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A Comprehensive Review of Multi-Criteria Decision-Making Approaches in Mining Method Selection: Evolution, Trends, and Applications

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Abstract

The selection of an appropriate mining method is a complex decision-making problem influenced by a multitude of geological, technical, economic, environmental, and safety-related parameters. This study presents a comprehensive review of multi-criteria decision-making (MCDM) approaches applied to mining method selection, with a focus on their historical evolution, integration with fuzzy logic, artificial intelligence, and machine learning, as well as bibliometric trends and parameter analysis. The findings reveal a growing tendency toward hybrid and intelligent MCDM models that enhance decision accuracy and adaptability under uncertainty. A bibliometric analysis of key authors, countries, journals, and citation patterns highlights the global scope and scientific impact of research in this area. Furthermore, the findings of this study indicate that Iran ranks foremost in global research output within this field, accounting for 37% of total publications. Also, among the intrinsic variables examined, the parameters pertaining to ore morphology or thickness, ore dip, and ore depth exhibit the highest prevalence in the literature, representing 69% of reported studies, while economic, environmental, and operational considerations represent significant extrinsic influences. This review emphasizes the vital role of MCDM techniques in optimizing mining operations, and advocates for further development of dynamic, data-driven models to meet the evolving challenges of modern mining.

1. Introduction

Selecting appropriate mining methods and determining suitable extraction techniques are foundational decisions in any mining operation. These choices establish the framework for all subsequent stages of a mining project, including production planning, equipment selection, safety protocols, and technical design development. The selected extraction method has a direct and lasting influence on the economic viability, environmental sustainability, and overall success of a mining endeavour.

Mining method selection (MMS) is inherently complex due to the multitude of factors that must be evaluated. These include geological and geotechnical properties of the ore body—such as deposit geometry, ore grade, depth, and rock mechanics—as well as economic variables like cost-efficiency, ore recovery rates, and prevailing market conditions. Moreover, contemporary mining practices are increasingly required to consider environmental impacts, safety standards, and social acceptance. The integration of these diverse and often conflicting criteria renders the selection process a multidimensional and challenging task. Following the United Nations Conference on Environment and Development in 1992, the significance of sustainable development for governments has expanded, highlighting the environmental and social impacts alongside economic considerations in the mining process and the selection of mining methods. Consequently, selecting an appropriate mining method based on sustainable development indicators presents a challenge for developers in the mining sector who

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seek to obtain social and environmental permits for mining activities. Therefore, future models for selecting mining methods should simultaneously evaluate economic, environmental, and social factors, rather than focusing solely on technical and economic parameters.

No single extraction method can be universally applied to all mineral deposits, as each deposit presents unique geological and operational constraints. The optimal method should not only satisfy technical and economic requirements but also minimize environmental disruption and social conflict. Poor decisions at this stage can result in operational inefficiencies, increased safety risks, and, in extreme cases, premature mine closure. Additionally, once a method is implemented, switching to an alternative approach is often economically unfeasible and technically impractical.

Efforts to formalize and standardize mining method selection began with Peel's model in 1941, which laid the groundwork for subsequent classification systems. From 1941 through the late 1980s, qualitative assessments based on expert opinion and empirical guidelines dominated the field. In the 1990s and early 2000s, more quantitative models emerged, introducing numerical scoring and weighted parameters. Over the past decade, however, there has been a marked shift toward Multi-Criteria Decision-Making (MCDM) techniques. These methods provide a structured, transparent, and systematic framework capable of navigating the complexity and trade-offs inherent in mining method selection.

The growing adoption of MCDM techniques is part of a broader transition in mining engineering towards data-driven, evidence-based decision-making that integrates various performance criteria. This paper aims to provide a comprehensive overview of the evolution of mining method selection approaches, focusing on the efficacy and application of MCDM methodologies in addressing the complexities of modern mining challenges.

2. Qualitative Methods for Mining Method Selection

Qualitative models constitute some of the earliest approaches developed for mining method selection. Table 1 presents qualitative methods for selecting mining methods and the parameters affecting them. These models primarily rely on expert judgment, empirical rules, and qualitative assessments of key geological and geomechanically attributes—such as ore body geometry, depth, rock strength, and surrounding strata. Based on these attributes, qualitative models aim to recommend mining methods that best align with specific deposit characteristics.

Typically, qualitative models classify deposits into categories and associate each category with a preferred mining technique, providing a simplified yet practical tool for preliminary evaluations. Although less precise than quantitative or MCDM approaches, qualitative methods remain useful in the early stages of project development or when comprehensive datasets are unavailable.

Figure 1 presents a chronological overview of key qualitative models introduced for mining method selection. These models laid the groundwork for more advanced decision-making tools and continue to serve as valuable references.

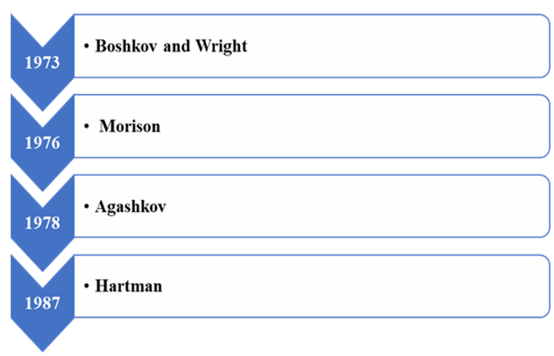

Figure 1. Timeline diagram for qualitative methods

Table 1. Qualitative Mining Method Selection

ROW	Method provider	Effective parameters in the presented method	Considerations
1	Boshkov and Wright	deposit shape, dip, ore strength, host rock strength	-Ignoring the possibility of surface mining. -Classify up to 4 applicable methods
2	Morrison	Ore thickness, Type of support, Tensile potential energy	-Continuity of the process of reviewing methods and selecting one method from other options based on different combinations of ground conditions.
3	Agoshkov	Based on type of Support	-Lack of attention to technical parameters.
4	Hartman	deposit shape, dip, ore strength, Deposit size, host rock strength	-Assign a specific extraction method for each of the different conditions. -The type of classification is subjective.

The earliest formal qualitative classification system for underground mining was introduced by Boshkov and Wright in 1973 [1]. Their model utilized four parameters—deposit shape, dip, ore strength, and host rock strength—to classify and recommend appropriate underground mining techniques. Despite its pioneering nature, the model was limited to underground scenarios and excluded surface mining options. Furthermore, its narrow parameter scope reduced its applicability to complex mining environments.

In 1976, Morrison [2] proposed a model that categorized underground mining methods into three main types based on ore body thickness, support requirements, and tensile potential energy: rigid support systems, longwall mining with controlled subsidence, and destructive methods. Like its predecessor, Morrison's approach was limited in scope, neglecting economic, environmental, and social factors.

Agoshkov's [3] 1978 model introduced greater detail by dividing underground mining methods into seven main groups: workshop methods without maintenance, warehouse methods, workshop methods with maintenance, cut-and-fill methods, roof destruction methods, deposit and roof destruction methods, and combined methods. Each group was further subdivided, and specific geological and operational conditions were outlined for their application. While more granular, Agoshkov's approach remained primarily descriptive and qualitative.

A significant advancement occurred in 1987 with Hartman's [4] model, which included both underground and surface mining methods. Based on four deposit characteristics—shape, dip, thickness, and depth—along with ore strength, the model proposed 18 mining methods tailored to different geological scenarios. Despite its broader scope, Hartman's framework still relied on a limited set of parameters and failed to consider economic, environmental, and social dimensions. Moreover, it recommended a single method per scenario, limiting its utility for optimization.

In summary, while qualitative models played a crucial role in the initial development of systematic mining method selection, their reliance on limited geological parameters and lack of multidimensional evaluation criteria have restricted their relevance in modern mining contexts. These shortcomings have led to the development of more sophisticated, data-driven methods such as quantitative models and MCDM techniques.

3. Quantitative and Numerical Methods for Mining Method Selection

Quantitative and numerical models represent a major advancement in mining method selection, incorporating structured evaluation criteria and numerical scoring systems. These methods assign specific values and weights to key geological, geotechnical, and operational parameters. The method with the highest aggregate score is deemed the most suitable, reflecting a better alignment between the deposit's characteristics and the selected mining technique. The following sections review the major quantitative models and their contributions to mining method selection. Figure 2 presents a chronological overview of key quantitative models introduced for mining method selection.

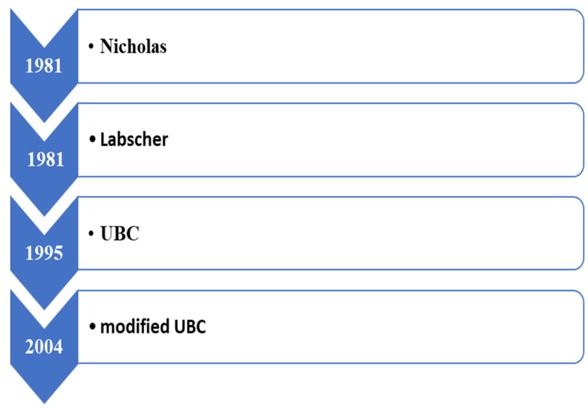

Figure 2. Timeline diagram for numerical and quantitative MMS

3.1. Nicholas's Model (1981)

The first widely recognized quantitative model was introduced by Nicholas in 1981 [5]. After mineral exploration and resource estimation, ten mining methods—including open-pit, cut-and-fill, longwall, room-and-pillar, stop-and-pillar, sublevel stoping, sublevel caving, block caving, and panel caving—are evaluated using 13 parameters, such as deposit thickness, dip, shape, grade distribution, ore strength, and Rock Quality Designation (RQD). Each parameter is scored on a scale from 0 to 4, where: 0 represents low feasibility, 1–2 represent moderate feasibility, and 3–4 indicate high suitability.

A score of -49 is assigned when a method is deemed completely infeasible due to critical constraints. In fact, whenever a method for the deposit is in no way acceptable, score -49 is used. The reason for using score -49 is to make the total scores of the inappropriate method negative, thus eliminating that method from the selection process.

While Nicholas's model provided a systematic framework, it had limitations, such as omitting key parameters like depth, safety, environmental, and social factors. The narrow scoring range limited sensitivity, and the equal weighting of all parameters could lead to biased results. Nicholas [6] later refined his model in 1992 by introducing weighting coefficients to address these concerns and better reflect the relative importance of parameters.

3.2. Labscher's Numerical System (1981)

In 1981, Labscher [7] proposed a numerical system specifically focused on destructive mining methods. This system evaluates geomechanically factors such as joint spacing, density, filling, and groundwater conditions. Indicators were grouped into two categories:

Group 1: Rock Quality Designation (RQD) and joint spacing

Group 2: Groundwater conditions and joint fillings

Based on the combined scores, four feasibility categories were defined: easy to destroy, suitable for destruction, difficult to destroy, and open-pit mining without support. This method provided a specialized approach for destructive mining techniques but was limited to geomechanical factors.

3.3. University of British Columbia (UBC) Model (1995)

In 1995, the University of British Columbia (UBC) introduced a model for Canadian mining operations by Miller [8]. The model incorporated parameters such as deposit thickness, dip, shape, grade distribution, depth, and both Rock Structure Score (RSS) and Rock Mass Rating (RMR). Mining methods were then scored based on these parameters, with a preference for self-supporting techniques over destructive or heavily supported methods. This model was significant in broadening the scope of quantitative evaluation by including geotechnical factors in addition to basic geological parameters.

3.4. Pakalins et al. Model (2002)

In 2002, Pakalins et al. [9] improved the UBC model by integrating fuzzy logic to address uncertainties inherent in geological parameters. This adaptation maintained the original scoring structure while providing a more flexible framework for dealing with ambiguous or uncertain geological conditions. The introduction of fuzzy logic allowed for more nuanced evaluations and helped mitigate the limitations of rigid boundary definitions in the original model.

4. Multi-Criteria Decision-Making Models for Mining Method Selection

4.1. Introduction to MCDM in Mining

Multi-Criteria Decision-Making (MCDM) represents a significant advancement in decision science, providing a systematic framework for evaluating both qualitative and quantitative factors. In the context of mining, selecting the most suitable mining method requires consideration of various conflicting criteria, including geological characteristics, economic viability, safety, and environmental impacts. MCDM can be divided into two main branches: Multi-Attribute Decision-Making (MADM) and Multi-Objective Decision-Making (MODM). MADM focuses on choosing the best alternative from a finite set of options. MODM Concerned with optimizing multiple, often conflicting objectives. Additionally, MCDM methods can be either compensatory or non-compensatory. In non-compensatory decision-making models, each criterion is evaluated independently, without allowing trade-offs among them. These models are typically categorized into three principal groups:

Absence of Criterion Importance Information: This category includes approaches where no data regarding the relative significance of criteria is provided, such as dominance-based techniques, the max–min rule, and the max–max rule.

Ordinal Representation of Criterion Importance: In this group, the importance of criteria is expressed in a ranked or ordinal format. Representative methods include lexicographic ordering, permutation-based strategies, and elimination procedures.

Availability of Threshold or Acceptability Standards: This classification encompasses models that incorporate predefined acceptable limits or thresholds for each criterion, such as the inverse satisfactory method and the specific satisfactory method.

Compensatory methods allow trade-offs between criteria, which can be useful when certain criteria can compensate for others. Figure 3 shows the types of MCDM compensation models and the methods presented in each section. Compensation methodologies can be classified into three principal categories: scoring methods, compromise methods, and outranking methods. In scoring methods, the alternative attaining the highest aggregated score—computed through various algorithmic approaches—is considered superior. Compromise methods identify the alternative exhibiting the greatest proximity and similarity to a theoretically ideal solution. In outranking methods, the preferred alternative is determined as the one occupying the most advantageous position according to a predefined composite or coordinated index. Compensatory models aggregate weighted scores across criteria, enabling a clear ranking of alternatives. These methods also allow poor performance in one criterion (e.g., environmental impact) to be offset by strong performance in another (e.g., economic return). This is particularly useful in mining, where conflicting objectives—like profitability vs. sustainability—must be balanced. A major drawback of these methods is that high scores on some criteria can mask serious deficiencies on others. For example, a site with excellent economic potential but severe environmental risks may still be ranked high, leading to unsustainable decisions. Many modern MCDM approaches have been adapted to fuzzy environments, to better handle uncertainty and the variability of geological data as well as the subjective nature of expert input, common in mining.

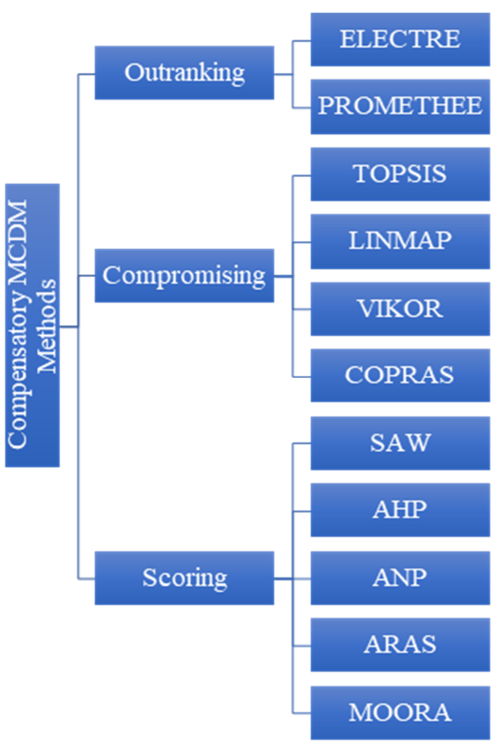

Figure 3. Types of MCDM compensation methods

4.2. Historical Development of MCDM Models in Mining

The application of MCDM in mining began in the late 20th century and has steadily evolved. Some key early developments include:

- 1987 – Yun: Proposed a fuzzy similarity-based approach incorporating geometric, geological, and economic factors in a multi-objective decision-making framework [10].
- 2003 – Guray: Developed a neuro-fuzzy system combining expert knowledge with user inputs to assess mining method suitability [11].
- 2004 – Bitarafan & Ataei: Applied fuzzy MADM to select a mining method for the Gol Gohar iron ore mine, representing one of the first uses of fuzzy logic in mining decision-making [12].

4.3. Evolution and Hybridization of MCDM Techniques

As MCDM methods matured, researchers began combining multiple techniques to enhance decision-making. These hybrid models integrated the strengths of different methods, allowing for more comprehensive and adaptable evaluations:

- 2008 – Alpay: Introduced a six-step SH model for mining method selection at the Eskisehir-Karaburun chromite mine [13].
- 2008 – Ataei et al.: Developed a hybrid AHP-TOPSIS model for the Jajarm bauxite mine, integrating criteria weighting with ranking alternatives [14].
- 2009 – Zare & Ataei: Combined FAHP and TOPSIS to rank methods for a bauxite mine in Iran, demonstrating the value of hybridization [15].

These hybrid models contributed to more nuanced assessments, incorporating additional tools such as PROMETHEE, DEMATEL, and mathematical optimization models to handle diverse geological contexts.

4.4. Integration with AI and Advanced Computing (2016–2024)

The integration of artificial intelligence (AI) and advanced computational techniques into MCDM models in recent years has led to smarter and more adaptive systems capable of managing complex mining environments:

- 2016 – Dehghani: Applied Gray MCDM and TODIM to the Gol Gohar mine, addressing uncertainty and improving decision-making [16].

• 2018 – Balusa: Used FAHP with sensitivity analysis to select uranium mining methods, assessing the impact of each parameter [17].

• 2019 – Liang: Implemented MULTIMOORA with linguistic neutrosophic numbers to evaluate the Kaiyang phosphate mine, introducing cutting-edge fuzzy approaches [18].

• 2020 – Ozyurt: Combined neural networks with game theory to optimize safety and cost in underground mining, emphasizing AI's growing role in mining decisions [19].

• 2021 – Ali: Integrated the UBC classification system with TOPSIS for the Boleo iron ore mine, providing a balanced decision-making framework [20].

• 2022 – Abdelrasoul: Used a cascade-forward back propagation neural network (CFBPNN) at the Chengchao iron mine, enhancing predictive accuracy [21].

The term Cascade Forward Backpropagation Neural Network (CFBPNN) denotes a specialized architecture within artificial neural networks designed for modeling and forecasting complex systems. This approach integrates two foundational principles of machine learning:

• Cascade Forward Connectivity: In contrast to traditional feedforward networks, where each layer transmits information solely to the immediate subsequent layer, the cascade forward structure enables each layer to establish direct connections with all succeeding layers. This enhanced connectivity facilitates more rapid and efficient propagation of input data and extracted features toward the output layer.

• Backpropagation Learning Algorithm: The network is trained using the backpropagation technique, wherein the predicted output is compared against the actual target value to compute the error. This error is then used to iteratively adjust the synaptic weights throughout the network, thereby improving its predictive accuracy over successive training cycles.

The application of artificial intelligence models in mining method selection faces several challenges and limitations. One of the primary concerns is the quality and quantity of training data; incomplete, imbalanced, or geologically specific datasets can significantly reduce model accuracy and generalizability. Moreover, the issue of overfitting is prevalent in models trained on limited data, resulting in poor performance when exposed to new or unseen scenarios. Another critical limitation is the transferability of models across different geological environments, as models trained on data from a specific mine may not perform reliably in other contexts. Additionally, the complexity of certain algorithms, such as neural networks, often leads to reduced interpretability of results, which can hinder their practical acceptance among mining professionals. Finally, the effective development and implementation of AI models in mining require interdisciplinary collaboration among geologists, mining engineers, and data scientists—an endeavor that demands appropriate educational and research infrastructure.

4.5. Recent Innovations and Comprehensive Frameworks (2023–2024)

Recent studies showcase the trend toward fully integrated decision-support systems combining hybrid MCDM models with AI and machine learning:

• 2023 – Barrios: Applied AHP and TOPSIS for the Gol Gohar Mine No. 3, demonstrating the effectiveness of pairwise comparisons in real-world applications [22].

• 2024 – Bogdanović: Prioritized environmental and labor-related criteria using AHP, reflecting the increasing focus on socio-economic sustainability [23].

• 2024 – Jahanbani: Proposed a hybrid DEMATEL-Z-number model for the Angoran lead and zinc mine, improving accuracy through causal relationship analysis [24].

• 2024 – Manjate: Developed the AI-MMRS system, using non-negative matrix factorization and machine learning for mining method recommendations [25].

• 2024 – Samimi: Conducted a comparative study of MMS techniques using SECA and fuzzy TOPSIS across several Iranian mines, offering a robust evaluation framework [26].

Over the last few decades, MCDM models have transitioned from fuzzy logic-based methods to advanced AI-integrated systems, significantly enhancing the robustness, adaptability, and accuracy of mining method selection processes. These models are now capable of considering a wide range of technical, economic, environmental, and social factors, making them indispensable for modern mining decision-making. As mining operations continue to grow in complexity and data availability increases, future models are expected to become even more dynamic, predictive, and capable of providing real-time decision support.

5. Analysis of MCDM-Based Studies in Mining Method Selection

To better understand how multi-criteria decision-making (MCDM) methods are applied in selecting mining methods, a comprehensive review of 59 scientific articles published in reputable journals was conducted. The list of reviewed articles is given in Table 2. The primary goal was to identify key trends, methods, and insights that have shaped mining method selection over the years.

Among these studies, 4 articles specifically focused on analyzing and weighting the key parameters influencing the selection of mining methods—such as geological, economic, and environmental factors. These works were mostly quantitative in nature, aiming to determine the relative importance of each parameter.

The remaining 55 articles not only assessed the influencing parameters but also applied MCDM models to identify and rank suitable mining methods. These papers employed various decision-making techniques, including AHP, TOPSIS, fuzzy logic, and hybrid models, to provide comprehensive frameworks for mining method selection. The considered mining techniques ranged from surface to underground mining, reflecting the adaptability of MCDM tools in various geological and operational contexts.

Figure 4 illustrates the temporal evolution of research from 1987 to 2024. Between 1987 and 2011, the focus was on introducing different mining methods and using decision-support tools for method selection. A peak was observed in 2008, with five articles published in that year—highlighting growing interest in this research domain.

From 2012 to 2024, publication frequency fluctuated between 1 and 7 articles per year, with notable spikes in 2017, 2018, and 2024—each having seven publications. These peaks correlate with the increasing integration of advanced technologies such as AI, machine learning, and data mining into MCDM-based mining applications.

This trend reflects a shift from traditional decision-making models to more complex and integrated approaches capable of handling dynamic geological, economic, and environmental conditions.

5.1. Article Distribution by Journal Quality

An analysis of the selected papers reveals that a significant portion were published in high-quality journals. Approximately 37% appeared in Q1-ranked journals, indicating high academic standards and rigorous peer review processes. Additionally, 20% were published in Q2 journals, and 13.5% in Q3 and Q4.

This distribution reflects researchers' efforts to disseminate findings through reputable platforms. Notable journals contributing to this field include Expert Systems with Applications and the Journal of Mining Science.

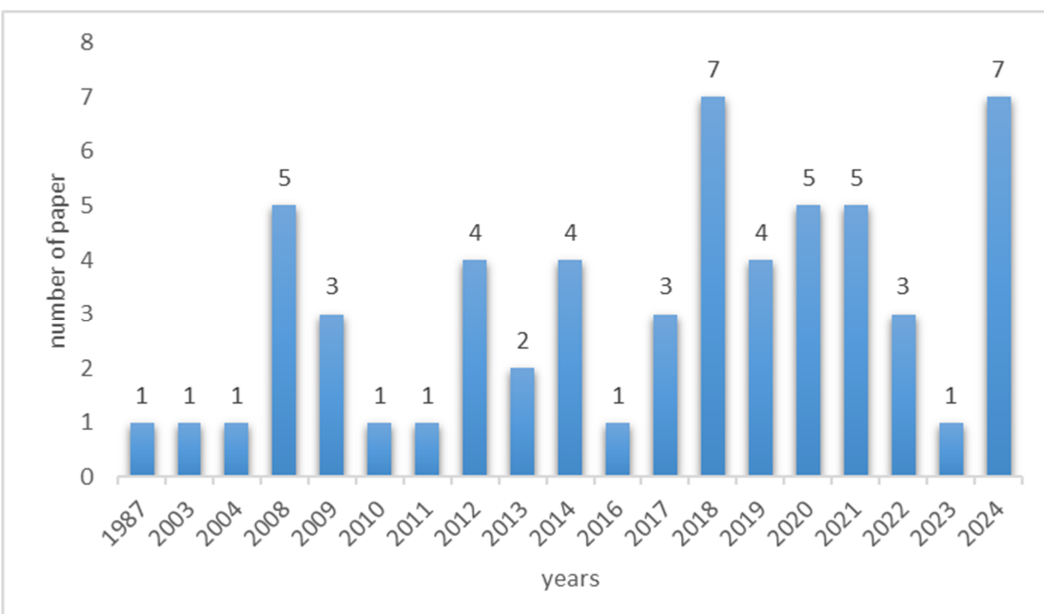

Figure 4. The number of papers published each year from 1987 to 2024

Table 2. Multi-Criteria Decision-Making (MCDM) research works on Mining Method Selection

Row	year	researcher	Journal name	The Q scores of a journal
1	1987	Yun	Mining Science and Technology	_
2	2003	Guray	Expert Systems with Applications	Q1
3	2004	Bitarafan	Journal of the Southern African Institute of Mining and Metallurgy	Q2
4	2008	alpay	Tunnelling and Underground Space Technology	Q1
5	2008	Yavuz [27]	Journal of Mining Science	Q2
6	2009	JAMSHIDI [28]	Archives Of Mining Science	Q2
7	2008	ataei	Transactions Of the Institution of Mining and Metallurgy, Section A: Mining Technology	Q2
8	2008	Karadogan [29]	Journal of the Southern African Institute of Mining and Metallurgy	Q2
9	2009	Zare Naghadehi	Expert Systems with Applications	Q1
10	2009	SAMIMI NAMIN [30]	Gospodarka Surowcami Mineralnymi - Mineral Resources Management	Q3
11	2009	Azadeh [31]	Applied Soft Computing	Q1
12	2010	LIU [32]	Journal of Central South University of Technology	Q2
13	2011	Bogdanovic [33]	Anais da Academia Brasileira de Ciências	Q1
14	2012	Gupta [34]	International Journal of Mining, Reclamation and Environment	Q2
15	2012	Samimi Namin [35]	Journal of the Operational Research Society	Q1
16	2012	Yazdani [36]	Economic Research-Ekonomska Istraživanja	Q4
17	2012	Nourali [37]	Archives Of Mining Science	Q2
18	2013	Ataei [38]	International Journal of Mining Science and Technology	Q2
19	2013	Shariati [39]	International Journal of Sciences: Basic and Applied Research	_
20	2014	Yavuz [40]	international Journal of Mining, Reclamation and Environment	Q3
21	2014	Karimnia [41]	International Journal of Mining Science and Technology	Q1
22	2014	Gelvez [42]	International Journal of the Analytic Hierarchy Process	_
23	2014	Ghazikalayeh [43]	Journal of Applied Sciences research	Q3
24	2016	Dehghani	Journal of Mining & Environment	_
25	2017	Balusa [44]	Journal of The Institution of Engineers (India): Series D	Q3
26	2017	Javanshirgiv [45]	Int. J. Mining and Mineral Engineering	Q3
27	2017	Kabwe [46]	Mining Technology	_
28	2018	Balusa	Journal of Sustainable Mining	Q3
29	2018	Iphar [47]	International Journal of Mining, reclamation and environment	Q2
30	2018	Balusa [48]	Journal of The Institution of Engineers (India) Series D	Q4
31	2018	Asadi Ooriad [49]	Rudarsko-geološko-naftni zbornik	Q2
32	2018	FU [50]	IEEE Access	Q1
33	2018	Stevanović [51]	Advances in Science and Technology research journal	_
34	2018	Liang [52]	Neural Computing and Applications	Q2
35	2019	Yetkin [53]	Journal of Engineering and Technology for Industrial Applications	_
36	2019	Kangwa [54]	International Journal of Engineering and Advanced Technology	Q4
37	2019	Popović [55]	INDUSTRIJA	_
38	2019	LIANG	Transactions of Nonferrous Metals Society of China	Q1
39	2020	Bajic´ [56]	Symmetry	Q2
40	2020	Balt [57].	The Southern African Institute of mining and metallurgy	Q3
41	2020	Özyurta	Journal of Mining Science	Q3
42	2020	Ibishi [58]	Mining of Mineral Deposits	Q2
43	2020	Banda [59]	Natural Resources Research	Q1
44	2021	Ali	Journal of Sustainable Mining	Q1

Continuous of Table 2

45	2021	Balusa [60]	Intelligent Decision Technologies	Q4
46	2021	Mijalkovski [61]	Podzemni radovi (underground mining engineering)	_
47	2021	Mijalkovski [62]	Mining Science	Q3
48	2021	Durai [63]	Intelligent Automation & Soft Computing	Q3
49	2022	Abdelrasoul	Advances in Civil Engineering	Q3
50	2022	Manjate [64]	Journal of Sustainable Mining	Q2
51	2022	Mijalkovsk [65]	GeoScience Engineering	_
52	2023	Barrios	Mathematical Modelling of Engineering Problems	Q3
53	2024	Bogdanović	Podzemni radovi (underground mining engineering)	_
54	2024	Jahanbani [66]	Rock Mechanics and Rock Engineering	Q1
55	2024	Jahanbani	Resources Policy	Q1
56	2024	Balusa [67]	Journal of Mines, Metals and Fuels	Q4
57	2024	Manjate	Mining	Q2
58	2024	Manjate [68]	International Journal of the Society of Materials Engineering for Resources	Q4
59	2024	Samimi	Rudarsko-geološko-naftni zbornik	Q2

5.2. Geographic Distribution of Publications

From a geographical perspective, Iran contributed the most with 37% of the reviewed publications, underscoring the strategic and economic importance of mining in the country. India (15%) and China (12%) followed, with other contributors including Turkey (10%) and Serbia (8%).

This distribution highlights the active involvement of countries with substantial mineral reserves and ongoing mining activities in MCDM-based research for mining method selection.

5.3. Challenges and Opportunities in MCDM Applications

One of the main challenges in applying MCDM methods to mining is the complexity and diversity of the data, along with inherent uncertainties in evaluations. However, the integration of advanced techniques such as fuzzy logic and artificial intelligence offers promising solutions for improving sensitivity analysis, risk assessment, and overall decision reliability.

Modern MCDM models provide flexibility to adapt to real-world mining scenarios, enhancing the robustness, sustainability, and accuracy of decision-making processes.

Figure 5 indicates that Gol-Gohar mine (Iran) received the most attention, being the focus of six articles. This was followed by Chah-Gonbad (Iran) and Tummalapalle (India) with four mentions each, and Angoran mine with three. The focus on these mines reflects their economic importance, geological complexity, or unique environmental considerations.

Figure 6 displays author contributions, distinguishing between first authors (blue) and co-authors (orange). Among them, Balusa stands out with five first-author publications, highlighting a leading role in advancing MCDM-based mining method selection. Ataei also contributed significantly, with two first-author and five co-authored papers, along with Samimi-Namin and Mijalkovski, who each had four first-author papers.

Figure 7 shows the distribution of decision-making methods across the reviewed studies. AHP (Analytic Hierarchy Process) was the most widely used method with 16 occurrences, reflecting its structured and widely accepted nature. TOPSIS followed with 12 uses.

Other methods included generic MCDM models (11 cases), fuzzy logic (6), and VIKOR (5). The variety of methods used indicates a growing interest in combining and adapting models to address the multi-dimensional challenges of mining method selection.

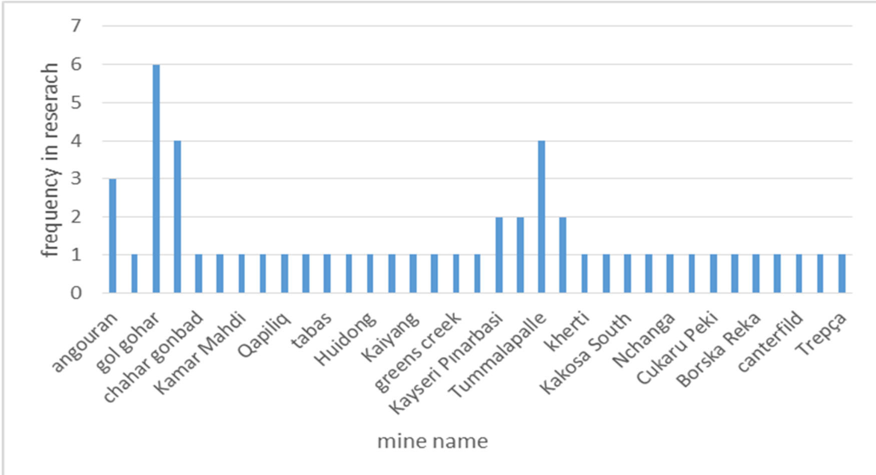

Figure 5. Distribution of studies conducted on the application of decision-making models in MMS in different mines

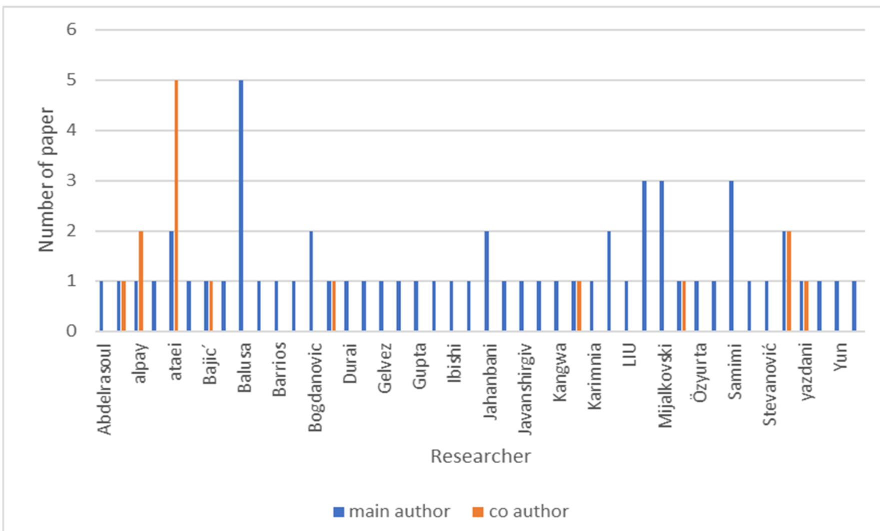

Figure 6. Researchers and the number of their articles on determining the mining method with multi-criteria decision-making

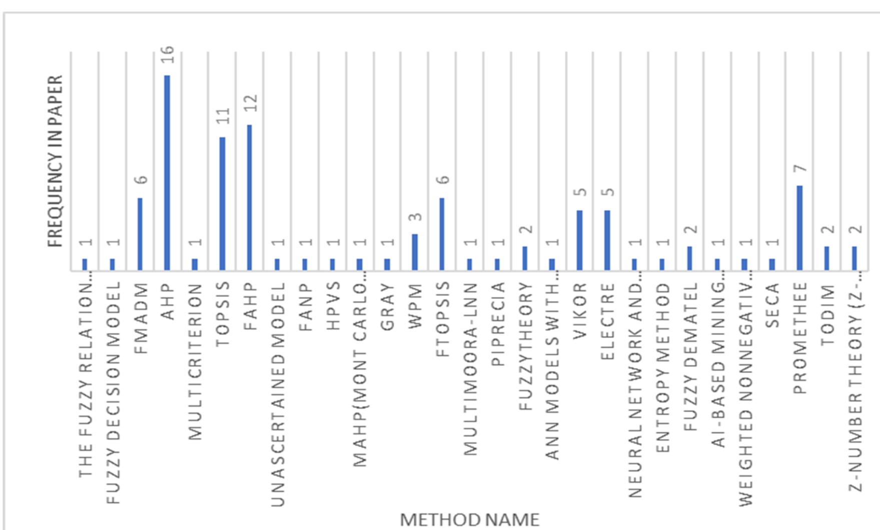

Figure 7. Number of decision-making methods in selecting the mining method

6. Analysis of Parameters Influencing Mining Method Selection

To evaluate the key factors that influence mining method selection in the reviewed literature, the parameters were classified into two main categories: intrinsic and extrinsic, as presented in Tables 3 and 4. This classification allows for a clearer understanding of factors that are inherent to the ore deposit versus those that are shaped by external conditions and operational decisions.

6.1. Intrinsic Parameters

Intrinsic parameters are defined as the inherent and relatively stable characteristics of the ore body and surrounding geological environment. These include geological attributes, geometric features, and rock mechanical properties, which remain largely unaffected by mining activities.

6.1.1. Geological Parameters

Among the geological factors, "grade distribution" was the most frequently cited parameter, appearing in 29 studies. This highlights its pivotal role in determining the efficiency of ore extraction and overall feasibility of mining methods. "Ore grade" was also commonly referenced, with 12 mentions, reflecting its importance in evaluating ore quality and profitability. Other parameters, such as mineralization type and deposit geometry, were mentioned less frequently, suggesting that research tends to prioritize directly quantifiable variables linked to resource extraction.

6.1.2. Geometric Parameters

Geometric characteristics of the ore body are critical for planning and implementing mining techniques. "Ore shape" was cited in 37 studies, while "ore dip" and "ore thickness" were each mentioned 38 times, and "ore depth" appeared in 33 studies. These features were emphasized in over 60% of the reviewed articles, underscoring their influence on selecting and adapting mining methods based on deposit morphology.

6.1.3. Rock Mechanical Properties

Rock mechanical parameters—such as rock strength, fracture patterns, and overall stability—are essential for determining the technical feasibility and safety of mining methods. Among these, the Rock Mass Rating (RMR) and Rock Strength Scale (RSS) were particularly emphasized:

- RMR of the ore: 25 mentions
- RMR of the hanging wall: 23 mentions
- RSS of the ore: 20 mentions
- RSS of the hanging wall: 15 mentions
- RSS of the footwall: 14 mentions

These parameters are vital for assessing structural stability and designing appropriate ground support systems, making them integral to the selection process.

6.2. Extrinsic Parameters

Extrinsic parameters are variable and influenced by external factors such as economic conditions, technology, and regulatory or environmental constraints. These include economic metrics, technical capabilities, environmental impacts, and safety concerns.

6.3. Non-Intrinsic Criteria

Beyond geological and mechanical characteristics, non-intrinsic criteria play a crucial role in MCDM-based mining method selection, often determining the feasibility and sustainability of operations.

6.3.1. Environmental Aspects

The subsidence effect—cited in 13 studies—was the most prominent environmental parameter. Ground subsidence, a common consequence of underground mining, can have severe impacts on surface structures and ecosystems, necessitating comprehensive evaluation during method selection.

6.3.2. Safety and Health

Safety-related parameters were frequently emphasized. “Access to skilled manpower” appeared in 16 studies, while “operational safety degree” was cited in 14. These highlight the importance of workforce competency and operational safety in minimizing risks and ensuring smooth mining activities.

6.3.3. Economic Factors

Economic considerations were among the most frequently cited extrinsic parameters. "Mining cost" was mentioned in 18 studies, and "capital cost" in 16. These underscore the emphasis on cost-efficiency and investment feasibility in the selection of appropriate mining methods.

Table 3. Frequency of using effective intrinsic criteria and sub-criteria in MMS

Geology		Geometric		Specifications of rock mechanics	
sub criteria	**Frequency (%)**	**sub criteria**	**Frequency (%)**	**sub criteria**	**frequency (%)**
overall geology condition	3.3	overall geometric condition	3.3	overall rock mechanic condition	3.3
grade distribution	49.1	ore shape	62.7	ore RSS	33.8
Ore grade	20.3	ore thickness	64.4	RMR of hanging wall	38.9
hydrologic condition	15.2	ore dip	64.4	RMR of footwall	30.5
Ore body volume	10.1	ore depth	56	RMR of ore	42.3
Adaptive degree to change of orebody	1.7	hanging wall and footwall quartzite	1.7	Soundness degree of the hanging wall	3.3
Presence of Surface feature	3.3			Soundness degree of the footwall	3.3
Form of ore body and contact with neighboring rocks	1.7			Hanging wall RSS	25.4
Mineral and chemical composition of ore	3.3			Footwall RSS	23.7
				Hang wall RQD	8.4
				crack system of ore	1.7
				Strength of ore	6.7
				Strength of host rock	6.7
				Stability rock	3.3
				Stone blocks quality	1.7
				Compressive strength of coal	1.7
				Compressive strength of footwall	1.7
				Fracture shear strength—hanging wall	1.7
				Fracture frequency—hanging wall	1.7
				Ore zone RQD	1.7
				Foot wall RQD	1.7

6.3.4. Technical and Operational Considerations

Parameters such as dilution, mineral recovery, productivity, degree of mechanization, and operational flexibility were also highlighted. These technical factors are essential for ensuring optimal performance of the selected mining method and are frequently integrated into MCDM models for comprehensive evaluations.

7. Conclusions

This comprehensive review has examined the evolution and application of multi-criteria decision-making (MCDM) models in the context of mining method selection. The historical development of MCDM techniques—ranging from classical approaches like AHP and TOPSIS to more recent integrations with fuzzy logic and artificial intelligence—demonstrates the growing complexity and precision required for optimal decision-making in mining operations. The increasing application of hybrid models and machine learning-based frameworks reflects a significant paradigm shift toward more adaptive, data-driven systems that can address uncertainty and dynamic operational variables.

A critical aspect of this study was the bibliometric analysis, which revealed that research activity in this field is globally distributed, with significant contributions from countries such as Iran, India, and China. Key authors, journals, and highly cited works were identified, providing insight into the intellectual structure and scholarly impact of the domain.

The analysis of influencing parameters further reinforced that intrinsic factors—especially ore geometry, grade distribution, and rock mechanics—remain the most decisive in method selection. However, extrinsic and non-intrinsic criteria such as cost, safety, environmental concerns, and operational flexibility are increasingly integrated into decision-making models, highlighting the multidimensional nature of modern mining challenges.

In conclusion, the study underscores the essential role of MCDM approaches in enhancing the strategic planning and sustainability of mining operations. The integration of intelligent systems and robust parameter analysis enables decision-makers to design mining methods that are not only technically feasible and economically viable but also environmentally responsible and adaptable to future innovations. Future research should focus on refining these hybrid models and incorporating real-time data streams to support dynamic, automated decision-making processes in mining method selection.

By adopting hybrid MCDM frameworks –such as fuzzy logic models augmented with AI– decision makers can dynamically address operational uncertainties (such as fluctuating ore grade) while balancing intrinsic factors such as geology and rock mechanics with extrinsic priorities such as cost efficiency, safety protocols, and environmental regulations.

Table 4. Frequency of using effective non-intrinsic criteria and sub criteria in MMS

Environmental aspect		Safety and health		Economic factors		Technical and operational	
sub criteria	**Frequency (%)**	**sub criteria**	**Frequency (%)**	**sub criteria**	**Frequency (%)**	**sub criteria**	**Frequency (%)**
overall environmental condition	13.5	overall safety condition	20.3	overall economic condition	8.4	overall technical condition	6.7
Nearness of the settlement areas	3.3	Skilled manpower	27.1	annual profit	1.7	ore recovery	39
Subsidence effect	22	Operation safety degree	23.7	capital cost	27.1	productivity	27.1
		Stability of openings	1.7	pay-back period and profitability	1.7	ratio between opening and ore	3.3
				Mining cost	30.5	Mining mechanization	22
				Labor cost	3.3	flexibility	22
				Reclamation/ rehabilitation costs	6.7	opportunity to modernize mining scheme	5
				income per ton of ore	1.7	possible selective extraction	15.2
				Production cost	5	ore production rate	1.7
				Comparative costs of possible mining methods	1.7	possible increase in production volume	1.7
				Selling price	1.7	technological complexity and technological controllability	16.9
				Mineral value Mineable ore tones	10.1	Production	16.9
				Maintenance costs	1.7	Dilution	42.3
				NPV	3.3	Support necessity	3.3
				Modified internal rate of return (MIRR)	1.7	Burning property of the lignite	3.3
				Profitability index (PI)	1.7	Methane existence	6.7
				Discounted payback period (DPP)	1.7	Soundness degree of the lignite	3.3
				Cost of one ton of ore	5.1	Contact state of the lignite seam-hanging and footwall	3.3
				IRR	1.7	Output per man shift	8.4
				Optimal use of financial equipment and manpower	1.7	Climate of area	3.3
				The desire to invest in any method	1.7	Production rate	15.2
				Associate with any machinery in the company	1.7	Development production	3.3
						Development rate	5
						Occupational interests	1.7
						Equipment worth and its usages	1.7

Continuous of Table 4

	Ventilation condition	101
	coefficient of development	1.7
	Block size	1.7
	Electricity requirement	1.7
	Water requirement	1.7
	Waste rock production	1.7
	Auxiliary equipment needs	1.7
	Condition of dirt band	1.7
	Degree of disturbance to overlying rock formation	1.7
	High mining height	1.7
	Suitability to underground infrastructure	1.7
	Real option to abandon	1.7
	Coefficient of preparation works	5
	Depth capacity	1.7
	Life of mine	1.7
	Minimum access time to mineral	1.7

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«بررسی جامع روش‌های تصمیم‌گیری چندمعیاره در انتخاب شیوه معدنکاری: سیر تحول، گرایش‌ها و کاربردها»

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یادگیری ماشین

چکیده

انتخاب روش استخراج مناسب، مسئله‌ای پیچیده در فرآیند تصمیم‌گیری است که تحت تأثیر مجموعه‌ای از عوامل زمین‌شناسی، فنی، اقتصادی، زیست‌محیطی و ایمنی قرار دارد. این مطالعه، مروری جامع بر رویکردهای تصمیم‌گیری چندمعیاره (MCDM) در انتخاب روش استخراج ارائه می‌دهد و بر سیر تاریخی این روش‌ها، تلفیق آن‌ها با منطق فازی، هوش مصنوعی و یادگیری ماشین، همچنین روندهای علم‌سنجی و تحلیل پارامترها تمرکز دارد. یافته‌ها نشان‌دهنده گرایش فزاینده به سوی مدل‌های ترکیبی و هوشمند تصمیم‌گیری چندمعیاره هستند که دقت تصمیم‌گیری و قابلیت انطباق در شرایط عدم قطعیت را بهبود می‌بخشند.تحلیل علم‌سنجی نویسندگان کلیدی، کشورها، نشریات و الگوهای استنادی، گستره جهانی و تأثیر علمی این حوزه را برجسته می‌سازد. همچنین، نتایج این پژوهش نشان می‌دهد که ایران در زمینه تولید علمی مرتبط با این حوزه در جایگاه نخست جهانی قرار دارد و ۳۷٪ از کل انتشارات را به خود اختصاص داده است. در میان متغیرهای درونی بررسی‌شده، پارامترهایی مانند مورفولوژی یا ضخامت کانسار، شیب کانسار و عمق کانسار بیشترین فراوانی را در متون علمی دارند و ۶۹٪ از مطالعات گزارش‌شده را شامل می‌شوند؛ در حالی که ملاحظات اقتصادی، زیست‌محیطی و عملیاتی به‌عنوان عوامل بیرونی تأثیرگذار شناخته می‌شوند. این مرور، نقش حیاتی تکنیک‌های تصمیم‌گیری چندمعیاره در بهینه‌سازی عملیات استخراج را مورد تأکید قرار داده و بر توسعه بیشتر مدل‌های پویا و داده‌محور برای پاسخ‌گویی به چالش‌های نوین صنعت معدن تأکید می‌ورزد.

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