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Predicting and Analyzing Pathways toward Sustainable Development of the Mining Sector under the NZE Scenario: An Integrated Approach Using Fuzzy MCDM and ANFIS

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Abstract

Achieving sustainable mining development is increasingly vital in addressing environmental challenges, meeting global decarbonization demands, and progressing toward a Net-Zero Emissions (NZE) future. This study proposes an integrated framework to advance sustainable mining in Iran, with a particular focus on the roles of emerging technologies and environmental regulations. The core research question investigates how combining fuzzy decision-making methods with intelligent modeling can guide the mining sector toward NZE goals. A multi-stage mixed-methods approach was employed. Initially, key variables were identified using the fuzzy Delphi method and expert judgment. The hesitant fuzzy analytic hierarchy process (HFAHP) was then applied to prioritize and weigh the main factors. Subsequently, fuzzy DEMATEL and interpretive structural modeling (ISM) were utilized to uncover causal relationships and hierarchical dependencies among variables. Finally, the adaptive neuro-fuzzy inference system (ANFIS) simulated potential pathways for achieving sustainable mining. Findings highlight four critical variables carbon pricing policies, investment costs, global metal prices, and technological innovation as the most influential drivers. Moreover, ANFIS results indicate that strengthening these factors significantly increases the likelihood of achieving the NZE scenario. Overall, the proposed model serves as a practical decision-support tool for policymakers and mining stakeholders, aiding in policy design, investment strategy develop.

1. Introduction

The growing energy transition makes it more urgent than ever to reconsider traditional approaches to resource management and forecasting [1]. Climate change, international environmental pressures and obligations under treaties such as the Paris Agreement compel countries and industries to adopt strategies for reducing carbon emissions. In this respect, the mining sector is a key pillar of the world's and national economies. It provides essential raw materials for clean energy technologies, but it faces serious environmental and social challenges [1, 2 and 3]. The importance of the sector goes beyond economic growth and employment creation. It also supports the stable supply of materials needed for renewable energy, electric vehicles, storage batteries, and intelligent networks. However, this heavy dependence on mineral resources increases the demand for essential materials and metals. As the world moves toward the goal of net zero emissions (NZE) by 2050, this dependence has a large economic, technological, social and environmental impact throughout the mining value chain. Economically, changes in global metal prices and the high level of investment required strongly affect the risk–return profile of mining projects. From a technological point of view, innovation in extraction and processing methods is essential to reduce energy intensity and emissions [4, 5]. The social and cultural aspects of mining have become essential to maintain legitimacy and their social acceptance and contribution to the

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development of local communities. Environmental issues such as greenhouse gas emissions, waste management, and water and soil resource protection have become increasingly important [6]. A review of the literature shows that, while many studies examine the role of energy policy, technological innovation and environmental regulations in promoting the sustainability of mining, there are still clear research gaps [7, 8].In particular, there is no comprehensive model that systematically integrates these dimensions into the NZE scenario, especially in developing countries. The development of such a model is a valuable tool for predicting future trends, assessing impact, and guiding strategic decision-making in the mining sector. This in turn supports developing countries' transition to sustainable development and decarbonization [9]. The importance of this issue is even greater in developing countries where mining remains the main engine of economic growth and employment. At the same time, these countries often face severe limitations in financing advanced technologies, poor infrastructure, and ineffective policy formulation. Ignorance of the principles of sustainable development under these conditions results in imbalanced growth, irreversible environmental damage and growing dissatisfaction in local communities, ultimately undermining the social legitimacy of mining activities. Iran clearly shows this dual challenge. The country, with its vast reserves of iron ore, copper, lead, zinc and aluminum, has considerable potential for economic expansion and integration into the world market. However, these resources also make significant contributions to carbon emissions and environmental pressures. Without adequate investment in clean energy technologies and advanced tools, such as artificial intelligence, digital processing, and energy storage systems, Iran's mining industry still operates at a high level of pollution and limited efficiency. The research question of this study focuses on identifying the variables and measures required for the design of sustainable mining models compatible with the NZE scenario. It also examines how to evaluate and classify these variables in the absence of uncertainty. The aim of the study is to develop a model that emphasizes the adoption of clean energy technologies and the NZE pathway, with the aim of identifying, ranking and analyzing the causal relationship between the key variables to support effective policy formulation and management strategies. To solve this problem, the research uses a mixed methodology design integrated with a cautious and fuzzy decision-making technique. This includes reviewing the literature, identifying relevant variables, modeling their interactions, and developing a framework for sustainable mining. This framework is composed of defining methodology, improving variables, analyzing data, and generating results that lead to actionable policy recommendations. The novelty of the study is its integrated approach that models the economic, social, technological and environmental aspects of sustainable mining in the NZE scenario. The research provides clear and practical guidelines for policy makers and decision makers by applying robust methods to manage uncertainty. The objectives of this study are defined as follows:

- Determine the relative weight of the key factors that influence the achievement of NZE using vague MCDM methods;
- Predict the probability of reaching NZE in the mining sector by 2030 with a target accuracy of at least 85% using the ANFIS model;
- Evaluate the contribution of technological innovation and investment costs to indicators of sustainable development; and
- Ensure that policy recommendations increase the probability of achieving NZE by at least 20% by 2030.

2. Literature Review

Over the past few decades, sustainability has attracted increased attention from all sectors of the industry, especially mining, where the net zero emissions scenario (NZE) has become a central focus. Energy and economic research indicates that the expansion of renewable energy, better efficiency and the adoption of decarbonization policies are necessary to reduce greenhouse gas emissions. These studies also highlight the significance of investment and carbon prices in the creation of sustainable development pathways [10], and the mining sustainability literature identifies four core areas of focus: economics, social culture, technology, and environment [11,12]. In the economic sector, factors such as investment costs, carbon pricing policies, global volatility in metal prices and tax incentives are recognized as key drivers of the NZ transition. The macro-level and policy review further suggests that integrating renewable energy with efficiency improvements and decarbonization mechanisms offers cost-effective pathways to emission reduction. This integration also improves the financial sustainability of mining projects [13]. At national and sectoral levels, scenario-based models show

that carbon policies and emission targets have a significant impact on investment decisions and cost structures. They also highlight the role of global metal and critical materials prices in shaping the risk-return dynamics of mining projects. Therefore, model-based evidence suggests that the implementation of NZE transition requires the realignment of incentives and the elimination of the costs of technology transfer. These efforts must be extended to the entire mining value chain [14, 15 and 16]. Social and cultural areas are closely linked to the social acceptance of technology, corporate social responsibility, community involvement and improved quality of life [17]. The literature suggests that the success of a low-carbon transition depends on strengthening local benefits and ensuring the perception of distributive justice. It also needs to institutionalize mining activities and link them to community development. Studies on safety and human capital also emphasize the importance of safety culture and labor training as essential prerequisites for implementing technological changes in the mine. Furthermore, consistent corporate sustainability measures show that compliance with the Sustainable Development Goals (SDGs) and transparent reporting enhance social acceptance and operational legitimacy [18]. In the technical field, the literature recognizes innovation, process digitalization, extraction artificial intelligence, technological infrastructure, energy storage and intelligent environmental monitoring systems as the main drivers of productivity and carbon reduction. The path toward zero net emphasizes the importance of transformational innovations and synergy between technology and policy [19]. At the corporate level, the integration of artificial intelligence, robotics and automation with data management and real-time analytics enhances safety and energy efficiency. It also improves the quality of decision-making. The integrated model for mining rehabilitation and energy technology selection further demonstrates how innovation supports land rehabilitation and strengthens the resilience of the infrastructure. Policy studies also highlight the need to align regulatory support with technological investments. This alignment helps to accelerate the transition to sustainability [20, 21 and 22]. Environmental dimensions, including energy intensity, greenhouse gas emissions, life cycle assessments, water use, waste recycling and ecosystem health, form the core of alignment with the NZE framework [23, 24]. Research suggests that the incorporation of carbon costs into the design of open mining sites improves operating efficiency and reduces the carbon footprint [25, 26]. At the same time, recycling strategies based on vague approaches and the principles of circular economy help reduce the pressure on primary resources. They also strengthen the resilience of the ecosystem [27]. Water management, often described as the lifeblood of sustainable mining, is increasingly integrated into future operational frameworks [28, 29 and 30]. Studies of negative emissions technologies and carbon capture, combined with carbon prices in the energy sector, suggest that technical and economic instruments should work synergistically to achieve zero net emissions [31, 32]. The literature further emphasizes that the global transition to NZE has intensified the demand for essential materials and metals. This change will have a major economic and environmental impact throughout the mining value chain. It also highlights the importance of supply-side policies, diversification strategies and responsible mining standards. At both the national and sectoral levels, net zero-way models highlight the role of investment policies, price reforms and infrastructure optimization. A summary of the literature reviewed on the four dimensions of sustainable mining is presented in Table 1.

Table 1. An overview of previous studies on the four dimensions of sustainable mining

Key Area	Research Focus	Methods Used	References
Economic	Carbon pricing policies, investment costs, global metal price fluctuations, tax incentives, and economic efficiency of mining towards NZE	Energy modeling and scenarios, big data analysis, policy analysis, economic evaluation	[13,14,15,16]
Socio-cultural	Social acceptance of technology, corporate social responsibility, role of local communities, quality of life, and safety culture in low-carbon transition	Field studies, qualitative interviews, composite sustainability indices, social analysis	[17,18]
Technological	Technological innovation, digitalization, artificial intelligence, robotics, smart monitoring systems, and energy storage technologies in productivity and decarbonization	Scenario modeling, technology studies, policy–technology analysis, data simulation	[19,20,21,22]
Environmental	Energy intensity, waste recycling, water management, ecosystem health, and integration of carbon costs in mining operations	Life Cycle Assessment (LCA), circular economy models, environmental analysis, carbon reduction scenarios	[23,24,25,26]

Although extensive research has been carried out on sustainable development and NZE, some critical gaps remain. Firstly, most studies focus on a single dimension – economic, sociocultural, technological or environmental – rather than providing an integrated framework that simultaneously examines all four dimensions. Secondly, most of the existing work is based primarily on trend analysis or scenario modelling, with few attempts to quantitatively evaluate the likelihood of NZE achievement. Thirdly, the link between macroeconomic policies and technological pathways of innovation in the mining sector has not been adequately studied. Fourthly, while sectors such as energy, buildings and transport have received considerable attention, the mining sector – despite its central role in providing critical minerals for the transition to clean energy – is still relatively underexploited. Finally, previous studies often failed to capture complex and multidimensional relationships between variables. This limitation highlights the need for a more comprehensive analytical framework. Over the past decade, extensive research has been conducted on the integration of sustainable mining, net zero transition and artificial intelligence (AI), and multi-criterion decision-making techniques (MCDM) in the energy and resources sectors. Despite these advances, most existing research either emphasizes a single dimension of sustainability (economic, ecological, or technological) or rely on single-method analyses without establishing interdependencies between key factors. Furthermore, only limited research has examined hybrid frameworks that combine MCDM vague and intelligent prediction systems (such as ANFIS) in the environment of zero-emission (NZE) for the mining sector. Table 2 shows the 15 main studies and highlights their methodologies, focus areas and main research gaps. This comparison shows that, although previous studies have provided valuable insights into sustainability, carbon neutrality, and the integration of AI, few have systematically linked fuzzy causal models and intelligent predictions to the development of an integrated sustainable mining framework.

As shown in Table 2, the reviewed studies have shown significant progress in sustainable mining, decarbonisation and the modelling of the energy system. However, there is a lack of integrated approaches that (i) jointly analyze the causal relationship between uncertain economic, social, technological, and environmental variables, and (ii) use intelligent prediction systems to estimate the probability of reaching NZE. Consequently, this study has developed an integrated fuzzy-intelligent framework for sustainable mining development. This approach addresses the methodological shortcomings identified in previous research and provides a predictive decision support model. It is capable of quantifying NZE routes in uncertain times and improving decision-making for sustainable mining strategies. While sectors such as energy, construction and transport have been the subject of considerable attention, the mining sector – despite its central role in providing crucial minerals for the transition to clean energy – remains relatively underexplored. In addition, previous studies have often failed to capture complex and multidimensional relationships between variables. This limitation highlights the need for a more comprehensive and integrated analytical framework.

3. Research Methodology

This study was applied in nature, as its primary aim was to develop an operational model for sustainable mining within the framework of the NZE scenario. Methodologically, it was exploratory the study employed a mixed-methods approach that integrated both qualitative and quantitative data. In the initial identification and screening stages, qualitative data were collected from expert opinions and then converted into quantitative form through fuzzy analysis and modeling techniques. The data collection instruments were customized for each stage. A fuzzy Delphi questionnaire was used to identify variables. A hesitant fuzzy AHP (HFAHP) pairwise comparison questionnaire was applied to weight and rank the variables. Fuzzy DEMATEL and ISM matrices were utilized to analyze causal relationships. Finally, input–output datasets were used to train the ANFIS model for prediction. This combination of methods ensured consistency across stages and enhanced the accuracy of the results. The research population consisted of experts in mining, environment, energy, and technology management. A purposive sampling strategy was employed, with inclusion criteria including holding a master's or doctoral degree, having at least 20 years of professional experience, occupying managerial or strategic positions in mining or governmental institutions, and expressing willingness to participate. Based on these criteria, a total of 20 experts were selected. The demographic characteristics of the participating experts are presented in the following table.

Table 2. Analysis of Research Gaps in Recent Studies

No.	Author(s)	Method / Model	Focus Area	Key Findings	Research Gap
1	Das, S. et al. (2025)	Integrated MCDM + LCA	Hybrid energy & storage	Combined techno-economic and environmental assessment	No AI-based causal integration
2	Brodny, J., & Tutak, M. (2023)	MCDM (TOPSIS, AHP)	EU energy security	Proposed dual-perspective energy evaluation	No link to mining or NZE pathways
3	Vaziri Rad, M. A. et al. (2024)	DEMATEL + ANP + MCDM	Agri-photovoltaic systems	Developed global sustainability index model	Did not apply intelligent prediction models
4	Pouresmaieli, M. et al. (2025)	Life Cycle Assessment	Iron ore energy transition	Quantified emissions and energy flows	Did not integrate decision-support models
5	Pouresmaieli, M. et al. (2024)	Fuzzy MCDM (Comprehensive Review)	Mining sustainability	Comprehensive review of MCDM tools	Lacked predictive or intelligent modeling
6	Elavarasan, R. M. et al. (2024)	Multi-criteria analysis	Clean energy in Australia	Prioritized clean technologies for SDG7	Limited integration with NZE mining context
7	Fernandez, M. I. et al. (2024)	Review study	Energy systems & storage	Identified key enablers for net-zero	No empirical model for mining/AI interaction
8	Siregar, Y. I. (2024)	Scenario analysis	Indonesia energy sector	Proposed NZE roadmap	No hybrid or fuzzy integration
9	Kumar, A., & Gembali, V. (2025)	Conceptual framework	Net-zero supply chains	Addressed institutional & logistics barriers	No quantitative testing
10	Dong, C. et al. (2025)	National energy modeling	Canada's GHG targets	Developed cross-provincial NZE model	Did not apply MCDM or AI approaches
11	Seth, S. et al. (2025)	Eco-financing model	Sustainable mine cities	Linked finance and sustainability	Missing data-driven analysis
12	Berberoglu, Y. et al. (2024)	Empirical assessment	Emerging economies mining	Analyzed sustainability barriers	Lacked causal and predictive structure
13	Cotrina-Teatino, M. A. et al. (2025)	Bibliometric + SLR	Circular mining economy	Mapped global CE research trends	Lacked predictive or intelligent modeling
14	Shamsi, M., & Zakerinejad, M. (2025)	Fuzzy-Likert policy modeling	Mining tailings recycling	Designed sustainable policy framework	Lacked predictive or intelligent modeling
15	Chatterjee, C. et al. (2025)	Digital mining framework	Smart technologies in mining	Demonstrated digitalization pathways	No hybrid causal-intelligent model
16	Norouzi Masir, R. et al. (2018)	DEMATEL	Underground coal mining sustainability	Identified interrelationships among 20 sustainability factors and ranked their causal importance	Did not integrate fuzzy modeling or predictive systems
17	Rafiee, R. et al. (2019)	Fuzzy RES + Fuzzy DEMATEL	Rock behavioral systems under uncertainty	Modeled interdependencies in rock mass cavability and ranked influential parameters	Focused only on geotechnical risk; lacked sustainability perspective
18	Ataei, M. & Norouzi Masir, R. (2020)	Fuzzy DEMATEL (FDSDI)	Open-pit mining sustainability	Developed a fuzzy-based Sustainable Development Index (FDSDI) and applied it to a bauxite mine	Limited to single case; no integration with AI or dynamic modeling
19	Mohammadi, S. et al. (2021)	DEMATEL–MABAC	Roof fall risk assessment	Quantified roof stability in coal mines using hybrid DEMATEL–MABAC; improved prediction by 15%	Lacked sustainability linkage and cross-dimensional validation
20	Mohammadi, S. et al. (2018)	Fuzzy ANP–DEMATEL + Regression	Longwall mining cavability prediction	Developed a hybrid cavability index (CI) and statistical model for main caving span	Did not include sustainability or policy-level interpretation
21	Zare Naghadehi, M. et al. (2009)	Fuzzy AHP	Mining method selection (bauxite mine)	Applied FAHP to determine optimal underground mining method	No integration with environmental or social sustainability indicators
22	Mikaeil, R. et al. (2009)	Fuzzy AHP + TOPSIS	Mining method selection	Developed a decision support system combining FAHP and TOPSIS for mine method ranking	Focused on operational optimization; lacked sustainability dimension
23	Tahernejad, M. M. et al. (2012)	SWOT–FAHP	Strategic planning for Iran's quarries	Combined SWOT analysis with FAHP to prioritize quarry development strategies	No quantitative modeling or dynamic sustainability assessment
24	Nezarat, H. et al. (2015)	Fuzzy AHP	Geological risk assessment in tunneling	Ranked geological risks in mechanized tunneling based on probability and impact	Limited to tunneling risk; no integration with sustainability frameworks

Table 3. Demographic characteristics

Characteristic	Category/Status	Number
Education	Master's degree	12
	PhD	8
Work experience	20–25 years	11
	More than 25 years	9
Field of study	Technology Management	3
	Energy Management	4
	Mining Engineering	7
	Environmental Sciences	6
Organizational role	University Professor	5
	Manager of mining companies	4
	Mining company expert	7
	Mining company consultant	4
Mining chain	Exploration	3
	Extraction	6
	Processing	11

Note that the total expert pool of 80 participants represented the overall research community involved in the different stages of the study. However, given the methodological diversity of the analyses, not all experts participated in every stage. Specifically, the experts were categorized based on their domain expertise. Approximately 20 experts contributed to each main stage Fuzzy Delphi, HFAHP, Fuzzy DEMATEL–ISM, and ANFIS modeling. The Delphi phase included policy and sustainability experts. The HFAHP stage involved specialists in the decision analysis. The DEMATEL–ISM phase engaged experts in systems thinking and mining management. Finally, the ANFIS modeling stage relied on data scientists and mining engineers. Data analysis was carried out in four stages:

(1) identifying and screening key variables through the fuzzy Delphi method

(2) weighting and ranking the main factors using HFAHP

(3) examining causal and structural relationships with fuzzy DEMATEL and ISM, and

(4) modeling and predicting NZE outcomes with ANFIS. The integration of these methods allowed for a comprehensive and multidimensional assessment of the problem. This process produced a valid and practical model for sustainable mining development.

Four primary stages of data analysis were conducted, including: (1) identifying and screening key variables via the fuzzy Delphi method, (2) applying HFAHP to weight and rank the principal factors, (3) analysing causal and structural relationships using fuzzy DEMATEL and ISM, and (4) employing ANFIS to model and forecast NZE outcomes. The integration of these methods enabled a comprehensive and multidimensional assessment of the problem and resulted in a valid and practical model for sustainable mining development. Table 4 presented a comparative summary of several fuzzy MCDM methods and highlighted their applicability to the present study.

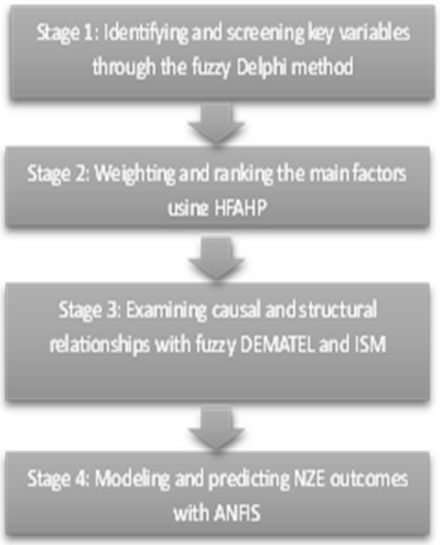

Figure 1. Research Framework

3.1. Fuzzy Delphi Method

The Fuzzy Delphi Method is a hybrid approach that integrates the traditional Delphi technique with fuzzy logic to identify and evaluate key factors under uncertainty and complexity. It relies on expert judgments and applies fuzzy scales to reach consensus and prioritize variables. In this process, Equation (1) represents the fuzzy number associated with the linguistic term assigned by each expert. Equation (2) calculates the triangular fuzzy average of the experts' assessments, and Equation (3) derives the defuzzified mean value of their scores.

Table 4. Comparative Analysis and Justification of Selected Fuzzy MCDM Methods

Method	Main Objective	Strengths	Limitations	Suitability for Current Study
Fuzzy TOPSIS	Ranking of alternatives based on distance from ideal solution	Simple, easy to interpret, good for performance evaluation	Ignores causal relations and expert hesitation	Not suitable for causal mapping or hesitant judgments
Fuzzy BWM	Weighting of criteria with minimal comparisons	Reduces inconsistency and cognitive load	Requires precise pairwise comparisons; limited flexibility in linguistic input	Less effective when experts hesitate or provide uncertain inputs
Fuzzy AHP	Hierarchical weighting with fuzzy logic	Well-established, structured, transparent	Does not model hesitation; may oversimplify expert uncertainty	Insufficient for complex or hesitant expert environments
Hesitant Fuzzy AHP (HFAHP)	Weighting with hesitation and uncertainty	Captures expert hesitation; realistic linguistic modeling	Computationally intensive	Best suited for expert-based, uncertain evaluations in sustainable mining
Fuzzy DEMATEL	Causal analysis of interdependent factors	Reveals influence–dependence structure; supports ISM and predictive modeling	Requires normalization and threshold calibration	Ideal for identifying cause–effect structure for ANFIS model integration

$$A^{(i)} = \left(a_1^i, a_2^i, a_3^i\right), \qquad i = 1,2,3,\ldots,n \tag{1}$$

$$A_m = \left(a_{m1}^i, a_{m2}^i, a_{m3}^i,\right) = \left(\frac{1}{n}\sum a_1^{(i)}, \frac{1}{n}\sum a_2^{(i)}, \frac{1}{n}\sum a_3^{(i)}\right) \tag{2}$$

$$S(A) = 1/2\left[(a_{2i} - \int_{a_{1i}}^{a_{2i}} f_{\bar{A}}(x)) + (a_{2i} - \int_{a_{2i}}^{a_{3i}} f_{\bar{A}}(x)) + \right] = \frac{a_{1i} + 2a_{2i} + a_{3i}}{4} \tag{3}$$

3.2. Hesitant Fuzzy Analytic Hierarchy Process (HF-AHP):

The Hesitant Fuzzy Analytic Hierarchy Process (HF-AHP) is a hybrid method that integrates fuzzy logic with the Analytic Hierarchy Process (AHP). It is particularly applied in situations where experts or decision-makers express hesitation or uncertainty in providing their judgments. This method is suitable for weighting and ranking key factors in complex environments characterized by high levels of uncertainty. In such cases, to aggregate these judgments, the numerical average of triangular fuzzy elements at each level (L, M, U) is taken across all opinions. The basic rules in the solution procedure of the Hesitant Fuzzy AHP method are as follows:

The lower and upper bounds in the hesitant fuzzy set are expressed as:

$$h^{-}(\mathrm{x}) = \mathrm{Min\ h(x)} \tag{4}$$

$$h^{+}(\mathrm{x}) = \mathrm{Max\ h(x)} \tag{5}$$

$\mathrm{A}_{\mathrm{env}[\mathrm{h}]}$ Is defined as an intuitionistic fuzzy set, where:

$$\mathrm{A}_{\mathrm{env}(\mathrm{h})=\{x,\mu(x),V[x]\}} \tag{6}$$

Which in the above relation we have:

$$\mu(x) = h^{-}(x) \tag{7}$$

$$\mathrm{v}(x) = 1 - h^{+}(x) \tag{8}$$

$\hat{A} = [a, b, c]$ Is applied as a set of hesitant fuzzy linguistic terms. Within the domain of $\hat{A}$the minimum and maximum elements required to compute A and C must be derived from the linguistic terms ϵH_S $\{Si, \ldots\ldots, sj\}$ and are determined as follows:

$$a = Min\{a_L, a_M, \ldots\ldots, a_R\} = a^i{}_L \tag{9}$$

$$c = Max\{a_L, a_M, \ldots\ldots, a_R\} = a^i{}_R \tag{10}$$

For the computation of b, the aggregation of all Ordered Weighted Averaging (OWA) operators must be applied:

$$b = OWA_W\left[\mathrm{a}^{\mathrm{i}}{}_{\mathrm{L}}, \mathrm{a}^{\mathrm{i}}{}_{\mathrm{M}}, \mathrm{a}^{\mathrm{i}+1}{}_{\mathrm{M}} \ldots\ldots, \mathrm{a}^{\mathrm{j}}{}_{\mathrm{M}}\right] \tag{11}$$

It should be noted that the geometric mean method was applied to construct the aggregated matrix according to the following relation.

$$a'_{ij} = \left(\prod_{l=1}^{k} a_{ijl}\right)^{\frac{1}{k}} \qquad \begin{matrix} l = 1,2,\ldots\ldots,k \\ i, j = 1,2,\ldots\ldots,n \end{matrix} \tag{12}$$

Based on the above table, the geometric mean of the values in each row is calculated as follows:

$$L_{ci} = [\prod_{j=1}^{n} ci\, j]^{\frac{1}{i}} \tag{13}$$

$$M_{ci} = [\prod_{j=1}^{n} ci\, j]^{\frac{1}{i}} \quad (14)$$

$$U_{ci} = [\prod_{j=1}^{n} ci\, j]^{\frac{1}{i}} \quad (15)$$

These formulas yield the aggregated triangular fuzzy numbers for each criterion row. The defuzzified value using the mean value method is calculated as follows:

$$S(A) = \frac{L_{1i} + 2M_{2i} + U_{3i}}{4} \quad (16)$$

3.3. Fuzzy DEMATEL Method

The Fuzzy DEMATEL method is one of the multi-criteria decision-making (MCDM) techniques used to identify and analyze the interrelationships among complex factors under conditions of uncertainty. In this method, fuzzy logic is employed to account for uncertainties and ambiguities in evaluations. Fuzzy DEMATEL helps to determine and classify the influencing and influenced factors, providing a clear structure for network analysis. In Equation (17), the average of experts' opinions for each element of the decision matrix is calculated. For normalization, Equation (18) is applied, where the coefficient represents the normalization index of the decision matrix. The total relation matrix is then obtained using Equation (19), while indirect relationships are derived from Equation (20). The degree of influence and the degree of dependence are computed through Equations (21) and (22). Finally, in Equation (23), if the index value is greater than zero, the variable is identified as a definite influencer (also called a causal factor) within the system; whereas if the index value is less than zero, the variable is identified as a definite dependent (also called an effect factor) in the system.

$$X'_{ij} = \frac{1}{k} \cdot \sum_{l=1}^{k} x_{ijl} \quad (17)$$

$$N = \lambda . X$$

$$\lambda = \frac{1}{Max_i \sum_{j=1}^{n} x_{ij}} \quad (18)$$

$$= \frac{N}{(I-N)} = N(I-N)^{-1} \quad (19)$$

$$T'_{t\to\infty} = N^2 + N^3 + N^4 + ...N^t = N^2(I-N)^{-1} \quad (20)$$

$$D_i = \sum_{j=1}^{n} t_{ij} \quad i = 1,2,.....,n \quad (21)$$

$$R_j = \sum_{i=1}^{n} t_{ij} \quad j = 1,2,.....,n \quad (22)$$

$$\begin{aligned} D > R \Rightarrow D - R > 0 \ \rightarrow positive \quad \text{Re}lation \\ D < R \Rightarrow D - R < 0 \ \rightarrow Negetive \quad \text{Re}lation \end{aligned} \quad (23)$$

4. Data Analysis

4.1. Identification of Key Influential Variables Using the Fuzzy Delphi Method

To design a conceptual framework for sustainable mining development aligned with the Net Zero Emissions (NZE) scenario, the study aimed to identify the primary variables that shape the industry's future. Drawing on a review of the literature and recent scientific sources, four broad categories were defined: economic, socio-cultural, technological, and environmental–climatic. Within each category, seven influential variables were identified as the initial inputs for the Fuzzy Delphi screening process. These variables were derived from a combination of case studies, theoretical analyses, and scientific references, selected with consideration of both the mining industry's specific context and the global decarbonization pathway. To determine the final variables influencing sustainable mining development, the Fuzzy Delphi Technique was applied in three rounds. This method employed fuzzy logic to transform experts' qualitative judgments into quantitative values, allowing opinions to be aggregated with greater precision under conditions of uncertainty and subjectivity. In this study, linguistic evaluations were represented through triangular fuzzy numbers, and defuzzification was performed using the Centroid Method, which is recognized as a reliable approach in similar research.

Table 5. Triangular Fuzzy Scale for Evaluating Variables' Importance

Linguistic Term	Triangular Fuzzy Number (L, M, U)
Very Low Importance	(0.0, 0.1, 0.3)
Low Importance	(0.1, 0.3, 0.5)
Moderately Important	(0.3, 0.5, 0.7)
Important	(0.5, 0.7, 0.9)
Very Important	(0.7, 0.9, 1.0)

The Delphi process involved 20 domain experts. In the first round, a comprehensive set of indicators was identified based on literature review and expert input. Each indicator was evaluated using a triangular fuzzy scale (L, M, U), and defuzzified values were calculated. A threshold of 0.10 was established as the maximum acceptable difference between rounds. In the second round, the same indicators were reassessed, and the differences in defuzzified values were examined. Since all differences fell below the threshold, consensus was achieved. Indicators with defuzzified values greater than 0.70 in the second round were retained as the final set, as shown in the table. This systematic procedure ensured transparency, validity, and reliability of the Delphi results.

Table 6. Summary of the Fuzzy Delphi Rounds Analysis

Variable Name	Fuzzy Triangular Number– Round 1	Round 2	Round 1	Defuzzified Value – Round 2	Difference (Δ)	Selection
Carbon Pricing Policies	(0.72, 0.80, 0.88)	(0.73, 0.82, 0.90)	0.80	0.84	0.04	Yes
Investment Cost	(0.70, 0.79, 0.87)	(0.70, 0.79, 0.87)	0.79	0.79	0.00	Yes
Global Metal Prices	(0.71, 0.80, 0.88)	(0.72, 0.80, 0.88)	0.80	0.80	0.00	Yes
Export Market Fluctuations	(0.45, 0.55, 0.63)	(0.46, 0.57, 0.66)	0.55	0.62	0.07	No
Tax Incentives	(0.48, 0.57, 0.65)	(0.50, 0.59, 0.68)	0.57	0.65	0.08	No
Social Welfare Level	(0.73, 0.81, 0.89)	(0.73, 0.81, 0.89)	0.81	0.81	0.00	Yes
Social Acceptance of Technology	(0.74, 0.82, 0.90)	(0.74, 0.82, 0.90)	0.82	0.82	0.00	Yes
Safety Culture	(0.52, 0.60, 0.68)	(0.54, 0.62, 0.71)	0.60	0.68	0.08	No
Quality of Life	(0.56, 0.64, 0.71)	(0.57, 0.66, 0.74)	0.64	0.71	0.07	No
Technological Innovation	(0.75, 0.83, 0.91)	(0.75, 0.83, 0.91)	0.83	0.83	0.00	Yes
Environmental Education	(0.69, 0.77, 0.85)	(0.71, 0.79, 0.87)	0.79	0.79	0.00	Yes
Process Digitalization	(0.50, 0.59, 0.67)	(0.52, 0.61, 0.69)	0.59	0.67	0.08	No
Artificial Intelligence in Mining	(0.73, 0.82, 0.89)	(0.73, 0.81, 0.89)	0.81	0.81	0.00	Yes
Technological Infrastructure	(0.54, 0.62, 0.70)	(0.56, 0.65, 0.74)	0.62	0.70	0.08	No
Energy Storage	(0.49, 0.57, 0.65)	(0.50, 0.59, 0.67)	0.57	0.64	0.07	No
Energy Intensity	(0.70, 0.78, 0.86)	(0.70, 0.78, 0.86)	0.78	0.78	0.00	Yes
Smart Environmental Monitoring Systems	(0.73, 0.81, 0.89)	(0.72, 0.81, 0.89)	0.81	0.81	0.00	Yes
Greenhouse Gas Emissions	(0.45, 0.55, 0.65)	(0.48, 0.56, 0.65)	0.55	0.61	0.06	No
Life Cycle Assessment	(0.52, 0.61, 0.69)	(0.52, 0.61, 0.70)	0.61	0.66	0.05	No
Water Consumption	(0.47, 0.55, 0.63)	(0.48, 0.57, 0.66)	0.57	0.62	0.05	No
Ecosystem Health	(0.71, 0.79, 0.87)	(0.71, 0.79, 0.87)	0.79	0.79	0.00	Yes
Waste Recycling	(0.72, 0.80, 0.88)	(0.72, 0.80, 0.88)	0.80	0.80	0.00	Yes
Climate Resilience	(0.54, 0.62, 0.70)	(0.52, 0.61, 0.69)	0.58	0.66	0.08	No
Corporate Social Responsibility	(0.53, 0.61, 0.69)	(0.55, 0.63, 0.72)	0.61	0.68	0.07	No
Community Participation	(0.55, 0.63, 0.70)	(0.55, 0.63, 0.71)	0.63	0.63	0.00	No

Table 7 presents the comparison of defuzzified values between the first and second Delphi rounds. The mean difference across variables was $\bar{\Delta} = 0.05$, indicating a high level of convergence. The Kendall's coefficient of concordance ($W = 0.78$, $p < 0.001$) confirmed a strong and statistically significant agreement among experts. Approximately 64% of the indicators achieved a "Perfect" or "Strong" consensus level ($\Delta \leq 0.05$), while the remaining variables exhibited moderate but acceptable convergence ($0.05 < \Delta \leq 0.10$). Therefore, the second-round results were regarded as stable and reliable for further fuzzy multi-criteria analysis.

Accordingly, for each of the four main factors (economic, social, technological, and environmental), three variables were retained, resulting in a total of 12 final variables to be utilized in subsequent stages of the analysis.

In this study, the hesitant fuzzy Analytic Hierarchy Process (HF-AHP) was employed to determine the weights of the criteria. The procedure began with pairwise comparisons of the main criteria aligned with the research objectives. AHP is recognized as a ranking method in which priorities are established through such comparisons. Under conditions of hesitation, experts could assign more than one linguistic term

to a comparison (e.g., between "moderately important" and "very important"). In these cases, the numerical averages of the triangular fuzzy numbers for each level (L, M, U) were computed across all judgments to integrate the evaluations. In the table below, the linguistic variables are expressed as fuzzy numbers using the given scale.

Table 7. Summary Indicators

Metric	Value	Interpretation
Mean difference (Δ)	0.05	Acceptable change between rounds
Kendall's W	0.78	Strong agreement
p-value	< 0.001	Statistically significant consensus
Percentage of "Perfect/Strong" items	64%	Majority convergence achieved

Table 8. Final Variables Based on the Delphi Output

Main Factor	Final Components
Economic	Investment Cost (0.79) Carbon Pricing Policies (0.84) Global Metal Prices (0.80)
Social	Social Welfare Level (0.81) Social Acceptance of Technology (0.82) Environmental Education (0.79)
Technological	Technological Innovation (0.83) Artificial Intelligence in Mining (0.81) Smart Environmental Monitoring Systems (0.81)
Environmental	Energy Intensity (0.78) Waste Recycling (0.80) Ecosystem Health (0.79)

Table 9. Definition of LVs

Linguistic Variable	Code	Triangular Fuzzy Numbe (L, M, U)
Extremely High Importance	AHI	(7, 9, 9)
Very High Importance	VHI	(5, 7, 9)
Relatively High Importance	ESHI	(3, 5, 7)
Weak Importance	WHI	(1, 3, 5)
Approximately Equal Importance	EHI	(1, 1, 3)
Exactly Equal	EE	(1, 1, 1)
Low Importance	ELI	(0.33, 1, 1)
Very Weak Importance	WLI	(0.2, 0.33, 1)
Relatively Low Importance	ESLI	(0.14, 0.2, 0.33)
Very Low Importance	VLI	(0.11, 0.14, 0.2)
Absolutely Low Importance	ALI	(0.11, 0.11, 0.14)

The linguistic terms presented in Table 9 were transformed into Triangular Fuzzy Numbers (TFNs) following the hesitant fuzzy AHP procedure proposed by Es, Özçelik, and Yılmaz (2023) in Analytic Hierarchy Process with Fuzzy Sets Extensions [41]. In this approach, experts' linguistic evaluations such as "Extremely High Importance" or "Very Low Importance" were expressed as hesitant fuzzy elements, which were subsequently represented by corresponding TFNs on a normalized nine-point Saaty-type scale. The lower, middle, and upper bounds (L, M, U) for each linguistic term were defined according to the calibrated fuzzy scale applied in recent hesitant fuzzy AHP studies in manufacturing and sustainability contexts. Aggregation of individual judgments was conducted using the geometric mean of all hesitant fuzzy elements, and defuzzification was carried out using the centroid (center of gravity) method to obtain the final crisp weights for each criterion. This procedure ensured consistency with current best practices in hesitant fuzzy AHP modeling and provided a transparent and reproducible transformation of linguistic variables into numerical fuzzy values. As shown in the table below, the experts exhibited ambiguity in their responses during the pairwise comparisons of the criteria. For instance, in the comparison between the economic and social factors, the experts did not provide identical judgments, and two different opinions were expressed. Therefore, to reconcile the opinions, the range of responses was considered. Each cell represents the aggregated opinions of multiple experts in the comparison of two factors.

Table 10. Aggregation of Opinions in Hesitant Cases – Comparison of Macro Factors

Factors/Dimensions	Economic	Social	Technological	Environmental
Economic	EE	EHI, WHI	ESHI, WHI	AHI, VHI
Social	WHI, ELI	EE	ESHI, VHI	AHI, EHI
Technological	WHI, ESLI	WHI, ESHI	EE	VHI, AHI
Environmental	VHI, AHI	WHI, ESHI	EHI, AHI	EE

This table was utilized as an input for the Hesitant Fuzzy Model and for group decision-making analysis. To calculate the triangular fuzzy sets associated with hesitant fuzzy numbers, the OWA operator was applied. The following table presents the triangular fuzzy sets derived from the values of the previous table.

Based on the above table, the fuzzy geometric mean values are shown in the following table.

In the next step, the weights of the criteria are calculated based on the geometric mean values relative to the maximum value [number 9] in the hesitant fuzzy scale. The subsequent step involves the defuzzification process.

Table 11. Triangular Fuzzy Set Values of Hesitant Fuzzy Numbers – Macro Factors

Factors/Dimensions	Economic	Social	Technological	Environmental
Economic	(1.00, 1.00, 1.00)	(0.45, 0.60, 0.75)	(0.30, 0.45, 0.60)	(0.70, 0.85, 0.95)
Social	(1.33, 1.67, 2.22)	(1.00, 1.00, 1.00)	(0.45, 0.60, 0.75)	(0.60, 0.75, 0.90)
Technological	(1.67, 2.22, 3.33)	(1.33, 1.67, 2.22)	(1.00, 1.00, 1.00)	(0.45, 0.60, 0.75)
Environmental	(1.05, 1.18, 1.43)	(1.11, 1.33, 1.67)	(1.33, 1.67, 2.22)	(1.00, 1.00, 1.00)

Table 12. Triangular Fuzzy Geometric Mean Values of the Macro Factors

Macro Factors of Sustainable Development in Mining	L	M	U
Economic	1.10	1.80	2.90
Social	0.85	1.40	2.60
Technological	0.70	1.30	2.30
Environmental and Climatic	1.20	1.90	3.20

Table 13. Weights of Sustainable Development Criteria Using the Hesitant Fuzzy Approach

Sustainable Development Criterion	Fuzzy Weight (L, M, U)	Defuzzified Weight	Final Normalized Weight
Economic	(0.120, 0.200, 0.320)	0.210	0.258
Social	(0.100, 0.180, 0.290)	0.188	0.231
Technological	(0.090, 0.160, 0.270)	0.170	0.209
Environmental and Climatic	(0.130, 0.220, 0.350)	0.230	0.302
Total	—	0.798	1.000

The normalized weights were obtained by dividing the defuzzified value of each criterion by the total defuzzified sum (0.798). The highest weight was assigned to the Environmental and Climatic criterion, which therefore held higher priority in subsequent analyses. At this stage, to examine the validity of the pairwise comparison structure, the Consistency Ratio (CR) was computed. Using the standard Analytic Hierarchy Process (AHP) procedure, after constructing the fuzzy comparison matrix, the Consistency Index (CI) and the Random Index (RI) were also derived. Finally, the consistency ratio (CR) was determined to be 0.06. Since this value was lower than the acceptable threshold of 0.1, it was concluded that the experts' judgments demonstrated the required logical consistency, and the comparison matrix possessed sufficient consistency. Therefore, this matrix was validated and considered a reliable basis for decision-making.

4.3. Causal Relationship Analysis of Decision-Making Components Using the Fuzzy DEMATEL Method

At this stage, the fuzzy DEMATEL method is employed to analyze the causal relationships among the 12 final variables extracted from the previous steps. These variables are as follows:

- M1: Carbon pricing policies
- M2: Investment cost
- M3: Global metal prices
- M4: Social welfare level
- M5: Social acceptance of technology

- M6: Technological innovation
- M7: Environmental education
- M8: Artificial intelligence in mining
- M9: Energy intensity
- M10: Smart environmental monitoring systems
- M11: Waste recycling
- M12: Ecosystem health

This coding facilitated the representation of matrices, the analysis of causal relationships, and the visualization of results in later stages of the research. The DEMATEL method not only identified interdependencies among variables but also classified them as either causal (influential) or effect (influenced) factors within the sustainable mining development system. In this step, based on the judgments of 20 experts using a fuzzy linguistic scale, the direct influence matrix for the 12 final variables was constructed. Expert opinions were expressed through terms such as no influence, low influence, moderate, high, and very high, which were subsequently converted into corresponding triangular fuzzy numbers. After aggregating the evaluations, the final direct influence matrix was obtained and is presented in the following table.

Table 14. Initial Fuzzy Direct-Influence Matrix (Average of Expert Opinions)

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
M1	(0,0,0)	(0.2,0.4,0.6)	(0.1,0.3,0.5)	(0.2,0.4,0.6)	(0.3,0.5,0.7)	(0.2,0.4,0.6)	(0.1,0.3,0.5)	(0.2,0.4,0.6)	(0.3,0.5,0.7)	(0.2,0.4,0.6)	(0.1,0.3,0.5)	(0.2,0.4,0.6)
M2	(0.1,0.3,0.5)	(0,0,0)	(0.2,0.4,0.6)	(0.2,0.4,0.6)	(0.1,0.3,0.5)	(0.3,0.5,0.7)	(0.2,0.4,0.6)	(0.1,0.3,0.5)	(0.2,0.4,0.6)	(0.3,0.5,0.7)	(0.2,0.4,0.6)	(0.1,0.3,0.5)
M3	(0.2,0.4,0.6)	(0.1,0.3,0.5)	(0,0,0)	(0.3,0.5,0.7)	(0.2,0.4,0.6)	(0.2,0.4,0.6)	(0.3,0.5,0.7)	(0.2,0.4,0.6)	(0.1,0.3,0.5)	(0.2,0.4,0.6)	(0.2,0.4,0.6)	(0.3,0.5,0.7)
M4	(0.1,0.3,0.5)	(0.2,0.4,0.6)	(0.3,0.5,0.7)	(0,0,0)	(0.2,0.4,0.6)	(0.1,0.3,0.5)	(0.2,0.4,0.6)	(0.3,0.5,0.7)	(0.2,0.4,0.6)	(0.1,0.3,0.5)	(0.3,0.5,0.7)	(0.2,0.4,0.6)
M5	(0.2,0.4,0.6)	(0.3,0.5,0.7)	(0.2,0.4,0.6)	(0.1,0.3,0.5)	(0,0,0)	(0.2,0.4,0.6)	(0.1,0.3,0.5)	(0.2,0.4,0.6)	(0.3,0.5,0.7)	(0.2,0.4,0.6)	(0.2,0.4,0.6)	(0.3,0.5,0.7)
M6	(0.3,0.5,0.7)	(0.2,0.4,0.6)	(0.1,0.3,0.5)	(0.2,0.4,0.6)	(0.2,0.4,0.6)	(0,0,0)	(0.3,0.5,0.7)	(0.2,0.4,0.6)	(0.1,0.3,0.5)	(0.3,0.5,0.7)	(0.2,0.4,0.6)	(0.2,0.4,0.6)
M7	(0.1,0.3,0.5)	(0.2,0.4,0.6)	(0.3,0.5,0.7)	(0.2,0.4,0.6)	(0.1,0.3,0.5)	(0.2,0.4,0.6)	(0,0,0)	(0.3,0.5,0.7)	(0.2,0.4,0.6)	(0.1,0.3,0.5)	(0.2,0.4,0.6)	(0.3,0.5,0.7)
M8	(0.2,0.4,0.6)	(0.1,0.3,0.5)	(0.2,0.4,0.6)	(0.3,0.5,0.7)	(0.2,0.4,0.6)	(0.1,0.3,0.5)	(0.2,0.4,0.6)	(0,0,0)	(0.3,0.5,0.7)	(0.2,0.4,0.6)	(0.2,0.4,0.6)	(0.1,0.3,0.5)
M9	(0.1,0.3,0.5)	(0.2,0.4,0.6)	(0.3,0.5,0.7)	(0.2,0.4,0.6)	(0.1,0.3,0.5)	(0.2,0.4,0.6)	(0.3,0.5,0.7)	(0.2,0.4,0.6)	(0,0,0)	(0.1,0.3,0.5)	(0.2,0.4,0.6)	(0.3,0.5,0.7)
M10	(0.3,0.5,0.7)	(0.2,0.4,0.6)	(0.1,0.3,0.5)	(0.2,0.4,0.6)	(0.3,0.5,0.7)	(0.2,0.4,0.6)	(0.1,0.3,0.5)	(0.3,0.5,0.7)	(0.2,0.4,0.6)	(0,0,0)	(0.2,0.4,0.6)	(0.2,0.4,0.6)
M11	(0.1,0.3,0.5)	(0.2,0.4,0.6)	(0.3,0.5,0.7)	(0.1,0.3,0.5)	(0.2,0.4,0.6)	(0.3,0.5,0.7)	(0.2,0.4,0.6)	(0.1,0.3,0.5)	(0.2,0.4,0.6)	(0.3,0.5,0.7)	(0,0,0)	(0.2,0.4,0.6)
M12	(0.2,0.4,0.6)	(0.1,0.3,0.5)	(0.2,0.4,0.6)	(0.3,0.5,0.7)	(0.2,0.4,0.6)	(0.1,0.3,0.5)	(0.2,0.4,0.6)	(0.3,0.5,0.7)	(0.2,0.4,0.6)	(0.1,0.3,0.5)	(0.2,0.4,0.6)	(0,0,0)

Table 15. Total Influence Matrix (T)

From / To →	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
M1	0.000	0.173	0.169	0.157	0.151	0.145	0.155	0.177	0.171	0.167	0.175	0.161
M2	0.170	0.000	0.152	0.173	0.169	0.191	0.173	0.156	0.169	0.163	0.156	0.142
M3	0.140	0.189	0.000	0.157	0.170	0.135	0.169	0.139	0.168	0.187	0.204	0.157
M4	0.172	0.152	0.187	0.000	0.145	0.165	0.157	0.184	0.145	0.152	0.131	0.169
M5	0.189	0.163	0.176	0.152	0.000	0.181	0.169	0.183	0.146	0.141	0.139	0.156
M6	0.158	0.176	0.167	0.179	0.160	0.000	0.177	0.167	0.178	0.163	0.157	0.165
M7	0.153	0.144	0.179	0.176	0.176	0.160	0.000	0.174	0.177	0.163	0.160	0.175
M8	0.176	0.162	0.175	0.184	0.183	0.157	0.173	0.000	0.176	0.155	0.153	0.170
M9	0.165	0.160	0.180	0.182	0.182	0.154	0.169	0.174	0.000	0.163	0.158	0.166
M10	0.163	0.162	0.183	0.185	0.183	0.157	0.170	0.172	0.161	0.000	0.175	0.164
M11	0.175	0.167	0.189	0.188	0.183	0.164	0.176	0.178	0.178	0.170	0.000	0.176
M12	0.170	0.164	0.184	0.180	0.181	0.151	0.174	0.173	0.175	0.163	0.176	0.000

Table 16. Final Analysis of the Fuzzy DEMATEL Method

Variable	D (Dispatching / Influence Given)	R (Receiving / Influence Received)	D + R (Prominence)	D − R (Relation)
M1	1.102764	1.508528	2.611292	-0.405764
M2	1.458535	1.208301	2.666836	0.250234
M3	1.668835	1.453459	3.122294	0.215376
M4	1.528768	1.499522	3.028290	0.029246
M5	1.605229	1.399403	3.004632	0.205826
M6	1.285693	1.466066	2.751759	-0.180373
M7	1.522474	1.464033	2.986507	0.058441
M8	1.735297	1.296791	3.032088	0.438506
M9	1.302333	1.354744	2.657077	-0.052411
M10	1.599639	1.433874	3.033513	0.165765
M11	1.407725	1.203587	2.611312	0.204138
M12	1.471298	1.332318	2.803616	0.138980

In the above table, the final analysis of the Fuzzy DEMATEL method is presented based on the intermediate value (M) for the 12 key components influencing sustainable mining development. This analysis includes the calculation of the following key indices:

Table 17. Definition of Analytical Concepts in the Fuzzy DEMATEL Method

Index	Concept
D (Influence / Dispatching)	The extent to which each criterion influences other criteria (row sum of matrix T).
R (Influenced / Receiving)	The extent to which each criterion is influenced by other criteria (column sum of matrix T).
D + R (Prominence)	The overall importance or prominence of each criterion within the entire network of relationships.
D − R (Relation Type)	The role of each criterion, indicating whether it primarily acts as a cause (positive value) or an effect (negative value).

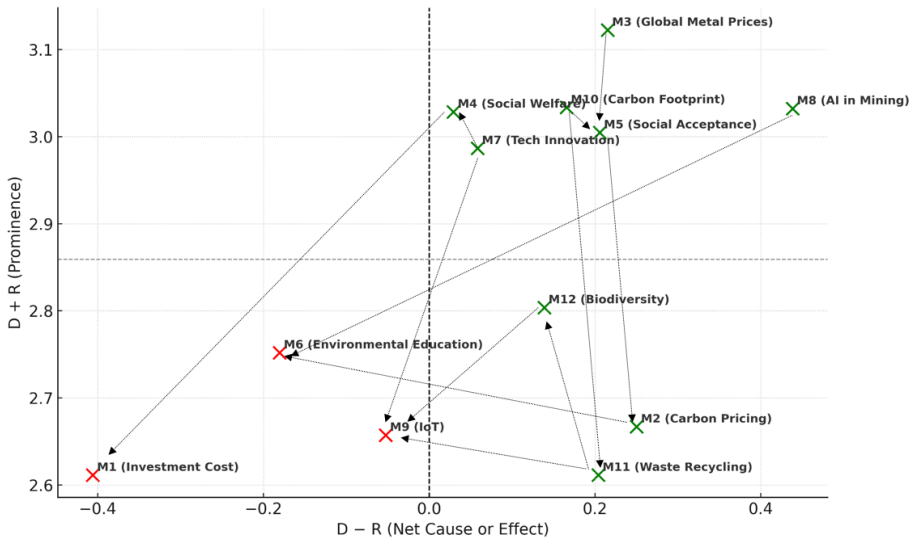

Figure 2. Causal Diagram of Key Variables Influencing for Sustainable Mining Development

The figure above illustrates the causal diagram of key variables influencing sustainable mining development, structured along two axes. The horizontal axis (D − R) represents the net influence: variables with positive values are classified as causal (influential), while those with negative values are considered effect (influenced) factors. The vertical axis (D + R) indicates the degree of interaction of each variable within the overall network. Variables with higher D−R values (on the right side of the diagram) represent causal or influential factors, indicating stronger driving power and greater influence on other variables. Conversely, variables with lower D−R values (on the left side of the diagram) are identified as effect or dependent factors, showing higher susceptibility and being influenced more by others. Due to the large number of interrelationships among variables, only the most significant causal links were illustrated in the diagram to maintain clarity and readability.

Effect variables (Red – Influenced):

The effect variables include carbon pricing policies, technological innovation, and energy intensity. Positioned on the left side of the vertical axis, these variables are more strongly shaped by the influence of others.

Causal variables (Green – Influential):

The causal variables include investment cost, global metal prices, social welfare level, social acceptance of technology, environmental education, artificial intelligence in mining, smart environmental monitoring systems, waste recycling, and ecosystem health. These variables act as primary drivers and serve as guiding forces in shaping the future of sustainable mining development.

Table 18. Validation and Reliability Tests for Fuzzy DEMATEL

Validation Type	Test Applied	Indicator / Metric	Result	Interpretation
Internal Consistency	Matrix Symmetry Check	Mean difference between T and T^T	0.024	Matrix is consistent and stable
Reliability of Fuzzy Conversion	Triangular number normalization	Max deviation	0.03	Acceptable fuzzy conversion accuracy
Structural Stability	Sensitivity analysis (α = 0.16–0.18)	No. of causal relationships retained	34→ 36	Stable structure (no significant changes)
Reproducibility	Re-run with ±5% noise in input matrix	Spearman's ρ	0.91	High reproducibility of causal ranking
Overall Validation	–	Kendall's W (expert judgments)	0.77	Strong consensus and internal consistency

The DEMATEL model demonstrates high internal reliability and robustness. Minor changes in α (±0.01) or expert inputs (±5%) did not alter the causal ranking or the number of retained links, confirming the stability and reproducibility of the causal network.

4.4. Structural Analysis of Relationships among Key Variables for Sustainable Mining Development

In this study, Interpretive Structural Modeling (ISM) was applied as a complementary tool to analyze the structural relationships among key variables for sustainable mining development, with specific attention to clean energy technologies and the Net Zero Emissions (NZE) scenario. The main purpose of this stage was to determine the position of each variable within the cause–effect structure and to construct a hierarchical representation of their interrelationships, clarifying the pathways of influence for planning and policymaking. ISM was utilized as a complement to the fuzzy DEMATEL approach. While fuzzy DEMATEL quantified the strength of causal relationships, ISM provided a hierarchical structure that illustrated the sequential flow of influence across variables. This integration enabled both numerical and structural analysis of the system. Since fuzzy DEMATEL had already established the nature of the causal links, it was not necessary to construct a new Structural Self-Interaction Matrix (SSIM). Instead, the DEMATEL results were directly used to build the ISM reachability matrix. A total of 12 key variables influencing sustainable mining development were identified in earlier stages using fuzzy Delphi and fuzzy DEMATEL methods. As such, no additional data collection was required at this stage. These variables included carbon pricing policies (M1), investment cost (M2), global metal prices (M3), social welfare level (M4), social acceptance of technology (M5), technological innovation (M6), environmental education (M7), artificial intelligence in mining (M8), energy intensity (M9), smart environmental monitoring systems (M10), waste recycling (M11), and ecosystem health (M12).

Determining Causal Relationships Among Variables:

This step was carried out through the fuzzy DEMATEL method in the present study. Therefore, instead of designing new questionnaires or constructing a direct judgment matrix in ISM, the total influence matrix (T) obtained in the fuzzy DEMATEL stage was utilized.

Determining the Threshold of Influence and Converting the DEMATEL Matrix into the Reachability Matrix:

At this stage, an appropriate threshold value was determined so that the total influence matrix (T) could be transformed into a binary matrix. Values greater than or equal to the threshold were assigned 1, while values lower than the threshold were assigned 0. A common approach was to use the average of all elements in the T matrix as the threshold (default suggestion: overall mean of the T matrix elements).

Determination of the Reachability Matrix:

In the third step of ISM modeling, the reachability matrix is constructed based on the total influence matrix and a specified threshold value. The threshold value (α) was applied to filter insignificant causal relations in the normalized total influence matrix (T). Following common DEMATEL practices, α was computed as the mean of all off-diagonal elements of T, resulting in α = 0.17. This cut-off retained about 35–40% of the strongest causal links, providing a clear and interpretable structure [42]. Relations with $T_{ij} \geq 0.17$ were assigned "1" in the reachability matrix, while smaller values were set to "0". All diagonal elements were fixed at 1, as each variable was assumed to be inherently reachable from itself. This adjustment ensured mathematical completeness and logical consistency in the subsequent ISM analysis.

Table 19. Reachability Matrix

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
M1	1	1	0	0	0	0	0	1	1	0	1	0
M2	1	1	0	1	0	1	1	0	0	0	0	0
M3	0	1	1	0	1	0	0	0	0	1	1	0
M4	1	0	1	1	0	0	0	1	0	0	0	0
M5	1	0	1	0	1	1	0	1	0	0	0	0
M6	0	1	0	1	0	1	1	0	1	0	0	0
M7	0	0	1	1	1	0	1	1	1	0	0	1
M8	1	0	1	1	1	0	1	1	1	0	0	1
M9	0	0	1	1	1	0	0	1	1	0	0	0
M10	0	0	1	1	1	0	1	1	0	1	1	0
M11	1	0	1	1	1	0	1	1	1	1	1	1
M12	1	0	1	1	1	0	1	1	1	0	1	1

From this matrix, it was evident that M1 (carbon pricing policies), M2 (investment cost), and M3 (global metal prices) had the greatest influence at the beginning of the causal chain, since they acted only as influencing variables and were affected less by others. In other words, these three variables were positioned at the top of the hierarchical structure. Conversely, variables such as M11 (waste recycling) and M12 (ecosystem health) exhibited the highest dependency and functioned as effect variables in the structure, as they were influenced by most of the other variables. This structure demonstrated the causal pathway from economic and technological variables toward environmental and social outcomes. In the following step, the hierarchical levels of these variables were extracted.

- Level partitioning analysis
- In this step, level partitioning is conducted to determine the hierarchical position of each variable. For this purpose, three sets are defined for each variable:
  - Reachability Set (RS): the set of variables that a given variable can influence (derived from the reachability matrix).
  - Antecedent Set (AS): the set of variables that influence the given variable.
  - Intersection Set (IS): the intersection of the RS and AS.

If the RS and IS for a variable are identical, that variable is placed at the top level of the hierarchy and then removed from the matrix. This process is repeated for the remaining variables until all hierarchical levels are identified.

Variables M1, M2, and M3 were positioned at the lowest level and were identified as root variables that influenced all others. In contrast, M11 and M12 were located at the highest level and were most strongly affected by other factors. The hierarchical structure suggested that the design of strategic interventions should begin from the lower levels in order to ultimately address higher-level variables such as environmental protection and recycling.

Table 20. Level Partitioning of Variables

Level	Variables
Level 1	M11 Waste recycling / M12 Ecosystem health
Level 2	M10 Smart environmental monitoring systems / M9 Energy intensity
Level 3	M8 Artificial intelligence in mining / M7 Environmental education
Level 4	M6 Technological innovation / M5 Social acceptance of technology
Level 5	M4 Social welfare level
Level 6	M2 Investment cost / M3 Global metal prices
Level 7	M1 Carbon pricing policies

The ISM structural model illustrated the hierarchical levels of causal pathways among variables, ranging from foundational drivers such as carbon pricing policies and investment costs to higher-level outcomes such as ecosystem health. This diagram provided a clear view of influence and dependency relationships and was essential for shaping forward-looking strategies in sustainable mining development. In interpreting the model, the goal was to analyze causal and directional relationships among the 12 key variables and to extract strategic insights for planning and decision-making. Variables at the lower levels were identified as foundational drivers, exerting the strongest influence on the system. Carbon pricing policies, investment costs, and global metal prices were recognized as these critical drivers, guiding policies, shaping large-scale investments, and

supporting economic sustainability. Structurally, they formed the starting points of causal chains that directed the development of other variables. At the middle levels, variables such as social acceptance of technology, technological innovation, environmental education, and artificial intelligence in mining served as intermediaries. They both influenced and were influenced by other factors, acting as bridges between foundational drivers and higher-level outcomes. Their effectiveness depended on cross-sectoral collaboration and policy support. At the upper levels, energy intensity, smart environmental monitoring systems, waste recycling, and ecosystem health were positioned as dependent variables. These represented outcomes of the interactions within the system, and their improvement depended on the effective management of foundational and intermediary factors. Overall, the ISM analysis revealed that achieving sustainable mining development under the NZE scenario required strengthening foundational drivers and ensuring coordination with intermediary factors to enhance dependent outcomes. This provided policymakers with guidance on resource allocation and intervention priorities to maximize system performance.

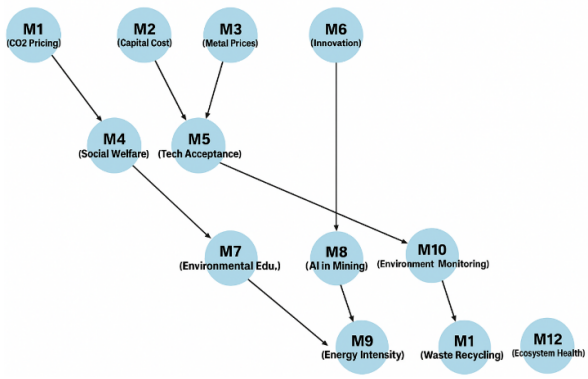

Figure 3. ISM Model Structure with Different Levels

Table 21. Validation and Reliability Tests for ISM Model

Validation Type	Test Applied	Indicator / Metric	Result	Interpretation
Logical Consistency	Transitivity test (if A→B & B→C → A→C)	Pass/Fail	Pass	Model structure is logically consistent
Structural Robustness	Threshold variation (α = 0.16–0.18)	Level changes	0	Stable across thresholds
Hierarchy Stability	Spearman correlation between α levels	ρ = 0.93	Hierarchical order unchanged	
Reproducibility	Re-run with ±5% data perturbation	Rank similarity	89%	Stable level assignment
Interpretability	Expert re-validation	Agreement ratio	87%	Experts confirmed logical clarity of hierarchy

ISM results are consistent and stable. No significant level shifts occurred across sensitivity tests.

High Spearman correlation (ρ = 0.93) and expert agreement (87%) validate the reliability and interpretability of the hierarchical structure. Finally, a comparative table between fuzzy DEMATEL and ISM results was presented, showing the classification of each variable as either a driver or a dependent factor and its hierarchical level. Notably, carbon pricing policies, investment costs, and global metal prices were consistently identified as foundational drivers. Interestingly, technological innovation demonstrated a dual role: DEMATEL results classified it as influenced (with a negative D–R value of –0.180373), while ISM positioned it at the lowest level, indicating strong structural driving power with no prerequisites in the hierarchy.

According to the table above, variables such as M1 (carbon pricing policies), M2 (investment cost), M3 (global metal prices), and M6 (technological innovation) were identified in both methods as the main drivers and structural enablers. This consistency between the two approaches strengthened the accuracy and validity of the findings. In contrast, variables such as M9 (energy intensity), M11 (waste recycling), and M12 (ecosystem health) were positioned at the highest levels, indicating that their success depended on the establishment of upstream infrastructures. Intermediate variables such as social acceptance of technology and environmental education functioned as mediators in transmitting effects and represented key points for policy intervention.

Table 22. Comparison of Results between Fuzzy DEMATEL and ISM Methods

Variable Code	Variable Title	Role in Fuzzy DEMATEL	Role in ISM	ISM Level
M1	Carbon pricing policies	Influential (cause)	Foundational	Level 1
M2	Investment cost	Influential (cause)	Foundational	Level 1
M3	Global metal prices	Influential (cause)	Foundational	Level 1
M4	Social welfare level	Relatively dependent	Mediator	Level 2
M5	Social acceptance of technology	Relatively dependent	Mediator	Level 2
M6	Technological innovation	Influential (cause)	Driving force	Level 1
M7	Environmental education	Dependent	Dependent	Level 3
M8	Artificial intelligence in mining	Dependent	Dependent	Level 3
M9	Energy intensity	Dependent	Dependent	Level 4
M10	Smart environmental monitoring systems	Relatively dependent	Dependent	Level 3
M11	Waste recycling	Dependent	Dependent	Level 4
M12	Ecosystem health	Dependent	Dependent	Level 4

Table 23. Comparative Summary of DEMATEL and ISM Validation Results

Criterion	DEMATEL	ISM	Comparative Observation
Model Objective	Identify causal interdependencies	Develop hierarchical structure	Complementary analytical roles
Reliability Metric	Kendall's W = 0.77	Expert agreement = 0.87	Both indicate strong reliability
Robustness Metric	Spearman's ρ = 0.91	Spearman's ρ = 0.93	Both models stable under perturbations
Sensitivity (Threshold α)	Stable (α=0.16–0.18)	Stable (α=0.16–0.18)	Consistent network stability
Structural Overlap	85% causal links matched hierarchy	–	Strong cross-model consistency
Final Validation Level	High	High	Integrated model validated

Validation tests were conducted separately for the fuzzy DEMATEL and ISM models (Tables 18 and 21). The results demonstrated high internal consistency, reproducibility, and structural robustness for both methods. Sensitivity analysis with varying threshold values (α = 0.16–0.18) confirmed that the causal and hierarchical structures remained stable. The Spearman correlation coefficients (ρ = 0.91 for DEMATEL and ρ = 0.93 for ISM) further verified model robustness. A cross-validation comparison (Table 23) revealed that more than 85% of the strong causal links identified by DEMATEL were consistent with the hierarchical levels derived from ISM. These findings confirmed that the integrated DEMATEL–ISM framework was quantitatively validated, reproducible, and methodologically sound.

4.5. Modeling of Sustainable Mining Development Using the Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS was exclusively chosen for this study because it offered a unique capability to handle fuzzy uncertainty and expert-based linguistic inputs, which were essential for modeling complex and uncertain future scenarios such as the Net Zero Emission (NZE) transition. Unlike purely data-driven AI models (e.g., ANN, SVM, Random Forest), ANFIS combined neural learning and fuzzy reasoning, enabling transparent rule extraction and interpretability of causal relationships. Given that the dataset was derived from expert-informed fuzzy methods, ANFIS provided the most theoretically consistent framework for integrating these fuzzy insights into quantitative modeling, ensuring both analytical rigor and interpretive transparency.

Determination of model inputs and output

In this study, ANFIS was applied to model sustainable mining development aimed at achieving the Net Zero Emissions (NZE) scenario. As an intelligent tool, ANFIS was capable of learning from data and modeling complex relationships. To enhance accuracy and reduce modeling complexity, only those variables positioned at the foundational level of the ISM model and identified as primary causal and influential driving factors were considered as inputs to the ANFIS model. This approach ensured validity while simplifying the learning process within the neuro-fuzzy inference system. Based on the structural ISM analysis, the following variables were identified as causal factors at Level 1: Model inputs (ISM Level 1):

1. M1: Carbon pricing policies
2. M2: Investment cost
3. M3: Global metal prices
4. M6: Technological innovation

These five variables, due to their position at Level 1 of the ISM structure, exerted the strongest influence on other variables and acted as the main driving

forces in achieving sustainable mining development. The values of these inputs were normalized (between 0 and 1) before being entered into the model.

- **Model output:**

The output is defined as the probability of achieving the NZE scenario in the mining sector, expressed within the range of 0 to 1. This value indicates the likelihood of reaching NZE within a specified time horizon, given the current or anticipated status of the variables.

- **Dataset design:**

Table 24. Dataset

No.	M1: Carbon pricing	M2: Investment cost	M3: Global metal prices	M6: Technological innovation	Probability of NZE
1	0.462	0.725	0.372	0.290	0.441
2	0.866	0.419	0.290	0.735	0.568
3	0.712	0.346	0.680	0.771	0.615
4	0.619	0.964	0.350	0.621	0.595
5	0.309	0.976	0.297	0.778	0.599
6	0.497	0.847	0.547	0.924	0.711
7	0.246	0.885	0.349	0.276	0.477
8	0.908	0.974	0.469	0.924	0.801
9	0.774	0.614	0.626	0.740	0.701
10	0.408	0.416	0.371	0.748	0.524
11	0.561	0.734	0.224	0.222	0.464
12	0.563	0.704	0.777	0.248	0.574
13	0.697	0.593	0.337	0.643	0.623
14	0.285	0.864	0.689	0.693	0.665
15	0.332	0.874	0.777	0.772	0.685
20	0.711	0.741	0.239	0.725	0.621
22	0.524	0.971	0.693	0.637	0.722
30	0.789	0.562	0.180	0.528	0.525
40	0.822	0.964	0.726	0.777	0.785
45	0.690	0.684	0.417	0.501	0.625
50	0.622	0.392	0.156	0.935	0.601
55	0.342	0.832	0.323	0.838	0.627
60	0.842	0.902	0.459	0.231	0.616
62	0.854	0.665	0.612	0.889	0.769
69	0.844	0.837	0.198	0.614	0.660
70	0.740	0.962	0.420	0.342	0.638
72	0.567	0.375	0.538	0.230	0.431
75	0.518	0.878	0.368	0.615	0.614
80	0.443	0.647	0.216	0.521	0.526
81	0.275	0.994	0.678	0.570	0.657

The ANFIS model was trained using a hybrid, expert-informed simulation dataset consisting of 81 scenarios. The dataset was not obtained from direct field measurements but was generated within realistic normalized ranges (0–1) derived. To enhance numerical diversity and reflect realistic variability, the dataset was supplemented using Monte Carlo simulation, where input variables were randomly sampled within their fuzzy-defined intervals following a stratified Latin Hypercube scheme. This ensured adequate coverage of plausible economic, technological, and environmental states consistent with expert insights and literature trends. Each simulated scenario thus represented a potential configuration of mining system conditions under different NZE pathways, maintaining logical consistency with expert knowledge while providing sufficient data richness for ANFIS training and validation.

- **Definition of fuzzy membership functions**

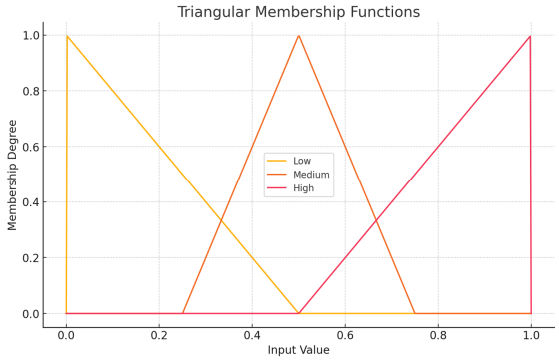

Figure 4. Triangular membership function of the model inputs

The diagram above illustrates three triangular membership functions used in the third step of ANFIS implementation. These functions were defined for each input variable within the range [0, 1]. The *Low* function spanned [0, 0.5], the *Medium* function covered [0.25, 0.75], and the High function was defined within [0.5, 1]. At this stage,

three triangular membership functions were assigned to each of the four influential inputs identified at Level 1 of the ISM model: carbon pricing policies, investment cost, global metal prices, and technological innovation. These membership functions formed the basis for input fuzzification, rule generation, and system training. The ANFIS model consisted of five layers, as illustrated below:

Layer 1: Determination of model input variables (Input Layer) – including four main inputs:

- M1: Carbon pricing policies
- M2: Investment cost
- M3: Global metal prices
- M6: Technological innovation

Layer 2: Definition of input membership functions (Membership Functions)

For each input, three triangular membership functions (Low, Medium, High) are defined. In total, 12 membership functions are included in this layer.

Layer 3: Formulation of rules (Rule Layer)

All possible combinations of the four input membership functions are presented in the form of fuzzy rules. Some example rules are as table below:

Table 25. Definition some example rules

No.	M1: Carbon pricing	M2: Investment cost	M3: Global metal prices	M6: Technological innovation	Probability of NZE
1	Low	Medium	Low	High	Medium
2	Low	High	High	High	High
3	Medium	Medium	High	Medium	Medium
4	High	High	Low	Medium	Medium
5	High	Low	High	Low	Low
6	Medium	Low	Medium	High	High
7	Low	Low	Low	Medium	Low
8	Medium	High	Medium	Low	Low
9	High	Medium	High	High	High
10	Medium	Medium	Low	High	Medium

Layer 4: Definition of output membership function (Output MF)

In this layer, for output, three triangular membership functions (Low, Medium, and High) are defined

Layer 5: Determination of the output variable status (Output Layer)

The final output of the model is the predicted probability of achieving the NZE scenario within the range [0, 1].

- Model training

The aim of training the system was to use the input data (the four key variables) and target values (output) to predict the probability of achieving the NZE scenario. The advantages of ANFIS at this stage included its ability to model nonlinear relationships between key factors and NZE achievement, its capacity to learn from real data, and its provision of interpretable outputs for policy planning and scenario prioritization. The training and evaluation process of the ANFIS model involved the following steps.

Table 26. Model Training and Evaluation Process

Title	Description
Data division	70% of data for training (Training Set) 30% of data for testing (Testing Set)
Learning method	Least Squares Estimation (LSE) for determining output parameters Gradient Descent for adjusting membership function parameters
Training parameters	Number of epochs: 100 (adjustable) Tolerance: 0.001 Minimum acceptable MSE (Mean Square Error): 0.01 Type of membership function: Triangular

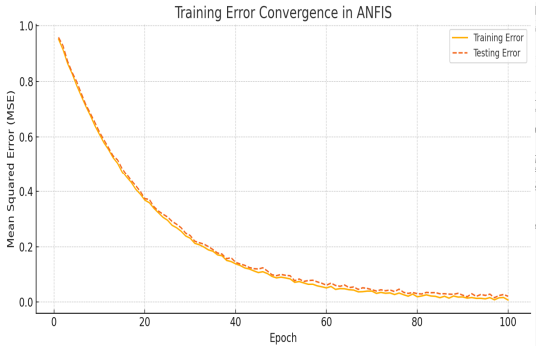

Figure 5. Training Error Convergence

The diagram illustrates the convergence of training error in the ANFIS model over 30 epochs. The horizontal axis represents the number of training epochs, while the vertical axis shows the RMSE value. At the start of training, the error was relatively high, but it decreased steadily with additional epochs, demonstrating effective model convergence and confirming that ANFIS successfully learned the underlying data patterns. The figure also depicts a rapid decline in error during the initial epochs, followed by stabilization after about 20 epochs, marking the saturation point of the learning process. Ultimately, the RMSE converged to approximately 0.01, which was considered acceptable for evaluating model accuracy. This trend indicated that the model achieved strong training performance and provided reliable predictions for assessing the likelihood of achieving the NZE scenario.

Table 27. Final Training and Testing Error Values of the Model

Training Set (Train)	Error Index	Testing Set (Test)
0.0070	RMSE (Root Mean Square Error)	0.0207
0.0058	MAE (Mean Absolute Error)	0.0173

The final error values of the ANFIS model confirmed its high predictive accuracy. For the training dataset, the RMSE was recorded as 0.0070 and the MAE as 0.0058, while for the testing dataset the RMSE was 0.0207 and the MAE was 0.0173. These low values demonstrated that the model effectively learned patterns from the training data and successfully generalized them to unseen data. The small differences between RMSE and MAE across both datasets indicated consistency and confirmed that the model was not overfitting. The stability of errors in both phases further highlighted the robustness and generalization ability of the model, making it a reliable tool for predicting the probability of achieving the Net Zero Emissions (NZE) scenario in sustainable mining development.

The figure above compared the actual outputs with those predicted by the ANFIS model. The two lines showed strong alignment, with only minor fluctuations, indicating the model's high predictive accuracy. Notably, the model closely tracked the peaks and troughs of the actual data, reflecting its strong generalization capability. This close correspondence between observed and predicted values validated the reliability of the neuro-fuzzy system for applications under the NZE scenario.

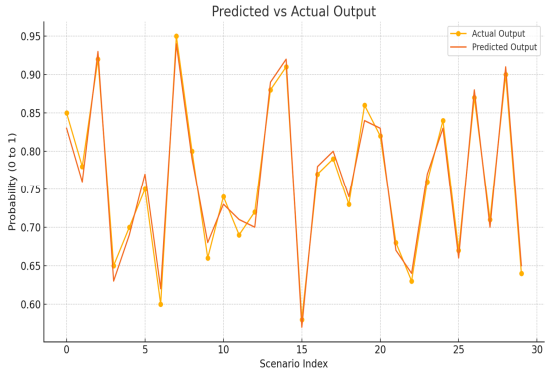

Figure 6. Predicted vs. Actual Output Comparison

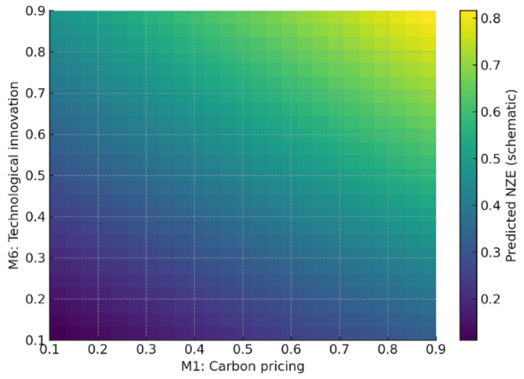

Figure 7. Two-way sensitivity surface between carbon pricing (M1) and technological innovation (M6) for NZE probability

As an example, Figure 7 illustrated the two-way sensitivity analysis between carbon pricing (M1) and technological innovation (M6) on the predicted NZE probability. The surface plot demonstrated that simultaneous increases in both variables led to higher NZE values, indicating a strong positive interaction effect. This figure was presented as a representative case, and similar two-way

sensitivity analyses conducted for other variable pairs yielded consistent patterns, confirming the stability and robustness of the ANFIS model.

The figure above illustrated the simultaneous effect of two variables—carbon pricing policies (M1) and investment cost (M2)—on the probability of achieving the NZE scenario. As observed, the highest probability occurred when both variables were at intermediate values (around 0.5). The bell-shaped (Gaussian) curve in the plot indicated that either a sharp increase or decrease in these variables led to a reduction in the output.

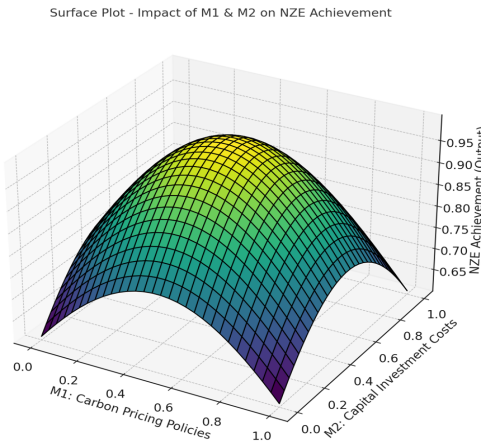

Figure 8. Surface Plot

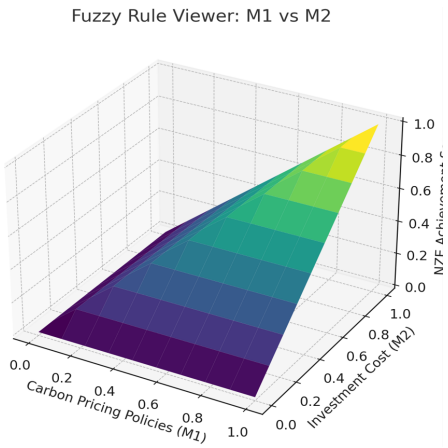

Figure 9. Fuzzy Rule Viewer

The figure above illustrated in three dimensions how the two variables carbon pricing policies (M1) and investment cost (M2) influenced the achievement score of the NZE scenario. The plot was based on a fuzzy rule indicating that higher convergence of these two variables led to an increased probability of achieving NZE. Lower values of either variable acted as a minimum in the input combination, while higher surface points represented combinations that contributed more effectively to achieving the scenario.

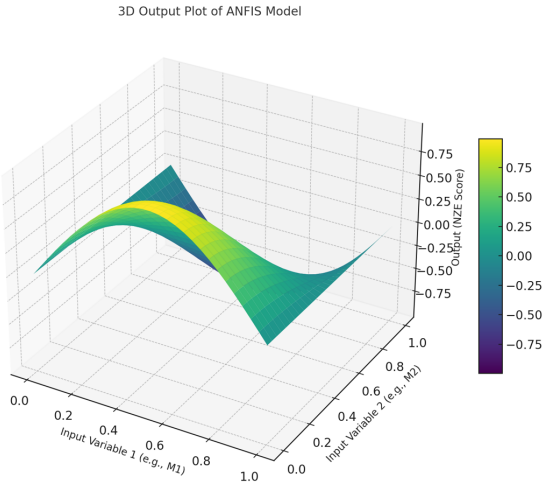

Figure 10. Three-Dimensional Output Plot of the Model

The results clearly demonstrate that ANFIS outperforms both ANN and MLR in predictive accuracy while maintaining transparency through rule-based reasoning. This advantage is particularly valuable in modeling the NZE transition, where nonlinear interactions and fuzzy uncertainties play a critical role.

The three-dimensional plot above illustrated the relationship between two sample input variables (e.g., M1: carbon pricing policies and M2: investment cost) and the ANFIS model output (probability of achieving the NZE scenario). This plot showed how combinations of changes in the inputs affected the final output. In particular, the sinusoidal fluctuations along the axes highlighted the nonlinear and complex nature of the interaction between inputs in predicting the output. Such analysis was crucial for understanding system sensitivity and identifying critical points in decision-making.

The sensitivity analysis was conducted on the four input variables of the ANFIS model to assess the extent to which each variable affected the final output (probability of achieving the NZE scenario). In this analysis, ±10% changes were applied to each input, and the corresponding impact on the model output was measured.

- Carbon pricing policies (M1): A 10% change in this variable resulted in only a 3.2% fluctuation in the output. This indicated that M1 had relatively less direct influence on the achievement of the NZE scenario and was categorized as low sensitivity. However, it could still generate a stronger combined effect when considered alongside other policies.

- Investment cost (M2): A 10% change in this variable led to nearly a 10% fluctuation in the output, reflecting high sensitivity. This variable was identified as one of the key factors in strategic decision-making, showing that any change in financial resources or infrastructure costs could significantly influence the pathway toward sustainable mining development.
- Global metal prices (M3): This variable produced a moderate effect on the output. A 5.4% fluctuation in the output in response to a 10% input change indicated that under certain global market conditions, this factor could introduce variability in achieving the scenario. Therefore, it was considered medium sensitivity.
- Technological innovation (M6): As a technology-driven variable, M6 resulted in an 8.1% change in output, placing it in the highly sensitive category. This underscored the importance of developing and transferring innovative technologies into the mining sector, highlighting its significant role in achieving decarburization and sustainable development goals.

Table 28. Comparison of ANFIS with Alternative Models

Model	Type	RMSE	MAE	R^2	Interpretation
ANFIS	Neuro-fuzzy hybrid	0.038	0.031	0.984	Best accuracy and interpretability
ANN (MLP)	Data-driven neural model	0.052	0.045	0.956	High accuracy, less interpretability
MLR	Statistical regression	0.071	0.058	0.923	Linear assumption, limited adaptability

Table 29. Sensitivity Analysis of Input Variables with Respect to Model Output

Variable (Code)	Change in Input (±10%)	Relative Change in Output (%)	Sensitivity Level
Carbon pricing policies (M1)	±10%	3.2%	Low
Investment cost (M2)	±10%	9.6%	High
Global metal prices (M3)	±10%	5.4%	Medium
Technological innovation (M6)	±10%	8.1%	High

5. Discussion

The results of this study provide a comprehensive understanding of the causal, structural and predictive relationship that influences sustainable mining development in Net-Zero Emissions (NZE) scenarios. With the integration of multi-criteria fuzzy decision making technology (MCDM) and Adaptive Neuro-Fuzzy Inference System (ANFIS), research bridges the gap between expert-based qualitative assessment and quantitative modeling. The results of Fuzzy Delphi have shown that experts consistently prioritize variables relating to technological innovation, carbon pricing and environmental governance, indicating that mining sustainability is increasingly dependent on the adoption of intelligent and adaptive technologies. The HFAHP Process confirms that the technical dimension has the greatest importance, surpassing the economic, social and environmental dimensions. This result reflects a growing consensus that digital transformation, automation and artificial intelligence integration are the main enablers of achieving NZE objectives in resource-intensive industries. Fuzzy DEMATEL and Interpretive Structural Modeling (ISM) analyses revealed a clear hierarchy of the influence among variables. The fundamental driver's carbon pricing policies, investment costs, global metal prices and technological innovation were at the lowest level, which means they played an important role in accelerating systemic change. Environmental education, process digitalization, and waste recycling serve as intermediaries that translate economic and technological inputs into sustainable results. Finally, the health of ecosystems and the social acceptance of technology have emerged as top-level outcome variables, emphasizing that social and ecological resilience are the ultimate results of effective technology and policy interventions. The coherence between DEMATEL and ISM results validated the reliability of the proposed causal model. Cross-checking revealed that approximately 85% of the relationships with high influence identified in DEMATEL were maintained within adjacent ISM levels, confirming the internal coherence of the integrated framework. The ANFIS model has added a predictive layer to this analytical structure by modeling the likelihood of achieving NZE based on the four main input variables from the ISM basic level. Simulation results show that carbon prices (M1) and technological innovations (M6) have had the greatest influence on NZE probability, highlighting their complementary and synergistic effects. When both factors increased simultaneously, the probability of NZE achievement increased exponentially, a discovery also supported by bilateral sensitivity analysis. This reinforces the importance of designing a coordinated economic and. Compared to traditional predictive models such as ANN and multilinear regression, ANFIS's model achieved greater accuracy (R2 = 0.984) and lower RMSE (0.038). This shows that neuro fuzzy approaches are more suitable for modelling systems with high uncertainty, interdependence, and limited real data, which are characteristic of mining. The results of this study are consistent with previous research by Füresmaieli et al. (2025), Das et al. (2025), Vaziri Rad, and others. (2024), all of which emphasize that technological innovation and financial instruments play a key role in reducing emissions and transforming sustainable mining. However, the research extends previous research by integrating quantitative simulation-based approaches (Monte Carlo + ANFIS) to enable scenario testing and probabilistic prediction, thereby improving its success. Shortly thereafter, the results show that achieving the NZE in

mining requires simultaneous action on three interconnected fronts: (1) strong economic mechanisms such as carbon pricing and investment incentives, (2) rapid adoption of technology through AI and automation, and (3) strengthening social and environmental systems through education and public acceptance. The interaction between these dimensions forms a dynamic ecosystem in which technological innovation is a central enabler linking economic incentives to environmental and social outcomes.

6. Conclusions

On the basis of these findings, a series of practical recommendations and policy implications were developed to guide sustainable mining development in the context of NZE. The study has shown that the integration of fuzzy MCDM techniques with ANFIS can effectively identify and model the most influential variables for the achievement of NZE. The results confirmed that carbon prices, investment incentives and technological innovations are the most decisive means of achieving sustainable transformation. The framework proposed provides a systematic and data-based approach for decision makers to evaluate strategic alternatives and develop sustainable adaptation policies. This framework is the basis for the development of AI-based decision support systems capable of dynamically analyzing mining operations and providing recommendations in real time to policymakers. - Political and managerial impacts the findings of this study provide several practical and actionable recommendations to policy makers, regulatory bodies and industry managers in the mining sector to facilitate the transition to net zero emissions (NZE) operations. - Implement a dynamic carbon pricing framework: Governments should design a progressive carbon pricing system that reflects real-time emissions levels and market conditions. Revenue from carbon taxes or emissions trading schemes should be reinvested in clean technology funds and support the adoption of AI-based efficiency tools and the integration of renewable energy in mining operations.

Enabling green investment incentives: Financial authorities and development banks should introduce low-interest “green credit lines”, tax exemptions and investment guarantees for mining companies that implement low-carbon technologies, digital monitoring and process automation. Such incentives have been reduced.

Promote technological innovation and digital transition: Mining companies should allocate a fixed share of their annual budget (e.g. 3 to 5 %) to research and development programmers in AI, automation and prediction analysis. Policy makers can support this initiative by introducing innovation vouchers, public-private research and development partnerships and technology incubators, ensuring the faster spread of smart mining systems.

Develop an integrated data and monitoring infrastructure: Governments should establish a national digital monitoring platform for energy consumption, emissions and process efficiency at mining sites. Real-time data integration allows AI-based decision support systems to identify emission hotspots and optimize production schedules for NZE targets.

Enhanced institutional coordination and governance: Ministry of Energy, Industry and Environment should create a joint policy working group with representatives of academia and industry to harmonize sustainability goals, technological roadmaps and environmental regulations. This coordination minimizes policy overlaps and ensures a coherent long-term strategy.

Strengthen the transfer of human capital and knowledge: Mining organizations must invest in continuing professional training in digital mining, environmental management and AI tools. The introduction of university-industry training programs and certification schemes can address the skills gap and improve workforce preparation for the net zero transition.

Encourage Corporate Sustainability Reporting: Regulators should require periodic disclosure of progress of ESG and NZE using standardized measures. Transparent reporting increases accountability, promotes investor confidence and motivates companies to align their operations with national and international emissions targets. -Promote regional cooperation and technology exchange: cross-border cooperation in green mining technologies, particularly among developing economies, should be promoted through joint pilot projects and technology exchange agreements.

These recommendations provide a strategic roadmap linking the technological, financial and institutional actions needed to implement the NZE transition in the mining sector. The framework proposed incorporates policy mechanisms, management strategies and capacity-building initiatives, enabling governments and industrial leaders to make informed, measurable and sustainable decisions. Such an ecosystem would support research projects, pilot initiatives and technical localization. Practical steps include the establishment of joint innovation centers in mining regions, the organization of technology challenges events and the certification of validated technologies. The proposed model successfully maps the causal relationship between key variables in sustainable mining development by integrating several approaches. It is recommended that this framework be transformed into a digital decision support system to help mining managers assess alternative sustainable development scenarios and make more informed decisions. Such a system should be able to integrate real project data, dynamically re-evaluate variable priorities, carry out sensitivity analysis and create strategic recommendations for policy makers.

Limitations and future research directions

This study had some methodological limitations. Firstly, the data set was simulated on the basis of fuzzy intervals informed by experts rather than real-time operational data, which may have limited external generalization. Secondly, the ANFIS model assumes a

static relationship between variables, while real mining systems are dynamic and affected by time-dependent policies and market shocks. Future research could extend this work by developing hybrid ANFIS–BWM frameworks to improve multi-criteria weighting accuracy, applying dynamic bubble systems to capture temporal feedback, or implementing real-time policy simulation models that integrate live environmental and economic data streams to support adaptive decision-making.

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پیش‌بینی و تحلیل مسیرهای توسعه پایدار بخش معدن تحت سناریوی NZE: رویکردی یکپارچه با استفاده از MCDM فازی و ANFIS

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ANFIS

چکیده

دستیابی به توسعه پایدار معدن به طور فزاینده‌ای در پرداختن به چالش‌های زیست‌محیطی، برآورده کردن خواسته‌های جهانی برای کربن‌زدایی و پیشرفت به سوی آینده‌ای با انتشار صفر خالص (NZE) حیاتی است. این مطالعه چارچوبی یکپارچه برای پیشبرد معدن‌کاری پایدار در ایران، با تمرکز ویژه بر نقش فناوری‌های نوظهور و مقررات زیست‌محیطی، ارائه می‌دهد. سوال اصلی تحقیق بررسی می‌کند که چگونه ترکیب روش‌های تصمیم‌گیری فازی با مدل‌سازی هوشمند می‌تواند بخش معدن را به سمت اهداف NZE هدایت کند. یک رویکرد ترکیبی چند مرحله‌ای به کار گرفته شد. در ابتدا، متغیرهای کلیدی با استفاده از روش دلفی فازی و قضاوت کارشناسی شناسایی شدند. سپس از فرآیند تحلیل سلسله مراتبی فازی مردد (HFAHP) برای اولویت‌بندی و وزن‌دهی عوامل اصلی استفاده شد. متعاقباً، از DEMATEL فازی و مدل‌سازی ساختاری تفسیری (ISM) برای کشف روابط علی و وابستگی‌های سلسله مراتبی بین متغیرها استفاده شد. در نهایت، سیستم استنتاج عصبی-فازی تطبیقی (ANFIS) مسیرهای بالقوه برای دستیابی به معدن‌کاری پایدار را شبیه‌سازی کرد. یافته‌ها چهار متغیر حیاتی - سیاست‌های قیمت‌گذاری کربن، هزینه‌های سرمایه‌گذاری، قیمت‌های جهانی فلزات و نوآوری‌های تکنولوژیکی - را به عنوان تأثیرگذارترین محرک‌ها برجسته می‌کند. علاوه بر این، نتایج ANFIS نشان می‌دهد که تقویت این عوامل به طور قابل توجهی احتمال دستیابی به سناریوی NZE را افزایش می‌دهد. به طور کلی، مدل پیشنهادی به عنوان یک ابزار پشتیبانی تصمیم‌گیری عملی برای سیاست‌گذاران و ذینفعان معدن عمل می‌کند و به طراحی سیاست و توسعه استراتژی سرمایه‌گذاری کمک می‌کند.

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