \tilde{t}_{21} & \tilde{t}_{22} & \dots & \tilde{t}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{t}_{n1} & \tilde{t}_{n2} & \dots & \tilde{t}_{nm} \end{bmatrix} \quad [5]$$

Where elements are $\tilde{t}_{ij} = (l''_{ij}, m''_{ij}, u''_{ij})$. According to the crisp case, the crisp elements of total relation matrices can be calculated as:

$$T_l = [l''_{ij}] = X_l (I - X_l)^{-1}; \quad T_m = [m''_{ij}] = X_m (I - X_m)^{-1}; \quad T_u = [u''_{ij}] = X_u (I - X_u)^{-1}$$

Set up the causal diagram. After acquiring matrix \tilde{T} , the sum of rows (\tilde{D}) (Equation 6) and the sum of columns (\tilde{R}) (Equation 7) of the total relation matrix can be calculated as follows:

$$[\tilde{D}_{ij}]_{n \times 1} = \left(\sum_{j=1}^n l_{ij}, \sum_{j=1}^n m_{ij}, \sum_{j=1}^n u_{ij} \right), \quad i, j = 1, 2, \dots, n \quad [6]$$

$$[\tilde{R}_{ij}]_{1 \times n} = \left(\sum_{i=1}^n l_{ij}, \sum_{i=1}^n m_{ij}, \sum_{i=1}^n u_{ij} \right), \quad i, j = 1, 2, \dots, n \quad [7]$$

Calculating the weight of the factor (Equation 8). The fuzzy weight of each parameter (\tilde{w}_i) can be calculated as follows:

$$\tilde{w}_i = \left(\frac{l_{\tilde{D}_i} + l_{\tilde{R}_i}}{\sum_{i=1}^n l_{\tilde{D}_i} + \sum_{i=1}^n l_{\tilde{R}_i}}, \frac{m_{\tilde{D}_i} + m_{\tilde{R}_i}}{\sum_{i=1}^n m_{\tilde{D}_i} + \sum_{i=1}^n m_{\tilde{R}_i}}, \frac{u_{\tilde{D}_i} + u_{\tilde{R}_i}}{\sum_{i=1}^n u_{\tilde{D}_i} + \sum_{i=1}^n u_{\tilde{R}_i}} \right) \quad [8]$$

Defuzzification weight of factors: to defuzzify weights of, the Best Non-fuzzy Performance (BNP) method (Equation 9) was used to defuzzify the values of \tilde{D} , \tilde{R} , and \tilde{W}_i as follows:

$$BNP = l + \frac{(u-l) + (m-l)}{3} \quad [9]$$

Where l , m , and u show lower, middle, and upper bounds of TFN values, respectively

Appendix B

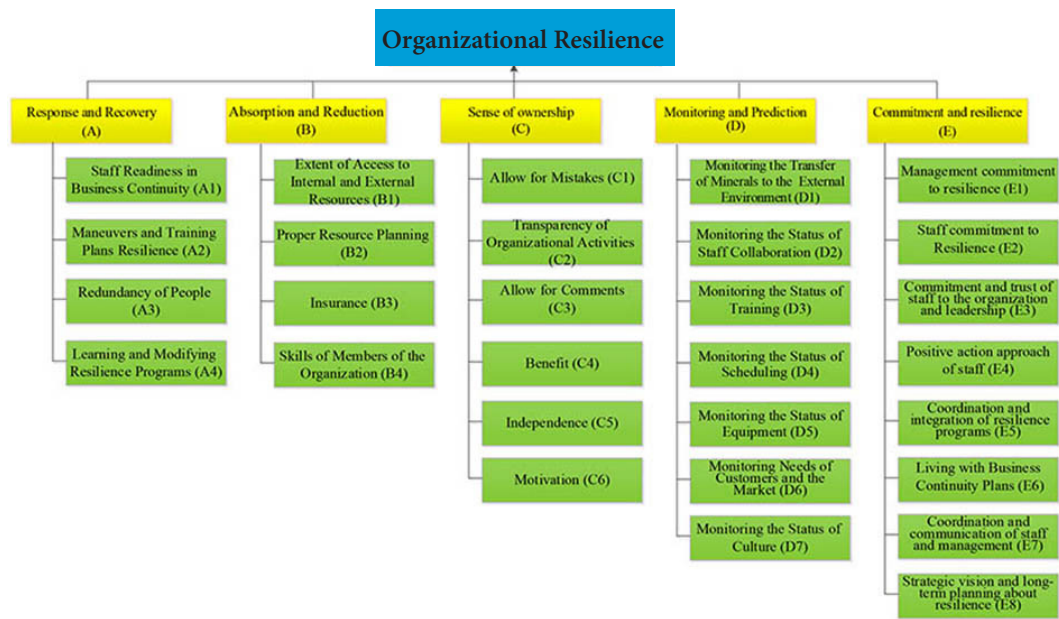


Figure 2—Factors for organisational resilience index

Appendix C

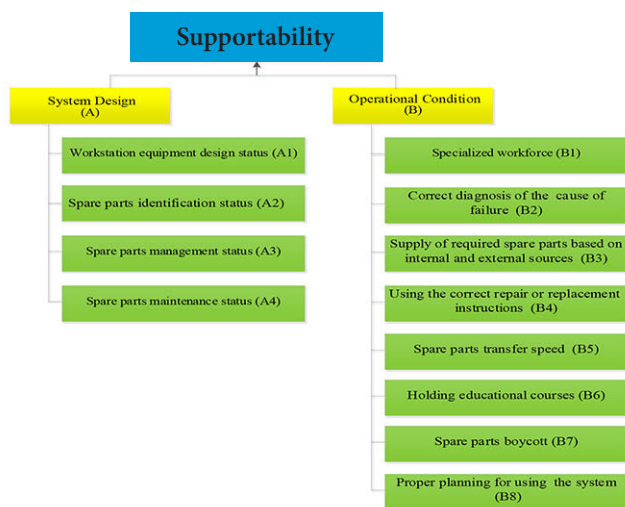


Figure 3—Factors for supportability index

Appendix D

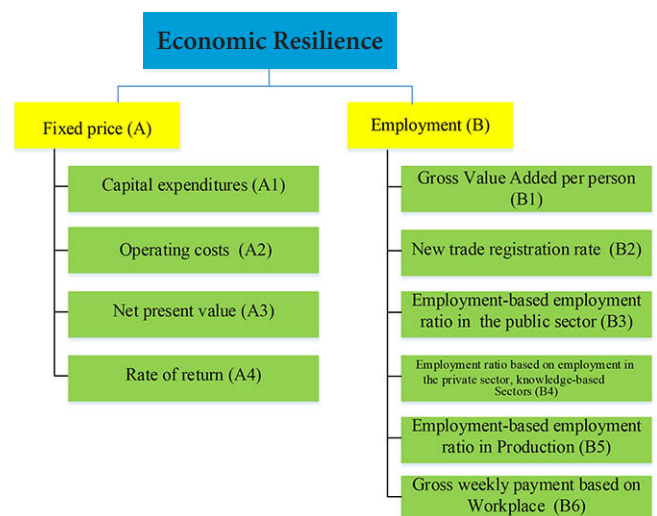


Figure 4—Factors for economic resilience index