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(Review Article)

Ethical and Sustainable Deployment of AI for Critical Mineral Extraction in the U.S.: A Multi-Objective Optimization Framework for Advancing Energy Transition and Environmental Stewardship

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Abstract

The rapid development of renewable energy systems has created an unprecedented demand for critical minerals, which places the United States at a crossroads of energy security, environmental sustainability and social responsibility. Traditionally, mining has focused on production efficiency, often leading to extensive environmental damage, displacement of communities and worker safety concerns, thereby undermining long-term sustainability goals. This paper introduces a multi-objective optimization model that combines Artificial Intelligence with ethical considerations and sustainable development goals, which offers a rigorous approach to responsible critical mineral mining across the United States. The paper conducts a systematic literature review to examine five key areas: 1) the vulnerabilities of the critical mineral supply chain and its geopolitical implications; 2) the environmental and social impacts of conventional mining; 3) the role of Artificial Intelligence in the mining industry; 4) ethical principles guiding responsible AI management; and 5) multi-objective optimization of decision-support systems. Synthesis of recent empirical research shows that AI technologies improve ore-grade prediction accuracy by about 30 percent, however, geopolitical risks significantly influence mineral price volatility and supply stability. The analysis reveals that 54% of global mining operations are located on Indigenous land, often without permission and that by 2035, automation could displace 30-45% of the mining workforce. The proposed framework addresses the complex trade-offs among production efficiency, environmental protection, social equity and economic viability, using advanced optimization algorithms. These algorithms incorporate environmental monitoring, community impact considerations and regulatory compliance, which ensures comprehensive decision-making.

Keywords: Artificial Intelligence; Critical Minerals; Sustainable Mining; Energy Transition; Environmental Stewardship

1. Introduction

The rapid growth of renewables and electric vehicles has driven an insatiable appetite for key minerals, putting the United States at a critical juncture where energy security, environmental sustainability, and technological innovation intersect (Nassar et al., 2022). Critically, the minerals lithium, cobalt, rare earth elements and graphite are the foundation for solar panels and wind turbines as well as battery systems (and other clean energy technologies) that can help nations attain stronger climate goals while minimizing reliance on fossil fuels (Sovacool et al., 2020). The International Energy Agency forecasts that the demand for critical minerals may increase by 600% in some climate policy scenarios by 2040, and lithium and cobalt could rise up to 40 times and 25 times, respectively (IEA, 2021). But the US is also heavily reliant on mineral imports from geologically uncertain parts of the world, which creates an over-

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reliance on supply chains that could ultimately jeopardise its transition to clean energy (Fizaine 2023). The domestication of critical mineral production is a strategic necessity, as evidenced by the Biden Administration's prioritization of Inflation Reduction Act and the Defense Production Act, to build resilient supply chains that ensure long-term energy extraction security and provide an advantage in emerging clean technology markets (Habib and Wenzel, 2021).

The conventional mineral extraction processes have tended to emphasize production efficiency and low cost of mining, with less emphasis on environmental and social concerns, leading to extensive ecological degradation, community dislocation and threatened long-term sustainability. Traditional mining operations are commonly associated with high waste production, water consumption, greenhouse gas emissions and long-term impacts on local environments and indigenous communities (Northey et al., 2021; Valenta et al., 2019). Recent evaluations suggest that mining makes up for 4-7% of worldwide greenhouse gas emissions, and the production of copper and aluminum stands out as highly carbon-intensive (Azadi et al., 2020). The environmental burdens associated with conventional extraction practices have called into question the feasibility of increasing mineral production in order to satisfy expanding demand for clean energy technologies (Klinger, 2022). Land degradation, contamination of soil with metals and other toxic materials, pollution of water bodies, and deterioration of air quality are common impacts that mining may cause and because these can be long-lasting (decades at least), well past the life span of removal operations (Ali et al., 2022). The environmental externalities described above have facilitated more stringent regulation, local resistance and investor inquiry into the sustainability of conventional mining practices as they seek to decouple mineral production from environmental degradation (Church and Crawford, 2020).

The Artificial Intelligence (AI) technologies have promising opportunities to revolutionize the process of critical minerals extraction, enhancing accuracy, predictivity, and optimization of the multi-parameter environment of operations, which underlie the whole mining value chain. Machine learning can search large volumes of data collected as geological maps and satellite images, as well as sensor networks, to outline high-value mineral deposits more precisely than traditional exploration methods, thus minimizing the environmental footprint of exploratory drilling and site preparation (McCoy and Auret, 2019; Zhai et al., 2020; Minnoh, 2025). The latest developments in deep learning have demonstrated around a 30 percent improvement in the accuracy of ore grade predictions compared to the traditional geostatistical models (Li et al., 2021). The real-time optimization of extraction processes with the help of AI that constantly monitors the state of equipment, predicts their maintenance, and changes the operational parameters to achieve maximum efficiency, along with the minimum amount of waste generation due to intelligent resource allocation (Dutta et al., 2020). AI-controllable advanced robotics and autonomous systems can perform dangerous mining tasks in dangerous settings, reducing the amount of human contact with toxic compounds and making the work environment safer, which maintains consistent levels of operational efficiency (Paraszczak and Laflamme, 2022). In addition, AI-based environmental monitoring schemes allow assessing air quality, water quality, and ecosystem health as well as the effect on biodiversity in real time, which allows swiftly reacting to any ecological abnormalities and contributes to adaptive management, minimising ecological disturbance (Zhang et al., 2021).

Leading AI technologies in critical mineral mining should be steered by well-rounded ethical principles that ensure the preservation of the environment, community participation, human wellbeing, and sustainability in the long term rather than focusing on short-term economic benefits. Among the ethical aspects, it is necessary to provide AI systems with transparency, accountability, and their absence of algorithmic bias that may disproportionately affect vulnerable communities or cause the continuation of the social disparities present in the mining regions (Jobin et al., 2019; Ressesguier and Rodrigues, 2020). Any AI integration should acknowledge indigenous rights, traditional ecological knowledge and self-determination of communities and offer meaningful opportunities to the local population to participate in decision-making processes that have impacts on their territories and livelihoods (Owen and Kemp, 2023). The most important aspect is data privacy and security regarding the implementation of AI systems gathering confidential data on mineral resources, the ability to operate under specific conditions, and environmental conditions that may hold strategic or commercial importance (Wirth et al., 2020). Moreover, the ethical use of AI needs to be vigilant of the effects on labour markets, so that technological change brings benefits in terms of workforce development and fair transition programmes to help mining communities as operational practices become more and more automated and digitalized (Goger et al., 2022).

The study creates an all-encompassing multi-objective optimisation model to incorporate Artificial Intelligence capabilities with ethical considerations and sustainability goals to inform responsible critical mineral extraction in the United States. The presented framework deals with the multifaceted trade-offs between the efficiency of production, environmental responsibility, social justice, and economic feasibility by means of advanced optimisation algorithms that are able to simultaneously optimise on various competing goals and sets of constraints (Miettinen et al., 2021). This framework can help the mining operators to find the best suitable strategies that maximise the societal benefits and reduce the negative externalities by integrating real-time environmental monitoring data, community impact assessments, economic indicators and regulatory compliance requirements in the integrated decision models (Kumar et al., 2020). The study represents one of the increasing numbers of research on the topic of sustainable mining practices that offer practical tools and techniques that could be applied to various geological and regulatory contexts as well as community circumstances and will support advancing the nationwide goals of energy transition without sacrificing the utmost principles of environmental stewardship and social responsibility (Mancini and Sala, 2018; Mudd, 2019).

2. Literature review

This literature review focuses on the essential knowledge base for ethically and sustainably deploying Artificial Intelligence in the US critical mineral extraction. The review integrates studies in the areas of mining engineering, Artificial Intelligence, environmental science and ethics, as well as optimization methods to provide readers with an initial understanding of how each field can be linked. Based on a review of the literature and existing research findings under five major themes, this work reveals current knowledge gaps and illustrates how the proposed multi-objective optimization framework can significantly contribute to research and practice in sustainable mineral extraction.

2.1. Critical Minerals and the Global Energy Transition: Supply Chain Vulnerabilities and Geopolitical Implications

The rapidly increasing global transition to renewable energy technologies has stimulated the demand for strategic minerals, which is generating new dependencies on international supply chains and vulnerabilities that threaten both energy security as well as climate goals. This section discusses how geographic concentration of mineral resources, geopolitical uncertainties and trade relationships among major economies affect the stable supply and sustainable supply chains of critical minerals that are indispensable to the energy transition.

Research by Islam (2025) explores the bilateral mineral trade between the United States and China and how it affects the energy transition under pressures exerted by global value chains, geo-economic fragmentation and geopolitical risks. Their study used cross-quantilogram and wavelet local multiple correlation methods on a monthly dataset of monthly data beginning in January 2000 and ending in December 2023. The analysis shows that the bilateral mineral trade is positively correlated with clean-energy transitions in both nations in various market conditions. Their results indicated that the long-term adverse effects of the different risks to energy transitions using mineral exports are stronger than the risk dynamics over the short-term. Global geo-economic fragmentation risk has the most negative influence when compared to global value-chain risks and bilateral geo-political risks. In this regard, the research indicates that building good diplomatic relations and cooperation between the United States and China is necessary to reduce multifaceted world pressures and support a seamless mineral trade that would help in meeting the energy-transformation objectives.

Another study by Saadaoui et al (2025) explores how geopolitical risk affects the prices of six key minerals, which are: aluminum, copper, nickel, platinum, tin and zinc. They ask questions about the nature of the geopolitical risk in the price dynamics with constant-parameter and time-varying-parameter local-projection regression models. They found that the sensitivity of critical mineral prices to geopolitical risk depends on whether a particular resource has non-technical procurement risk. Importantly, their data showed that the influence of geopolitical risk on mineral prices is non-linear; there were considerable changes in response to such hallmark events as the Gulf War, 9/11 terrorist attacks and the COVID-19 pandemic. Moreover, the analysis shows that geopolitical threat-induced shocks tend to be larger than those associated with geopolitical action and that mineral prices are more responsive to the threat than to the actual action.

Similarly, Siddi (2023) adds that the energy transition in the Euro-Atlantic region is a geopolitical subject deserving a subtle exploration and analysis, especially in terms of new resources, technologies that are remaking the strategic situation. His research closely follows the chronicle of how the allocation of crucial raw components, including, but not limited to, rare earth components, lithium and cobalt, has emerged as a subject of global competition as they are now invaluable components of contemporary energy solutions. Siddi emphasizes that these materials are not distributed equally all over the globe, but rather, they are very geographically concentrated. This concentration has, in its turn, intensified competition among nation-states and corporate players in the quest to have access to these vital elements reliably. The implications are obvious: control over the supply chains of these substances will directly translate into a geopolitical impact on the process of energy transition. His study also argues that achieving an effective transition of a fossil-fuel-based economy necessitates the development of technological solutions for a new electrical grid and increased storage capacities. This is necessary to optimise how the renewable energy is generated and distributed, so that it remains resilient and efficient in a fast-changing market. Finally, Siddi assumes the energy transition will slowly change the conventional geopolitics of fossil fuels. Along with the increasing importance of decentralized energy production, a long-held monopoly will slow down as the conventional energy states transform, yielding to a new competitive landscape that focuses on how the most important raw materials, which comprise the energy systems of tomorrow, are acquired and managed.

Equally, Hira (2025) conducted a study using a realist model of political economics to examine the consequences of reliance on strategic minerals as a crucial strategic asset in the twentieth century, in a similar vein as the impact of petroleum resources. His critique argues that these minerals have an economic and security aspect and dependence on them is based on the geostrategic parameters that they share with fossil fuels. It also addresses how the shift to fossil fuels gives states a chance to develop new areas of the green economy by gaining the necessary inputs that would support the creation of a sustainable economy. His study contains the traces of the continued geopolitical rivalry over the dominance of the major sources of vital strategic minerals in sub-Saharan Africa and Latin America, together with the involvement of China in rare-earth reserves. Finally, his study suggests that, similarly to how the scramble for petroleum defined the international relations of the twentieth century, the current race towards strategic mineral resources will equally determine the future of global politics in the rest of the century.

2.2. Environmental and Social Impacts of Traditional Mining Practices: Challenges and Imperatives for Sustainable Extraction.

Traditional mining companies have subjected the environment to significant levels of environmental degradation over a continuum of ecological levels. Mining activities contribute to about 47 percent to 7 percent of the global greenhouse gas production, with the carbon-intensive rates of the production of aluminum, copper and other resistant metals being very high (Azabi et al., 2020). Mineral extraction and processing produce vast amounts of waste rock and tailings. Every year, the mining sector in the world generates more than 100 billion tonnes of waste, some of which consists of toxic materials that can contaminate soil and water for decades (Kinnunen and Kaksonen, 2019). Climate change acts as a significant threat multiplier, introducing new degradation mechanisms such as extreme precipitation, freeze-thaw cycles, thermal fluctuations, biogeochemical alterations, and drying/wetting cycles, which systematically weaken rock structures and increase instability risks (Armah et al., 2025). Acid mine drainage is one of the most insistent environmental problems. It happens when sulfide minerals that are exposed during the mining process react with water and oxygen to produce sulfuric acid that may leak into the watersheds around the mining areas (Simate and Ndlovu, 2014). The mining activities use massive amounts of fresh water. It consumes 23000-300000 percent of the world's water extraction, causing a heavy burden on the availability of water sources, specifically in arid areas where most of the mineral deposits are found (Northey et al., 2019).

The environmental consequences of the mining business are much deeper than mere pollution, as numerous habitats are destroyed and biodiversity is reduced significantly. As part of a full-scale evaluation, Sonter et al. (2020) concluded that over 57,000 square kilometres of land globally are directly impacted by mining activities. The indirect effects extend over even greater regions, e.g., land fragmentation and edge effects, or hydrological regimes. The mining activity is especially acute when located in the biodiversity hotspots. Empirical evidence suggests that mining concessions cover an area of about 50 million hectares in the overlap of the protected areas and important biodiversity areas (Rehbein et al., 2020). Surface mining activities that strip vegetation and topsoil essentially destroy complete ecosystems. Mining underground also creates surface subsidence and adjusts the movement of groundwater and creates empty spaces that may remain unchanged over time (Lèbre et al., 2020). In addition, deforestation comes with the mining access roads and other infrastructure construction facilities, which present further environmental costs. The examples of case studies in the Amazon basin show that deforestation caused by mining activities extends far beyond the direct extraction zones (Sonter et al., 2017). The overall environmental impact of the mining activities makes it quite apparent that the present mining activity cannot be sustained alongside the larger goal of global sustainability.

The mining system influences the levels of well-being and the rights of native peoples, and its traditional mining form has significant social aspects. Mining activities usually result in the forced eviction of the locals. According to recent estimates, a substantial number of people (ten to twenty million) are displaced by giant projects all over the world every year (Owen and Kemp, 2015). Indigenous people bear the disproportionately high cost of mining activities. Approximately half of the world's mining operations occur on or near indigenous lands, often being conducted without free, prior and informed consent (Kemp and Owen, 2013). Examples of health effects that are a result of mining exposure include respiratory illnesses that can be traced to dust and particulate matter. Communities also experience neurological damage because of heavy-metal pollution and the highest level of increased cancer rates (Basu et al., 2015). The economic dividends that are brought about by mining exercises are often inequitably shared. The local populations are compensated insignificantly, with most environmental and social damages being borne on their shoulders (Gilberthorpe 2015; Adukpo and Bethel, 2025). The role of gender in the mining industry is particularly high. Women are faced with increased domestic roles and also face the loss of employment and the erosion of traditional livelihoods, whilst employment opportunities are predominantly favoring men (Jenkins, 2014).

The historical occupational safety and health legacy of conventional mining still affects mines today, as it takes time to improve the working environment. Mining represents 1% of the labour force worldwide; however, mining contributes to 8% of fatal accidents at workplaces (ILO, 2020). Subsurface mining has its own unique challenges, such as the collapse of tunnels, explosions, or accidents with equipment. There are also long-term health effects to construction workers due to exposure to silica dust and diesel fumes (Donoghue, 2004). The proportion of miners with pneumoconiosis and other chronic respiratory diseases remains unacceptably high. Recent studies have reported an increase in CWP prevalence in some areas (Blackley et al., 2018). Psychosocial effects of mining work, like stress and anxiety, impact large proportions of the mining workforce (Bowers et al., 2018). The casualisation of the mining workforce and growth in the use of contractors have only served to weaken worker protections. These build the vulnerability of work to maximize cost and minimize concern for worker welfare (Franks et al., 2014).

There is now a body of evidence documenting both environmental and social disruption that creates a compelling imperative to fundamentally change the way we extract. The potential financial size of the environmental liabilities created by historic mining is believed to run into the hundreds of billions of US$ worldwide (i.e., Mudd, 2021). When one adds in the urgency of responding to climate change, the case becomes even clearer. Mining has to deliver more value by creating mutually beneficial partnerships with stakeholders and making further strides in both productivity improvement and technological innovation (Dowling, 2018). Legal standards in many countries do not cover the whole range of impacts that mining could have on local societies (Dashwood, 2012). Growing awareness that business-as-usual is not sustainable has aroused interest in technologies for transformation. This fact calls for the implementation of more advanced technologies like Artificial Intelligence in conjunction with holistic ethical frameworks to develop mining systems that are both productive and environmentally sustainable, but also socially fair (Lèbre et al., 2020).

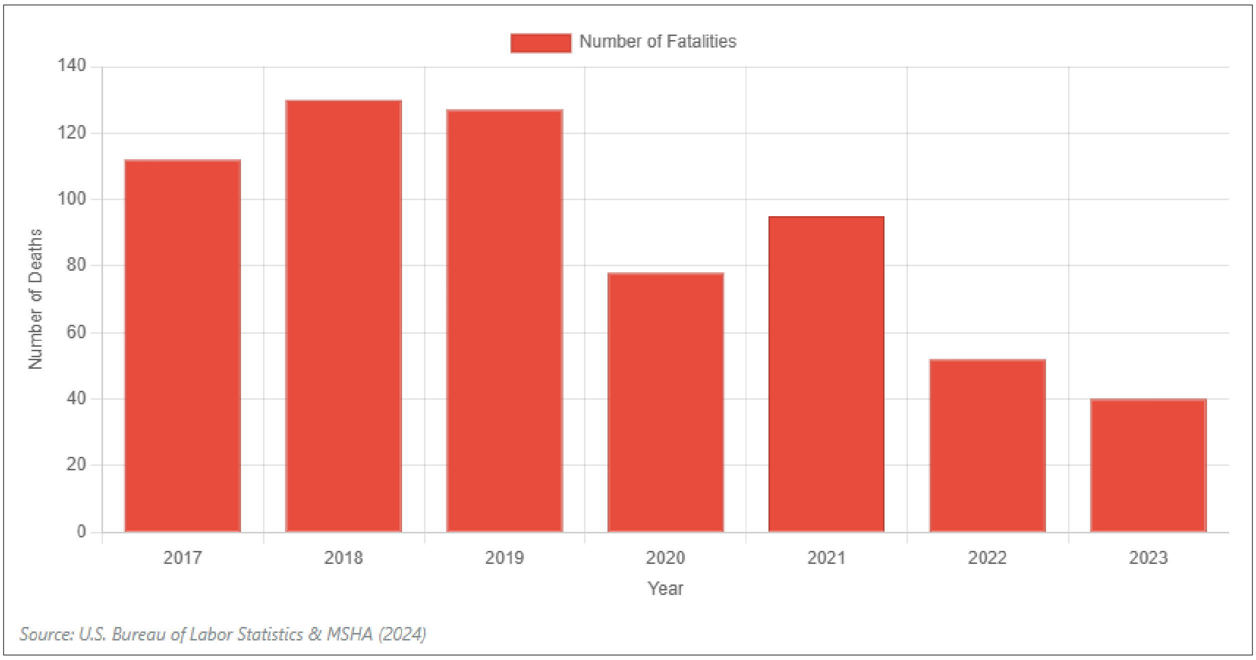


Figure 1 Environmental and Social Impacts of Mining in the United States

The chart reports annual U.S. mining workplace deaths by year from 2017 to 2023. Deaths reached a peak in 2018 with about 130 deaths, and they stayed high in 2019 before plummeting last year. After a temporary peak in 2021, deaths fell steadily in subsequent years to an average low in 2023 of about 40. On the whole, this trend signifies a progressive development towards better safety standards.

2.3. Artificial Intelligence Applications in Mining Operations: Current Capabilities, Technological Advances, and Performance Outcomes.

AI is changing mining operations, from better safety to improving opportunities for the workforce. Emerging technologies, including Machine Learning, Computer Vision and Predictive Analytics, have made it possible to monitor in real time and automate vital processes. These are applications that have delivered clear performance results from Nemours, such as lower operations risks, reduced costs and better resource allocation.

Ali and Frimpong (2020) have comprehensively reviewed the application of machine learning and AI in the mining industry as a whole. Their paper studies the current developments in the application of these new technologies, which are expected to lead to operational autonomy with intellect, touching on areas such as mineral prospecting and exploration, mine planning, equipment selection, underground or surface equipment operation, drilling and blasting, as well as mineral processing. Their work concludes that, except for some operational fields that have been working on new technologies, mining has not contributed much and is left behind in this innovation trend; although it starts to change with researchers taking up machine learning and Artificial Intelligence for enhancing current technologies. The authors define the present boundaries of technology development and point out deficiencies with current research. Recommendations are made for advancing current technologies through the application of deep learning, machine learning and Artificial Intelligence to allow for smart and intelligence-based common sense evolution in mining by which such innovation should set a new reference standard going forward towards the mine-of-the-future with efficient, effective and safer machines that support sustainable operations.

A study from Leung et al (2021) provides an overview of automation and Artificial Intelligence in surface mining, also focusing on open-pit operations in the Pilbara iron-ore province of Western Australia. Their paper gives an overview of engineering challenges, technology advances, robot development and automation results as they relate to mining. Principal mining activities, some of which are specific to resource development and mine, rail or port operations, are broadly categorized in 9 stages from mineral exploration to ore shipment such as geological assessment, mine planning/development, production drilling/assaying, blast/excavation, hauling ore/waste material transport/crush and screen operations/stockpile/load-out/rail distribution and ore-car dump. The purpose of their study is to portray this process and offer suggestions on challenges and opportunities based on the frame of reference of a decade-long industry-university RandD partnership. Their survey is intended to provide a picture of the technology landscape and identify challenges that engineering professionals should be aware of related to Artificial Intelligence (AI) and automation trends in mining.

A study carried out by Mutovina et al. (2025) discusses the role of Artificial Intelligence and machine learning in expert systems for the mining industry by reviewing the methods and technologies. Their study addresses the significant transformation of the mining industry in recent decades through the emergence of advanced technologies, including Artificial Intelligence and machine learning, that enable on development of expert systems supporting process optimization as well as ensuring greater safety and sustainability in operational aspects. Their research work examines different intelligent and expert systems aimed at productivity enhancement, cost-effectiveness to reduce operating costs, health and safety at workplace improvement, environment-friendly operation process (green production), machine automation control facilities, predictive maintenance program support features, quality monitoring and control implementation facility, as well as inventory management support facility in the logistics. Their study looks at the pros and cons of some different options and weighs up what impact they could have on the future of mining. Their paper demonstrates that integrating Artificial Intelligence and machine learning into mining operations results in better, safer and sustainable solutions.

Mutovina et al. (2025) provide a new literature review that narrows down to the disruptive role of Artificial Intelligence and machine learning in the mining industry within expert systems. The authors emphasize that these innovations are the ones that the design of the systems aimed at both simplifying the extraction processes and enhancing the safety of the operations and supporting the sustainability. Their study includes a systematic review of modern AI and ML systems and technologies that are currently being used in the mining industry and evaluates their effectiveness in improving different aspects of operations. Their broad survey brings to light the implementation of high-tech algorithms in the technical environment of the industry. The authors carefully examine how the technologies lead to productivity gains, reduction in costs, safety standards and stewardship of the environment via automation, predictive analytics and intelligent monitoring systems. Their discussion showed how AI-driven systems have multifaceted advantages in the contemporary mining practice. Their research concludes, ultimately, that the implementation of Artificial Intelligence and machine learning into the mining process represents a critical direction of the way towards more efficient, safer, and environmentally-friendly operations that can cater to the demands of sustainable development, at the same time being economically viable.

2.4. Ethical Frameworks and Responsible AI Governance in Resource Extraction: Principles, Challenges, and Implementation Strategies

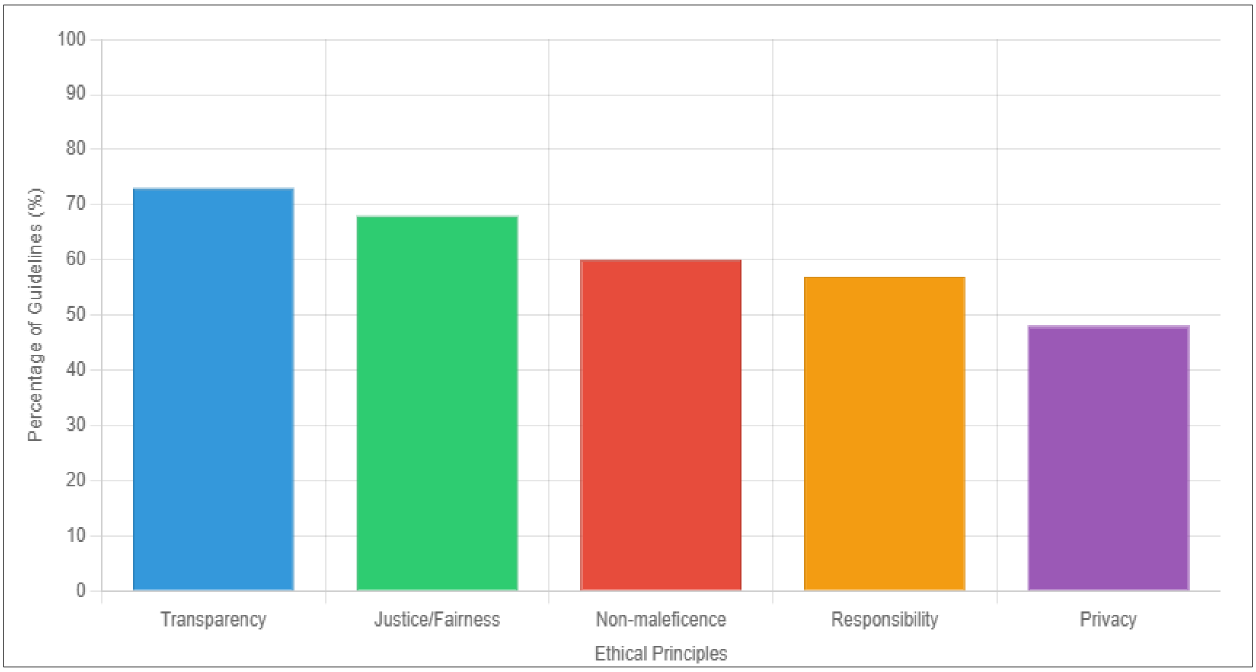
The implementation of Artificial Intelligence systems in the sphere of mining and other resource extraction implies the strong ethical frameworks that have to contend with the underlying issues related to fairness, transparency, accountability and protection of human rights. Jobin et al (2019) conducted a systematic review of 84 ethics guidelines on Artificial Intelligence worldwide and narrowed them down to five principles that keep reappearing in them: transparency, justice and fairness, non-maleficence, responsibility and privacy. Such principles present a skeleton of a framework of controlling Artificial Intelligence in the extractive industries, but their application in mining situations is unique, due to the complex network of stakeholder relationships, environmental risks and the effects on the communities living in the area. Floridi et al. (2018) argue that ethical AI frameworks should go beyond abstract principles and develop to find solutions to the tangible implementation issues. These issues are defined by how to make fairness operational in the decision-making of autonomous AI systems, mechanisms of accountability when autonomous systems make critical decisions and ensuring that human oversight continues to play a meaningful role and is effective in automated processes. Conceptually, these ethical imperatives are particularly sharp in the context of mining, with decisions being of high stakes and impacting on the safety of workers, at the environmental level and the well-being of communities. As a result, strong systems of governance are not negotiable-systems that can transform institutional principles into action.

Algorithmic transparency and explainability are fundamental ethical demands when it comes to AI applications in the context of resource extraction, but can be hard to reach due to technical and organizational barriers. Mittelstadt et al. (2016), who identify a multi-dimensional analysis of algorithmic accountability, such as epistemic dimensions about the transparency and interpretability of machine learning models, normative considerations around who is responsible for decisions executed by algorithms and finally, practical issues in explaining trade-offs raised between affordances offered to different stakeholders. In particular, the transparency of the mining industry is problematic as AI systems usually function in intricate sociotechnical scenarios featuring decisions using a set of interacting variables and uncertain results. The idea, supported by Wachter et al.'s (2017) proposal of the right to explanation, is that transparent decision-making does not simply consist of technically explaining why an algorithm made a decision P rather than Q; it also entails providing a satisfactory context capable of making stakeholders comprehend how autonomous decisions can consider their interests and values. This is particularly relevant in mining, where indigenous groups, environmental activists, workers and investors all have different information needs and ideas about what makes for a reasonable explanation. Recent studies by Selbst et al. (2019) have identified the phenomenon of fairness gerrymandering, where overly specific fairness measures in AI systems can sideline more fundamental issues concerning justice and equity, implying that transparency guidelines should pay attention to both technical performance and substantive ethical impact.

Indigenous rights, traditional ecological knowledge and community participation an inseparable aspect of responsible technology use in extractive industries that have increasingly become an important but often overlooked component of Artificial Intelligence governance frameworks. The principles of AI should be developed about indigenous data sovereignty as proposed by Kukutai and Taylor (2016), which ensures that the indigenous communities have a say on how AI is developed and used on their lands and that they can have control over the collection, analysis and use of such data. This crisis demands a break with its traditional stakeholder consultation approaches and towards more meaningful co-governance schemes, which provide indigenous people with decision-making power about the application of Artificial Intelligence. Whyte (2018) emphasizes that indigenous communities have highly developed knowledge regimes that were mastered throughout generations and they can greatly contribute to environmental monitoring and sustainability measurement. But these knowledge systems are still tainted or taken over in the technical decision-making procedures, a situation that requires immediate correction. Recent studies by Montana and Bainbridge (2020) show that Artificial Intelligence systems developed using participatory design strategies can address indigenous perspectives and values in a meaningful way. Yet these approaches entail long-term investments in relationship building, capacity building and power sharing-investments which many mining firms struggle to maintain. The implementation of this principle in the setting of Artificial Intelligence applications is a challenge in itself, and on which innovative methods of governance.

Data governance, privacy protection and security concerns in the field of Artificial Intelligence in mining are complex ethical problems that require a tradeoff between productivity and the preservation of individual and societal rights. According to Zuboff (2019), surveillance capitalism creates inherent conflicts between the collection of data in a commercial way and personal independence, which are issues that can be applied to a mining situation, where the Artificial Intelligence device is constantly collecting information about people, communities and nature. The mining sector generates enormous amounts of sensitive information, including geological data of market worth, operational data with security consequences, surveillance data of environmental importance and personal data regarding employees and community members that may have privacy implications. Pasquale (2015) shows how algorithmic transparency creates systems of black boxes where users facing Artificial Intelligence-based judgments have little ability to contest, understand, or rectify the mistakes and this issue is especially severe when vulnerable groups are being exposed to mining activities. Some recent privacy-preserving machine learning methods can offer a solution, but Veale and Binns (2017) warn that technical privacy protection should be supported by strong legal frameworks and institutional protection. This problem is particularly acute in foreign mining practice, where conflicting jurisdictions offer different data protection norms and where enterprises can be tempted to take advantage of any opportunities of regulatory arbitrage.

The ethical implications of labor rights, workforce transition and distributional effects of artificial-intelligence automation should be approached with great caution on the one hand, as they may contribute to increased injustice instead of human prosperity. As Acemoglu and Restrepo (2020) show, automation technologies have asymmetric impacts on workers, both between higher and lower workforce groups. These dynamics raise some important questions about the ability of just-transition policies that protect workers and populations as mining activities become increasingly automated in the mining milieu. Manyika et al. (2017) estimate that automation renders large segments of the mining workforce unemployed and, at the same time, provides new employment opportunities that demand new skills and, consequently, will have a strong need for investments in education, training and social safety nets. According to Kalleberg and Vallas (2018), the ethical issue is not with automation itself but with the fact that the productivity benefits of Artificial Intelligence are distributed equally instead of being concentrated in the hands of the owners of capital and highly skilled workers. Recent research by Korinek and Stiglitz (2021) suggests policy tools, such as robot taxes, universal basic income and profit-sharing schemes, to solve the problem of distribution, but the adoption of these measures in mining practice is faced with serious political and economic barriers. As a result, the moral requirement is to ensure that the implementation of Artificial Intelligence in mining promotes inclusive prosperity and community resilience, and not recreate or increase the existing inequalities.



Source: Jobin, Ienca and Vayena (2019)-Analysis of 84 AI Ethics Guidelines

Figure 2 Core AI Ethics Principles in Global Guidelines

2.5. Multi-Objective Optimization in Sustainable Mining: Methodologies, Trade-off Analysis and Decision Support Systems.

A study by Dudas et al (2014) integrates data mining methods into a multi-objective optimization algorithm for decision support in the development of production systems. Their study also focuses on the problem faced by a decision maker when he/she must select from many solutions in the Pareto front and they argue that current methods are not adequate when: a) The set of Pareto points is small and b) Alternatives near the efficient frontier have similar features. The authors present a distance learning data mining method for solution sets resulting from simulation-based optimization to solve them. Data mining and a multi-objective optimization procedure for efficient cost optimization are demonstrated by an industrial cost optimization example, highlighting how the proposed procedure can help decision-makers to analyze and visualize alternative design characteristics in various regions of the objective space. The results prove the importance of appropriate analysis/visualization methodology for supporting decisions in production system development, especially when introducing competing trade-offs as part of a multi-criteria problem.

Mattiussi et al (2014) have contributed a decision support system for sustainable energy supply in their research that uses multi-objective analysis in combination with multi-attribute applied to an Australian case study. In their proposed approach, the model combines a novel hybrid multi-objective decision-making and multi-attribute decision-making framework with impact assessment between emission outputs. A three-step model starting from the assessment of total emissions inventory and impacts is used for CO2 emission reductions, which is a multi-objective mathematical model considering both economic and environmental objectives in Pareto-frontier optimization analysis with the analytic hierarchy process (AHP) technique to select solutions that are efficient to the Pareto-frontier. They then applied the model to study a case in an eco-industrial park situated in the Kwinana Industrial Area, Perth, Western Australia and examined four scenarios where different combinations of combined heating power (CHP) and photovoltaic technologies were employed. They accordingly proved that employing multi-objective optimization techniques in combination with a suitable decision-making tool leads to an integrated framework for sustainable plant design and operation (which considers economic and environmental criteria simultaneously).

Another study by Qiu et al (2025) suggests the hybrid machine-learning and multi-objective optimization to improve the process of decision-making in Australian gold-mining activities. The study deals with the poor performance of traditional heuristics due to variances inherent to the process by the use of machine-learning models; in particular, the CatBoost regressor is used to predict such key performance indicators as ore processed, energy, cost and greenhouse-gas emissions. The CatBoost model optimized with the help of the Grey Wolf Optimizer provides decent predictive results, with an R2 of 0.978 to predict the intensity of greenhouse gas emission. Their study evaluates six bi-objective scenarios, which analyse the trade-offs between production-cost, production-energy, production-emissions, cost-energy, cost-emissions and energy-emissions by using this hyperparameter-optimised CatBoost model as the objective function in a multi-objective optimisation framework (implemented using the Constrained Two-Archive Evolutionary Algorithm). Their findings affirm the efficiency and expediency of the suggested composite strategy, thus providing a long-term course of action to streamline economic and environmental efficiency in the gold mining activities, as well as providing a sound infrastructure for the green mining operations.

A study by Gorzałczany and Rudziinski (2016) describes a process of creating fuzzy decision systems through a multi-objective evolutionary optimisation algorithm like NSGA-II, epsilon-NSGA-II, SPEA2 and its variation SPEA3. The authors support the fact that SPEA3 gives a more balanced distribution and a spread of solutions that is larger than those of SPEA2, with the choice of benchmark tests. The authors also present fuzzy rule-based classifiers with an accuracy-interpretability trade-off that is refined genetically, to take the place of a modern and effective tool in supporting intelligent decision making in a wide variety of application fields. To illustrate the practical usefulness of the proposed framework, their paper applies the model to the design of a credit-granting decision support system based on the Statlog German Credit Approval benchmark dataset, thus showing that antagonistic goals such as accuracy and interpretability can be balanced by multi-objective evolutionary optimisation. Their comparative study of several multi-objective evolutionary optimization algorithms has also shown that the choice of the optimisation scheme significantly affects the quality and distribution of the Pareto-optimal solutions, which highlights the importance of the selection of the algorithm in real-world decision support.

3. Conclusion

This paper reviews the use of Artificial Intelligence in conjunction with multi-objective optimization approaches applied to sustainable mining for critical minerals in the US. The review integrates studies in five major subject areas: critical mineral supply chain risks; environmental and social impact of classical mining; Artificial Intelligence in mining operation processes; ethical guidelines for responsible AI regulation; and multi-objective optimization. The results suggest that geopolitical fault lines and dependence on supply chains create risk of progress towards energy transition ambitions, while conventional mining operations are characterised by considerable environmental despoliation and social turmoil, which call for transformation. The findings revealed that Artificial Intelligence has the potential to improve the accuracy of exploration, increase efficiency in mineral/oil recovery and systems that can improve safety outcomes for workers, as well as real-time environmental monitoring, with 30 percent improvement shown in ore grade prediction so far. However, this means the AI system should be underpinned with strong ethics around algorithmic transparency, indigenous rights, data governance and fairness of returns to avoid exacerbating existing inequalities. The review also notes several gaps in the present state of research, which include a lack of fairness metrics that are operationalized across different stakeholder communities, a lack of ethical considerations incorporated early on into technical optimization frameworks, limited integration of indigenous systems knowledge and problems related to fair transition mechanisms for formally employed displaced labor. This is where the proposed multi-objective framework targeting optimization gaps as described previously comes into the picture by leveraging AI capabilities, ethical considerations and sustainability targets to ensure responsible decision making in a way that advances energy transition objectives being equally mindful about environmentally friendly and socially just critical mineral extraction activities.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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