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REVIEW ARTICLE

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A review on rockburst prediction and prevention to shape an ontology-based framework for better decision-making for underground excavations

Hongchuan Yan[1] | **Haijiang Li**[2] | **Hongqiang Xie**[1] | **Mingli Xiao**[1] | **Jianliang Pei**[1] | **Huaizhong Liu**[1] | **Jiangda He**[1]

[1]State Key Laboratory of Hydraulics and Mountain River Engineering, College of Water Resource and Hydropower, Sichuan University, Chengdu, China

[2]School of Engineering, Cardiff University, Cardiff, UK

Correspondence

Haijiang Li, School of Engineering, Cardiff University, Cardiff CF24 3AA, UK.
Email: LiH@cardiff.ac.uk

Hongqiang Xie, State Key Laboratory of Hydraulics and Mountain River Engineering, College of Water Resource and Hydropower, Sichuan University, Chengdu 610065, China.
Email: alex_xhq@scu.edu.cn

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Abstract

With underground engineering projects becoming deeper and more complex, the associated safety problems, especially rockburst, have increasingly increased. Despite decades of research, effective management of rockburst continues to be a formidable challenge in underground excavations. This study presents a scientometric visualization analysis of 2449 papers and conducts a comprehensive review of 336 key studies to explore the state-of-the-art developments in rockburst research. With a primary focus on the prediction and prevention of rockburst, this review identifies existing research gaps and proposes a novel framework aimed at addressing these challenges in underground excavations. The results underscore a critical disconnect between advanced prediction methods and engineering practices, which limits the ability of engineers to carry out reliable assessments of rockburst potential. This disconnection prevents the prompt development of targeted prevention strategies, further aggravated by inadequate data sharing across large-scale projects. The review also describes the limitations of relying solely on data-driven methodologies to address the complex challenges in the lifecycle management of underground excavations. To overcome these challenges, this study proposes an innovative framework based on an ontological knowledge base. This framework is designed to integrate multisource data and diverse analysis techniques, exploring the means toward better decision-making in future digital underground projects.

KEYWORDS

decision support system, ontology, rockburst, scientometric analysis, underground engineering

Highlights

- A scientometric analysis of 2449 journal articles and critical review of 336 papers were conducted.
- Challenges and research gaps in rockburst prediction and prevention were discussed and identified.
- An ontology-based framework for better decision-making for underground excavations was proposed.

1 | INTRODUCTION

Rockburst is a hazardous phenomenon encountered during underground excavations, especially in projects involving brittle and hard rocks (Blake & Hedley, 2003). The earliest report of a rockburst dates back to 1738 in a tin mine in England, although it was not officially recorded until 1938, in a coal mine in Stafford, England (Askaripour et al., 2022). Globally, similar incidents with varying intensities and consequences have been reported in mines, tunnels, and hydropower caverns across China, the United States, Africa, Australia, Canada, and so on (Kaiser et al., 1996; Keneti & Sainsbury, 2018; Leger, 1991; Li et al., 2012; Mark, 2016; Rehbock-Sander & Jesel, 2018; Simser, 2019). Nowadays, the challenge of ensuring the safety and stability of increasingly deep and complex underground engineering has intensified, resulting in substantial casualties and property damage. Addressing this pressing issue remains a formidable challenge as the demand for underground space and resources grows.

The term "rockburst" was originally introduced by Terzaghi (1946) to define the spalling or failure of hard rock from tunnel walls under the influence of high stress. This phenomenon is primarily characterized by the sudden release of strain energy due to high geo-stress disturbances during underground excavation, leading to severe and violent damage (Singh, 1987; Zhang et al., 2021). Due to complex influencing factors, such as the geomechanical conditions, rock mass characteristics, and excavation strategy, it remains difficult for scholars even today to arrive at a universally accepted definition or to fully comprehend its causation and progression mechanisms (Brown, 1988; Zhou et al., 2018). As a result, how to develop comprehensive strategies for rockburst management during underground construction is still an open question.

In response to this challenge, the past several decades have witnessed substantial progress in the development of rockburst control methodologies. These prediction methods range from rockburst classification to criteria, including empirical (Kwasniewski et al., 1994; Russenes, 1974; Turchaninov et al., 1972), numerical simulation (Huang & Wang, 1999; Qian & Zhou, 2011; Zubelewicz & Mroz, 1983), and mathematical approaches (Ghasemi et al., 2020; Li, Feng, et al., 2017; Liu, Xue, et al., 2023; Wu, Wu, et al., 2019). They can effectively forecast rockburst in terms of various aspects, resulting in significant advancements in rockburst prediction. However, the complexity and variability of conditions in underground engineering conditions have hindered the establishment of an applicable and practical criterion for rockburst prediction. The variation and inconsistency in the threshold values among different criteria further complicate the timely identification and assessment of rockburst potential (Afraei et al., 2019; Kaiser & Cai, 2012). Improvement of prediction accuracy is a key focus in the digital-driven era, but design and implementation of effective prevention systems targeting rockburst are even more important for engineering. Unlike support systems at shallower depths, which mainly aim to manage the self-weight of rock to prevent falls, support designs for deep excavations must consider the capacity to bear and mitigate the effects of dynamic loads to prevent the disintegration of fractured rock (Bacha et al., 2020; Cai, 2013; Kaiser & Cai, 2013). The selection of appropriate support measures requires a reliable assessment of rockburst risks tackling instability problems in high geo-stress conditions. Nevertheless, the unpredictable nature of rockburst and the uncertainties of underground conditions make the design of effective support systems a complex task, often delaying the implementation of timely preventive measures.

As mentioned above, reduction of the risk of rockburst still remains a significant challenge for engineers and researchers worldwide. The lack of effective rockburst management technologies may significantly increase the risk of severe disasters in deep underground engineering under high geo-stress. There have been several reviews summarizing the state-of-the-art advancements in the rockburst research, for example, He et al. (2023) provided a comprehensive analysis of rockburst based on experiments, theories, and simulations. Askaripour et al. (2022) reviewed the classification and mechanism of rockburst and summarized the current empirical methods of rockburst prediction. Pu, Apel, Liu et al. (2019) and Basnet et al. (2023) surveyed the current applications of machine learning in rockburst prediction and discussed their features and performances, respectively. Zhou et al. (2018) and Zhou, Zhang, et al. (2023) discussed rockburst classification and characteristics, and reviewed research related to rockburst prediction and prevention. Ghorbani et al. (2020) provided a critical review of the advancement of rock support systems in high geostress conditions and discussed the uniqueness of support systems in this area. Despite providing a comprehensive review of rockburst mechanisms, prediction, and prevention, these articles have not further explored a holistic and feasible framework for underground engineering in the age of artificial intelligence (AI). Therefore, to bridge these gaps, this paper first reviews the rockburst research based on the publications in the Web of Science Core Collection (WoSCC) database. With the aid of CiteSpace software, a scientometric analysis on rockburst research from 2000 to 2023 is presented, covering the number of studies, journal co-citation, document co-citation, and keywords analysis (Section 3). Subsequently, by conducting a comprehensive review of rockburst prediction methods (Section 4) and prevention strategies (Section 5), key tasks and challenges in underground engineering are identified and discussed. Based on the above review and analysis, a novel ontology-based framework throughout the underground engineering lifecycle is proposed (Section 6).

2 | REVIEW AND ANALYSIS METHODOLOGY

This study reviews the literature on rockburst in underground engineering using the WoSCC database, which is an influential database specifically in science and engineering fields. The WoSCC offers advanced retrieval capabilities for comprehensive literature searches, including logical operators such as "AND" and "OR" to refine searches (Vanderstraeten & Vandermoere, 2021). As illustrated in Figure 1, the literature retrieval process comprised three steps. In Step 1, a basic search was executed with the search code: TS = (Rockburst* OR Rock burst*), where "TS" signifies the article's topic and "*" is for fuzzy searches. Meanwhile, only articles and review articles published between January 1, 2000 and December 31, 2023, in English and Chinese, were selected. After preliminarily filtering out unrelated papers, a total of 2449 papers focused mainly on rockburst prediction and prevention were collected. Then, Step 2 refined the rockburst search in terms of the aspects of prediction and prevention using keywords that are commonly used in rockburst publications: "prediction," "evaluation," "assessment," "estimation," "prevention," "protection," "control," and "support." To ensure that no potential papers were omitted, the snowballing technique

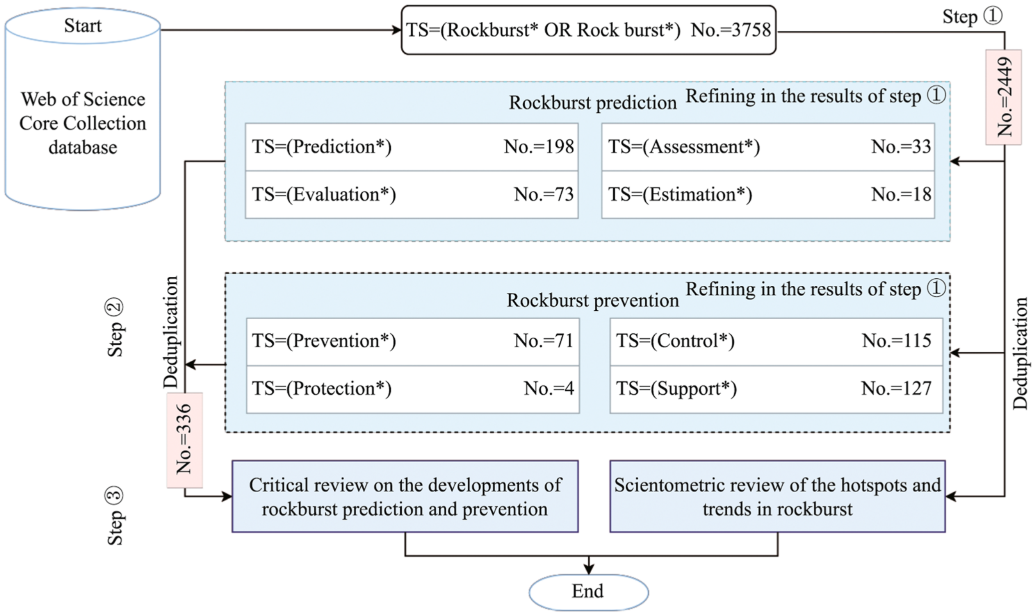

FIGURE 1 Steps to search for papers in the Web of Science Core Collection database.

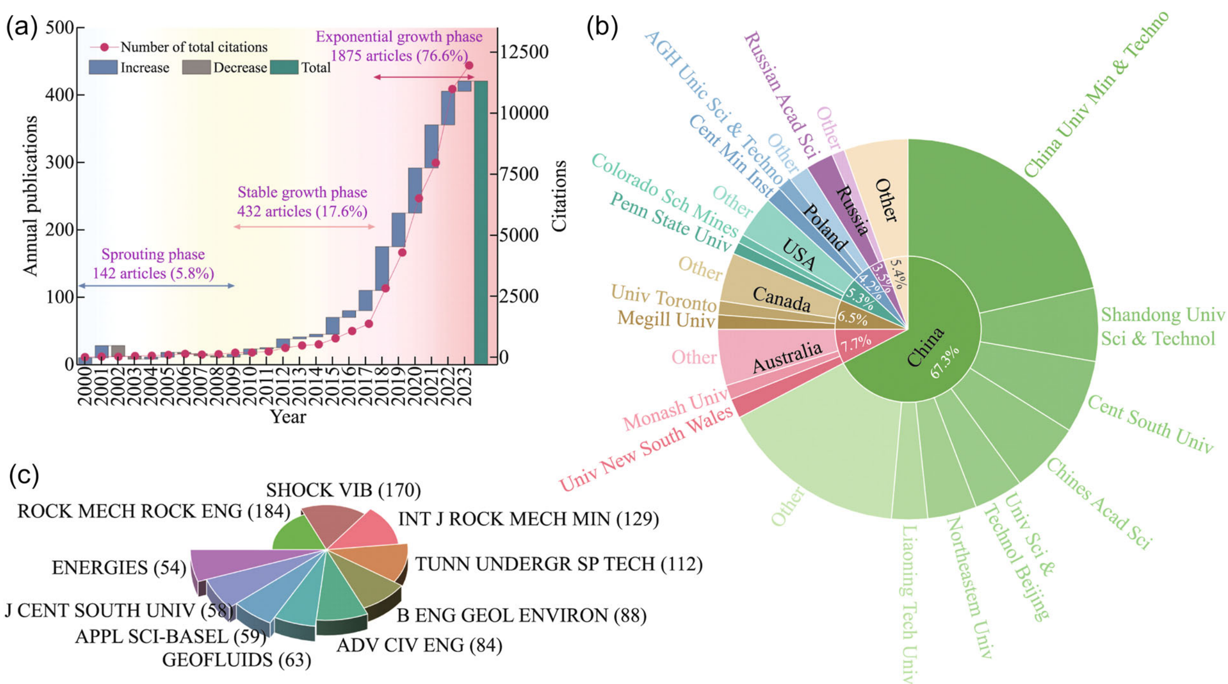

FIGURE 2 (a) Numbers of annual publications and total publications, (b) research countries and institutions, and (c) major journals in the field of rockburst.

was also to be used in the subsequent comprehensive review analyses. Ultimately, Step 3 utilizes CiteSpace for scientometric analysis of the 2449 articles to identify research hotspots and trends in rockburst and critically analyzes 336 articles to summarize the latest developments in rockburst prediction and prevention.

3 | LITERATURE SCIENTOMETRIC ANALYSIS

CiteSpace (Chen & Song, 2019) is a specialized tool for scientometric analysis and provides insights into the development, hot topics, and future trends of a research field. The scientometric analysis is conducted in four parts: analysis of number of studies, journal co-citation analysis, reference co-citation analysis, and keywords analysis. These analyses aid in comprehensively visualizing the state-of-the-art development of the rockburst field and provide possible directions for future research.

3.1 | Analysis of number of studies

The trend in publication volumes within the rockburst field can be a key indicator for examining the field's development and forecasting future directions, as shown in Figure 2a. Since the 21st century, rockburst research has roughly progressed through three phases. In the initial sprouting phase before 2010, 142 papers were published, constituting only 5.8% of the total literature and marking the early exploration of rockburst studies. During this period, the limited scholarly research resulted in a slow increase in publications. From 2010 to 2017, rockburst research entered a stable growth phase, with a consistent increase in publication numbers, indicating the growing importance of rockburst in underground engineering research. Since 2018, there has been an exponential surge in rockburst publications, with 1875 papers making up 76.6% of the total output, signaling a period of rapid development and the heightened academic interest in rockburst.

Figure 2b shows the leading countries and their key research institutions in rockburst research. The top six countries in terms of publication volume are China (1539), Australia (175), Canada (149), the United States (122), Poland (97), and Russia (79). Notably, China, the largest contributor to rockburst research in underground engineering over the past two decades, represents 67.3% of all publications. The China University of Mining and Technology leads as the primary issuing institution in China, contributing 21.5% of the total publications, significantly ahead of the second-ranked Shandong University of Science and Technology, which contributes 6.23%. These figures suggest China's dominance in rockburst research and indicate that rockburst issues are nowadays formidable challenges and hotspots in mining and underground engineering.

3.2 | Journal co-citation analysis

The journal co-citation network for rockburst research in underground engineering, as shown in Figure 3, reveals the citation relationships and influence among academic journals. Each node in this map signifies a journal, with the node's size indicating the journal's co-citation frequency, reflecting its impact in the rockburst field. The *International Journal of Rock Mechanics and Mining Sciences*, *Rock Mechanics and Rock Engineering*, and *Tunneling and Underground Space Technology* have the top three co-citations, with over 1300 co-citations each and more than 100 rockburst publications (Figure 2c).

Additionally, the centrality of journals can also suggest the journals' central roles within the network, as shown in Table 1. For instance, with a centrality value of 0.40, the *International Journal of Rock Mechanics and Mining Sciences* occupies a central position in the knowledge map, showing its significant influence in rockburst research. These analyses provide guidance in identifying key journals and literature in the rockburst field.

TABLE 1 Cited journals sorted by count.

Cited journals	Count	Centrality
International Journal of Rock Mechanics and Mining Sciences	1922	0.40
Rock Mechanics and Rock Engineering	1596	0.15
Tunnelling and Underground Space Technology	1327	0.07
Chinese Journal of Rock Mechanics and Engineering	1055	0.12
Engineering Geology	1020	0.13
International Journal of Mining Science and Technology	866	0.02
Journal of Rock Mechanics and Geotechnical Engineering	866	0.03
Bulletin of Engineering Geology and the Environment	724	0.01

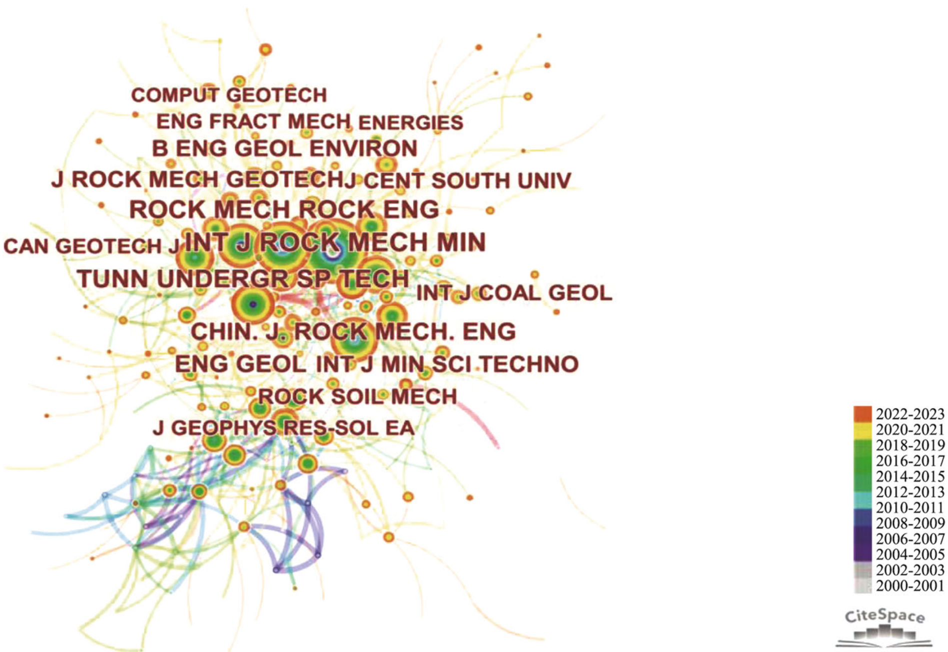

FIGURE 3 Journal co-citation network.

3.3 | Document co-citation analysis

In scientometric analysis, co-citation analysis of references is also a common way to identify key research and influential scholars in a field. Figure 4 shows the reference co-citation network, where each node represents an article. The size of a node indicates the citation frequency of this document, labeled with the first author's name and publication year. Table 2 lists the top 10 documents by the citation count. Notably, the articles by Keneti and Sainsbury (2018) and Zhou et al. (2018) have over 130 citations, highlighting the high level of interest that their research has attracted from academia. Gong's three publications (Gong et al., 2018; Gong, Si, et al., 2019; Gong, Yan, et al., 2019), with a total of 281 citations, also show his influence in the rockburst field.

Further analysis of centrality, as shown in Table 3, identifies key publications that function as connectors in the reference co-citation network. The articles of He et al. (2015, 2018), Ma, Tang, et al. (2018), Zhao and Cai (2015), and Chen et al. (2015), with centrality values of 0.1 or higher, are also shown to be key and foundational literature. Therefore, all the papers listed above can be deemed critical reference materials for rockburst

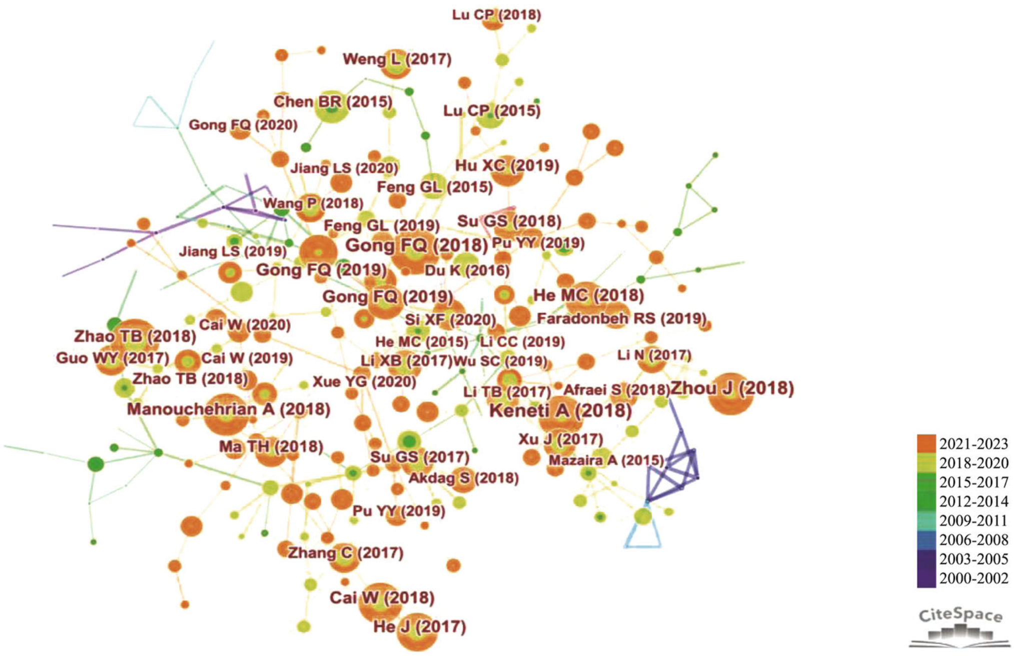

FIGURE 4 Document co-citation network.

TABLE 2 Cited documents sorted by count.

Cited references	CiteSpace metrics Count	CiteSpace metrics Centrality	WoSCC citation metrics Publication
Review of published rockburst events and their contributing factors (Keneti & Sainsbury, 2018)	135	0.16	176
Evaluation method of rockburst: State-of-the-art literature review (Zhou et al., 2018)	133	0.12	272
Experimental simulation investigation on rockburst induced by spalling failure in deep circular tunnels (Gong et al., 2018)	113	0.08	184
Experimental investigation of strain rockburst in circular caverns under deep three-dimensional high-stress conditions (Gong, Si, et al., 2019)	86	0.03	123
Numerical modeling of rockburst near fault zones in deep tunnels (Manouchehrian & Cai, 2018)	86	0.04	119
A fuzzy comprehensive evaluation methodology for rock burst forecasting using microseismic monitoring (Cai et al., 2018)	84	0.10	144
A peak-strength strain energy storage index for rock burst proneness of rock materials (Gong, Yan, et al., 2019)	82	0.07	166
Rockburst mechanism research and its control (He et al., 2018)	77	0.01	115
Rock burst assessment and prediction by dynamic and static stress analysis based on micro-seismic monitoring (He et al., 2017)	76	0.04	146
Case studies of rock bursts under complicated geological conditions during multiseam mining at a depth of 800 m (Zhao et al., 2018)	73	0.01	145

TABLE 3 Cited documents sorted by centrality.

Cited references	CiteSpace metrics		WoSCC citation metrics
	Count	Centrality	Publication
Review of published rockburst events and their contributing factors (Keneti & Sainsbury, 2018)	135	0.16	176
Evaluation method of rockburst: State-of-the-art literature review (Zhou et al., 2018)	133	0.12	272
Rockburst laboratory tests database—Application of data mining techniques (He et al., 2015)	37	0.11	119
Rockburst mechanism and prediction based on microseismic monitoring (Ma, Tang, et al., 2018)	72	0.11	112
A fuzzy comprehensive evaluation methodology for rock burst forecasting using microseismic monitoring (Cai et al., 2018)	84	0.10	144
Influence of specimen height-to-width ratio on the strainburst characteristics of Tianhu granite under true-triaxial unloading conditions (Zhao & Cai, 2015)	30	0.10	64
Rock burst intensity classification based on the radiated energy with damage intensity at Jinping II Hydropower Station, China (Chen et al., 2015)	51	0.10	131

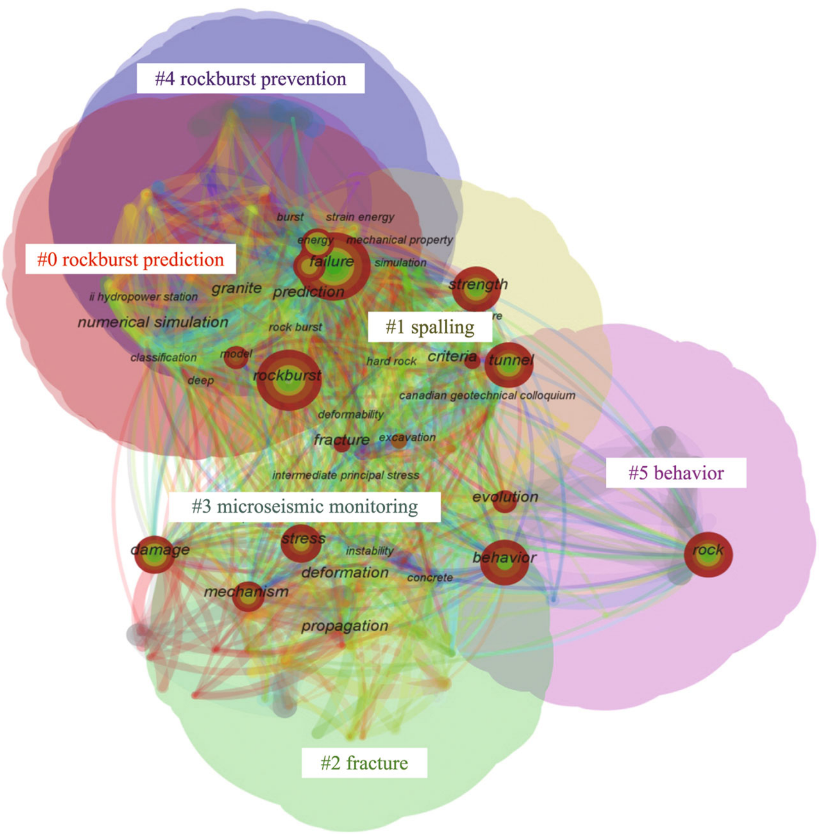

FIGURE 5 Main clusters in the field of rockburst (#0: rockburst prediction, #1: spalling, #2: fracture, #3: microseismic monitoring, #4: rockburst prevention, and #5: behavior).

research, providing meaningful guidance for future direction.

3.4 | Keywords clustering and burst analysis

Keywords succinctly capture the essence of academic papers, providing a concise overview of the research focus. Using the log likelihood ratio (LLR) clustering algorithm from CiteSpace (Chen, 2017), an analysis of keywords and trends in the rockburst field was conducted. The keyword clustering analysis can not only reveal relationships between keywords (Figure 5) but can also provide insights into their time evolution (Figure 6). Cluster #0 "rockburst prediction," the largest cluster, includes keywords related to prediction models, classification methods, and rockburst proneness. Clusters #1 "splitting," #2 "fracture," and #3 "microseismic monitoring" represent the main directions in exploring rockburst mechanisms and on-site rockburst monitoring technologies. Meanwhile, recent advances in computer technology have made machine learning and AI growing trends in rockburst prediction. Cluster #4 "rockburst prevention" focuses on another aspect of rockburst research, namely, reducing rockburst risks through engineering design optimization, construction method adjustments, and new technologies.

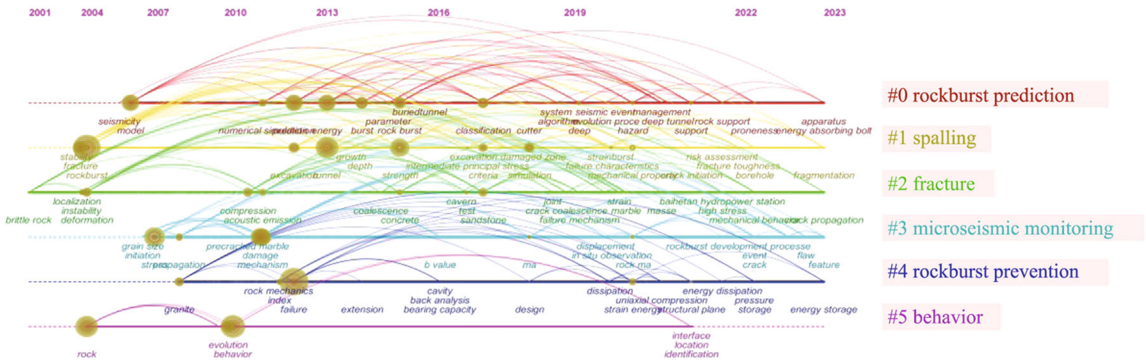

FIGURE 6 Timeline chart for rockburst keywords.

TABLE 4 Common classification of rockburst.

Rockburst intensity	Failure characteristics
None	No rockburst activities have been observed.
Weak	The surrounding rock experiences deformation accompanied by cracks or rib spalling with weak sound without any ejection phenomena.
Moderate	The surrounding rock is deformed and fractured. There is considerable rock chip ejection, and loose and sudden destruction, accompanied by crisp crackling noises, frequently occurring in the local cavern of surrounding rock.
Strong	The surrounding rock bursts severely, with rock suddenly being expelled or ejected into the tunnel, accompanied by a strong burst and a roaring sound that quickly spreads to the deeper surrounding rock.

Interestingly, Figure 5 shows a noticeable overlap between #0 cluster "rockburst prediction" and #4 cluster "rockburst prevention," indicating their close interrelation. This relationship underscores rockburst research's main dual aims: predicting rockburst occurrences and adopting effective rockburst control strategies. These two research areas complement each other; accurate predictions lead to better control measures, which in turn improve prediction model accuracy. Therefore, the subsequent sections will critically review rockburst research in terms of prediction and prevention, aiming to explore gaps and provide guidance toward developing a comprehensive rockburst risk management framework.

4 | ROCKBURST PREDICTION

Since rockburst issues received attention, development of reliable and accurate prediction models has been a primary goal for researchers in this field. Significant efforts have been made, from case analyses to experimental studies to computational models, for laying a preliminary foundation for addressing rockburst problems. This review does not aim to exhaustively summarize every model but to explore and analyze the key challenges and issues that current research encounters. For more detailed research on rockburst prediction, the following references are recommended (Adoko et al., 2013; Afraei et al., 2018; Cai et al., 2016; Farhadian, 2021; Gong et al., 2023; He et al., 2021; Li, Li, et al., 2017; Liang, Zhao, Wu, et al., 2019; Liu et al., 2013; Miao et al., 2016; Wang et al., 2015, 2019; Wu et al., 2023; Zhou et al., 2012). Thus, this section will examine the three principal methodologies in rockburst prediction: empirical, simulation, and AI-based techniques. By reviewing their advantages and limitations, it aims to identify research gaps and analyze future directions in rockburst prediction research. The classification of rockburst used in this study is shown in Table 4.

4.1 | Empirical methods

Empirical methods are the most commonly used approach in rockburst prediction, utilizing a series of parameters or indicators to assess the intensity and risk of rockburst. Their wide application stems from operational simplicity and proven effectiveness in many case studies (Dai et al., 2022; Feng, Chen, Li, et al., 2012; Liu, Wang, et al., 2023; Ma, Chen, et al., 2018). Generally, empirical methods can be divided into two categories: single-indicator and multi-indicator prediction methods.

The single-indicator empirical criterion method, one of the earliest and simplest, is based in a summary from historical rockburst cases and theoretical analysis, for example, the brittleness ratio (BR, ratio of the uniaxial compressive (σ_c) to the tensile strength (σ_t) of rock) (Qiao & Tian, 1998), the stress ratio (SR, ratio of the maximum tangential stress (σ_θ) to the uniaxial compressive strength of rock) (Russenes, 1974), and the mean stress (ratio of the uniaxial compressive strength of rock to the maximum principal stress) (Hou & Wang, 1989). These indicators mainly focus on the rock's mechanical properties and its in situ stress conditions, which can also be called stress index-based criteria. Another main single-indicator criterion emphasizes the analysis of energy for describing rockburst types and intensities, such as the elastic strain energy index (Wet) (Wang & Park, 2001), the rock mass integrity coefficient (KV) (Zhou et al., 2012), and the linear elastic energy and burst potential index (BPI) (Singh, 1988). These energy-based criteria are considered to reflect the rockburst tendencies and origins more directly because of the close relationship between rockburst and energy dynamics of rock masses.

In fact, the empirical criteria with a single indicator may have some limitations due to the complex contributing factors of rockburst. To address this problem, some researchers have attempted to develop multi-indicator integration methods for comprehensive risk assessments (Qiu et al., 2011; Shang et al., 2013; Zhang, 2008; Zhang et al., 2016). Although this approach takes various factors into account, it may complicate rockburst classification, as the mechanical meanings of its integrated parameter could be unclear. Additionally, different empirical criteria may provide different rockburst predictions or even contradictions. For instance, as shown in Table 5, the predicted rockburst risks from the two systems with the same rock brittleness coefficient might be the opposite. Such potential confusions could lead to complex challenges for underground engineering construction.

4.2 | Simulation methods

In this study, simulation methods in rockburst prediction are the approaches used to reproduce rockburst through experimental or numerical simulations. Currently, the common experiment tests for rockburst research include the triaxial unloading test, true triaxial rockburst tests, and the load relaxation test after the peak value. These tests are designed to mimic the complex stress states that rocks encounter during excavation, making them valuable approaches for analyzing the failure processes of rockburst. In addition to experiment tests, laboratory simulations serve as a powerful tool for further investigating rockburst mechanisms, offering detailed insights that may be difficult to obtain through physical experiments alone (Gong et al., 2015; Shirani Faradonbeh, Taheri, et al., 2020; Su et al., 2017). Although these tests provide direct data on rockburst, limitations due to certain experimental conditions and the influence of size effects make them suitable for exploring rockburst failure mechanisms and evolution, rather than for direct rockburst prediction.

Hence, numerical simulations form the bulk of simulation research on rockburst prediction (Cai, 2008; Sepehri et al., 2020; Xue et al., 2021), divided into continuum, discontinuum, and hybrid methods. Continuum methods, like the finite element method (FEM) and the finite difference method (FDM), are widely used for their well-developed software and lower computational costs. For example, Blake (1971) used FEM to study pillar bursts and considered high-stress concentrations as indicators of rockburst locations. Zubelewicz and Mroz (1983) performed quantitative analyses of rockburst by superposing dynamic disturbances on initial static calculations. Tang et al. (1998) introduced the realistic failure process analysis (RFPA), a novel linear continuum mechanics approach, to reveal the evolution process of microcracks during rock failure. Wang et al. (2012) used FEM to simulate the evolution of rockburst zone and strain energy release, elucidating the rock's irreversible damage mechanism.

However, sometimes, continuum methods may struggle to simulate rock fracturing process and the dynamic characteristics of rockburst, a challenge that can be addressed by the use of discontinuum and hybrid methods. Ryder (1987) proposed the discrete element method (DEM) and the excess shear stress (ESS) index to assess rockburst potential and fault impacts. Procházka (2004) investigated rockburst mechanics with discrete hexagonal elements and particle flow code (PFC). Sun et al. (2007) combined RFPA and DDA to study failure modes and rockburst prevention in high geostress tunnels. Although effective in simulating microcrack evolution, the high computational costs and complicated demands for micro-parameter calibration limit their widespread engineering application.

Currently, existing numerical simulations provide a scientific basis for rock failure analysis, rockburst potential assessment, and prevention strategy development, and yet, most studies are based on static analysis. Although static numerical methods could reveal rock failure's progressive evolution and provide a qualitative rockburst assessment, it may struggle to accurately reflect real dynamic processes of rockburst (Wang et al., 2021). Additionally, the results of simulation methods heavily rely on the chosen constitutive model and input mechanical parameters, still requiring further validation through engineering cases. Hence, sole dependence on simulation methods for an effective and comprehensive rockburst prediction system remains a challenge.

4.3 | Artificial intelligence (AI)-based methods

AI, a key technology of the Fourth Industrial Revolution, has shown significant potential and advantages in geotechnical engineering, particularly in underground engineering (Jong et al., 2021; Phoon & Zhang, 2022; Zhang & Phoon, 2022; Zhang et al., 2020, 2022). Compared to traditional methods, AI provides a more efficient way to handle complex, nonlinear, and multidimensional problems. This data-driven method applies prediction just by learning from the input and output data, avoiding

TABLE 5 Empirical criteria based on the brittleness coefficient.

Prediction method	Equation	No rockburst	Weak	Moderate	Strong
Wang and Park (2001)	σ_c/σ_t	>40	26.7–40.0	14.5–26.7	<14.5
Zhang et al. (2003)		<10	10–18		>18

oversimplification problems or excessive assumptions, as shown in Figure 7.

In the field of rockburst prediction, AI technologies, especially machine learning (ML) models, have been proven to be powerful tools for building reliable prediction models (Liang, Zhao, Wang, et al., 2019; Mahesh, 2020; Pu, Apel, & Xu, 2019; Qiu & Zhou, 2023; Xu et al., 2018). These models generally use physical and mechanical parameters of rock (e.g., σ_θ, σ_c, σ_t, BR, SR, Wet, etc.) as inputs to predict rockburst intensity. The ML models for rockburst prediction can be divided into supervised and unsupervised learning. Supervised learning uses labeled data to identify patterns and relationships between inputs and outputs. Pioneers like Feng and Wang (1994) used neural networks for rockburst prediction, assessing the risk with a trained database of labeled cases. Zhao (2005) used Support Vector Machines for risk classification, and Ghasemi et al. (2020) applied C5.0 decision trees to predict rockburst occurrence and intensity. Zhou, Li, et al. (2016) compared 10 supervised learning algorithms for rockburst prediction, highlighting the superior performance of gradient-boosting machine and random forest algorithms, based on 246 cases, as shown in Figure 8.

Sometimes, it is difficult to determine the rockburst intensity in engineering cases, or there are inconsistencies in rockburst classification, which poses a challenge in rockburst prediction. To consider this scenario, some scholars suggest using unsupervised learning methods to manage the uncertainty and vagueness of rockburst (Pu, Apel, & Xu, 2018; Zhou & Gu, 2004; Zhou, Yun, et al., 2016). The main feature of unsupervised learning is its ability to reveal hidden patterns by finding commonalities in unlabeled data sets. This implies that after grouping or classifying data sets, the different rockburst risk can be identified without predefined rockburst intensities. For example, Gao (2015) used a biomimetic clustering method, the ant colony algorithm, to assess rockburst risk. Chen et al. (2015) proposed a new quantitative grading method for rockburst using hierarchical clustering analysis based on radiated energy data from the Jinping II Hydropower Station. Shirani Faradonbeh, Shaffiee Haghshenas, et al. (2020) conducted clustering analysis of rockburst using self-organizing map and fuzzy c-mean techniques, exploring the potential relationships between rockburst-related parameters.

5 | ROCKBURST PREVENTION

As mentioned by Hoek and Marinos (2009), the complete elimination of rockburst occurrences remains an elusive goal, especially under overstressing conditions. However, there are several support methods that can be adopted to at least mitigate their impacts, as shown in Figure 9. The generally accepted strategies for rockburst prevention are as follows: (i) optimization of construction designs to reduce the incidence of rockburst; (ii) preconditioning technology of the rock mass to alleviate stress concentration during excavation; and (iii) use of a strategic rockburst support system in rockburst-prone excavation. It is worth noting that the executed

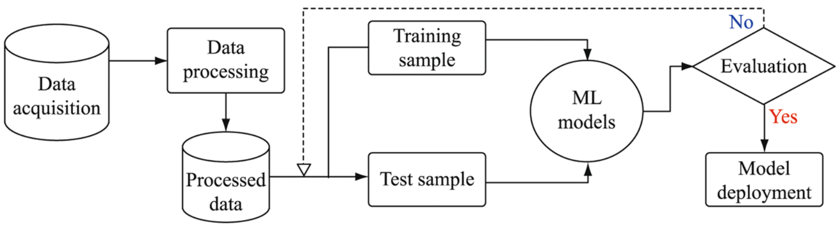

FIGURE 7 General process of machine learning (ML) methods (modified from Basnet et al., 2023).

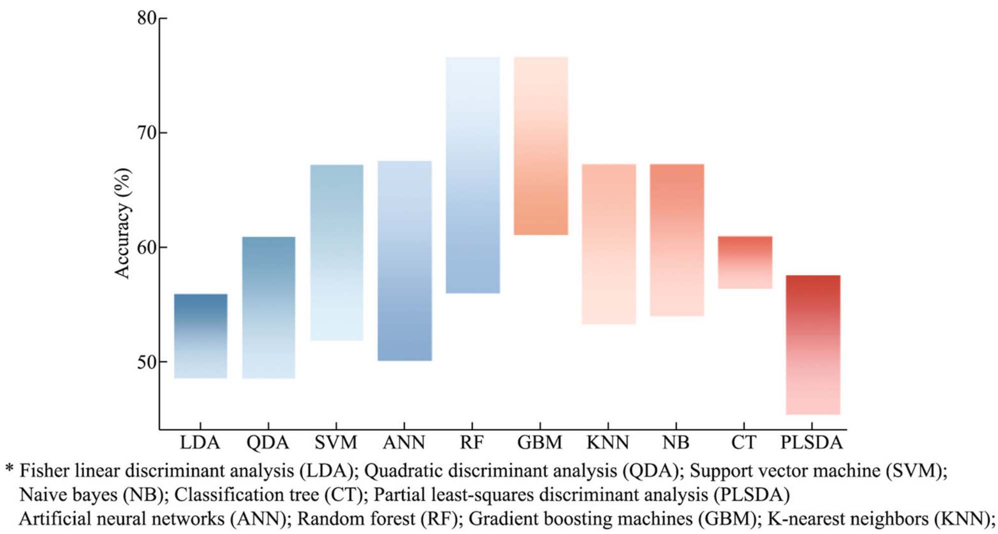

FIGURE 8 Comparison of 10 supervised learning methods (Zhou, Li, et al., 2016).

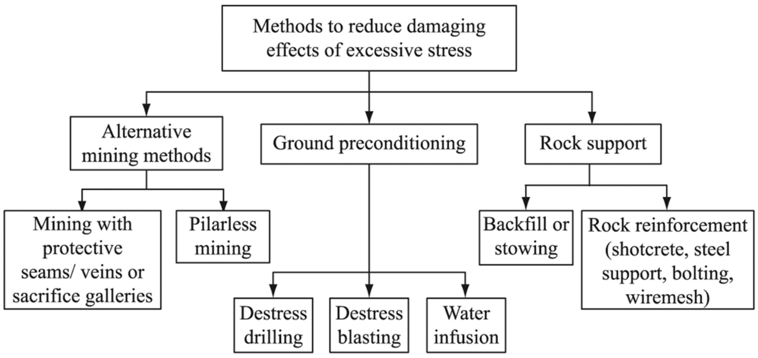

FIGURE 9 Methods to reduce damaging effects of excessive stress in underground mining (Mitri, 2000).

sequence of these strategies is critical as well. The final rockburst support should be considered and deployed only after preliminary efforts. This section aims to provide a succinct overview of these strategies for rockburst prevention, while recognizing the existing gaps. For more comprehensive and detailed information about the support measures and technologies, further reading is recommended.

5.1 | Optimization of the project layout scheme

The primary objective in rockburst research is to avoid conditions conducive to rockburst, thereby minimizing or potentially eliminating the necessity for rockburst support in excavation (Kaiser & Cai, 2013). This suggests that the priority of rockburst prevention is not the immediate consideration of a support system against rockburst, but rather an assessment into the feasibility of inherently preventing rockburst occurrences. Thus, an effective and optimized engineering construction design becomes crucial, as it presents possibilities for control rockburst with less support. The "three-step strategy" for rockburst prevention, as proposed by Feng, Chen, Ming, et al. (2012), begins with "reducing energy accumulation." Their first step also explains the significance of optimizing the project scheme from the perspective of rockburst mechanisms. Minimizing the build-up of internal energy due to excavation activities, while ensuring the project's function, is the principal consideration in rockburst engineering design.

Several optimization techniques for construction plans include the following: (i) Sectional size and shape optimization: It is known that larger excavation is predisposed to stability challenge, and thus, achieving a more suitable section is critical for rockburst-prone excavation. For example, excavation sections with circular geometries tend to alleviate stress concentration, which is effective for rockburst prevention. (ii) Appropriate excavation methodology: Tunnel boring machines (TBM) is often used for rapid and highly mechanized excavation. However, in rockburst-prone locales, traditional drilling and blasting techniques may be optimal options sometimes, as they can effectively mitigate rockburst risk by stress relief. (iii) Excavation strategy optimization: Considerable research suggests a direct correlation between the unloading rate (i.e., excavation velocity) and the extent of resultant rock failure (Karakuş & Fowell, 2004; Tonon, 2010). Thus, adopting a deliberate excavation pace and zoning, for example, the new Austrian tunneling method (NATM), is another critical factor for rockburst prevention.

5.2 | Rock mass preconditioning

The preconditioning of surrounding rock serves as a proactive approach in rockburst prevention, before or at the initial stages of excavation. This method focuses on changing the rock mass's properties, from external conditions to internal factors, to facilitate the prerelease or redistribution of the rock's stored energy. Borehole stress relief is a standard preconditioning technique in low to moderate rockburst areas. For high-risk rockburst, advance stress relief blasting is commonly employed, using targeted blasting to relieve stress concentrations in particular zones (Drover et al., 2018; Roux et al., 1957). Targeting the internal factors of rockburst, techniques like high-pressure water jetting or borehole water injection are usually applied to mitigate the risk of rockburst at the workface. As shown in many studies (Cai et al., 2021; Luo, 2020; Zhou, Cai, et al., 2016), water decreases the strength of hard rock. Despite the effectiveness of such water-based methods, they are usually considered supplementary in rockburst prevention due to their limited range of effect. As localized solutions, it is essential to combine them with additional control strategies to obtain an effective rockburst prevention system.

5.3 | Support in rockburst-prone excavation

Although early proactive prevention strategies play an important role in avoiding rockburst, it is often impractical to eliminate all potential risks of rockburst. The development of a support system that is both timely and effective during the excavation is essential for improving rock stability and maintain project safety (Wang et al., 2020; Wu, Jiang, et al., 2019). Based on practical experience, as shown in Figure 10, Cai and Champaigne (2009) have introduced seven guiding principles for designing rockburst support. These principles are intended to offer rockburst engineers a

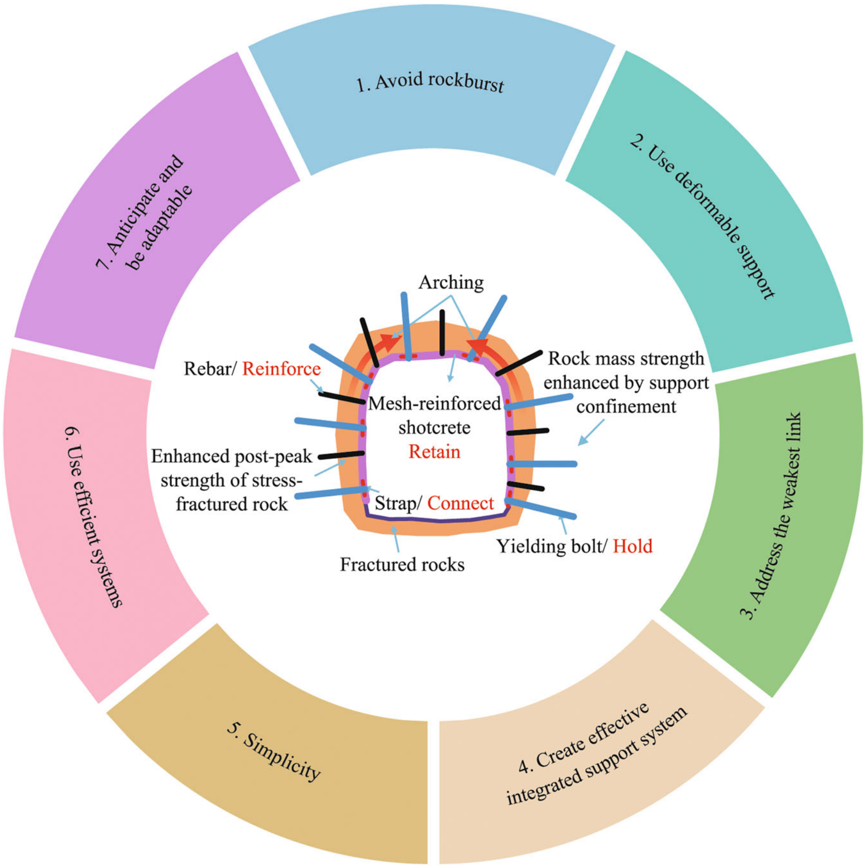

FIGURE 10 Seven rockburst support principles and the support functions (Cai, 2019).

fundamental framework for tackling the many challenges presented by rockburst.

The first principle focuses on avoiding rockburst: The most effective strategy for avoiding rockburst involves proactive risk reduction through careful early-stage planning and design optimization, as discussed in Section 5.1 and 5.2. By minimizing the potential for rockburst, these early prevention strategies lower the requirement for extra support measures to fortify the surrounding rock against loads and stresses. The second principle involves the utilization of deformable support components: Given that brittle rock failure often accompanies significant expansion deformation, the design of rockburst support should consider the volumetric changes of the surrounding rock mass. By reinforcing the rock and absorbing the dynamic energy produced during a rockburst, these deformable support components contribute to the overall stability of the rock structure. The third principle focuses on addressing the weakest link within the support system. The design of the support system must prioritize the reinforcement of the structural junctions among its components, as the overall capability of the system is highly dependent on its most vulnerable part (Ansell, 2005; Ortlepp, 2000). Through targeted optimization of these critical connections, the system's overall performance can be markedly improved with relatively modest efforts. Accordingly, the fourth principle advocates the creation of an effective and integrated support system. An ideal rockburst support system is not solely assessed by a single component's energy absorption capabilities, but by the effective integration of diverse elements to develop a feasible, deformable, and comprehensive support system. The following two principles advocate for the simplicity (the fifth) and efficiency (the sixth) in the design of support systems for rockburst. It is imperative to understand that while initial costs for these rockburst support measurements may exceed those of conventional supports, such expenditures are justified when contrasted with considering the significant maintenance costs incurred by potential incidents. Data from numerous cases indicate that the maintenance cost can be 10–20 times more than the initial investment, highlighting the economic efficacy of rockburst support. Thus, the adoption of efficient and easy-to-use support systems not only mitigates the risk of rockburst but also provides notable economic benefits especially in rockburst engineering. The last principle is related to risk management in rockburst-prone projects to "anticipate and adapt." Because of the difficulty in precisely predicting rockburst events, combined with the complexity of the underground rock masses and the unpredictability of excavation activities, the initial design of support strategies frequently fails to fulfill later support requirements. Therefore, it is essential to assess in a timely manner potential rockburst risks and to adjust the support system in accordance with the real-time engineering conditions. Cai (2019) also defined four primary support functions, namely, reinforce, retain, hold, and connect, as shown in Figure 10. These foundational design principles for rockburst support, together with the required functions of such support, provide a comprehensive framework for managing rockburst risks during underground excavation.

6 | DATA-DRIVEN ONTOLOGY-SUPPORTED DECISION-MAKING FRAMEWORK FOR UNDERGROUND EXCAVATIONS

6.1 | Semantic web technology

The semantic web, as proposed by Berners-Lee and Hendler (2001), extends the capabilities of the world wide web (WWW) by addressing its inherent limitations in data interoperability and automated processing. By incorporating explicit, machine-readable semantics into data, the Semantic Web enables efficient information exchange and intelligent processing, especially for automated reasoning based on knowledge models (Rožanec et al., 2022). According to the world wide web consortium (W3C), the Semantic Web's primary goal is to provide data with explicit meanings closely linked to real-world entities. Through the use of structured graph representations, the Semantic Web facilitates data unification and reusability, offering substantial advantages in managing large-scale, heterogeneous data sets (Schmachtenberg et al., 2014). This innovative technology has found extensive applications in architecture, engineering, and construction (AEC), where it supports the integration of diverse engineering data across multiple stakeholders (Niknam & Karshenas, 2017; Venugopal et al., 2015; Yang & Zhang, 2006). The Semantic Web's contributions to the AEC industry are typically classified into three key perspectives: interoperability, linking across domains, and logical inference and proofs (Pauwels et al., 2017), as shown in Figure 11.

1. Interoperability: The Semantic Web enhances seamless collaboration across various systems and programs by standardizing data formats and using ontologies for better understanding and processing (Zhou, Zhang, et al., 2023). Unlike traditional Web environments, where data often occur in siloed applications and formats, creating integration challenges, the Semantic Web addresses these issues through its standards, including the resource description framework (RDF) and the web ontology language (OWL). These standards establish a unified framework for data exchange, improving information reusability and interoperability. Figure 11a shows a simple RDF graph, which is used to represent the graph structure of the RDF triples {subject, predicate, object}. Each entity or relationship is explicitly defined and uniquely identified using uniform resource identifiers (URIs), thereby enabling more efficient data sharing and reuse. Additionally, this standardized data representation allows systems to flexibly incorporate new data resources without necessitating extensive custom integration efforts.
2. Linking across domains: In the AEC industry, multidisciplinary collaboration is crucial during the design, construction, and operational phases. Effective integration of diverse elements, including geological exploration, structural design, construction methodologies, and engineering management, is critical for the smooth execution of projects. Semantic Web technology offers significant promise in this context by enabling the integration of heterogeneous data from domains such as building information modeling (BIM), geographic information systems, real-time monitoring systems, and simulation data into a unified data network. This integrated network supports informed decision-making throughout the project lifecycle. As illustrated in Figure 11b, Le and David Jeong (2016) proposed a lifecycle data exchange mechanism tailored for multidomain decision-making in project management. This mechanism transforms disparate data sources across the project lifecycle into meaningful and actionable insights for users. It operates through three primary stages: domain and merged ontologies, data wrappers, and a data query and reasoning system.

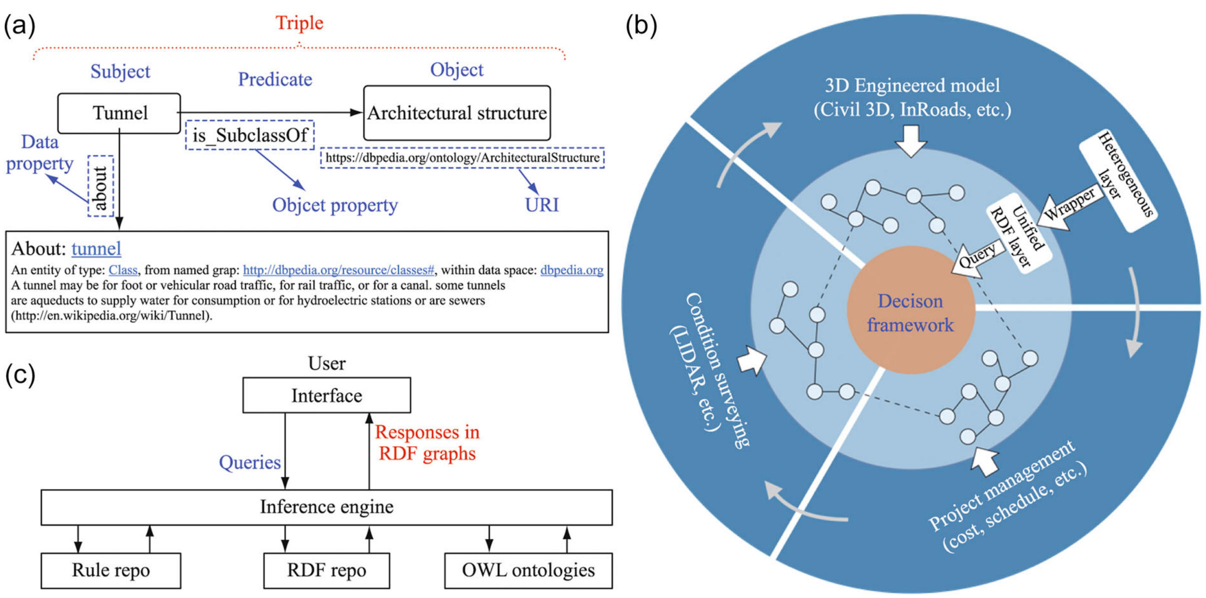

FIGURE 11 Three benefits of Semantic web technologies in the architecture, engineering, and construction industry (a) RDF triple structure example, (b) cross-domain data integration, and (c) semantic inference process (Le & David Jeong, 2016; Pauwels et al., 2017; Zangeneh & McCabe, 2020).

3. Logical inference and proofs: Semantic Web technology allows computers to perform inferring tasks for extra knowledge based on the information in RDF and OWL. OWL plays a pivotal role in this process, as it supports the definition of complex relationships between concepts through its advanced semantic capabilities. By extending the vocabulary of RDF Schema and incorporating more expressive elements, OWL enhances the system's ability to process and infer information with higher precision (Pauwels et al., 2017). For more complex logical reasoning, semantic web technologies utilize specialized rule languages such as the semantic web rule language and the rule interchange format (RIF). These languages allow the creation of customized logical rules, significantly improving the accuracy and robustness of inference processes. When integrated with comprehensive knowledge models, these rules enhance the system's capability to derive actionable insights and provide robust decision support. As illustrated in Figure 11c, this integration not only improves the intelligence of the system but also extends their applicability to complex data analysis and decision-making challenges in large-scale projects.

6.2 | Ontology applications

Ontology, originally a philosophical concept about the nature of existence, has evolved significantly with the development of computer science. Today, ontology is a pivotal concept in information technology, particularly in the realms of semantic web development and artificial intelligence, where it plays a critical role (Ashraf et al., 2015; Farghaly et al., 2023; Zhou & El-Gohary, 2017). In computer science, ontology is most commonly defined as a formal and explicit specification of a shared conceptualization within a specific domain (Studer et al., 1998; Zhang et al., 2023). This definition indicates its utility in facilitating a formalized, structured representation and exchange of knowledge through clear ontological definitions, enabling a common understanding and consensus among diverse systems and users. Additionally, ontology allows for the flexible extension of frameworks, making it easier to integrate and apply across virous domains (García-Castro & Gómez-Pérez, 2010). This adaptability is especially beneficial in complex projects such as underground excavation, which are often characterized by numerous data and information, including geological conditions, structural parameters, construction monitoring, and so on (Gao et al., 2022; Khadir et al., 2021; Kuster et al., 2020; Meng et al., 2021; Wang, 2021; Yu et al., 2023). For these benefits, there has been a significant surge in research over the past two decades focusing on ontology-based models for project management in the AEC industry. Farghaly et al. (2023) summarized the 10 primary applications of ontology in the AEC industry, which include smart cities, monitoring and control, operation and maintenance, health and safety, process, cost, sustainability, heritage BIM, compliance, and miscellaneous. These ontological application areas span the entire engineering lifecycle, demonstrating that ontology has become a potent framework to improve project management by integrating disparate pieces of information from various aspects (Chen et al., 2024; Costin & Eastman, 2019; Leite et al., 2016). This integration, driven by ontology, not only helps in reducing project costs but also significantly improves the quality of decision-making and engineering safety. Figure 12 illustrates a commonly used methodology for ontology development.

Specifically, domain ontologies are widely studied and applied across various engineering fields, providing a sophisticated and intelligent strategy for diverse purposes. Hou et al. (2015) developed an ontology model for concrete structure design, focusing on a sustainability index for bridge maintenance decisions. Zhang et al. (2018) proposed an intelligent ontology framework for the preliminary phase of structural design, with three key aspects: safety, environmental impact, and cost efficiency. Jiang et al. (2023) introduced an approach combining ontologies with machine learning to evaluate bridge corrosion, thereby enhancing structural safety. Zhou, Bao, et al. (2023) presented a novel dam safety monitoring model that integrates BIM technology with domain ontology, effectively improving data analysis and dam safety. Du et al. (2016) used a hybrid methodology combining hierarchical clustering techniques with ontologies to predict tunnel settlements, facilitating the identification of causative factors and the selection of appropriate preventive or support measures. Cui et al. (2023) designed an ontology-based model for seismic risk assessment of subway stations, using Monte Carlo simulations to provide a scientific foundation for managing seismic risks and improving emergency strategies. Hai et al. (2021) introduced a comprehensive ontology-driven corridor risk assessment model, incorporating Bayesian networks to offer a systematic tool for project management and decision-making. Collectively, these applications highlight not only the theoretical sophistication of ontology-based methodologies but also their significant

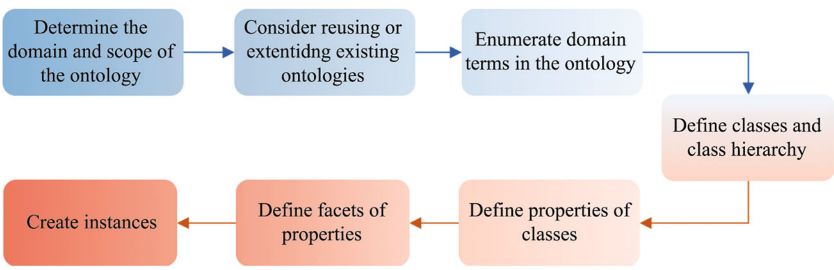

FIGURE 12 Seven steps to ontology development.

practical potential in addressing engineering challenges. The integration of ontology-based models into engineering lifecycle provides innovative solutions for managing complex, multi-domain, and multi-objective problems, empowering researchers and practitioners to enhance decision-making processes and improve project outcomes.

6.3 | Intelligent underground engineering management ontological framework

While the idea of a Semantic Web that seamlessly connects all human knowledge may seem overly ambitious, focusing on expanding the range of information accessible to computers represents a more pragmatic and attainable goal. From this perspective, Semantic Web development transcends the Web itself, influencing a wide range of domains. Its core capabilities—such as data integration, annotation, information retrieval, and natural language processing—demonstrate remarkable potential across diverse research and industrial fields (Abanda et al., 2013; Jung, 2009; Tah & Abanda, 2011). Building on these capabilities, this section explores how Semantic Web technology can support decision-making in the context of underground excavation.

Table 6 outlines the challenges faced in rockburst risk management in the era of artificial intelligence (Aydan, 2019; Masoudi & Sharifzadeh, 2018; Pu, Apel, & Lingga, 2018). While data-driven approaches provide a more efficient way to address problems compared to conventional approaches, there remains a significant gap between advanced prediction techniques and engineering practice. This disconnect notably limits engineers' ability to accurately predict rockburst, which in turn impedes effective rockburst prevention measures. One of the key issues is the complexity and uncertainty of geological conditions, which vary significantly during project construction. The variability in construction environments further complicates underground projects, particularly those that are long term and large scale. Such projects often require collaboration between multiple stakeholders, making it difficult to maintain real-time updates and ensure accurate risk assessments. For instance, dynamic optimization of rockburst control relies heavily on real-time data to adjust support measures as conditions change. However, in practice, the sharing of critical information at project sites may be delayed or prone to inaccuracies. This lag in data transfer can impede the timely deployment of support systems, which not only increases the risks associated with rockburst events but also drives up the overall cost of underground construction projects.

The integration of AI and real-time monitoring is crucial, but it must be combined with more advanced management frameworks to address these challenges effectively. A holistic and intelligent approach is required, one that can integrate real-time data, AI-based predictions, and decision-making processes into a cohesive system. In this context, ontologies—a framework for representing knowledge in a structured manner—have emerged as a potential solution. With their ability to bridge the gap between complex data analysis and practical engineering, ontologies can facilitate better communication between stakeholders, ensuring that data are both accurate and timely. This would allow for more efficient risk management, improved decision-making processes, and a more responsive approach to the dynamic conditions encountered in underground excavation projects.

Although the potential and benefits of ontology are widely acknowledged, there is, to the best of the authors' knowledge, a notable gap specifically targeted toward ontological frameworks for underground excavations. This gap underscores the necessity for focused research aimed at bridging these gaps and exploring avenues for future advancements in the field of underground engineering. As illustrated in Figure 13, the proposed ontology-based framework provides a comprehensive solution for managing the lifecycle of underground excavation projects. The framework is designed to enhance the efficiency of information integration, sharing, and analysis by unifying heterogeneous data sources into a semantically rich, machine-readable structure. It facilitates improved decision-making by enabling automated reasoning, real-time analysis, and cross-disciplinary collaboration.

The proposed methodology is composed of three main components: (1) data collection and preliminary processing; (2) ontology knowledge base and data analysis; and (3) intelligent decision support system. At the core of this framework lies the ontological model, which seamlessly integrates data, analysis, and decision-making processes to ensure a smooth and efficient operation. The detailed workflow of the methodology is outlined as follows: (1) Data collection and preliminary processing: Initially, data and information from various domains, such as geological surveys, structural designs, monitoring systems, and construction activities, are collected and subjected to preliminary processing to ensure data

TABLE 6 Challenges in rockburst management.

Rockburst prediction	Rockburst prevention
• Lack of general applicable empirical standards	• A certain understanding of the rockburst mechanism for support designers
• Project applicability of numerical simulation methods remains to be verified	• Support systems involve many factors, making the dynamic design process complex
• Limitations of data sets in data-driven methods	• Lack of effective collaboration between prediction and prevention

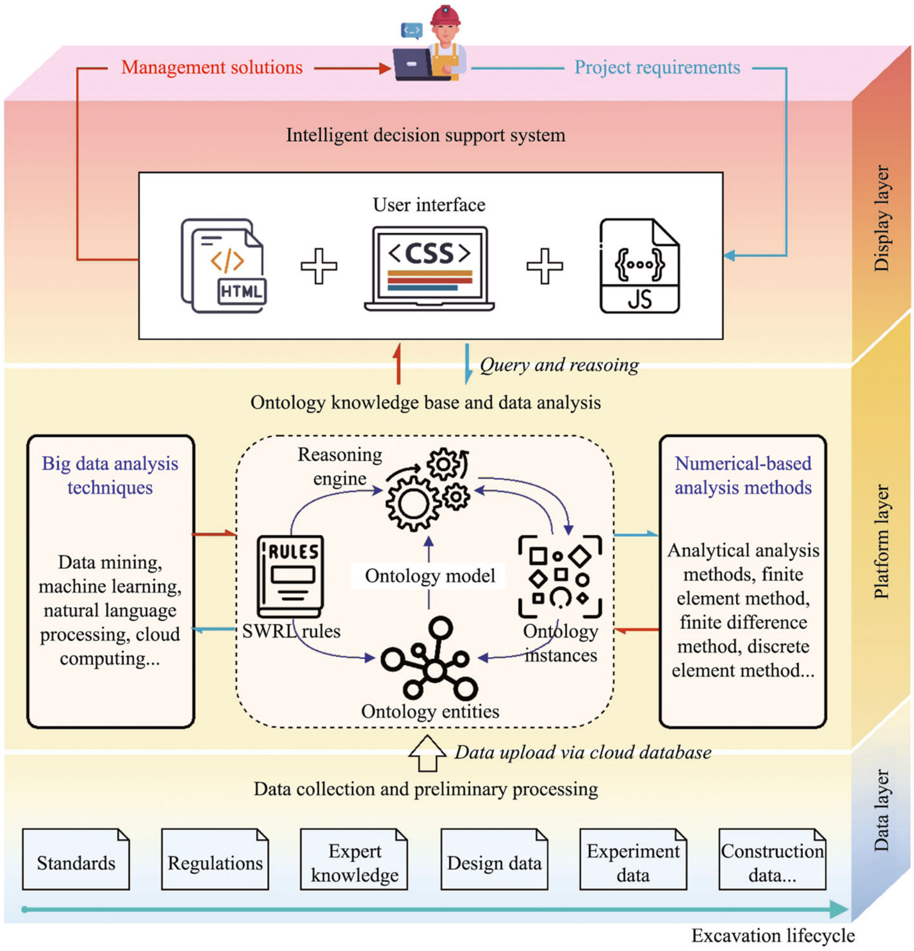

FIGURE 13 An ontological framework for risk management of underground engineering.

quality and consistency. These processed data are then uploaded to a cloud-based database, making them readily accessible for subsequent analysis and processing. (2) Ontology knowledge base and data analysis: When a user submits an engineering requirement through the user interface, the ontology knowledge base executes semantic queries and facilitates data transfer to identify and retrieve the relevant data corresponding to the specified requirement (illustrated by the blue line in the workflow). The ontological model then collaborates with advanced data-driven technologies, such as machine learning algorithms, simulation models, or finite element analysis, to analyze the data tailored to the specific engineering context. This stage leverages the semantic richness of the ontology to ensure accurate data interpretation and analysis. (3) Intelligent decision support system: The results of the data analysis and semantic reasoning are synthesized and fed back to the user in an intuitive and actionable format (depicted by the red line in the workflow). This enables stakeholders to make informed decisions based on a comprehensive understanding of the underlying data and inferred insights.

The proposed framework represents an open, computable, and evolvable knowledge-driven model built on big data principles, specifically tailored for underground excavation projects. These key characteristics are defined as follows: Openness: The framework accommodates diverse data sources, including geological exploration data, structural design parameters, construction engineering records, expert knowledge, industry standards, socio-environmental information, and real-time monitoring data. This inclusiveness ensures that the framework remains adaptable to multidisciplinary engineering contexts. Computability: By leveraging the ontological model, the framework uses various analytical technologies and methodologies to uncover hidden patterns and relationships within dynamically evolving engineering data sets. This enables efficient and scalable processing of complex, multidimensional data. Evolvability: The framework is designed to continuously update and expand its knowledge base and analytical capabilities, incorporating new data sources, evolving technologies, and emerging challenges. This adaptability ensures that the system remains robust and forward-compatible, capable of addressing future needs in underground engineering.

By integrating these components and capabilities, the framework provides a comprehensive and intelligent approach to managing the complexities of underground excavation. It not only enhances decision-making processes but also promotes higher efficiency, safety, and sustainability throughout the entire project lifecycle. The methodology bridges the gap between traditional engineering practices and advanced knowledge-driven technologies, paving the way for a more intelligent, data-centric future in underground engineering.

7 | CONCLUSION

Rockburst, as one of the major unsolved issues in geoscience, poses a major challenge to the safety and stability of underground projects. This paper presents a comprehensive review and comprehensive literature analysis of rockburst research published in the 21st century. Based on the scientometric analysis of 2449 relevant articles, an intuitive discussion for the development, hot topics, and future trends of rockburst is provided. Subsequently, a comprehensive review focusing on the rockburst prediction and prevention was conducted to explore the current challenges in managing rockburst. The analysis suggests that while the application of data-driven methods provides new insights into rockburst prediction, there is still a significant disconnect between these techniques and engineering practice, potentially hindering effective rockburst prevention. In addition, the complex design of rockburst support systems necessitates timely and effective optimization, but the challenges of delayed and inaccurate data sharing in large-scale engineering projects exacerbate these issues. To address these challenges, this paper introduces a novel methodology for managing underground excavations. Based on the ontology, the framework seeks to integrate multisource data and use advanced analysis techniques to improve decision-making, information sharing, and safety throughout underground excavations. This ontological framework includes three key components: data collection and preliminary processing, ontology knowledge base and data analysis, and an intelligent decision support system. The proposed methodology provides a systematic guide for digital advancements in underground excavations; however, it requires further validation and optimization in future research to guarantee its efficacy and reliability.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Haijiang Li https://orcid.org/0000-0001-6326-8133

Hongqiang Xie https://orcid.org/0000-0003-3203-7679

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AUTHOR BIOGRAPHIES

Haijiang Li is the chair professor in Smart Engineering, director of BIM for the Smart Engineering MSc program, Lab and Center, Cardiff University, UK. With over 20 years of experience, prof. Li specializes in the integration of supercomputing, big data, and AI algorithms for smart engineering. His research spans civil, structural, hydraulic, and maritime engineering, focusing on digital twinning, smart design, and sustainable infrastructure. He serves as the chair of EG-ICE—European Group of Intelligent Computing in Engineering and as the Standards Committee Technical Executive for Building SMART. Prof. Li is also the editor-in-chief of *Construction Innovation* and the associate editor of *Automation in Construction*.

Hongqiang Xie is a professor in Sichuan University, China. His research focuses on underground engineering, geological disasters, dam foundation stability, rock rheology, and multifield coupling. He has led over 100 research projects, including five funded by the National Natural Science Foundation of China, and has published one monograph, two textbooks, and over 100 academic papers. Prof. Xie serves as a standing director of the Higher Education Branch of the Chinese Hydraulic Engineering Society, a standing director of the Sichuan Rock Mechanics and Engineering Society, and a committee member of the Chinese Hydraulic Engineering Society's Geotechnical Engineering Division; he is also Vice Chairman of the Sichuan Hydropower Association's Geological Survey and Disaster Mitigation Committee.

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