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Artificial Intelligence in Energy Transition Mineral Exploration

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Abstract

This review explores the role of Artificial Intelligence (AI) in critical mineral exploration, examining key challenges and opportunities. Global decarbonisation efforts are driving a significant increase in the demand for critical minerals, intensifying the need to find new deposits, improve operational efficiencies and diversify global mineral supply capabilities. Challenges encountered in critical mineral exploration, such as increasingly complex geological settings in new exploration, declining ore grades and the need for sustainable practices, are calling for a more comprehensive analysis of a diverse set of aspects, including large geoscientific and economic datasets, as well as Environmental, Social and Governance (ESG) considerations. Traditional methods of analysing such extensive information are time-intensive, expensive and often result in lower predictability. This, combined with the growing need for faster and more accurate decision-making, has driven the adoption of innovative approaches such as AI-based techniques that bring vast amounts of multifaceted information into the analysis. Integrating AI applications in the exploration of critical minerals is bringing rapid transformation to the sector, driving new trends in the market dynamics. AI methodologies, Machine Learning (ML) and AI-enabled data analytics are improving the predictive modelling and automation of exploration studies and allowing enhanced decision-making capabilities. The shift towards data-driven strategies allows the use of both new and previously underutilised datasets owned by the companies, leading to better assessments of the project viability, more effective and rapid evaluation of a wide range of datasets for exploration potential and identification of opportunities for cost reduction. These advancements influence risk identification and management, bring strategic shifts in the critical minerals market and global supply chains and offer valuable insights to stakeholders shaping investment patterns. Challenges in the application of AI in critical mineral exploration include data requirements, technical complexity and ethical and regulatory concerns. Recognising AI's vast potential, extensive research and development efforts are underway, focussing on refining AI algorithms, developing novel approaches to integrate with geoscientific data, promoting collaboration between geoscientists and AI experts and addressing the ethical, regulatory and ESG considerations.

Keywords: *Artificial Intelligence, Critical Mineral, Energy Transition, Machine Learning*

1. Introduction

As the world transitions towards cleaner forms of energy, the increasing demand and rising prices have doubled the energy transition minerals market size in 2022 to USD320 billion compared to 2017. As per the International Energy Agency (IEA)[1], the average amount of minerals needed per power generation unit has increased by 50% since 2010 due to an increased share of renewables. Renewable technologies such as solar Photovoltaics (PV), lithium-ion batteries and wind turbines have become critical to energy transition, all requiring significant quantities of critical minerals. The transition towards cleaner energy systems is forecasted to be mineral and metal-intensive, resulting in the energy sector becoming a substantial player within mineral markets[2,3].



Figure 1. Pixabay. Solar panels on snow with windmill under clear day sky. Free Stock Photo [Internet]. Pexels. 2017 Available from: https://www.pexels.com/photo/solar-panels-on-snow-with-windmill-under-clear-daysky-433308/

As per IEA[2], to meet the Paris Agreement goals or keep the global temperature rise below 2 degrees would need quadrupling of mineral requirements for clean energy tech by 2040 and net-zero by 2050 would require a six fold increase in mineral inputs in 2040 than today.

1.1. Challenges to Mineral Exploration and Market Projections

Projections of demand and supply of critical minerals in the distant future have high uncertainty in estimates. While the International Renewable Energy Agency (IRENA)[3] mentions a relatively greater risk in mining and refining capabilities than the availability of reserves, other studies have estimated the demand for critical minerals to grow faster than known reserves, leading to supply shortages that can limit the rate of transition towards cleaner energy solutions[5,6].



Figure 2. Aleksandar P. Three yellow excavators near front end loader. Free stock photo [Internet]. Pexels 2018.

Declining ore grade quality puts pressure on costs as well as Greenhouse Gas (GHG) emissions, requiring these factors to be carefully considered during the economic viability evaluation of the projects for investment[8]. It has been reported that the increase of green energy production by 1% affects the 0.18% depletion of the Rare Earth Element (REE) reserve, while the known REE deposits are not sufficient for the required energy transition[9]. In addition, disruptive innovations add further uncertainties to the projections of future demand for critical minerals. For example, the evolution of electric vehicle battery chemistry has drastically shifted the demand for certain minerals[3].

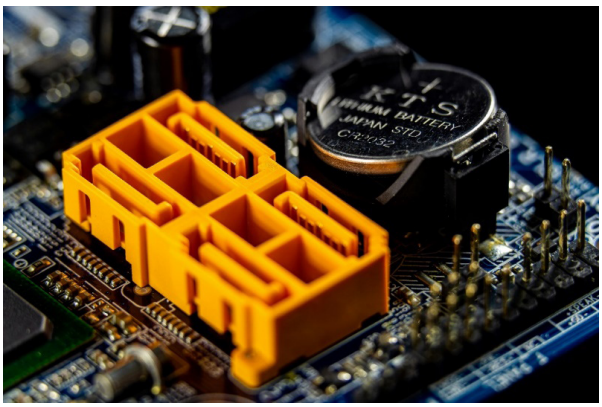


Figure 3. Sergei Starostin. Close-up view of an electronic circuit board. Free Stock Photo [Internet]. Pexels. 2021. Available from: https://www.pexels.com/photo/closeup-view-of-an-electronic-circuit-board-6636458/

Efficient exploration and extraction of critical minerals including rare earth minerals is vital to meet the increasing demand. Although metals and minerals are vital in mitigating the climate change risks from the utilisation of fossil fuels, their extraction often comes with land, water and air pollution and other challenges[11]. For example, copper and lithium are vulnerable to water stress due to their high water requirements. 80% of copper output in Chile comes from arid areas[12]. In addition, many copper-producing regions are susceptible to environmental risks such as floods or extreme heat. These could lead to spills of hazardous substances, resulting in environmental damage[13]. Along with climate-related challenges, economic development is a crucial factor due to the correlation between resource extraction and economic growth, with many mineral resource areas located in economically disadvantaged countries of the world[11].

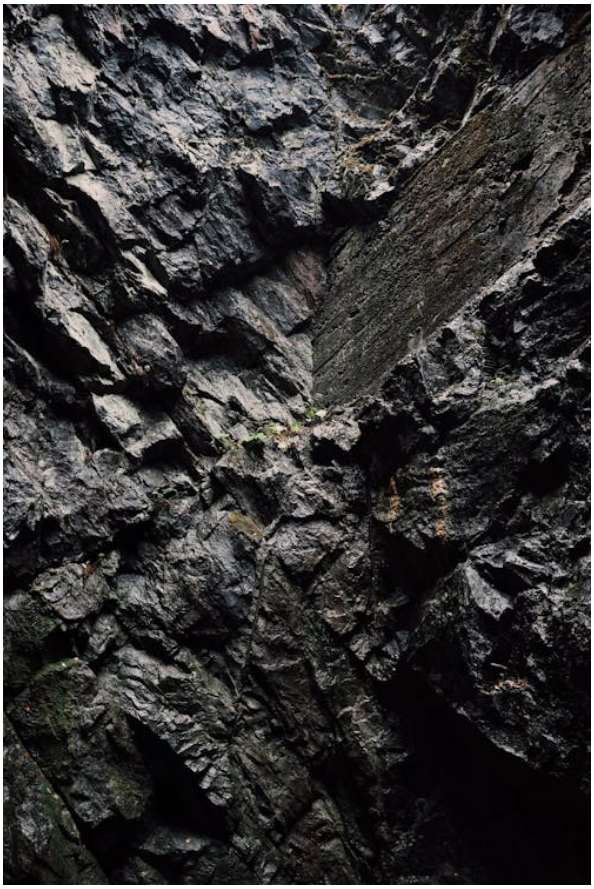


Figure 4. Kseniya K. Rough texture of a rock · Free Stock Photo
[Internet]. Pexels. 2023. Available from: https://www.pexels.com/photo/rough-texture-of-a-rock-18795070/

The current mining of energy transition minerals is concentrated in relatively few countries, increasing the exposure to geopolitical risks and possible supply chain vulnerabilities[3]. As per IEA's analysis of major mines between 2010 and 2019, the average lead times for exploration are currently more than 12 years and more than four years are needed for the construction phase[2]. Tightening scrutiny of ESG aspects is increasing the costs and supply chain[13].

Such a broad scope and multi-layered endeavour requires a wide range of data to be brought into the scope of evaluation for critical mineral resource strategy. Developments in AI-enabled solutions have shown promising potential for assimilating, analysing and identifying potential development options incorporating such a vast number of datasets while also helping to mitigate inherent risks[2].

This paper explores the opportunities and limitations of current AI applications in critical mineral exploration and addresses some of the key technical, regulatory and ethical challenges hindering the adoption of AI in the sector.

2. Methods

2.1. Review Approach

This review explores the relevant literature on the current trends and challenges of critical mineral exploration and how technological advancements, especially AI have been transforming the sector.

2.2. Role of AI

AI-enabled approaches have overcome several limitations faced by traditional mineral exploration methods[15]. Although there are challenges in the application of AI, including the requirement of suitable datasets, adequacy and transparency of AI models and the technical expertise of professionals in the sector, recent use of AI methodologies has shown the vast potential of such technologies[16]. For example, in the early stages of prospecting, AI has improved the ability to analyse economic and market conditions for investment. The processes, including reconnaissance of area of interest, analysis of large datasets of geophysical, geological, borehole logging and laboratory data and investigations of the identified prospects, have been made more accurate using AI-enabled applications.



Figure 5. Winstead T. Robot pointing on a wall · Free Stock Photo
[Internet]. Pexels. 2021. Available from: https://www.pexels.com/photo/robot-pointing-on-a-wall-8386440/

3. Results

3.1. Technological Advancements in Mineral Exploration

Mineral mining involves the phases of exploration, resource extraction and reclamation. Exploration consists of prospectively, identification of the mineral resource deposit locations, and analysis of its characteristics to assess the economic viability of production[11,18,19]. Exploration is a complex process that includes geological mapping, utilisation of geophysical data and drilling and the use of human expertise and extensive fieldwork[20]. Uncertainties of resource estimates from data and evaluation approaches lead to financial risks, which are often not adequately assessed.

Several advances in mineral exploration over the past decades have brought improvements in the ability to identify mineral resources and evaluate their economic potential. Out of these, the notable ones are as follows[20-23]:

- Progress in economic geology, such as the concept of ore genesis, transport and trapping mechanisms.
- Breakthroughs in the application of geophysical techniques such as airborne gravity, airborne gravity gradiometry, airborne electromagnetic and 3D electric and electromagnetic surveys.
- Multispectral remote sensing, GIS.
- Geochemical analysis.
- Unmanned and remotely operated vehicles.
- Advancements in computer systems and innovations such as AI.



Figure 6. Kelly. Birds eye view of river in countryside. Free Stock Photo [Internet]. Pexels 2024. Available from: https://www.pexels.com/photo/birds-eye-view-of-river-incountryside-23848569/

3.2. Current and Potential Use of AI in Mineral Exploration

The advent of technology and evaluation methodology has brought ever-increasing volume of data. The availability of massive multi-modal mineral exploration datasets worldwide provides both opportunities for resource discovery and poses the challenge of managing and analysing this data[25]. AI approaches have enabled the extraction of valuable insights by integrating such vast amounts of data, optimising drilling programs and improving mineral identification processes[26].

3.3. Evolution of AI Methodologies in Mineral Exploration

The application of AI in mineral identification evolved during the development of rule-based expert systems for data interpretation during exploration. Some examples of such expert systems included BIOMARKER, a system to evaluate depositional environments from the geochemical analysis of molecular parameter interpretation, which showed 96% accuracy against a test data set, INTERSTRAT that used X-ray diffraction data for identification of interstratified clay minerals, VIDES, a visual identification system for microfossils and expert systems to determine prospectively of lead, zinc, iron and barium mineralisation using modelling of basing dewatering[27]. However, these systems were limited by the way knowledge was stored and extracted from the database to be used by the inference engine, the two parts of the expert system. With substantial improvements in computer systems and the development of advanced techniques such as Machine Learning (ML), applications of AI systems have further grown into the different phases of mineral exploration.

Besides expert systems, fuzzy logic and various ML algorithms have been applied to mineral exploration, bringing significant prediction and knowledge integration capabilities[25].

3.4. Machine Learning

Machine Learning, a field of AI, consists of developing algorithms that can learn from data and perform a task[29]. Several ML algorithms, such as supervised, unsupervised and reinforcement learning are utilised for different

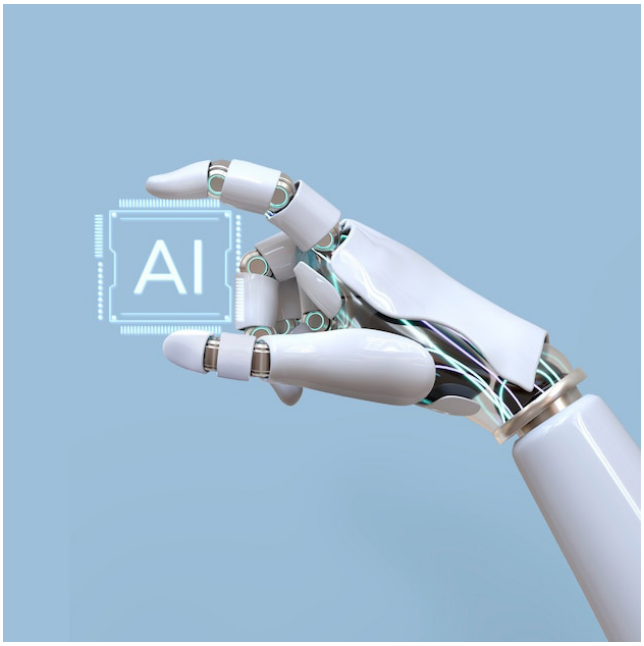


Figure 7. Free Photo. AI chip artificial intelligence, future technology innovation [Internet]. Freepik. 2021. Available from: https://www.freepik.com/free-photo/ai-chip-artificialintelligence-future-technology-innovation_17850485. htm#fromView=search&page=1&position=1&uuid=8fa1eb92-c07a-4c30-80b9-4dd8f5c3f0da

problems such as regression, classification, association, clustering and control[30-32] (Figure 8).

3.5. Opportunities Presented by AI Methodologies

AI approaches such as ML, predictive analytics and system automation are improving various stages of the mineral life cycle. With the growing prevalence of AI-driven technologies in mineral exploration, there is an increasing trend towards data-driven decision-making, leading to enhanced exploration strategies and operational efficiencies. These approaches are improving efficiencies and helping to reduce environmental footprints from mineral exploration and extraction.

3.5.1. Enhanced Data Analysis

ML approaches, including supervised and unsupervised learning methods, have been able to unravel patterns from data that could be overlooked in traditional workflows. There is a large amount of data, often unused within organisations that could lead to efficiencies on several fronts. AI methods such as ML are bringing new capabilities to analyse these data, identify trends and issues and even predict potential threats well before they occur,

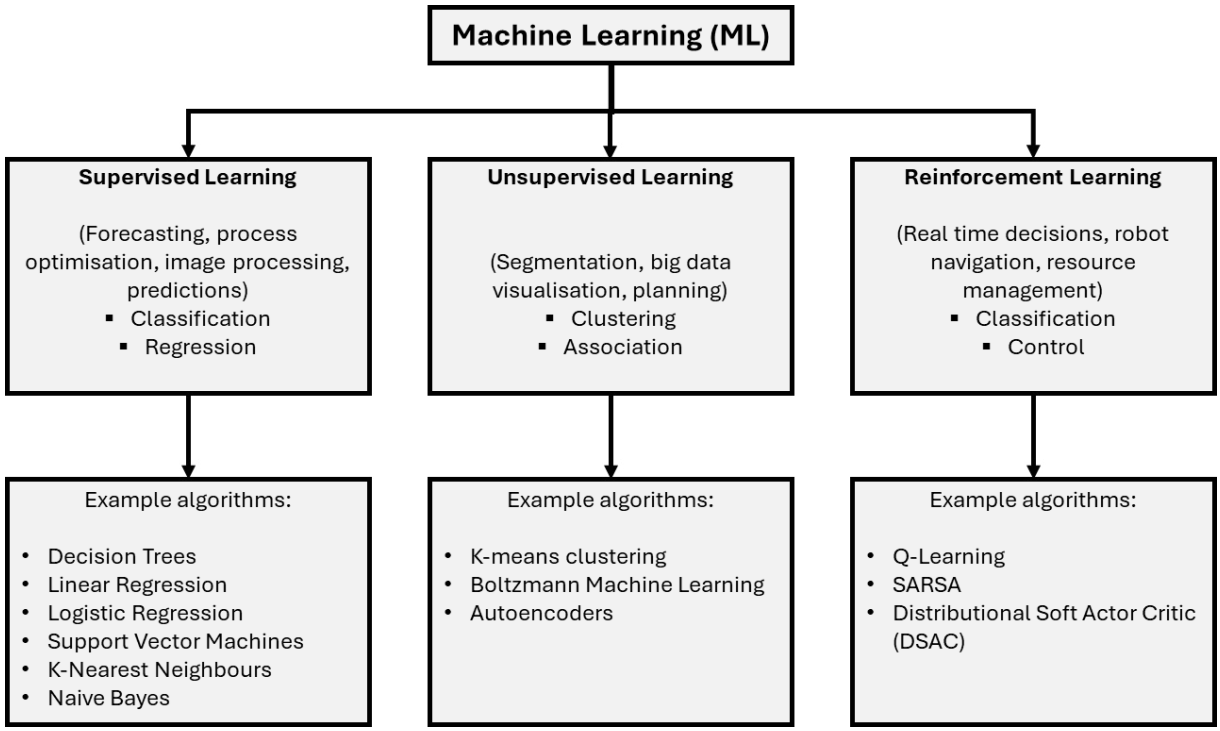


Figure 8. Overview of ML approaches[29-32].

leading to predictive maintenance. Such vast datasets also allow companies to create digital twins of their assets that can be used to test and monitor operational aspects of the physical equipment and lead to considerable improvements in safety and efficiency[33].

3.5.1.1. Example Cases

Some recent applications of ML include algorithms to prospect for ore deposits using geological datasets through Artificial Neural Networks (ANN), Decision Trees (DT), Support Vector Machines (SVM) and random forests. Advanced techniques such as convolutional neural networks have been used to analyse geological and remote sensing data[34,35]. Data from drilling and measurements have been collected, shared and analysed using ML models such as SVM.[34].

Generative adversarial network algorithm-based techniques have been used to create prospectivity maps of mafic-ultramafic intrusion-hosted mineralisation for Cobalt, nickel and chromium[36].

Python-based decision support systems and applied supervised ML methods such as SVM, DT, K-Nearest Neighbour (KNN) and logistic regression have been applied to large critical mineral datasets from the Critical Minerals Mapping Initiative (CMMI) to identify major and trace elements, lithologies, mineral features, textures and other deposit characteristics[37].

Unsupervised ML approaches such as Self-Organising Maps (SOM)-driven workflows have been used to identify exploration targets for REE from carbonate-alkaline complexes in Shillong Plateau and Western Rajasthan in India[38]. Deep learning techniques, including polygon feature extraction from geospatial databases using the U-Net model, have been used to assess critical minerals from historical maps, facilitating a significant reduction in time and effort compared to manual analysis and manual digitisation[39].

3.5.2. Predictive Modelling

Mineral exploration consists of evaluating various geoscientific and logging datasets to delineate new, undiscovered targets. AI allows the development of advanced predictive models that can forecast the presence of mineral deposits and provide effective predictive management during extraction based on available historical data. These models can optimise exploration efficiency by focusing on the areas with the highest potential.

Predictive modelling of prospective mineral targets has gained interest through current advancements in spatial modelling and ML algorithms, such as Random Forest (RF), SVM, ANN and deep learning convolutional neural networks, which have been able to reveal previously identified as well as missed anomalies[40]. ML algorithms have been applied in remote sensing-derived hydrothermal alternation data for copper exploration[41].

3.5.3. Automation

AI-driven automation has shown improvement in various exploration tasks such as surveying, data collection and automating remote surveys such as autonomous drones with AI capabilities in challenging environments. AI-augmented vision can automate mineral classification from rock samples, bringing efficiencies and precision over manual identification. AI has been used in diamond businesses to sort and dispose of waste by combining sensor and X-ray data, improving the diamond recovery process[42]. The integrated use of intelligent systems, computational frameworks and hybrid technologies enables automation to address several specific tasks in mining exploration[43]. The use of drones with sensors such as UAV, mobile LiDAR and drone photogrammetry has significantly improved the selection of areas for stockpiling and potential exploration corridors[44].

3.5.4. Real-Time Data Analysis

AI technologies are facilitating real-time data processing and analysis enabling geoscientists and engineers to make informed decisions while operating, improving operational efficiency and allowing decision making in case of unexpected results. The collection of real-time data from newly exposed surfaces utilising aerial data is enhancing the understanding from the conventional cores enabling improved prediction capabilities[45]. The integration of camera and sensor data from mines with AI for surveillance operations is being used to reduce the environmental impact of mining.

3.5.5. Collaboration

Sharing large amounts of data and expertise among different organisations is fostering innovation in this sector.

4. Discussion

4.1. Emerging Market Trends

As per globaldata.com[46], the global market size of AI in mining has grown at a Compound Annual Growth Rate (CAGR) of 10.0% from $634 million in 2019 to $767.9 million in 2021. As companies adopt more AI-enabled approaches to mineral exploration and economic assessment of the endeavour, AI brings value to complex tasks such as mineral commodity price forecasting and market study. From the automation of many roles by AI, it has been predicted that AI may replace many human labour-intensive as well as accuracy-demanding tasks in the coming decade, resulting in productivity gains that could alleviate part of the shortfall of critical minerals[47].



Figure 9. Energepic.com. Close-up photo of monitor. Free Stock Photo [Internet]. Pexels. 2016. Available from: https://www.pexels.com/photo/close-up-photo-ofmonitor-159888/

Out of the econometric and stochastic models, time series methods, chaos theory and ML approaches, ML methods show one of the highest accuracies in critical mineral price forecasting using past data. However, further work is ongoing, and improvements in ML are being explored for more complex patterns[44]. The energy security and global energy transition have led countries to ensure access to critical minerals. Due to the several advantages of AI in mineral exploration, this is taking centre stage in improving the affordable domestic supply of critical minerals and REE.

4.2. Challenges and Limitations

Existing challenges and potential limitations in the application of AI and ML in mineral exploration include technological, behavioural, regulatory and ethical factors. Addressing these challenges is crucial to the success of AI integration into sustainable energy transition mineral exploration.

4.2.1. Technology

The technological challenges of the application of AI in the critical mineral sector have been discussed in several relevant sections of this review. The AI-driven technology is still evolving, and case-specific development is often necessary in terms of relevancy appropriateness and adequacy of training data for the models.

4.2.2. Risk Perception of AI vs Proven Methodologies

Due to the capital-intensive nature of mining, the industry is inclined towards time-tested methods compared to newly evolving methods that require advanced technological skills to evaluate, implement and critique.

4.2.3. Regulatory Aspects

The regulations surrounding AI-driven technologies are still evolving, which can be challenging to navigate, delaying projects.

4.2.4. Ethical Considerations

With the increasing use of AI-enabled tools in the critical mineral mining sector, ethical considerations are coming to the forefront of discussions, such as autonomy and observation, balance and rewards, bias and prioritisation and explain ability and acceptance[49].

4.3. Future Research Directions

The number of datasets and factors involved in effective critical mineral exploration is increasingly becoming too large for manual interpretation, and AI has proven to be significantly valuable in this aspect. However, the various challenges of AI, such as poor generalisability, physical inconsistencies and difficulty in tracking the inherent working of the algorithms, have opened the potential for research and development to address these aspects. These,

in turn, are being applied to the specific requirements of different types of energy transition minerals[25,31,50,51].

5. Conclusion

In conclusion, the rising global demand for critical minerals, their importance in the energy transition and the geopolitical dynamics due to the geographical concentration of resource capabilities in specific regions highlight the essential value of critical mineral exploration to meet the energy transition strategy. The considerable advantages of AI approaches, including increased exploration efficiency, cost reduction and enhanced ESG monitoring capabilities are positioning AI as a key driver in critical mineral exploration and creating a more diverse and competitive market, contributing to greater stability in supply chain management. Despite the noteworthy benefits of AI in mineral exploration, challenges such as data quality and adequacy, integration of different geoscientific information, domain-specific expertise requirement, risk-averseness of organisations to use new technologies and ethical and regulatory complexities hinder the application of AI to its full potential. However, ongoing collaboration between the mineral industry, technology sector, regulatory bodies, investors and research organisations is driving technological innovation, presenting substantial potential for enhancing the benefits of AI in critical mineral exploration and mining.

6. References

1. IEA. Critical minerals market sees unprecedented growth as clean energy demand drives strong increase in investment - News [Internet]. IEA. 2023. Available from: https://www.iea.org/news/critical-minerals-market-sees-unprecedented-growth-as-clean-energy-demand-drives-strong-increase-in-investment
2. IEA. Executive summary - The role of critical minerals in clean energy transitions - Analysis [Internet]. IEA. 2021. Available from: https://www.iea.org/reports/the-role-of-critical-minerals-in-clean-energy-transitions/executive-summary
3. IRENA. Geopolitics of the energy transition: Critical Materials [Internet]. www.irena.org. 2023. Available from: https://www.irena.org/Digital-Report/Geopolitics-of-the-Energy-Transition-Critical-Materials
4. Pixabay. Solar panels on snow with windmill under clear day sky · Free Stock Photo [Internet]. Pexels. 2017 Available from: https://www.pexels.com/photo/solar-panels-on-snow-with-windmill-under-clear-day-sky-433308/
5. Calderon JL, Smith NM, Bazilian MD, Holley E. Critical mineral demand estimates for low-carbon technologies: What do they tell us and how can they evolve? Renew Sustain Energy Rev. [Internet]. 2024; 189:113938. https://doi.org/10.1016/j.rser.2023.113938
6. Review of critical metal dynamics to 2050 for 48 elements. Resour, Conserv Recycl. [Internet]. 2020; 155:104669. https://doi.org/10.1016/j.resconrec.2019.104669
7. Aleksandar P. Three yellow excavators near front end loader · Free stock photo [Internet]. Pexels. 2018.
8. Ulrich S, Trench A, Hagemann S. Gold mining greenhouse gas emissions, abatement measures, and the impact of a carbon price. J Clean Prod. 2022; 340:130851. https://doi.org/10.1016/j.jclepro.2022.130851
9. Golroudbary SR, Makarava I, Kraslawski A, Repo E. Global environmental cost of using rare earth elements in green energy technologies. Sci Total Environ. 2022; 832:155022. https://doi.org/10.1016/j.scitotenv.2022.155022
10. Sergei Starostin. Close-up view of an electronic circuit board · Free Stock Photo [Internet]. Pexels. 2021. Available from: https://www.pexels.com/photo/close-up-view-of-an-electronic-circuit-board-6636458/
11. Corrigan CC, Ikonnikova SA. A review of the use of AI in the mining industry: Insights and ethical considerations for multi-objective optimisation. Extr Ind Soc. 2024; 17:101440. https://doi.org/10.1016/j.exis.2024.101440
12. Negrete M, Fuentes M, Andrzej Kraslawski, Irarrazaval F, Sebastián Herrera-León. Socio-environmental implications of the decarbonisation of copper and lithium mining and mineral processing. Resou Policy. 2024; 95:105135. https://doi.org/10.1016/j.resourpol.2024.105135
13. Lee J, Bazilian M, Sovacool B, Greene S. Responsible or reckless? A critical review of the environmental and climate assessments of mineral supply chains. Environ Res Lett. 2020; 15(10):103009. https://doi.org/10.1088/1748-9326/ab9f8c
14. Kseniya K. Rough texture of a rock · Free Stock Photo [Internet]. Pexels. 2023. Available from: https://www.pexels.com/photo/rough-texture-of-a-rock-18795070/
15. Sánchez F, Hartlieb P. Innovation in the mining industry: Technological trends and a case study of the challenges of disruptive innovation. Mining Metall Explor. [Internet].

2020; 37. Available from: https://link.springer.com/article/10.1007/s42461-020-00262-1. https://doi.org/10.1007/s42461-020-00262-1
16. Savage N. Breaking into the black box of artificial intelligence. Nature [Internet]. 2022 Mar 29; Available from: https://www.nature.com/articles/d41586-022-00858-1 https://doi.org/10.1038/d41586-022-00858-1
17. Winstead T. Robot pointing on a wall · Free Stock Photo [Internet]. Pexels. 2021. Available from: https://www.pexels.com/photo/robot-pointing-on-a-wall-8386440/
18. Ali D, Frimpong S. Artificial intelligence, machine learning and process automation: Existing knowledge frontier and way forward for mining sector. Artif Intell Rev. 2020; https://doi.org/10.1007/s10462-020-09841-6
19. Sharma LK, Gupta R, Pandey PC. Future aspects and potential of the remote sensing technology to meet the natural resource needs. Advances in Remote Sensing for Natural Resource Monitoring. 2021 Jan 22;445-64. https://doi.org/10.1002/9781119616016.ch22
20. Okada K. A historical overview of the past three decades of mineral exploration technology. Nat Resour Res. 2020; 30:2839-60. https://doi.org/10.1007/s11053-020-09721-4
21. Agterberg FP, Bonham-Carter GF, Cheng QS, Wright DF. Weights Of evidence modelling and weighted logistic regression for mineral potential mapping. 1994; 132:13-32. https://doi.org/10.1093/oso/9780195085938.003.0007
22. Boardman J, Biehl L, Clark R, Kruse F, Mazer A, Torson J, *et al*. Development and implementation of software systems for imaging spectroscopy. 2006; https://doi.org/10.1109/IGARSS.2006.510
23. Tappert M, Rivard B, Giles D, Tappert R, Mauger A. Automated drill core logging using visible and near-infrared reflectance spectroscopy: A case study from the Olympic Dam IOCG deposit, South Australia. Econ Geol. 2011; 106(2):289-96. https://doi.org/10.2113/econgeo.106.2.289
24. Kelly. Birds eye view of river in countryside · Free Stock Photo [Internet]. Pexels. 2024. Available from: https://www.pexels.com/photo/birds-eye-view-of-river-in-countryside-23848569/
25. Yang F, Zuo R, Kreuzer OP. Artificial intelligence for mineral exploration: A review and perspectives on future directions from data science. Earth Sci Rev [Internet]. 2024 Nov;258:104941. Available from: https://www.sciencedirect.com/science/article/abs/pii/S0012825224002691 https://doi.org/10.1016/j.earscirev.2024.104941
26. Exploring the potential of artificial intelligence and machine learning in mineral exploration: A review article. Int Res J Modern Eng Technol Sci. 2023.
27. Wadge G, Vidler P. Expert systems: Can they aid geological interpretation and evaluation? J Geol Soc. 1992; 149(1):149-9. https://doi.org/10.1144/gsjgs.149.1.0149
28. Free Photo. AI chip artificial intelligence, future technology innovation [Internet]. Freepik. 2021. Available from: https://www.freepik.com/free-photo/ai-chip-artificial-intelligence-future-technology-innovation_17850485.htm#fromView=search&page=1&position=1&uuid=8fa1eb92-c07a-4c30-80b9-4dd8f5c3f0da
29. Sarker IH. Machine learning: Algorithms, real-world applications and research directions. SN Computer Science [Internet]. 2021;2(3):1-21. Available from: https://link.springer.com/article/10.1007/S42979-021-00592-X https://doi.org/10.1007/s42979-021-00592-x
30. Morales EF, Escalante HJ, Torres-García AA, Reyes-García CA, Villaseñor-Pineda L, Mendoza-Montoya O. Chapter 6 - A brief introduction to supervised, unsupervised and reinforcement learning [Internet]. Science Direct. Academic Press; 2022; 111-29. Available from: https://www.sciencedirect.com/science/article/abs/pii/B9780128201251000178
31. Ezugwu AE, Ikotun AM, Oyelade OO, Abualigah L, Agushaka JO, Eke CI, *et al*. A comprehensive survey of clustering algorithms: State-of-the-art machine learning applications, taxonomy, challenges and future research prospects. Eng Appl Artif Intell. 2022; 110:104743. https://doi.org/10.1016/j.engappai.2022.104743
32. Dev P, Jain S, Kumar Arora P, Kumar H. Machine learning and its impact on control systems: A review. Mater Today. Proceedings. 2021; 47:3744-9. https://doi.org/10.1016/j.matpr.2021.02.281
33. Hazrathosseini A, Moradi AA. The advent of digital twins in surface mining: Its time has finally arrived. Resour Policy. 2023: 103155. https://doi.org/10.1016/j.resourpol.2022.103155
34. Acosta ICC, Khodadadzadeh M, Tusa L, Ghamisi P, Gloaguen R. A machine learning framework for drill-core mineral mapping using hyperspectral and high-resolution mineralogical data fusion. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing. 2019; 12(12):4829-42. https://doi.org/10.1109/JSTARS.2019.2924292
35. Agrawal N, Govil H. A deep residual convolutional neural network for mineral classification. Adv Space Res. 2022; https://doi.org/10.1016/j.asr.2022.12.028

36. Farahbakhsh E, Maughan J, Müller RD. Prospectivity modelling of critical mineral deposits using a generative adversarial network with oversampling and positive-Unlabelled bagging. Ore Geol Rev. [Internet]. 2023; 162:105665. Available from: https://www.sciencedirect.com/science/article/pii/S0169136823003815 https://doi.org/10.1016/j.oregeorev.2023.105665
37. Davarpanah A, Babaie HA, Crawford EW, Banda JM. Analysis of the critical minerals datasets through machine learning [Internet]. AGU - AGU23. AGU; 2023. Available from: https://agu.confex.com/agu/fm23/meetingapp.cgi/Paper/1317941
38. Aranha M, Porwal M, González-Álvarez I. Unsupervised machine learning-based prospectivity analysis of NW and NE India for carbonatite-alkaline complex-related
39. Luo S, Saxton A, Bode A, Mazumdar P, Volodymyr Kindratenko. Critical minerals map feature extraction using deep learning. IEEE Geoscience and Remote Sensing Letters [Internet]. 2023; 20:1-5. Available from: https://ieeexplore.ieee.org/document/10236599 https://doi.org/10.1109/LGRS.2023.3310915
40. Sun T, Li H, Wu K, Chen F, Zhu Z, Hu Z. Data-driven predictive modelling of mineral prospectivity using machine learning and deep learning methods: A case study from Southern Jiangxi province, China. Minerals. 2020; 10(2):102. https://doi.org/10.3390/min10020102
41. Muhammad Ahsan Mahboob, Celik T, Bekir Genc. Predictive modelling of mineral prospectivity using satellite remote sensing and machine learning algorithms. Remote Sensing Applications Society and Environment. 2024 Nov 1;36:101316-6. https://doi.org/10.1016/j.rsase.2024.101316
42. Using artificial intelligence for mineral processing and exploration [Internet]. AZoMining.com. 2022. Available from: https://www.azomining.com/Article.aspx?ArticleID=1678
43. Leung R, Hill AJ, MelkumyanA. Automation and artificial intelligence technology in surface mining: A brief introduction to open-pit operations in the Pilbara. IEEE Robot Autom Mag. 2023; 2-21. https://doi.org/10.1109/MRA.2023.3328457
44. Ghosh R. Applications, promises and challenges of artificial intelligence in mining industry: A review. Tech Rxiv. 2022. https://doi.org/10.36227/techrxiv.21493761.v1
45. Gonçalves I, Frigo E. Towards AI-driven real-time deposit modelling: A case study in southern Brazil, EGU General Assembly 2024, Vienna, Austria, 14-19 Apr 2024, EGU24-6515. https://doi.org/10.5194/egusphere-egu24-6515
46. www.globaldata.com. Available from: https://www.globaldata.com/data-insights/mining/market-size-of-artificial-intelligence-in-mining/
47. Vespignani J, Smyth R. Artificial intelligence investments reduce risks to critical mineral supply. Nat Commun. [Internet]. 2024 Aug 24;15(1). Available from. https://doi.org/10.1038/s41467-024-51661-7
48. Energepic.com. Close-up photo of monitor. Free Stock Photo [Internet]. Pexels. 2016. Available from: https://www.pexels.com/photo/close-up-photo-of-monitor-159888/
49. Corrigan C, Laye P. The Use of AI in the mining industry - Insights and ethical considerations [Internet]. 2022. https://www.ieai.sot.tum.de/wp-content/uploads/2022/12/Dec-2022_-AI-and-Mining-Research-Brief_FINAL.pdf
50. Zuo R, Cheng Q, Xu Y. *et al*. Explainable artificial intelligence models for mineral prospectivity mapping. Sci. China Earth Sci. 2024; 67:2864-75. https://doi.org/10.1007/s11430-024-1309-9
51. Woodhead J, Landry M. Harnessing the power of artificial intelligence and machine learning in mineral exploration- Opportunities and cautionary notes. SEG Discovery. 2021; (127):19-31. https://doi.org/10.5382/Geo-and-Mining-13