Artificial Intelligence for Climate Resilience and Risk Management in Mining: A PRISMA-Based Review and Conceptual Framework

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Abstract. Mining operations are increasingly exposed to climate-related risks, including extreme rainfall, flooding, slope instability, tailings failures, and infrastructure disruptions, particularly in open-pit environments. Traditional risk management approaches often remain reactive and are limited in their ability to anticipate dynamic climate-related hazards. Artificial Intelligence (AI) offers predictive, data-driven, and adaptive capabilities that can support early warning, monitoring, and climate-informed decision-making in mining. This paper presents a PRISMA-based systematic literature review of empirical studies published between 2020 and 2025 to examine how AI has been applied to climate resilience and risk management in the mining sector. The review used Scopus, Web of Science, and ScienceDirect, screened 580 records after duplicate removal, and identified 16 studies for final analysis. The findings show that AI is mainly applied to geotechnical risk monitoring, flood and climate risk assessment, hazard detection, and environmental monitoring, using techniques such as machine learning, deep learning, remote sensing, digital twins, and hybrid physics-informed models. However, current applications remain fragmented, hazard-specific, and weakly connected to organisational governance and HSE decision workflows. In response, the paper proposes an AI-driven climate resilience framework that links climate and mine data, AI analytics, explainable risk outputs, decision workflows, data governance, and socio-technical adoption. The review contributes by clarifying the current evidence, identifying implementation gaps, and outlining how AI can shift mining risk management from reactive prediction to integrated, proactive climate resilience.

Keywords: Artificial Intelligence; Climate Resilience; Risk Management; Mining Sector; Open-Pit Mining

1. Introduction

Mining plays a vital role in supplying raw materials for energy, infrastructure, and modern technologies. However, in recent years, mining has become increasingly vulnerable to the impacts of climate change. The mining industry is particularly exposed to climate-related risks, such as flooding, extreme weather events, slope failures, and supply chain disruptions [1], [2]. These risks are particularly pronounced in open-pit mining operations, where large exposed slopes, extensive waste dumps, and surface infrastructure are directly affected by changing rainfall patterns, temperature variability, and extreme weather events[3]. Traditional mining risk management has been reactive, focusing on responding to problems after they occur. However, increasing climate variability and extreme events now require proactive resilience strategies that anticipate risks and reduce their impacts before they happen[4].

Managing climate resilience and risk in the mining sector can be complex and unpredictable, largely due to the interplay of environmental, technical, and socio-economic factors. Existing adaptation and risk management monitoring systems highly rely on static risk management assessment and manual monitoring systems that usually struggle to respond to dynamic climate changes, particularly in open-pit mines[5]. This limitation reduces the sector's capability to detect early warning signals and to integrate climate-related risk information into operational and strategic decision-making.

Artificial Intelligence (AI) offers new opportunities to strengthen climate resilience and risk management in mining through data-driven, predictive and adaptive approaches. Technologies such as machine learning-based predictive models, deep learning for geotechnical monitoring and remote sensing analysis, sensor-based monitoring and digital twins are enabling the sector[6],[7]. Despite these technological advances, AI adoption remains fragmented across mining operations, with persistent challenges related to data availability, organisational readiness, governance integration, and the long-term sustainability of AI systems themselves[8],[9].

Therefore, this paper is presented as a PRISMA-based systematic literature review with a conceptual framework derived from the evidence reviewed. Rather than presenting a deployed AI system, the study synthesizes empirical literature to (i) map current AI applications for climate resilience and risk management in mining, (ii) identify the dominant technologies, benefits, and implementation barriers, and (iii) propose an integrated AI-driven climate resilience framework that connects AI capabilities with data governance, explainable risk outputs, organisational practices, and decision-making workflows.

1.1. Research questions

The literature aims to answer the following research questions:

1. How has Artificial Intelligence (AI) been applied in the mining sector to enhance climate resilience and risk management?
2. What AI technologies are currently being used in the mining sector for climate resilience?
3. What are the main challenges in applying AI for climate resilience and risk management in mining?
4. Which areas of mining operations have benefited most from AI applications related to resilience and risk management?
5. How can AI applications in mining be adapted or improved to strengthen long-term climate resilience?

2. Methodology

The study adopts a PRISMA-guided systematic review approach to support transparent identification, screening, eligibility assessment, and synthesis of relevant literature. The review follows the PRISMA logic of documenting search sources, inclusion and exclusion criteria, record screening, and final study selection, while using thematic synthesis to interpret patterns across the included empirical studies. The updated PRISMA 2020 guidance was also used to improve reporting transparency[23].

2.1. Search strategy

The search was conducted in Scopus, Web of Science, and ScienceDirect to ensure consistency across the abstract, methodology, protocol table, and PRISMA diagram. Boolean operators were used to combine AI-related, climate resilience, risk management, and mining terms. The core search string was: ("Artificial Intelligence" OR "AI" OR "Machine Learning" OR "ML") AND ("Climate resilience" OR "Climate adaptation" OR "Climate risk") AND ("Risk management" OR "Disaster management" OR "Early warning") AND ("Mining" OR "Open-pit mining" OR "Tailings" OR "Slope stability"). Only English-language scholarly publications from 2020 to 2025 were considered. Table 1 summarizes the research protocol, outlining the digital libraries searched and the inclusion and exclusion criteria applied to select the studies.

Table 1. Research Protocol

Protocol Element	Translation in research
Digital Libraries	Scopus, Web of Science, and ScienceDirect
Inclusion Criteria	Research should emphasize the application of AI or ML technologies in the mining industry. Research should explicitly address at least aspects of climate resilience, climate adaptation, and risk management. To ensure that recent developments were included, only publications from 2020 to 2025 were considered. Only publications written in English were considered. Only publications from scholarly sources were considered, which include: Refereed (peer-reviewed) journal articles, Conference proceedings, and preprints
Exclusion Criteria	Studies that were purely conceptual or theoretical, without empirical support, were excluded, given the importance of evidence-based application of AI or ML technologies. Studies unrelated to the mining industry were excluded. Studies that do not explicitly address AI or ML technologies were excluded. Studies that do not explicitly address aspects of climate change were excluded, specifically those that do not address climate resilience, Climate change adaptation, or Risk management. Studies published before 2020 were excluded due to the importance of temporal relevance. Studies written in languages other than English were excluded to ensure consistency in analysis.

2.2. Screening Process

Using the PRISMA framework (Figure 1), the study began with 939 records from Scopus, Web of Science, and ScienceDirect. After removing 359 duplicate and irrelevant records, 580 records were screened based on titles and abstracts. This corrected database list is used consistently throughout the manuscript to improve methodological credibility.

During screening, 495 records were excluded for not meeting the criteria. 85 reports were retrieved for full text. Of these, 67 articles were assessed; 52 were excluded for reasons like being non-empirical (n=13), non-mining focus (n=12), conceptual or opinion-based (n=17), or lacking methodological detail (n=9).

Ultimately, 16 studies met all inclusion criteria and were included in the final review. These studies formed the empirical evidence base for analysing the application of artificial intelligence to enhance climate resilience and risk management within the mining sector.

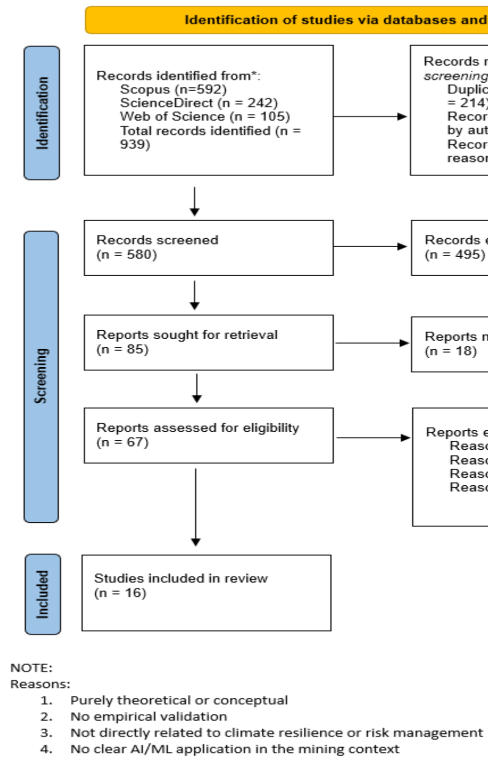

Figure. 1. Adapted PRISMA diagram depicting the selection process.

3. Results

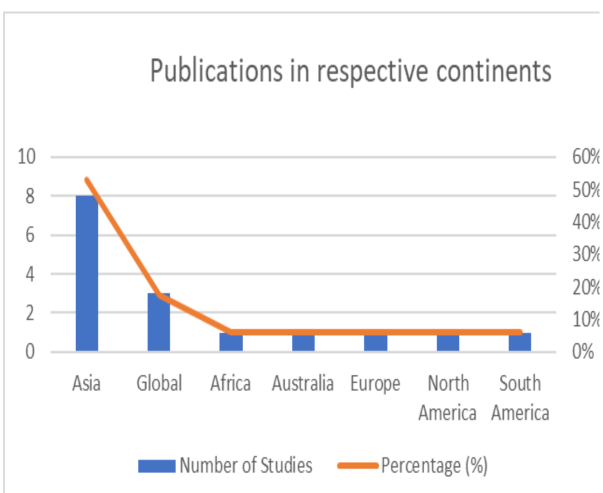

Figure 2. Publications in respective continents

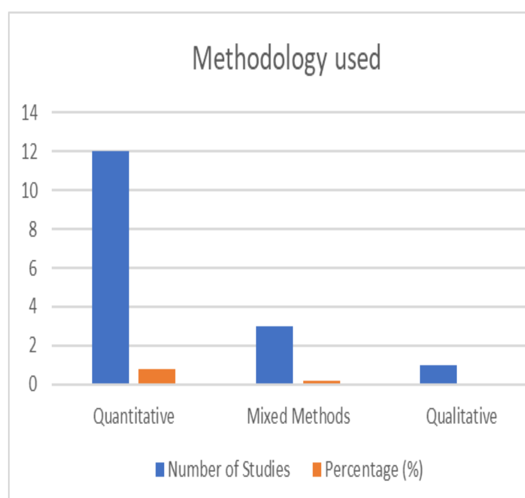

Figure 3. Count of the Methodologies used

3.1. Publications in respective Continents

Figure 2 illustrates the geographic distribution of the reviewed literature. The majority of the reviewed studies were conducted in Asia, accounting for 50% of the final sample (8/16). Global studies accounted for 18.8% (3/16), while Africa, Australia, Europe, North America, and South America each contributed 1 study (6.3% each). This distribution suggests that empirical AI mining research is concentrated in regions with strong digital mining investment, high open-pit activity, and greater availability of operational or remote-sensing datasets. The limited evidence from Africa is important because many African mining regions are highly exposed to climate stressors, yet often face data, infrastructure, and capacity constraints. Therefore, the geographic pattern not only describes where research has been conducted; it also shows where AI-enabled evidence on climate resilience remains underdeveloped.

3.2. Methodologies used by different authors

Figure 3 shows that quantitative approaches dominate the reviewed literature, with 12 studies relying mainly on modelling, sensor, satellite, geotechnical, or operational datasets. This dominance is expected because many AI applications in mining require numerical training data for prediction and classification. However, the limited number of mixed-methods and qualitative studies reveals an important methodological weakness: the literature explains model performance better than it explains adoption, trust, usability, governance, and decision-making. This imbalance partly explains why many AI tools remain technically promising but weakly embedded in routine mining risk management.

3.3. Application areas in the mining sector

Figure 4 shows that AI use in mining risk domains is uneven. Most studies focus on slope stability and reliability because slope failures are safety-critical, data-intensive, and strongly influenced by rainfall, groundwater, and geotechnical conditions in open-pit mines. Ground hazard detection and climate-related risk analysis also receive substantial attention because they can be supported by sensors, imagery, and predictive models. In contrast, tailings dam risk, infrastructure reliability, and operational resilience receive comparatively limited coverage despite their high-consequence nature. This pattern implies that AI in mining remains focused on detectable physical hazards rather than on broader resilience planning, climate governance, and adaptive operational workflows.

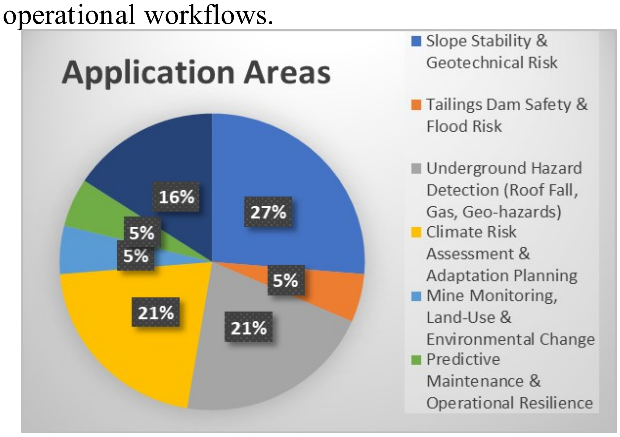

Figure 4. Application areas of AI in mining.

3.4. Challenges Identified

Table 2. Challenges Identified by Different Authors

Challenges	Authors	Description	Impact
Data scarcity and quality	[11], [12], [9]	Limited historical geotechnical and operational datasets and noisy or incomplete sensor data	Reduces the accuracy and generalisability of AI prediction models
Model generalisation across sites	[11], [13]	AI models trained on site-specific data perform poorly when transferred to other mines.	Limits the scalability of AI solutions across mining operations
Extreme climate uncertainty	[14], [1], [2]	Increasing unpredictability of rainfall, flooding, and temperature extremes	Complicates climate risk modelling and adaptation planning
Sensor reliability and integration	[3], [15], [16]	Inconsistent sensor performance and difficulties integrating heterogeneous data sources	Affects real-time monitoring and early warning effectiveness

Challenges	Authors	Description	Impact
High computational complexity	[16], [9], [17]	Deep learning, multimodal fusion, and physics-informed models require significant computing resources.	Increases implementation cost and limits adoption in resource-constrained mines
Lack of model interpretability	[15], [12], [18]	Black-box AI models provide a limited explanation for predictions	Reduces trust and acceptance among engineers and decision-makers
False alarms in early warning systems	[16]	Imbalanced datasets lead to high false-positive rates	Causes alarm fatigue and reduces operational confidence in AI systems
User adoption and usability issues	[19], [7]	Resistance from operators; lack of training and user-centered design	Slows practical deployment and limits realized benefits of AI
Climate data downscaling challenges	[20], [2]	Difficulty translating regional or global climate data to mine-scale decisions	Reduces the precision of climate risk assessments
Integration with existing mining systems	[7], [3], [17]	AI tools often operate in isolation from legacy monitoring and maintenance systems.	Limits organizational-level climate resilience and decision support

As summarized in Table 2, scarcity and poor quality of data, especially geotechnical and operational, reduce AI model accuracy and generalizability, as noted by several authors. Models trained on specific mines tend to perform poorly elsewhere, limiting their widespread use. Climate uncertainties, such as increased rainfall, flooding, and temperature extremes, make risk modelling more difficult. Technical issues like sensor reliability and data integration problems hinder real-time hazard detection. While advanced AI techniques like deep learning are powerful, they are costly and complex, which slows adoption in resource-limited mines. Limited model interpretability also diminishes trust among engineers and decision-makers. Operational challenges include false alarms leading to alarm fatigue and resistance to new technology, which delay deployment. Difficulties in scaling and integrating climate data with existing systems further restrict AI's effectiveness in enhancing climate resilience. Overall, these challenges underscore the need for more robust, interpretable, and integrated AI solutions tailored to the complex, climate-sensitive conditions of mining environment.

3.5. Framework Used

Table 3. Framework used in each research

Category	Framework / Analytical Approach	Use	Authors
Vision-Based Monitoring & Satellite Analytics	Deep Learning (CNNs, Mask R-CNN)	Focuses on automated identification, remote sensing, and satellite imagery to monitor surface changes or underground hazards.	[17], [19], [15], [20]
Predictive Geotechnical Modelling	Supervised ML (Random Forest, SVM, MLP)	Use of traditional and ensemble machine learning to calculate Factor of Safety (FoS) and slope reliability.	[13], [11], [12]
Advanced Simulations & Physics-Informed AI	Hybrid Modelling (PINNs, RAMMS)	Combining physical laws (fluid dynamics, rock mechanics) with AI to predict tailings failures and gas outbursts.	[14], [9]
Digital Systems & Data Fusion	Integrated Systems (Digital Twins, Multimodal Fusion):	Aggregating data from multiple sources (seismic, dust, sensors) into a single digital replica for real-time risk management.	[16],[6]
Strategic Climate Risk & ESG	Scenario Logic & Regression	Evaluating long-term climate vulnerabilities (2100 projections), water scarcity, and carbon mitigation via panel data and indicators.	[1], [2], [21]

Category	Framework / Analytical Approach	Use	Authors
Socio-Technical & Organisational Adaptation	Behavioural & Management Frameworks	Using TAM, TOE, and STS theories to study how mining organisations adopt AI and retain resilience expertise.	[22], [18]

Table 3 identifies major frameworks and techniques, including predictive, data-centric, and geotechnical risk-monitoring models, across three studies. These interact with slope stability, geotechnical predictions, and real-time risk mitigation, indicating a shift toward addressing geotechnical failures in climate-sensitive mining. Studies employ remote sensing and machine learning to analyse satellite imagery and assess climate risks across larger areas. Climate vulnerability frameworks evaluate risks at mining sites and across broader regions, especially during extreme weather events. Emerging methods include explainable AI and hybrid physics- and data-driven models for reliable predictions amid uncertainties. Decision-support systems, mobile apps, and predictive maintenance translate AI insights into actions, supporting proactive disaster risk reduction. Overall, frameworks emphasise applied, data-driven, and hybrid models to enhance long-term climate resilience in mining.

3.6. AI techniques used.

Table 4. AI techniques used

AI Technique Category	AI technique Type	Authors	Description of Application	Impact on Mining and Climate Resilience
Deep Learning & Computer Vision	*CNN, Mask R-CNN, Transfer Learning*	[17], [19], [15], [20]	Used for automatic identification of mine boundaries, underground rock geohazards, and roof fall hazards via imagery (satellite and mobile).	Enhances real-time monitoring of ecological recovery and flood-vulnerable infrastructure, allowing for rapid response to climate-induced shifts.
Predictive & Ensemble Machine Learning	*MLP, SVM, Random Forest Regression*	[13], [11], [12], [21]	Applied to predict slope reliability, Factor of Safety (FoS), and ESG/carbon footprints.	Provides predictive early warnings for landslides and stability failures triggered by groundwater flux and extreme precipitation.
Physics-Informed & Generative AI	*PINNs, GANs, RAMMS, Generative Models*	[9], [14], [12], [6]	Modelling tailings dam failures, coal/gas outbursts, and synthetic geotechnical parameters.	Solves the data scarcity problem by simulating physical laws to predict 1000-year flood impacts and shifting thermal gradients in deep mines.
Digital Systems & Integrated Frameworks	*Digital Twins, Multi-modal Fusion, Scenario Logic*	[16], [1], [2]	Integrating multi-source data and creating digital replicas of mine sites to map long-term risks.	Enables strategic adaptation to water scarcity, permafrost thaw, and supply chain disruptions through 2100 climate projections.
Socio-Technical & Behavioural Models	*TAM, TOE, STS Frameworks*	[22], [18]	Analyzing the acceptance of AI in construction and managing knowledge within the organization.	Ensures organisational resilience by overcoming cultural resistance and retaining expertise needed for high-tech climate adaptation.

Table 4 shows how artificial intelligence techniques are used in the mining sector across the included studies, highlighting the respective authors, the nature of each application, and its impact on climate resilience and risk management. It shows how data-driven, deep learning, remote sensing, and hybrid AI approaches are used to enhance hazard prediction, early warning systems, environmental monitoring, and operational resilience in climate-sensitive mining environments.

4. Discussion

This section discusses the key findings of the review in relation to the research questions, situating the results within the broader literature on artificial intelligence, climate resilience, and risk management in the mining sector. The discussion presents empirical patterns across application areas, methodologies, challenges, and analytical frameworks, while highlighting implications for research and practice.

4.1. AI Applications for Climate Resilience and Risk Management in Mining.

The findings indicate that AI has been predominantly used in the mining sector to address climate-sensitive safety and environmental risks, particularly geotechnical instability, flooding, tailings failure, and underground hazard conditions[11], [14], [12], [17]. This pattern occurs because these hazards generate measurable signals from sensors, imagery, geotechnical parameters, rainfall records, and satellite data, making them suitable for machine-learning and deep-learning models. It also reflects the immediate safety and regulatory pressure faced by mines when slope instability, flooding, and underground hazards threaten workers, equipment, and production continuity.

However, the evidence also shows that AI adoption remains largely hazard-specific and reactive. Many studies use AI to detect or predict a particular hazard after relevant data become available, but fewer studies show how predictions are converted into decisions, responsibilities, escalation procedures, maintenance actions, evacuation triggers, or long-term adaptation plans. This weak integration with risk governance is a major limitation. If AI is used only for prediction, mines may receive accurate warnings without clear organisational mechanisms for acting on them, which can lead to delayed responses, false-alarm fatigue, low trust, and limited contribution to long-term climate resilience.

4.2. AI Techniques Commonly Employed

The review shows a clear dominance of machine learning and deep learning techniques across empirical studies. Supervised learning methods such as artificial neural networks, support vector machines, random forests, and gradient boosting are widely used for predicting and classifying slope stability, gas outbursts, and equipment failures[9], [11], [12]. Deep learning architectures, including convolutional neural networks, are particularly prominent in applications involving image-based analysis, sensor data streams, and satellite imagery[15], [16], [20].

More recent studies demonstrate growing interest in advanced techniques such as physics-informed neural networks, multimodal data fusion, digital twins, and explainable AI[9]. These approaches are important because climate-related mining risks are uncertain, data-scarce, and site-specific. Hybrid and explainable models can combine historical data with domain knowledge and physical constraints to produce interpretable outputs. Nevertheless, these advanced techniques remain underrepresented, suggesting that most AI implementations still priorities predictive accuracy over interpretability, transferability, governance integration, and operational usability[3], [6].

4.3. Challenges and Limitations in Applying AI for Climate Resilience

Several persistent challenges limit the effectiveness and scalability of AI applications for climate resilience in mining. Data-related issues emerge as the most significant constraint, with many studies reporting limited availability of high-quality, long-term geotechnical and climate datasets[9], [11], [12]. Inconsistent sensor performance, missing data, and noisy measurements reduce model reliability and hinder generalization across different mine sites[3], [16].

Climate uncertainty further complicates AI modelling, as increasing variability in rainfall patterns, flooding frequency, and extreme weather events reduces the predictive stability of historical data-driven models[1], [2], [14]. In addition, the high computational requirements of deep learning, physics-informed models, and multimodal data fusion pose barriers to adoption, particularly in resource-constrained mining operations[9], [16].

Human and organisational challenges are also evident. Limited model interpretability reduces trust among engineers and decision-makers[15], while false alarms in early warning systems contribute to operational skepticism[13]. User adoption issues, including resistance to new technologies and insufficient training, further constrain the practical deployment of AI solutions[18], [19]. These challenges highlight that technical performance alone is insufficient to ensure successful AI-enabled climate resilience in mining.

4.4. Mining Areas Benefiting Most from AI Applications

The results demonstrate that AI applications have delivered the greatest benefits in safety-critical mining areas, particularly open-pit slope stability, underground hazard detection, and tailings dam risk management[15], [11], [16]. These domains benefit from AI's ability to process large volumes of sensor and environmental data to identify early warning signals and predict failure scenarios[3], [16]

Environmental monitoring and flood risk assessment also show substantial benefits, particularly through the integration of remote sensing and geospatial analytics. In contrast, operational resilience areas such as predictive maintenance, asset reliability, and climate-adaptive production planning receive comparatively limited empirical attention[7]. This imbalance suggests that while AI has strengthened risk detection and hazard mitigation, its potential to enhance systemic operational resilience in mining remains underexplored.

4.5. Strengthening AI for Long-Term Climate Resilience in Mining

The findings highlight pathways to enhance AI's role in strengthening long-term climate resilience in mining. First, focus on hybrid models that combine machine learning with physical principles, domain knowledge, and climate science[9], [14]. Such approaches improve model robustness in changing climates and reduce dependence on historical data. Incorporating explainable AI enhances transparency and trust, helping engineers and managers understand and act on AI insights.[15]. Third, improved data governance, including standardized data collection, sensor interoperability, and site-to-site data sharing, is essential for supporting scalable AI solutions [3], [16]. Finally, the limited use of Information Systems and socio-technical frameworks in the reviewed studies highlights a critical gap in understanding how AI tools are adopted, integrated, and sustained within mining organizations. Addressing this gap requires interdisciplinary research that combines technical AI development with organizational, behavioral, and governance perspectives to support climate-resilient decision-making across the mining lifecycle.

Overall, these findings demonstrate that while AI has strong potential to enhance climate-related risk management in mining, its current application remains highly technical, fragmented, and hazard-focused. The literature needs to move beyond model-centered evaluation toward system-centered evaluation, in which AI is assessed by its ability to improve early warning, decision quality, organisational learning, accountability, and long-term adaptation. The framework proposed below addresses this gap by linking AI analytics to governance and socio-technical decision-making processes.

4.6. Proposed AI-Driven Climate Resilience Framework

The proposed framework, illustrated in Figure 5, addresses the gap between descriptive mapping and integrated resilience design. It is derived from the synthesis of the included studies and shows how AI can be embedded into climate-resilient mining practice. The framework has seven connected components: climate and mine data, AI analytics, explainable risk outputs, operational decision workflows, governance and data quality, socio-technical adoption, and resilience outcomes. The relationship between these components is important: data feed AI models; AI models produce explainable risk outputs; risk outputs trigger HSE, maintenance, and adaptation decisions; governance and socio-technical adoption support trust, validation, and sustained use; and resilience outcomes generate feedback that improves future data, models, and organisational practice.

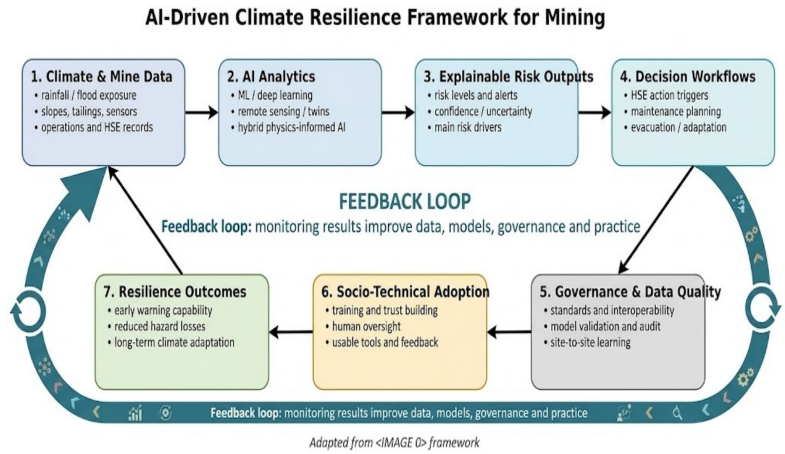

Figure 5. Proposed AI-driven climate resilience framework for mining.

The framework image/diagram used in this paper was generated with the assistance of Artificial Intelligence (AI) and edited by the author to fit the study context.

In this framework, AI does not operate as an isolated technical tool. It becomes useful for resilience only when predictive outputs are interpretable and connected to clear decision responsibilities. For example, a slope-failure probability or flood-risk score should be linked to predefined action thresholds, responsible personnel, communication channels, and post-event learning. This relationship addresses the main weakness found in the literature: AI can predict hazards, but organisational value is limited when predictions are not embedded in governance and operational workflows.

4.7. Summary of Answers to the Research Questions

RQ1: How has AI been applied in mining to enhance climate resilience and risk management? AI has mainly been applied to geotechnical monitoring, slope stability prediction, underground hazard detection, flood/climate risk assessment, tailings risk, environmental monitoring, and early warning.

RQ2: What AI technologies are currently being used? The dominant techniques are supervised machine learning, deep learning/computer vision, remote sensing analytics, digital twins, multimodal data fusion, and emerging hybrid or physics-informed AI models.

RQ3: What are the main challenges? Key challenges include data scarcity and poor data quality, site-specific model generalization, climate uncertainty, sensor integration, computational cost, black-box models, false alarms, user adoption, and weak governance integration.

RQ4: Which mining areas have benefited most? The strongest benefits appear in safety-critical and data-rich domains, especially open-pit slope stability, underground geohazard detection, flood-risk monitoring, and tailings-related risk assessment.

RQ5: How can AI be improved for long-term climate resilience? AI should be made more integrated, explainable, hybrid, and governance-oriented by connecting risk predictions to decision workflows, data standards, human oversight, and organisational learning.

5. Implications and Recommendations

The review has three main implications for mining practice. First, mining organizations should treat AI not only as a prediction tool but as part of a wider resilience system that includes data quality, model validation, explainable outputs, human oversight, and clear decision workflows. Second, climate-related AI systems should be connected to HSE procedures, maintenance planning, emergency response, and strategic adaptation plans so that predictions lead to timely action. Third, mines in data-constrained regions should priorities interoperable sensors, shared data standards, integration of remote sensing, and hybrid modelling approaches to reduce dependence on large historical datasets.

For research, the findings highlight the need for more empirical studies in climate-vulnerable mining regions, especially in Africa, and for mixed-methods research that examines how engineers, managers, and regulators understand and use AI outputs. Future work should validate the proposed framework through case studies, expert interviews, and mine-site implementation studies that assess not only model accuracy but also trust, usability, governance fit, and measurable resilience outcomes.

6. Research gap and potential contribution

6.1. Research Gap

The review identifies three gaps in AI applications for climate resilience in mining. The practical gap remains, as most AI tools are fragmented and hazard-specific, focusing on risks such as slope instability, flooding, or dam failure rather than supporting integrated resilience and risk management. These stand-alone solutions are rarely embedded into decision-making, risk governance, or long-term climate strategies, limiting AI's contribution to sustained resilience.

The gap is evident in the fact that few studies connect AI insights to resilience frameworks or theories. Lack of theory limits understanding of AI's role in organisational learning, coordination, and climate response. AI is often seen merely as a technical tool, with social and organisational influences ignored. Methodologically, most research uses single-method quantitative approaches, such as machine learning, with little integration of organisational, policy, or social insights. This restricts understanding of how decision-makers trust and use AI, hindering the development of effective, context-aware AI-driven climate strategies.

6.2. Potential Contribution

This study contributes to knowledge in three ways. First, it synthesizes recent empirical evidence on the current use of AI for climate resilience and risk management in mining. Second, it clarifies that the main limitation is not only technical performance but also weak integration between AI predictions, organisational decision workflows, governance, and socio-technical adoption. Third, it proposes a conceptual AI-driven climate resilience framework that bridges predictive analytics with data governance, explainable risk communication, HSE decision processes, and organisational learning. This contribution is therefore both review-based and conceptual: the paper maps the current literature and uses that synthesis to propose a framework for future validation.

7. Conclusion

This paper reviewed empirical studies on the use of artificial intelligence to improve climate resilience and risk management in mining. The evidence shows that AI is commonly used to address climate-related hazards such as slope instability, tailings failure, flooding, and underground safety risks through machine learning, deep learning, remote sensing, digital twins, and sensor-based predictive models. These applications have improved hazard detection, early warning, and short-term risk reduction in mining operations.

Existing AI applications in mining are fragmented, hazard-specific, and mainly focused on predictive accuracy and engineering. They overlook organisational integration, governance, and decision-making needed for climate resilience. The literature is skewed toward advanced regions, with little empirical evidence from climate-vulnerable areas like Africa.

The chapter highlighted ongoing issues like data scarcity, model generalisability, climate uncertainty, system interoperability, and user adoption. While emerging methods such as physics-informed modelling, explainable AI, and multimodal data fusion are promising, their use remains limited and uneven. The review also noted a lack of Information Systems and socio-technical frameworks guiding AI adoption for climate resilience in mining.

The paper therefore proposes an AI-driven climate resilience framework that combines climate and mine data, AI analytics, explainable risk outputs, decision workflows, data governance, socio-technical adoption, and resilience outcomes. This framework responds directly to the review findings by demonstrating how mining can shift from fragmented, reactive AI applications to integrated, proactive, and climate-resilient risk management. Future studies should validate the framework through mine-site case studies, expert evaluation, and implementation research in climate-vulnerable regions.

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