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Cutting-edge Global Technologies for Extraction and Processing of Critical and Strategic Raw Materials: A Review

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Abstract: To some extent, each country defines critical minerals differently, but in general, they are strategic commodities that have no substitutes, that are mined and processed in a similar way in the relevant regions of the world, and that encompass the raw materials needed to produce advanced technological products such as renewable energy equipment, electronics, batteries, and electric vehicles. In recent years, the global mining industry has had to deal with increasing public pressure to adopt more sustainable practices and to cope with growing environmental and social demands. The rise of digital transformation, fuelled by advances in artificial intelligence, blockchain, big data, the Internet of Things, robotics, 3D printing, nano- and biotechnology, quantum computing, network algorithms, machine learning, and other emerging technologies, presents a unique opportunity for the mining industry to innovate and improve its productivity. These technologies can enhance operational efficiency, reduce environmental impact, improve the sustainability of production chains, and encourage more responsible resource extraction.

Keywords: Critical raw materials, Technologies, Mining, Extraction, Processing

Introduction

In recent years, the demand for critical and strategic raw materials has been steadily growing, due to the role of these raw materials in the production of clean energy, modern digital technologies, defence industry equipment and modern technological products. Other key drivers influencing the increased demand for these elements are the escalating geopolitical tension, environmental regulations and the emerging resource nationalism in recent months. Therefore, ensuring a secure, sustainable and efficient supply of these important critical and strategic raw materials is becoming a national and global priority.

Table 1. Global lithium production by country (Statista.com, 2025)

Country	Metric tons
Australia	88,000
Chile	49,000
China	41,000
Zimbabwe	22,000
Argentina	18,000
Brazil	10,000
Canada	4,300
Namibia	2,700
Portugal	380

Raw materials containing lithium, cobalt, nickel, rare earth elements, which are essential for the production of batteries for electric cars, wind turbines, semiconductors, and at the same time have some other applications in the high-tech sector, have been in particular demand recently (European Commission, 2023). This growing demand is reflected in the global distribution of lithium production, which also underscores the strategic dominance of a limited number of countries in the supply chain (Table 1).

The geopolitical implications of lithium resource concentration are underscored by this data, which also highlights the urgent need for technological innovation and the deployment of advanced methods to ensure supply chain resilience. In a similar vein, silicon-another critical raw material essential for semiconductors, electronics, and clean energy systems-warrants close examination. Understanding its global production landscape is equally crucial for assessing supply chain security and technological readiness (Table 2).

Table 2. Global silicon production by country in 2024 (Statista.com, 2025)

Country	Production (1,000 metric tons)
China	7400
Russia	520
Brazil	390
Norway	300
Kazakhstan	137
Malaysia	130
France	110
Iceland	90
Bhutan	80
Germany	60
India	60
Canada	50
South Africa	50
Spain	45
Australia	40
Poland	30
Other countries	208

The overwhelming concentration of silicon production in a small number of nations, as indicated in Table 2, emphasizes the significance of technological innovation and digital resilience to lessen reliance and enhance strategic autonomy. Some traditional methods of raw material extraction and processing, such as the well-known energy-intensive approaches of pyrometallurgy and hydrometallurgy, have recently begun to be considered environmentally and economically unsustainable (Ali et al., 2017). In this regard, it is quite logical that scientific research and subsequent industrial innovations are directed towards more advanced modern technologies such as bioleaching, extraction of materials with ionic liquid solvents, deep-sea mining, resource modelling using AI technologies, as well as some plasma separation systems (Binnemans et al., 2013; Padinhattath et al., 2025; Quijada-Maldonado et al., 2020; Saldaña et al., 2022, 2023) Although these new technologies are quite young, they are still promising and can bring better efficiency, reduce the environmental footprint of activities, and also provide an opportunity to use such unconventional sources as electronic waste and tailings.

Major global strategic frameworks, such as the European Raw Materials Alliance Declaration and the US Department of Energy’s Critical Materials Strategy, also emphasize value chains that need to be developed through the introduction of modern innovation in supply chains. At the same time, the importance of taking into account the principles of the circular economy and the use of extracted resources in a closed loop to ensure sustainability is also emphasized. According to the declaration of the European Raw Materials Alliance, raw materials are crucial for European industrial ecosystems, contributing over €2 trillion in added value and employing more than 30 million Europeans. They are essential for achieving the European Green Deal and the EU's green and digital transitions (European Raw Materials Alliance (ERMA), n.d.). For its part, the US Department of Energy's Critical Materials Strategy has a goal to foster scientific innovation and develop technologies that will ensure resilient and secure critical mineral and material supply chains independent of resources and processing from foreign processing and resource control (U.S. Department of Energy, n.d.).

These initiatives are designed to lessen EU reliance on important critical raw materials from third countries and to gain the US increased capacity for domestic production for reasons of national security and economic sustainability. The ERMA and DOE projects are designed to support creation of a more sustainable and environmentally responsible supply chain for critical minerals by focusing on sustainable sourcing and reuse technologies and policies. Technologies that enable low-emission recovery, enhanced traceability, and adaptive mining systems are not only altering the technical environment but also the geopolitics of raw material access.

As demand for these materials grows, especially for technologies like electric vehicles, renewable energy, and high-tech electronics, the development of advanced and sustainable methods of extraction and processing become increasingly important.

Objective and Research Question:

The objective of this review is to identify, categorize, and critically assess cutting-edge technologies for the sustainable extraction and processing of critical and strategic raw materials. The analysis focuses on evaluating their sustainability, scalability, and compatibility with digital transformation and climate objectives, with particular attention to advanced robotics, artificial intelligence, and automation systems as core enablers of Mining 4.0. Emerging methods such as bioleaching, ionic liquids, deep-sea mining, and plasma separation are also considered in the background scope. Ultimately, reducing dependence on critical materials and creating resilient industrial ecosystems depends on the successful development, testing, and deployment of these innovations in industrial activity.

Guided by this objective, the central research question addressed in this paper is: What are the most promising emerging technologies for sustainable and efficient extraction and processing of critical and strategic raw materials, and how do they align with global digitalization and environmental goals?

Method

We conducted a structured narrative review drawing on Scopus, Web of Science, ScienceDirect and IEEE Xplore for the period 2010–2025 (emphasis on 2020–2025). The search strategy combined three main dimensions: materials such as lithium, rare earth elements, cobalt, nickel, and silicon; technologies including advanced robotics, artificial intelligence, and automation systems; and, as a background scope, emerging methods such as bioleaching, ionic liquids, deep-sea mining, and plasma separation. To ensure alignment with sustainability considerations, additional qualifiers were used, including life cycle assessment (LCA), energy and water use, technology readiness level (TRL), and scale-up potential. Database searches were complemented with backward and forward citation chasing as well as authoritative reports from standards bodies and government agencies.

Sources were included if they were peer-reviewed or otherwise authoritative, contained explicit process descriptions, and were directly relevant to the extraction or processing of critical or strategic raw materials. Excluded were purely conceptual papers without process detail, duplicate publications, and superseded reports. Rather than aiming for exhaustive count-based screening, we applied theoretical saturation and triangulated evidence across multiple sources for each technology. For every case, we extracted information on the input material, process type, Technology Readiness Level (TRL 1–9), application scale (laboratory, pilot, demonstration, or industrial), and sustainability indicators such as energy demand, water consumption, reagent use and toxicity, recovery rates, and waste generation. A quantitative meta-analysis was not feasible due to heterogeneous reporting; therefore, results were synthesized thematically and summarized in a TRL × sustainability scorecard.

Cutting-edge Technologies for Extraction and Processing Operations

The cutting-edge technologies for mining and processing of critical and strategic raw materials, which are discussed in this chapter, include three distinct categories – high-tech robots, artificial intelligence and advanced automation systems. Their application in industrial practice can lead to increased efficiency, on the one hand, and safety of mining operations, on the other. The introduction of such technologies in mining has the potential to revolutionize the industry by reducing costs, increasing productivity and, last but not least, minimizing environmental impact.

In this regard, resource engineering is gradually but steadily entering a new transformative era thanks to new generation technologies for mining and processing of raw materials important for industrial independence. In addition to improving operational efficiency and basic safety, advances in high-tech robots, artificial intelligence and advanced automation systems are leading to the rationalization of value chains throughout the mineral industry. To optimise the extraction and processing of critical materials, which processes are characterized by high complexity and labour intensity, the introduction of new digital technological tools into operation is essential.

Advanced Robotics in Harsh Environments and Safety

In recent years, there has been a wider application of robotic systems in practice, especially in dangerous and inaccessible environments, which include deep underground mines, oceanic crusts and polar regions. To increase the safety of exploration activities in such areas, exploration robots are used, the application of which helps to improve monitoring and, accordingly, minimize the risks to the lives of personnel. At the same time, such robots are particularly applicable in the study of underground galleries, in which chemical leaks may occur, and the same applies to ensuring the safety of archaeological excavations (Liu et al., 2015). Complex robotic systems used in mining operations are usually equipped with modern equipment, including cameras and sensors for collecting information, which allows the transmission of real-time feedback to the operators serving them. At the same time, modern robots can be programmed to work independently and also be guided remotely, as these capabilities improve productivity and safety in the work environment. Automated robotic systems are undergoing constant development and over time become more complex and sophisticated, integrating the latest hardware and software innovations, resulting in improved operational efficiency and reliability. These robotic systems increasingly integrate artificial intelligence, enabling real-time situational assessment and autonomous decision-making based on sensor data (Kokkinis et al., 2024). Some of the devices now also have built-in artificial intelligence, which allows them to make their own assessment of the current situation and make independent decisions based on real-time data analysis. Research data shows that the implementation of automated mining systems in practice leads to improvements in overall operational productivity, while at the same time significantly reducing the possibility of human error.

For example, the Minebot (see Figure 1), which was developed at the University of Leeds, has the ability to reconfigure itself to the environment in which it is located and is designed specifically for underground exploration with the option to pass through narrow boreholes. The weight of the robot is about 2.7 kg, which allows it to function in tunnels up to 200 m long.

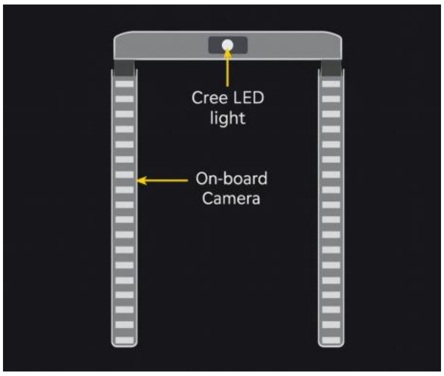

Figure 1. Schematic visualization of the fully deployed configuration of the *Minebot*, created by the authors based on technical descriptions and imagery in Liu et al. (2015).

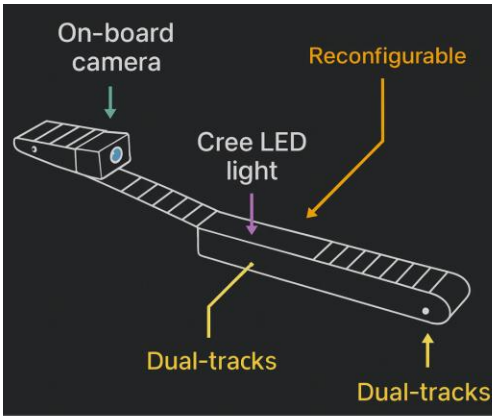

Figure 2. Schematic visualization of the Minebot in snake-like configuration, created by the authors based on technical descriptions and imagery in Liu et al. (2015).

The specialized design allows it to move on two rails and the so-called snake-shaped transformation (see Figure 2), through which the robot is able to overcome various obstacles (Liu et al., 2015). Optionally, this robot, as well as others in its class, can be equipped with 3D ceramic-packaged multifunctional sensors, intelligent navigation systems and an adaptive high-speed wireless network, which allows it to both communicate with the surface and make decisions autonomously based on collected real data. The high level of autonomy and adaptability of this Minebot robot makes it a valuable tool for effective and operational underground exploration.

By taking on dangerous tasks such as navigation, mapping and manipulation, autonomous robots designed for underground mining environments aim to improve safety. One such robot, named Julius (named after engineer Julius Ludwig Weisbach), is designed for underground operations. It uses a UR5 robotic arm (see Figure 3), sophisticated optical sensors and a four-wheeled mobile platform to communicate with the IoT infrastructure and control smart sensor boxes (SSBs).

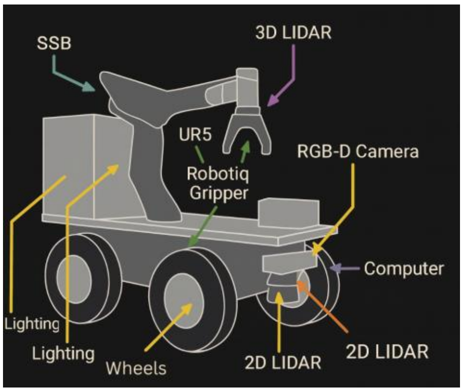

Figure 3. Schematic visualization of the Julius robot, created by the authors based on technical descriptions and imagery in Lösch et al. (2018).

Visual odometry and sophisticated sensor fusion are used to ensure more accurate navigation in the difficult-to-navigate underground passages, as GNSS signals are not available at such depths. Initial tests have yielded good results and show that the robot can navigate autonomously even in the presence of mud in the passages, while also being able to create 2D occupancy grid maps when the relevant area is sufficiently well lit (Lösch et al., 2018). The mapping results that the robot demonstrates are encouraging given the challenges that the dark and humid and almost liquid environment presents. The robot's operating time reaches three to four hours, and its compact design allows it to reach extremely narrow trenches or gaps. With the help of a robotic arm, the robot's manipulation capabilities are also increased, which gives it better chances of effective interaction with the components of the surrounding intelligent infrastructure. Such and similar systems will be essential for the development of Mining 4.0, as scientists' efforts are aimed at generally improving the autonomous functionality of robots, the precision of navigation controllers, and improving manipulation capabilities for working in complex, inaccessible and dangerous environments.

To improve further the autonomy and safety of robotic platforms in similar challenging environments, advanced terrain understanding becomes paramount. A major factor in this is traversability analysis-how a robot can evaluate and estimate the navigability of a terrain through sensory input and modelling techniques. Therefore, traversability analysis is an integral part of advanced robotics in harsh environments that directly impacts the safety and efficiency of UGVs. Xue, Fu, Xiao, Fan, Zhao & Dai (2023) proposed a new LiDAR-based terrain modelling method that gives a solution to problems posed by complex terrains-rugged off-road environments. Unlike traditional single-frame methods, the proposed approach exploits multi-frame information fusion through Normal Distributions Transform (NDT) mapping to produce stable and complete models of the terrain. Spatial-temporal Bayesian Generalized Kernel (BGK) inference and bilateral filtering further improve accuracy as well as edge preservation in predicting terrain elevation—apparently important for unobserved regions to be modelled reliably. Geometric connectivity between cells in the terrain is used in analysing traversability with an evaluation and an assignment of travel costs; therefore, slopes, ditches, and road curbs are distinguished from one another. Experiments with available datasets and in custom off-road scenarios show much better performance—state-of-the-art realtime modelling of terrain plus traversability analysis. The generated cost maps provide richer information for path planning. It allows UGVs to select safer and more efficient routes (Xue et al., 2023). It improves the robustness of autonomous navigation in dynamic and unstructured environments. Besides, it contributes a lot to enhancing operational safety. This is a valuable advancement in robotics for harsh environments. Future work will focus on negative obstacle detection and computational efficiency improvements.

LiDAR-based terrain and traversability model utilising may have valuable applications in mining since mines are generally located in rough terrains and require vehicles to be operated remotely for safety as well as efficiency. The laser scanning allows enough time of assessment of the setup environment of the mine despite several adverse challenges (Kumar Singh et al., 2023). Providing better accuracy in drilling, mapping, and ore handling, these autonomous and semi-autonomous robots keep human operators out of harm's way. Robotic platforms can map ore bodies in real-time with minimal disturbance to surrounding geology by being equipped with LIDAR as well as multispectral sensors. These robots are capable of navigating through hazardous, confined spaces that are unsafe for people to enter. By boosting output and lowering worker risks, this technology is completely changing the mining sector. Employing robots to perform these duties can also help businesses cut down on downtime brought on by safety concerns and the expenses related to accidents and injuries. All things considered, the use of semi-autonomous and autonomous robots in mining operations is opening the door to a more secure and productive sector.

In summary, advanced robotics improve operational safety and efficiency in challenging mining environments by enabling remote monitoring, autonomous navigation, and manipulation. However, limitations remain in terms of cost, robustness, and scalability, which require further research and development.

Artificial Intelligence and Automation Systems for Predictive Mining and Mineral Processing

Artificial intelligence has significantly enhanced predictive maintenance in the mining and mineral processing industry. Machine learning algorithms can facilitate the prediction of equipment failure, optimise scheduling of maintenance activities, and improve operational performance. Structured data from sensors together with unstructured data like logs of previous maintenance activities are used in current predictive models for estimating the Remaining Useful Life (RUL) of equipment (Dayo-Olupona et al., 2023). Lessons under supervised learning and unsupervised learning as well as deep learning include anomaly detection and fault diagnosis as well as degradation pattern prediction. For instance, Random Forests and Neural Networks among other ML models have given high accuracies towards predicting failures related to equipment and optimisation of maintenance strategies. Internet-of-Things (IoT) integrated with cyber-physical systems leads to real-time monitoring while digital twins enable support for proactive maintenance planning. Challenges about data quality, cost-effectiveness, and scalability remain even with all these advancements. Future research should therefore focus on model adaptability, external factors, and real-time decision-making to unleash the full potential of AI in predictive maintenance. This will drive the mining industry to work better, have less downtime, and operate sustainably.

Beyond artificial intelligence, advanced automation systems—including autonomous haulage systems (AHS), automated drilling rigs, and robotic inspection drones—are also reshaping the mining landscape (Cerna et al., 2023). These systems, integrated with AI analytics, enable round-the-clock operations, improve workplace safety, and reduce human error. Automation hardware combined with predictive software tools ensures not only efficiency but also the agility required to respond to changing geological conditions and operational demands.

The training of powerful artificial intelligence requires high-quality, consistent, and comprehensive datasets. The mining industry, however, mostly works with fragmented and noisy data. In addition to this, the cost of implementing the AI solution –hardware and software plus the skilled personnel to operate– will impose a big burden on small operations. Another problem is scalability: when built at a particular site but then applied to different geological conditions and different operational environments. Further study should first focus on creating adaptable AI models capable of learning external factors including environmental variations, market dynamics, and regulatory constraints. This will facilitate real-time decision-making supported by AI to enhance predictive maintenance in reducing downtime and achieving optimal utilization of resources. With the help of cloud computing development joined to IoT and digital twins, AI will assist in real-time monitoring as well as immediate adjustments in mining operations; thus improving cost-effectiveness and scalability in different mining scenarios (Yang et al., 2024). Therefore, such a challenge has to be accomplished toward more sustainable, efficient, resilient practices through the full potential breakthroughs promised by AI in predictive mining and mineral processing.

Artificial Intelligence and Machine Learning have already proven their considerable potential in the sphere of predictive mining and mineral processing by enhancing data analysis and decision-making capabilities. Indeed, ML techniques could be applied at any stage within the scope of mineral exploration activities, starting from a regional-scale targeting exercise down to resource definition with the use of complex geoscientific datasets—geochemical, geophysical, or hyperspectral (Davies et al., 2025). For instance, Random Forest algorithms have so far been among the best performers in geological parameter prediction as well as mineral prospectivity mapping exercises when compared to other ML models in terms of accuracy and computational efficiency. It is important to note, however, that the usability of ML tools depends on the interdisciplinary cooperation between geoscientists and data scientists through novel techniques applied to prepare data as well as human creativity in addressing special complexity in geoscientific challenges. Technological development amalgamated with human expertise is essential for attaining sustainable exploration success and improvement in discovery rates of critical mineral deposits.

Artificial intelligence (AI) has made a practice of being used as a revolutionary tool in predictive mining as well as mineral processing by throwing unique solutions for optimisation and consistency improvements. Applications of AI to concentration of minerals have thus far exhibited immense potential with gravity-based separation, density-based separation, magnetic and electric separation, and sensor-based sorting. Neural networks (NNs), support vector machines (SVMs), and random forests (RFs) (Gomez-Flores et al., 2022). Machine Learning models have so far been applied in prediction concerning grading, recovery, or efficiency in separation. Since multilayer perceptron NNs are supervised learning models that were used to predict recoveries in Falcon concentrators they can be used for the optimisation of operating parameters relating to magnetic separators. Sensor-based sorting is also made more accurate through machine vision techniques under problematical conditions through Artificial Intelligence. Difficulties stay, as there is a need for larger datasets and better instrumentation integration hydrodynamic modelling with AI tools. A future study should be about the application of AI to turbulence control and drag optimisation in addition to open-access dataset development for improved predictive capability and innovation facilitation in mineral processing.

An important use of deep learning models is that involving Convolutional Long Short-Term Memory (ConvLSTM) networks for real-time monitoring of the quality of mineral flotation froth (Bendaouia et al., 2024). The spatial and temporal information from video sequences representing the flotation process is input simultaneously with these models to predict chemical composition grades for minerals so that adjustment of flotation parameters can be done accurately, thereby improving mineral recovery rates. Traditionally implemented laboratory analysis or even X-ray fluorescence (XRF)-based monitoring would have high running costs and maintenance issues as well as latency problems that these AI approaches could solve since they are low-cost, low-maintenance, real-time insights.

AI can be applied in differential flotation, a complex process in which several mineral products such as zinc, copper, iron, and lead are derived. As a result of froth characteristic analysis (texture and bubble size) accurate model-based control optimisation can be ensured for optimal flotation performance with reduced reagent consumption—increased profitability with improved environmental sustainability (Bendaouia et al., 2024). The AI industrial models developed herein also ensure flexibility and consistency when implemented within on-premises architectures to provide the needed information for dynamic process control, which depicts the Mineral Process Automation as an evolution towards Industry 4.0 technologies.

Having laid a firm foundation in improved results of controlling flotation with AI input, these enhancements speak to the larger transformative power that artificial intelligence has over the mining sector. As automation further develops, Artificial Intelligence is being integrated towards predictive maintenance and strategy decisions considerably enabling nimbler, informed by data and environmentally sustainable mineral processing operations across the complete value chain. Artificial intelligence (AI) has, therefore, increasingly come into play in predictive mining and mineral processing across the spectrum to improve efficiency and effectiveness decision making. Real-time insights and predictive maintenance are enabled by AI from all the data being collected in operations within the mining industry. For example, Vale's investments included an Artificial Intelligence Centre based in Brazil that monitors AI initiatives being piloted globally within its extensive operations for process optimisation and downtime reduction that centralised, AI-driven systems might bring (Storey, 2025). These applications show how transformative artificial intelligence can become toward the improvement of equipment reliability as well as operational safety.

According to Storey (2025), "digitalization technologies, such as artificial intelligence and the Internet of Things (IoT) use those data to drive innovation, increase operational efficiency and productivity, lower costs, improve safety, increase overall business agility and unlock new revenue streams". All of these advancements point to a paradigm shift in mining operations management as well as a technological shift, putting intelligent systems at the centre of an industrial transformation that is resilient, sustainable, and value-driven.

Recent advances in artificial intelligence (AI) have radically transformed the future of mining and mineral processing. In effect, AI will offer highly creative solutions to hitherto longstanding problems. An example involves the integration of neuro-symbolic AI together with knowledge graphs, balancing between-based machine learning models and expert geological reasoning (Chen et al., 2025). More particularly, this hybrid methodology exploits large language models (LLMs) for extracting those symbolic rules embedded within geology literature and then dynamically knowledge graphs that reflect domain-specific insights.

They are incorporated into the machine learning workflow; hence, guiding the predictions to conform to geological principles as well as improving accuracy and transparency. For example, regarding copper deposits, neuro-symbolic AI models have been tested for their ability to indicate important geochemical elements Cu Fe and S with coherent explanations on mineralization patterns. This degree of interpretability is augmented further with tools such as SHAP (SHapley Additive exPlanations) values by which the importance of individual features concerning predictions can be measured (Chen et al., 2025). Incorporating expert knowledge into AI models improves predictive accuracy and increases trust among geoscientists, supporting more sustainable mineral exploration and processing. Such breakthroughs make Artificial Intelligence the building block of insightful, value-based business metamorphosis.

Artificial intelligence does not only improve its prediction validation, but geoscientists trust and validate it too, thereby making it a transformer in sustainable mineral exploration and processing. A key feature of the Multi-Model Decision System (MMDS) is that domain knowledge has been injected into AI systems for better capability to emulate complex geological processes and to more accurately predict mineral prospectivity (Soltani et al., 2025). The MMDS system applies state-of-the-art deep learning models such as Deep Neural Networks (DNN), Deep Belief Networks (DBN), Decision Forests (DF), and 1D Convolutional Neural Networks (1D-CNN) to create individual prediction synergies by lowering uncertainty, resulting in strong spatial patterns for mineralization.

The decision-making engine inspired by the MARCOS model weighs based on the performance of each model. The better models naturally get to have a significantly large effect on final predictions. This approach improves not only predictive accuracy but also aligns with geoscientific principles and therefore builds trust among professionals in this discipline. These prospectivity maps, which come out of MMDS have shown much better spatial coincidence with known mineral deposits and hence could be considered very good tools for finding lower risk exploration targets (Soltani et al., 2025). Such development put artificial intelligence as an essential input factor for informed, value-based decisions in mineral exploration leading to better and more efficient resource management.

Scoring Method

Each technology is rated on Efficiency, Sustainability, Scalability (1–5; higher is better) using extracted indicators (energy kWh/t, water m^3/t, reagents/toxicity, recovery %, waste reduction %, CAPEX/OPEX class, pilot/industrial evidence). Readiness is assessed using the Technology Readiness Level (TRL, 1–9). For compactness in Table 3, TRLs are grouped into three bands: Pilot (TRL 5–6), Applied (TRL 7–8), and Mature (TRL 9). Assignments are based on reported scale (lab/pilot/plant), evidence of operational deployments, and independent corroboration; where sources diverge, the lower defensible TRL is used. Technologies at ≤ TRL 4 are flagged as Pre-pilot in the text and omitted from Table 3. The following comparative table synthesizes these families together with robotics/AI/automation.

Table 3. Comparative Assessment of Technologies for Sustainable Resource Extraction

Technology	Efficiency	Sustainability	Scalability	Readiness band (mapped TRL)	TRL (1-9)
Advanced robotics	High	Medium	Medium	Applied (TRL 7-8)	7-8
Artificial intelligence	Medium	High	Medium	Applied (TRL 7-8)	8
Automation systems	High	Medium	High	Mature (TRL 9)	9

Legend: High (H) = 4–5; Medium (M) = 3; Low (L) = 1–2 (rating scale: 1–5)

TRL bands follow standard EC/NASA definitions. Individual TRLs reflect the most conservative interpretation of the available evidence.

In conclusion, AI technologies contribute to more efficient and sustainable mining operations by enabling predictive maintenance, resource mapping, and process optimisation. Remaining challenges concern data quality, scalability limitations, and the effective integration of domain-specific expertise.

Digital and autonomous technologies act as enablers rather than substitutes for process innovation. Policy instruments (e.g., localization incentives, reporting standards for energy/water, and pilot-to-demo financing) accelerate the transition from **TRL 4–6** to **TRL 7–9**. For operators, prioritizing sensor-based sorting, AI-assisted control, and selective separations typically yields early energy/water gains while preparing flowsheets for circular routes (e.g., black mass recycling).

Evidence across technologies is heterogeneous and often limited to pilot scale; sustainability indicators (energy, water, reagents, recovery) are inconsistently reported. We therefore used a structured narrative synthesis without PRISMA counts, focusing on triangulation. Future work should standardize reporting, develop open datasets for benchmarking AI-enabled control, and track TRL progression from pilot to commercial deployments.

Conclusion

The global demand for critical and strategic raw materials is driven by advances in green technologies, digitalization, and evolving geopolitical dynamics. This has put a lot of pressure on the mining and processing sectors to come up with new methods. This review examined how advanced robotics, artificial intelligence, and automation systems are transforming the extraction and processing of critical raw materials across the value chain.

Cutting-edge robotics is already improving safety and productivity in extreme mining conditions by enabling real-time surveillance, self-navigation, and exact manipulation within danger zones. At the same time, artificial intelligence has proven useful for predictive maintenance, mineral prospectivity mapping, process optimisation, and autonomous decision-making. These innovations reduce environmental effects and operating costs as well as allow the recovery of unconventional resources (e.g., electronic waste and tailings), which go straight toward the goals of a circular economy.

Digital innovation, properly matched with principles of sustainability, is an obvious path to improved efficiency, responsibility, and scalability of the extraction and processing of strategic materials. Challenges that remain, however, include problems with data quality and integration costs, in addition to system scalability and adequate interdisciplinary collaboration that have to be addressed through sustained investment leveraged by international cooperation integrated with domain expertise and data science.

Ultimately, resilience and sustainability in the supply of critical raw materials depend on the continued development, deployment, and scaling of such high technologies. As digitalization is changing the face of mining activities across the world, there is a need for stakeholders to embrace a proactive and cooperative approach that will ensure technological advancement supports industrial competitiveness as well as environmental stewardship and long-term global resource security.

This review contributes to the literature by synthesizing emerging technological innovations in mining, highlighting their advantages and limitations, and identifying research gaps. It provides a comparative assessment of technologies based on efficiency, scalability, and environmental performance, offering insights for stakeholders aiming to align digitalization with sustainability goals in the mining industry.

Scientific Ethics Declaration

*The authors declares that the scientific ethical and legal responsibility of this article published in EPSTEM Journal belongs to the authors.

Conflict of Interest

*The authors declare that they have no conflicts of interest

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References

Ali, S., Giurco, D., Arndt, N., Nickless, E., Brown, G., Demetriades, A., Durrheim, R., Enriquez, M., Kinnaird, J., Littleboy, A., Oberhänsli, R., Salem, J., Schodde, R., Schneider, G., Vidal, O., & Yakovleva, N. (2017). Mineral supply for sustainable development requires resource governance. *Nature*, *543*, 367–372.

Bendaouia, A., Abdelwahed, E. H., Qassimi, S., Boussetta, A., Benzakour, I., Amar, O., & Hasidi, O. (2024). Artificial intelligence for enhanced flotation monitoring in the mining industry: A ConvLSTM-based approach. *Computers & Chemical Engineering*, *180*, 108476.

Binnemans, K., Jones, P. T., Blanpain, B., Van Gerven, T., Yang, Y., Walton, A., & Buchert, M. (2013). Recycling of rare earths: A critical review. *Journal of Cleaner Production*, *51*, 1–22.

Cerna, G. E. P., Hernández, J. R. C., Herazo, J. C. M., & Castillo, A. P. (2023). Evaluation of the overall effectiveness (OEE) of autonomous transportation system (AHS) equipment and its impact on mine design. Open pit mine case study. *Procedia Computer Science*, *224*, 468–473.

Chen, W., Zhang, J., Li, W., Que, X., Li, C., & Ma, X. (2025). Integrating neuro-symbolic AI and knowledge graph for enhanced geochemical prediction in copper deposits. *Applied Computing and Geosciences*, *27*, 100259.

Davies, R. S., Trott, M., Georgi, J., & Farrar, A. (2025). Artificial intelligence and machine learning to enhance critical mineral deposit discovery. *Geosystems and Geoenvironment*, *4*(2), 100361.

Dayo-Olupona, O., Genc, B., Celik, T., & Bada, S. (2023). Adoptable approaches to predictive maintenance in mining industry: An overview. *Resources Policy*, *86*, 104291.

European Critical Raw Materials Act-European Commission. (n.d.). Retrieved July 23, 2025, from https://single-market-economy.ec.europa.eu/publications/european-critical-raw-materials-act_en

European Raw Materials Alliance (ERMA). (n.d.). European raw materials alliance (ERMA). Retrieved May 28, 2025, from https://erma.eu/

Gomez-Flores, A., Ilyas, S., Heyes, G. W., & Kim, H. (2022). A critical review of artificial intelligence in mineral concentration. *Minerals Engineering*, *189*, 107884.

Kokkinis, A., Frantzis, T., Skordis, K., Nikolakopoulos, G., & Koustoumpardis, P. (2024). Review of automated operations in drilling and mining. *Machines*, *12*, 845.

Kumar Singh, S., Pratap Banerjee, B., & Raval, S. (2023). A review of laser scanning for geological and geotechnical applications in underground mining. *International Journal of Mining Science and Technology*, *33*(2), 133–154.

Liu, J., Ma, B.-Y., Fry, N., Pickering, A., Whitehead, S., Somjit, N., Richardson, R. C., & Robertson, I. D. (2015). Exploration robots for harsh environments and safety. *IFAC-PapersOnLine*, *48*(10), 41–45.

Lösch, R., Grehl, S., Donner, M., Buhl, C., & Jung, B. (2018). Design of an autonomous robot for mapping, navigation, and manipulation in underground mines. *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 1407–1412.

Padinhattath, S. P., Shaibuna, M., & Gardas, R. L. (2025). Ionic liquids and deep eutectic solvents: A brief prologue and their applications in sustainable extraction and separation processes. *Journal of the Indian Chemical Society*, *102*(4), 101638.

Quijada-Maldonado, E., Olea, F., Sepúlveda, R., Castillo, J., Cabezas, R., Merlet, G., & Romero, J. (2020). Possibilities and challenges for ionic liquids in hydrometallurgy. *Separation and Purification Technology*, *251*, 117289.

Saldaña, M., Jeldres, M., Galleguillos Madrid, F. M., Gallegos, S., Salazar, I., Robles, P., & Toro, N. (2023). Bioleaching modeling-a review. *Materials*, *16*(10), 3812.

Saldaña, M., Neira, P., Gallegos, S., Salinas-Rodríguez, E., Pérez-Rey, I., & Toro, N. (2022). Mineral leaching modeling through machine learning algorithms − a review. *Frontiers in Earth Science*, *10*.

Soltani, Z., Hassani, H., & Esmaeiloghli, S. (2025). Multi-model decision system: An ensemble deep learning model to enhance predictive power in mineral prospectivity mapping. *Ore Geology Reviews*, *184*, 106768.

Storey, K. (2025). Digitalization in mining and the rise of the urban miner. *The Extractive Industries and Society*, *24*, 101718.

U.S. Department of Energy. (n.d.). *2021 DOE critical materials strategy. Energy.gov.* Retrieved May 28, 2025, from https://www.energy.gov/eere/ammto/2021-doe-critical-materials-strategy

Xue, H., Fu, H., Xiao, L., Fan, Y., Zhao, D., & Dai, B. (2023). Traversability analysis for autonomous driving in complex environment: A LiDAR-based terrain modeling approach. *Journal of Field Robotics*, *40*(7), 1779–1803.

Yang, F., Zuo, R., & Kreuzer, O. P. (2024). Artificial intelligence for mineral exploration: A review and perspectives on future directions from data science. *Earth-Science Reviews*, *258*, 104941.

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