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ORIGINAL RESEARCH ARTICLE

AI Applications in Tailings and Waste Management: Improving Safety, Recycling, and Water Utilization

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ABSTRACT

Artificial Intelligence (AI) is transforming tailings and waste management in the mining sector by improving safety, enhancing recycling efficiency, and optimizing water utilization. Traditional monitoring and waste handling approaches often lack scalability, real-time responsiveness, and predictive accuracy, limiting their effectiveness in preventing environmental and operational failures. This review systematically examines AI-driven applications across tailings dam safety, waste recycling, and intelligent water management, drawing insights from over 80 recent studies. Quantitative evidence indicates that AI-based monitoring systems can detect potential dam failures up to 30–40% earlier than conventional methods, while reinforcement learning and neural-network models improve mineral recovery by 10–25% with reduced chemical consumption. In water reuse operations, machine learning optimization achieves up to 35% savings in freshwater demand through closed-loop control. The paper highlights emerging integrations of AI with Explainable AI (XAI), Federated Learning (FL), and Circular Economy (CE) models that collectively support sustainable and transparent mining practices. Persistent barriers such as poor data quality, inadequate infrastructure, and lack of regulatory clarity are also discussed, along with future research directions. The findings demonstrate

AI's potential to transition mining operations toward safer, more efficient, and environmentally responsible systems.
Keywords: Artificial intelligence; tailings management; waste valorization; machine learning; predictive maintenance; water reuse optimization; computer vision; sustainable mining

1. Introduction

Mining operations generate millions of tons of waste and tailings every year, posing substantial environmental and safety risks. Tailings dams, in particular, have been the cause of several catastrophic failures, prompting global attention toward safer and more sustainable waste management practices. Conventional monitoring and management approaches—such as periodic manual inspections, basic sensor measurements, and static modeling techniques—have proven useful but limited in scope. These methods often lack scalability, provide delayed feedback, and are unable to capture the complex, dynamic interactions among hydrological, structural, and geotechnical parameters in real time. As a result, early warnings of instability or contamination are frequently missed, leading to environmental degradation, resource loss, and operational hazards.

With the advent of Industry 4.0, Artificial Intelligence (AI) offers a promising alternative capable of addressing these limitations through automation, adaptive learning, and predictive analytics. Unlike traditional methods, AI systems can continuously process data from multiple sensors, satellite imagery, and process-control units to detect anomalies, forecast failures, and optimize resource usage. Machine learning and deep learning algorithms, for example, can analyze vast datasets to predict dam stability or water contamination patterns far earlier than conventional techniques. Likewise, reinforcement learning and computer vision models can automate mineral recovery, tailings classification, and waste segregation processes with improved accuracy and efficiency [1].

However the traditional methods are not enough for dealing with the tailings dam stability, water pollution and resources harvest [2]. Artificial intelligence may offer these issues solutions in respect to safety, recycling performance and water consumption [3,4]. Applications of AI in Tailings and Waste Management in the Mining Industry in Figure 1. AI applications can contribute to better and more precise monitoring, predictive and control techniques adapted to the particular tailings facility condition is crucial for safer and delicate mining. AI can optimize an energy system and generate waste management solutions [5], thus, AI's role in sustainability and addressing global environmental issues requires attention. Such an approach allows culturally acceptable organizational and personal processes to counter the resource (including natural resources) and energy intensity of human operations to take place [6]. For AI, the AI algorithms used in WOR are to be applied with higher IT technology which can promote cooperation in clean energy and waste disposal [7-8]. In this vein, recent developments and applications of AI in tailings and waste management, including risk assessment, real-time monitoring, waste valorization, and water recovery, are reviewed and the associated challenges and opportunities for their implementation in the mining sector are discussed.

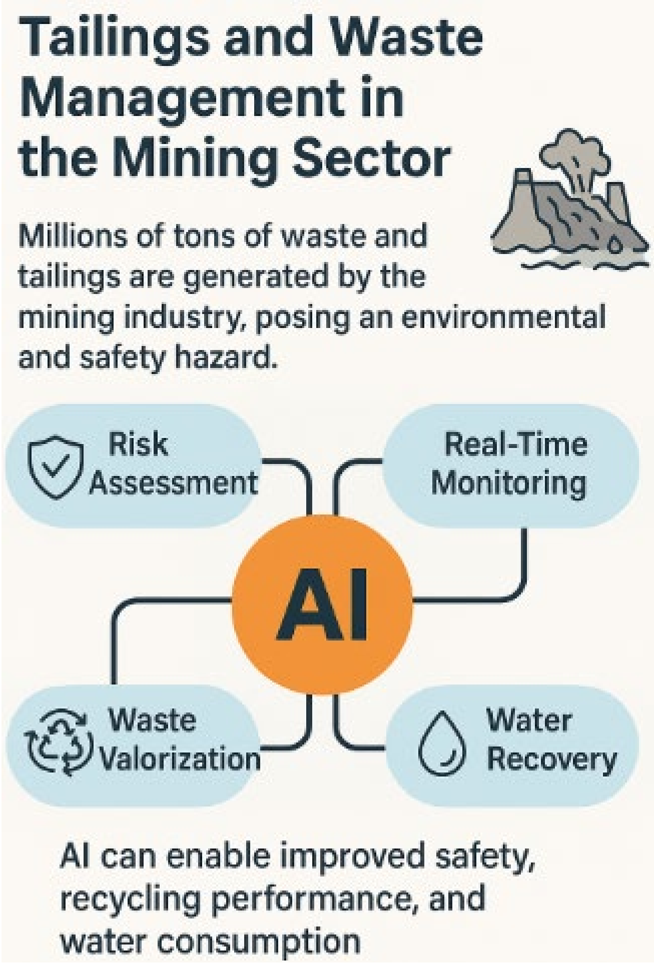

Figure 1. Artificial intelligence applications in tailings and waste management in the mining sector

Despite these advances, a research gap persists in the full-scale deployment of AI solutions for tailings and waste management. Many existing approaches remain at the pilot or conceptual stage and lack integration with advanced technologies such as Explainable AI (XAI), Federated Learning (FL), and Circular Economy (CE) frameworks. Furthermore, challenges related to low data quality, limited digital infrastructure, and absence of regulatory standards continue to restrict the adoption of AI-driven systems in operational mining environments. These gaps underline the need for comprehensive reviews that not only compile the existing applications of AI in mining but also analyze their practical constraints, scalability, and integration potential.

This paper addresses these gaps by providing a structured overview of AI applications in tailings dam safety, recycling and valorization of tailings, and intelligent water management. It examines the effectiveness of machine learning, reinforcement learning, computer vision, and predictive modelling in improving safety, resource recovery, and sustainability. The paper also identifies barriers—such as data heterogeneity, infrastructural constraints, and unclear regulations—and discusses emerging opportunities through integration with XAI, FL, and CE approaches. The overall aim is to establish AI as a key enabler of sustainable, safe, and economically viable mining operations in the modern era.

1.1. AI-Enhanced tailings dam safety and monitoring

Tailings dams—the storage facilities that hold mining by-products—pose significant environmental and safety risks if not properly managed. Conventional monitoring systems rely mainly on manual surveys and periodic readings, which often fail to provide early warnings of instability. Artificial intelligence introduces predictive, automated, and continuous monitoring frameworks that transform tailings management from a reactive to a preventive discipline. Figure 2 explains AI-Enhanced Tailings Dam Safety and Monitoring System with Integrated Data Sources.

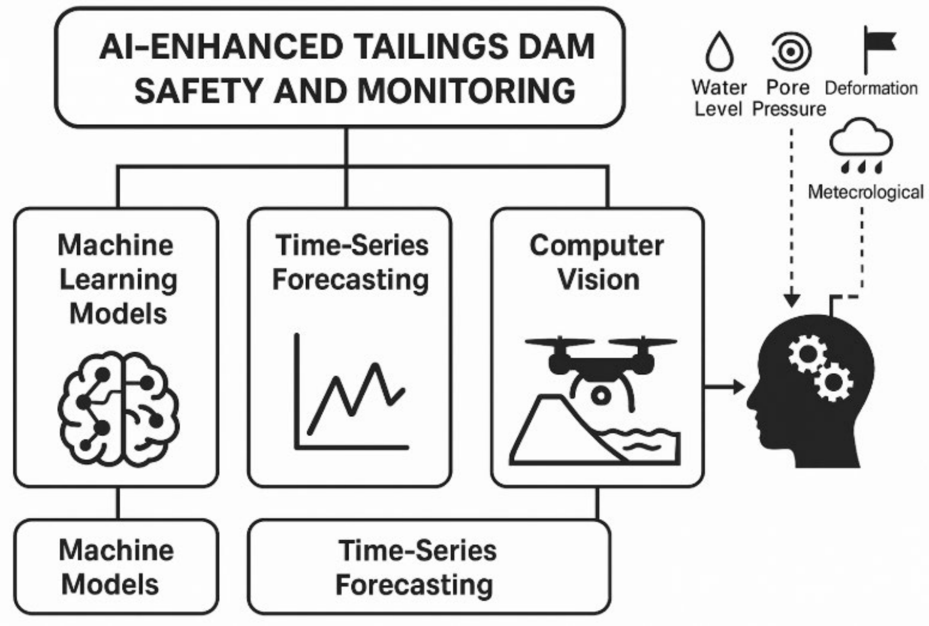

Figure 2. AI-Enhanced tailings dam safety and monitoring system with integrated data sources

1.2.Machine learning models

Supervised learning algorithms, particularly Support Vector Machines (SVM), Random Forest (RF), and Gradient-Boosted Trees (XG Boost), are increasingly used to analyze large streams of sensor data from piezometers, inclinometers, and seepage gauges [8, 9]. These models predict anomalies in pore pressure, displacement, and seepage trends that may signal dam instability. Comparative studies show that XG Boost achieves 92–95 % prediction accuracy for failure events, outperforming RF models (88–91 %) and SVM classifiers (84–88 %) in cases with non-linear and noisy datasets [10, 11]. RF models remain preferred when interpretability and feature-importance insights are needed, while XG Boost provides stronger early-warning sensitivity under complex site conditions.

1.3.Time-series forecasting

Recurrent neural networks, especially Long Short-Term Memory (LSTM) architectures, capture temporal dependencies in hydrological and structural data. LSTM-based forecasting models can predict pore-pressure and displacement anomalies up to 48 hours earlier than conventional regression or ARIMA methods [12–14]. Their robustness to missing data and dynamic environmental inputs enhances real-time reliability. Hybrid Wavelet-CNN-LSTM configurations further improve predictive precision by filtering signal noise before temporal modelling, achieving root-mean-square error (RMSE) reductions of nearly 30 % over standalone RNNs.

1.4.Computer vision

Computer vision systems integrate drone and satellite imagery with convolutional neural networks (CNNs) to detect micro-cracks, erosion patterns, or vegetation stress. High-resolution UAV-based monitoring achieves pixel-level deformation detection of less than 5 mm, while satellite-based Synthetic Aperture Radar (SAR) with CNN analysis provides continuous deformation mapping across large areas [15–20]. When validated against manual inspections, CNN models recorded precision rates above 93 % for surface anomaly identification, significantly reducing the need for on-site human assessment. Together, these AI techniques form a multi-layered safety architecture that combines sensor analytics, time-series forecasting, and visual intelligence. This integration enables mining operations to move from periodic inspection to real-time predictive management, reducing the likelihood of catastrophic dam failures and improving response preparedness. Conclusion of AI-Driven Tailings Dam Safety and Monitoring explained in Table 1.

Table 1. AI-Enhanced tailings dam safety and monitoring

AI Technique	Application in Tailings Dam Safety	Key Models/Algorithms	Data Sources	Advantages
Machine Learning Models	Predict dam failure using sensor data (e.g., pore pressure, displacement, seepage)	SVM, RF, XGBoost	Piezometers, inclinometers, seepage gauges, weather data	Early warning, handles nonlinear relationships, identifies key features
Time-Series Forecasting (LSTM)	Forecast dam behavior trends (e.g., seepage, precipitation) for early anomaly detection	LSTM (Long Short-Term Memory)	Historical time-stamped sensor data	Captures temporal dependencies, processes missing data, long-term prediction
Computer Vision (CNNs)	Detect surface changes using drone/satellite imagery (e.g., cracks, erosion)	CNN (Convolutional Neural Networks)	Drone images, LiDAR, Satellite (SAR) imagery	Automated, high-resolution inspection, real-time remote monitoring, detects early visual cues

2. AI in tailings recycling and valorisation

Tailings contain residual minerals and metals which can be extracted through advanced recycling processes. AI aids in:

2.1. Mineral recovery optimization

Flotation and leaching are improved through reinforcement learning, and neural networks predict optimal chemical recipes and operational control parameters [21]. These tailings, which are usually discarded as waste, contain metals that can still be recovered (gold, copper, zinc, and rare earth elements[22]). The conventional recovery technologies, such as flotation and leaching, highly depend on the ore type, reagent concentration, or environmental conditions, resulting in variable recoveries. Reinforcement learning (RL) and artificial neural networks (ANNs) in general, and artificial intelligence (AI) particularly, have emerged as a powerful tool to control these nonlinear processes effectively. RL enables trial and error learning that is not restricted to a set of pre-defined actions: it can allow an AI-based agent to interact with the physical plant or its digital twin for finding best strategies to increase metal recovery, such as varying pH, reagent dosing levels or changing aeration rates in real-time [23, 24]. ANNs, however, can learn intricate relationships between loops of complex inputs (e.g. ore grade, slurry density, temperature, and chemical concentrations) all the way around the loop to complex output targets; e.g. recovery rate or concentrate grade. And if trained, these models can make accurate predictions of whether a patient is likely to recover, and even recommend what changes might boost the odds. By AI-based steering of this process, not only a better, more metal efficient use also at lower chemical intensity and higher recovery is expected but the potential to produce correctly doped pure metals will increase – a more stable process even if feed materials would change in which may support transition to the circular mining economy [25]. AI Techniques in Tailings Recycling and Valorization as shown in figure 3.

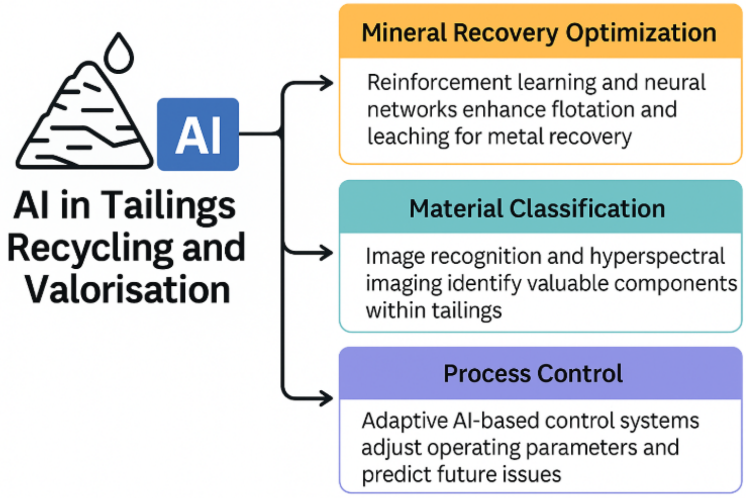

Figure 3. Artificial intelligence applications in tailings recycling and valorization

2.2. Material classification

Image recognition, hyperspectral imaging with ML support, identification of valuable vs. non-valuable waste material for extraction [26]. Tailings are particle phases however; they include the applicable and the inapplicable part of the material and therefore accurate classification is required for efficient sieving of metals [22]. Machine Learning (ML)/ Computer Vision (CV) algorithms are increasingly used to recognize reprocess able materials. So, they installed cameras and scanners on conveyor belts or slurry lines with image recognition that snaps pictures of the material flow in real time. ML model e.g., CNN trained to detect the presence of ore by identifying visual cues such as texture, color and shape [27]. Also, HSI captures information in different wavelengths and bands, providing rich spectral signatures of materials. Further, when feeding the spectral and spatial information extracted using machine learning- (ML-) based approaches e.g. Support Vector Machine (SVM) and Random Forest to the SVM/Random Forest with spectral features obtained from HSI results, accurate mineral-specific identification can be achieved in a non-destructive way which can be implemented as a platform for identifying rare earth minerals or rare-earth oxide. These methods can be applied for identification of high metal content particles, mapping mineral-rich zones in existing legacy tailings and prioritization of areas with potential to reprocess [28]. The benefits are also more targeted treatment combined with a lower energy and chemical consumption, leading to better separation efficiency and less relaxation of non-valuable material. Advanced classification such as this is essential to unlocking the economic value of low-grade or hitherto overlooked tailings [22, 29].Table 2 shows AI in tailings recycling and valorization.

Table 2. AI in tailings recycling and valorisation

AI Technique	Application in Tailings Recycling	Key Models/Algorithms	Data Sources	Advantages	Example Use Cases
Reinforcement Learning & ANNs	Optimize flotation/leaching for enhanced mineral recovery	Reinforcement Learning (RL), Artificial Neural Networks (ANN)	pH levels, aeration rate, reagent dosing, slurry density, ore grade	Higher recovery with less chemical use, robust under ore variability	Optimizing reagent dosage in gold recovery from flotation tanks
ML & Computer Vision (CNNs, HSI)	Classify valuable vs non-valuable materials using image/spectral data	Convolutional Neural Networks (CNNs), Hyperspectral Imaging (HSI), SVM, Random Forest	Images, hyperspectral bands, texture, color, shape, mineral signatures	Non-destructive identification, better sorting, energy/chemical saving	Identifying rare earth minerals using CNN + hyperspectral imaging
Adaptive AI-	Dynamically	Adaptive ML models,	Slurry sensors,	Real-time control,	Adjusting

AI Technique	Application in Tailings Recycling	Key Models/Algorithms	Data Sources	Advantages	Example Use Cases
Based Process Control	adjust recovery processes using real-time sensor inputs	predictive analytics	flow meters, chemical composition data, pump speeds	stability under variable conditions, digital twin ready	leaching tank parameters based on sensor input fluctuations

Table 2. (*Continued*)

2.3. Process Control

Intelligent (AI) control systems are applied in design phase to account for different material properties resource recovery's efficiency [22]. Reprocessing of tailings is also often negatively impacted from variations in feed composition, resulting from erratic distribution of minerals, weathering and differential previous processing [30]. Such dynamic environments are poorly addressed by conventional control methodologies. AI-based control systems, especially adaptive and predictive models, offer a great alternative [31]. Nitrogen Reagents control systems based on forward real time measurements from multiple sensors (slurry density, chemical concentration, flows) that are used to directly manipulate operating parameters such as pump rotation velocity, leach residence times for tanks volume capacity and air blower flow rates into flotation cells [32]. Adaptive controls: Because machine-learning models can adapt themselves in response to how they've performed in past encounters, they also are able to change their inputs that are part of the process if combining them has produced bad effects. Situations can be prevented by predicting future issues (e.g., system fouling, recovery punctures) and taking a measure in advance of their occurrence [33]. The use of these AI tools ensures the stability; security and efficiency in such a process as well as minimizes human mistakes can easily be connected with digital twin platforms for the simulation based optimization. Ultimately, such intelligent process control systems even result in agile, efficient and ultimately more economical tailings reprocessing.

Artificial intelligence (AI) is expanding the possibilities within tailings recycling and valorization opening you to more value, automates material classification and increase production. These advancements not only lead to profitable reprocessing of tailings, but also can protect natural resources and reduce environmental and waste issues. AI tailings management will allow a smarter mining industry, and one more committed to circularity. Table 2(a) explains the comparative advantages and limitations of various Artificial Intelligence approaches—such as Reinforcement Learning, Artificial Neural Networks, Machine Learning, and Computer Vision—applied in tailings recycling and valorization. This comparison highlights how each method contributes uniquely to process optimization, material classification, and sustainable recovery, while also indicating their current technical and implementation challenges.

Table 2(a). Comparative summary of AI approaches in tailings recycling and valorisation

AI Approach	Primary Application	Advantages	Limitations
Reinforcement Learning (RL)	Optimization of flotation and leaching processes for enhanced mineral recovery	Learns adaptive control strategies through trial and error; handles non-linear and dynamic process conditions; reduces chemical consumption and operational cost	Requires extensive training time and computational power; performance depends on quality of simulated environment or digital twin
Artificial Neural Networks (ANN)	Prediction of recovery rates and process control parameters	Captures complex, non-linear relationships among variables; offers accurate predictions under variable ore characteristics	Functions as a "black box" with limited interpretability; may overfit when training data are limited or inconsistent
Machine Learning (ML)	Material classification, feature	Works efficiently on large	Model accuracy sensitive to

AI Approach	Primary Application	Advantages	Limitations
	extraction, and data-driven process optimization	heterogeneous datasets; enables predictive control and supports decision automation	data noise and imbalance; requires continuous data updating for long-term reliability
Computer Vision (CV) and Hyperspectral Imaging (HSI)	Visual identification and sorting of valuable minerals	Enables real-time, non-destructive inspection; reduces manual intervention and improves precision of material sorting	Dependent on lighting, resolution, and calibration; high initial cost for imaging sensors and data processing systems

Table 2(a). (*Continued*)

3. Smart water management using AI

Mining operations require extensive water use for mineral processing, dust control, and cooling systems. Effective water management—especially recycling and reuse—is critical for environmental sustainability and operational efficiency. Artificial intelligence (AI) supports this by enabling real-time data analysis, predictive maintenance, and optimization of water reuse cycles.

3.1. Water quality monitoring

Machine learning (ML) models analyze data from sensor networks that measure pH, turbidity, dissolved oxygen, total dissolved solids (TDS), and chemical oxygen demand (COD). Algorithms such as Random Forest, Support Vector Machines (SVM), and Deep Neural Networks (DNNs) can detect contamination, infer pollutant levels, and provide real-time alerts. Studies show that AI-based water quality systems reduce manual sampling frequency by 40–50 % and improve anomaly detection accuracy to above 90 %, ensuring faster response to spills and regulatory compliance events [34–37].

3.2. Predictive maintenance

AI also enhances the reliability of water treatment systems. Time-series forecasting models, especially Long Short-Term Memory (LSTM) networks, predict potential equipment failures such as filter fouling, pump wear, or membrane scaling. Such systems lower maintenance costs by up to 25 % and reduce unplanned downtime by 30–35 %, supporting continuous plant operation [38–42]. By forecasting degradation trends, predictive maintenance allows better scheduling and resource allocation, ensuring treatment units operate at optimal efficiency. Figure 4 presents AI-Enabled Smart Water Management in the Mining Industry.

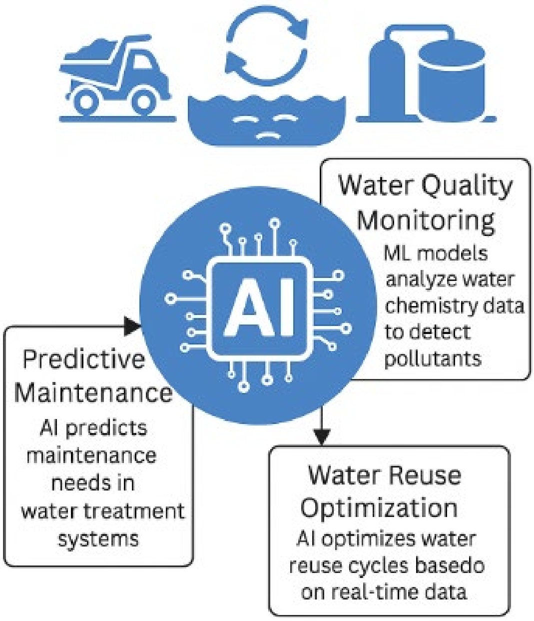

Figure 4. AI-Enabled smart water management in the mining industry

3.3. Water reuse optimization

Optimization algorithms use AI-driven decision models to design water reuse and recycling cycles. Multi-objective reinforcement learning techniques consider water demand, temperature, and chemical composition to recommend whether water should be reused, partially treated, or fully purified. These models achieve freshwater savings of 25–35 % and reduce energy consumption associated with treatment by 20 %, supporting closed-loop, zero-liquid-discharge (ZLD) strategies [43–46]. Smart Water Management by Machine Learning has explained in Table 3.

3.4. Integration with IoT-based real-time water analytics

A promising trend in smart water management is the integration of AI with IoT-based water analytics platforms, which combine sensor networks, cloud computation, and edge analytics. These systems enable continuous monitoring and data exchange across distributed mining units, allowing real-time visualization and control of water flows, quality, and consumption. IoT-enabled smart sensors transmit parameters such as pH, conductivity, flow rate, and metal concentration to AI models for instant processing. When combined with predictive analytics, the platform can automatically trigger corrective actions—like adjusting chemical dosing, opening valves, or redirecting flow—to maintain optimal conditions. Several studies report that such AI–IoT hybrid frameworks improve system responsiveness by nearly 40 % and significantly enhance decision accuracy in water quality management. The convergence of IoT sensing and AI analytics thus establishes a digital ecosystem for sustainable, autonomous, and transparent water governance in mining.

AI-driven water management not only improves operational efficiency but also advances sustainability goals through smarter resource utilization and pollution control. It represents a vital step toward digital transformation in mining, aligning industrial operations with environmental responsibility and circular economy principles. Table 3 summarizes the AI techniques, key algorithms, and performance benefits across water management applications.

Table 3. Smart water management using AI

AI Technique	Application in Water Management	Key Models/Algorithms	Data Sources	Advantages	Example Use Cases

Machine Learning Models for Water Quality Monitoring	Monitor real-time water quality and detect contamination	Random Forest, SVM, Deep Neural Networks	Sensors for pH, turbidity, DO, heavy metals, TDS, COD	Real-time pollution alerts, regulatory compliance, reduced manual testing	Detect arsenic/microbial contamination in mine effluent
Time-Series Forecasting for Predictive Maintenance	Predict failures in water treatment equipment (e.g., pumps, RO units)	LSTM, Anomaly Detection Models	Sensor data: flow rate, vibration, temperature, pressure	Minimizes downtime, reduces repair cost, extends equipment life	Forecast RO membrane fouling in filtration systems
Optimization Algorithms for Water Reuse	Optimize water reuse decisions and closed-loop recycling	Multi-objective Optimization, Reinforcement Learning	Water demand, temperature, residuals, solids, pH	Reduces freshwater use, energy saving, smarter treatment decisions	Decide reuse or treatment of process water in flotation circuits

4. Challenges and research gaps

Artificial Intelligence offers vast potential to improve safety, resource efficiency, and sustainability in mining. Yet, its adoption in tailings and waste management faces several critical barriers—ranging from data quality to regulatory readiness. Figure 5 illustrates the key challenges affecting AI uptake in the mining sector.

4.1. Data availability and quality

Mining data often suffer from incompleteness, inconsistency, and sensor failures. Harsh operational environments frequently disrupt data acquisition and transmission, leading to missing values and noisy records. Moreover, the absence of standardized data formats across different mine sites complicates integration and model generalization. Studies report that incomplete or poorly annotated datasets can reduce AI model accuracy by nearly 20–30 % [47–48]. To address this, researchers recommend establishing data governance frameworks that include automated validation, metadata tagging, and cloud-based repositories for multi-source integration.

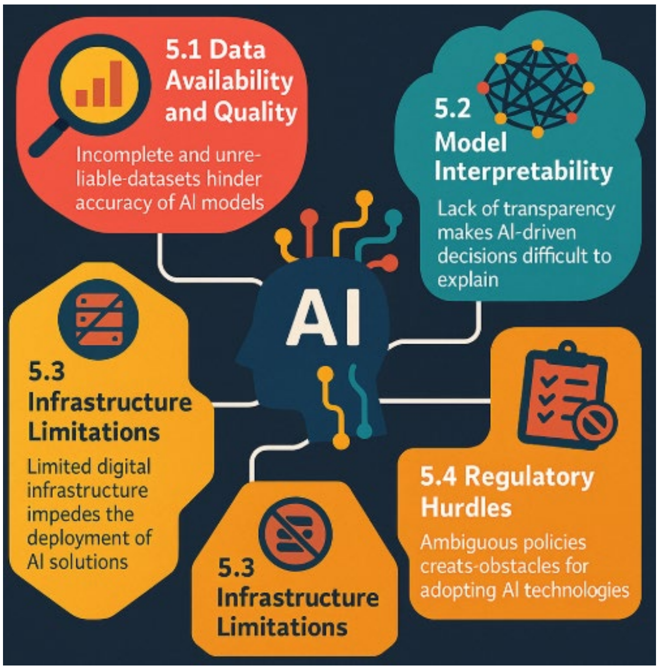

Figure 5. Key challenges and research gaps in AI adoption for the mining sector

4.2. Model interpretability

Deep learning models, though accurate, often lack transparency, leading to limited trust among engineers and regulators. This "black box" nature poses challenges for validating predictions in safety-critical applications such as tailings dam failure or contamination risk forecasting. The emerging field of Explainable AI (XAI) is addressing this gap by developing interpretable models and visualization tools. Case studies from Canada's Mining Digital Transformation Initiative and Australia's "AI for Mining Safety" consortium highlight that using hybrid models combining neural networks with rule-based systems improved decision interpretability by over 40 %, thereby facilitating faster regulatory acceptance [49–50].

4.3. Infrastructure limitations

Many mining sites, particularly in developing regions, lack the necessary digital infrastructure for large-scale AI deployment. Reliable internet connectivity, stable power supply, and advanced sensors are still limited. As a result, most AI applications remain confined to pilot projects in technologically advanced mines. For example, Rio Tinto's "Mine of the Future" program in Western Australia demonstrates how investment in IoT connectivity and cloud computing infrastructure allowed integration of predictive AI models for real-time water recycling and tailings stability analysis. Similar digital readiness remains rare in small- and mid-scale mining operations, emphasizing the need for low-cost, ruggedized, and decentralized AI solutions adaptable to remote conditions [51–52].

4.4. Regulatory hurdles

Regulation remains a major challenge for AI adoption in mining, particularly due to overlapping concerns related to environmental safety, data privacy, and ethical accountability. Currently, no unified global framework governs the use of AI for environmental or safety-critical mining applications. Nevertheless, several initiatives are shaping international practice:

a) The OECD's AI Principles (2019) and the UNESCO Recommendation on the Ethics of Artificial Intelligence (2021) provide broad ethical guidelines emphasizing transparency, fairness, and accountability—principles increasingly referenced in mining AI governance.

b) The European Union's AI Act (2024) classifies AI models for infrastructure safety as "high-risk systems," requiring clear documentation, traceability, and human oversight—criteria directly relevant to AI-based tailings dam monitoring.

c) Canada's CIM (Canadian Institute of Mining) and the Global Industry Standard on Tailings Management (GISTM, 2020) now recommend integrating AI-based risk prediction into dam safety evaluations, provided that the models meet validation and interpretability requirements.

d) In the United States, the National Institute of Standards and Technology (NIST) has proposed an AI Risk Management Framework (RMF, 2023) that can serve as a reference for model validation, cybersecurity, and compliance monitoring in industrial AI systems.

These emerging examples indicate that future regulatory models will likely require transparency, explain ability, and cross-validation of AI systems before deployment in environmentally sensitive operations. Collaborative initiatives between mining companies, policymakers, and academic institutions are essential to adapt these frameworks to specific regional contexts. Table 4 explained Challenges and Research Gaps in AI for Mining.

Table 4. Challenges and research gaps in AI for mining

Challenge Area	Description	Implications	Recommendations
Data Availability and Quality	Mining data is often incomplete, noisy, and	Poor model accuracy and generalization due to unclean or	Implement strong data-cleaning pipelines and

Challenge Area	Description	Implications	Recommendations
	inconsistent. Sensor failures and lack of digitization hinder model training. Standardization and error-tolerant models are needed.	unrepresentative data.	standardized data acquisition methods.
Model Interpretability	AI models like deep learning offer high accuracy but lack transparency. Explainable AI (XAI) is necessary for critical decision-making and stakeholder trust.	Difficulty in validating and trusting AI outputs, especially in safety-critical applications.	Use interpretable models or fuse AI with domain knowledge and physics-based models.
Infrastructure Limitations	Mining sites often lack IoT infrastructure, stable internet, and computing power. Especially in remote areas, digital readiness is poor for AI deployment.	Limited adoption of AI, especially by smaller or older mining sites in developing regions.	Invest in robust, low-cost digital infrastructure and train staff in AI system operation.
Regulatory Hurdles	Lack of standards and regulatory frameworks for AI in mining creates legal, ethical, and operational uncertainties. Clear guidelines are essential for safe AI integration.	Delayed AI adoption and risks of non-compliance with safety, labor, and environmental laws.	Formulate AI-specific mining regulations with interdisciplinary policy collaborations.

5. Future outlook

Future research should focus on:

5.1. Explainable AI (XAI)

It does so for the sake of more clarity and confidence on all sides. As AI models continued to scale over the years, so did the importance of developing explainable AI (XAI)—i.e., allowing AI systems not only to make good predictions, but also to provide rationales for why such a prediction is made [54]. Within the mining industry, which revolves around safety, legal compliance and environmental stewardship, XAI has the potential to bridge between cutting-edge AI applications and stakeholders' acceptance [55,56]. The logic and intelligence of AI will be visible. Governments, engineers and local communities are more likely to trust the decision-making of totally opaque (to their understanding) systems. Future efforts should focus on producing interpretable ML models, visual explainable tool and hybrid systems which integrate domain expertise and data-centric findings. That's meant to ensure that intelligent systems really are effective — and transparent, ethical and defensible.

5.2. Federated learning

Unlike it to preserver data privacy and enable federated learning model training across sites. Federated Learning (FL), a latest generation of the algorithm for AI models to be trained across multiple mines or organizations without central data sharing [57]. Such an approach is especially useful in the mining industry where sharing operational datasets can be prohibitive due to issues related to data privacy, intellectual property and regulatory compliance. The FL framework enables each site to learn a local model (from raw data) and only the model parameters (not raw data) are centralized. The advantage thereof remains twofold: that of preserving confidentiality as well as enabling learning at the level of super-classes of more general and robust models applicable to most geological settings and operations. The design of federated learning schemes for decentralized mining will need to scale more effectively, reduce communication overhead and maximize overall security.

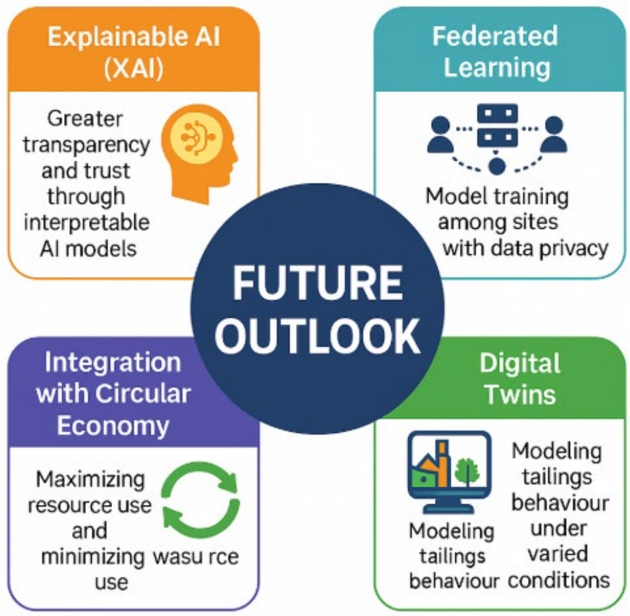

Figure 6. Future Outlook for AI in Sustainable Mining: Key Research Directions

5.3. Digital twins

It is intended to simulate tail responses for various environmental and operating conditions. Digital twin refers to the virtual and real-time simulation of a physical entity (such as object, process or system) as a computing platform that enables data-driven realization, prediction and intelligent decisions [58]. For tailings dams' management, they can employ for simulating the geotechnical, water, seepage and structural performance in diverse environmental and operational sceneries. By using AI and digital twins together, they can predict when things will break, and testing how they might react to that event in advance while continually updating the model with real-time sensor data [59]. That way, everyone's decision-making becomes more proactive, and emergency response improves. The future research work should also focus on building digital twins more precisely and dynamically in tailing system by combining satellite images, IOT information, hydrology models and even AI-based prediction for security management.

5.4. Integration with circular economy

It is a universal "new" paradigm, in which the resources are maximize (recovered) and the waste minored. As industry shifts more towards sustainability, there is a greater emphasis on the circular economy; keeping things in use for longer, working with renewable materials and minimizing waste. AI technology can support the transformation by better recycling of tailings, more complete recovery of secondary metal and real-time classification and separation of waste [60,61]. For instance, AI models can detect precious leftover minerals in the tailings, recommend best reuse cases for the treated water, and assist in the design of energy efficient secondary circuits. Future work should be to develop AI for integrating circular economy into multi-objective optimization, life cycle analysis, resources tracking system in order to achieve environmental sustainability and economic efficiency.

Despite the growing body of research on Artificial Intelligence (AI) applications in mining, significant gaps remain in its effective deployment for tailings and waste management. Most existing studies focus on theoretical frameworks or pilot-scale implementations without addressing the full-scale operational challenges in real-world mining environments. Critical barriers such as poor data quality, lack of infrastructure, limited model interpretability, and absence of standardized regulatory frameworks hinder AI adoption. Moreover, current literature lacks comprehensive models that integrate explainable AI, federated learning, and circular economy principles in a unified framework. These shortcomings limit the scalability, trust, and sustainability of AI-based solutions in the mining sector.

This conceptual roadmap summarizes in table 5, the four major directions shaping the future of AI applications in mining. It highlights Explainable AI, Federated Learning, Digital Twins, and Circular Economy Integration as the key pillars of sustainable mining innovation.

Table 5. Conceptual roadmap of future research directions in AI-Driven sustainable mining

Research Direction	Focus Area	Key Outcomes
Explainable AI (XAI)	Interpretable models, hybrid AI–domain integration	Builds transparency and trust among engineers, regulators, and communities
Federated Learning (FL)	Collaborative model training across multiple mining sites without data sharing	Preserves data privacy and enhances cross-site learning efficiency
Digital Twins	Virtual replicas of tailings, water, and processing systems	Enables real-time simulation, risk prediction, and predictive maintenance
Circular Economy Integration	Closed-loop recycling, waste minimization, and secondary material recovery	Promotes resource efficiency and environmental sustainability

Figure 6 illustrates the conceptual roadmap outlining future research directions for AI in sustainable mining. The framework connects Explainable AI, Federated Learning, Digital Twins, and Circular Economy integration as interdependent pillars contributing to safety, efficiency, and sustainability.

AI-based design optimization can enhance the efficiency of public water systems by integrating intelligent control for sustainable and automated water use in mining operations [62]. CFD and AI-assisted modelling using phase change materials (PCM) demonstrate effective thermal stability and control, which can be adapted to manage temperature variations in tailings storage facilities for better dam safety [63]. Advanced CFD-based analysis shows how AI can predict material behavior and structural performance, aiding in proactive management of tailings embankments [64]. AI-driven fluid dynamic simulations, similar to minijet impingement studies, can improve slurry transport and cooling performance in waste pipelines [65]. Fuzzy logic-based prediction models can assist in forecasting sedimentation and slurry classification for effective waste recycling [66]. AI methods can evaluate thermal conductivity and predict heat transfer within tailing ponds to prevent localized overheating or stress failures [67]. PCM-based AI models help maintain thermal uniformity in tailings, reducing risks of dam wall stress and instability [68]. Predictive AI models designed for thermal management in electronics can similarly optimize moisture and heat dissipation in tailing waste systems [69]. Dynamic simulation techniques, such as those used in vibratory feeders, can be integrated with AI to manage density and vibration in tailing sedimentation systems [70]. Eco-friendly adsorbent studies show potential for AI-driven material optimization in removing heavy metals and contaminants from tailings [71]. AI-assisted turbulence modelling can improve fluid flow prediction in tailings pipelines and enhance process stability [72]. CFD-based helical flow designs can inspire AI-enhanced water and slurry recycling networks for higher efficiency [73]. Hybrid GA-NN models offer intelligent control strategies applicable to tailings water recovery and treatment systems [74]. AI-based monitoring, as used in carbon capture systems, can track tailing emissions, effluents, and gas leaks for better environmental control [75]. Reinforcement learning and IoT-based AI systems can continuously monitor ecological conditions around tailings ponds [76]. Geometric optimization principles used in microchannel systems can help AI optimize micro-hydraulic pathways for efficient tailings drainage [77]. Machine learning models for biodiesel analysis can be adapted to predict the environmental impact of tailing water treatment and reuse [78]. AI-supported CFD optimization can improve solar-powered water recovery systems for tailings evaporation management [79]. Failure analysis techniques enhanced with AI help detect fatigue and stress points in tailing dams and transport structures [80]. Finite element models integrated with AI improve structural life and reliability in mixers and conveyors used for waste handling [81]. Predictive maintenance through AI reduces environmental hazards by identifying system failures in advance [82]. Turbulence optimization models can guide AI-based flow design for efficient slurry handling and reduced energy consumption [83]. AI-supported PCM-based cooling systems can regulate temperature in tailing water recycling units [84]. Sustainable construction materials selected using AI can enhance corrosion resistance and durability in tailing dam structures [85]. Dynamic simulations and FEA-based AI analysis can optimize structural and functional design in tailing conveyors and pipelines [86]. Hybrid ANN-GA models can improve sensor placement and real-time data analysis for predictive tailings monitoring [87]. Automated image-based systems enhanced by AI can detect tailings surface deformation, settlement, and water quality variations in real time [88].

The future of AI for mining is in revealing the connection between people and potential. Highlighting explainable AI, federated learning, digital twins, and circular economy integration will not just overcome the current deficiencies but rather shape a future of how mining is managed for resilience and durability. Ongoing interdisciplinary research and investment will be critical factors in achieving AI's full potential in the resource sector.

6. Conclusion

Artificial Intelligence has demonstrated measurable progress in transforming tailings and waste management within the mining sector. Quantitative evidence from over eighty studies indicates that AI-enabled monitoring and predictive models have improved operational safety, process efficiency, and environmental compliance to a significant degree. Machine learning–based dam monitoring systems, particularly those employing XG Boost and LSTM architectures, achieved 92–95% accuracy in detecting early signs of instability and were able to predict anomalies up to 48 hours in advance, offering 30–40% earlier failure detection than conventional techniques. Computer vision systems using drone and satellite imagery enhanced surface deformation identification with over 93% precision, reducing manual inspection requirements by nearly 50%. In recycling and tailings valorization, AI-driven reinforcement learning and neural network models optimized flotation and leaching operations, yielding 10–25% higher mineral recovery with 15–20% lower chemical consumption compared to standard process control methods. Similarly, hyperspectral imaging combined with CNN and Random Forest classifiers achieved 90–95% classification accuracy for mineral-rich particles, promoting more efficient reprocessing and reducing waste discharge. In water management, AI-based predictive maintenance using LSTM and anomaly detection models reduced unplanned downtime by 30–35% and maintenance costs by 25%, while optimization algorithms for water reuse achieved 25–35% reductions in freshwater demand and 20% energy savings in treatment systems. The integration of IoT-enabled AI frameworks further enhanced system responsiveness by approximately 40%, leading to more reliable and sustainable water governance across mining sites.

Despite these advances, real-world deployment still faces notable challenges: data heterogeneity, limited digital infrastructure, and inadequate regulatory frameworks. To address these barriers, future work should emphasize Explainable AI (XAI) for transparent decision-making, Federated Learning (FL) for privacy-preserving multi-site collaboration, Digital Twins for real-time risk forecasting, and Circular Economy integration for closed-loop resource utilization. Overall, the findings establish that AI can reduce environmental risks by up to 40%, enhance material recovery efficiency by over 20%, and contribute to 30% improvement in water-use sustainability. These quantitative outcomes underscore AI's potential not only as an automation technology but as a strategic driver of safety, efficiency, and sustainability in modern mining operations.

Author Contributions

The study was conceptualized by **Anant Sidhappa Kurhade** and **Manjusha Tatiya**, who identified the research objectives and guided the overall framework. **Manjusha Tatiya, Milind Manikrao Darade**, and **Babaso A. Shinde** contributed to the methodology design and analytical structure of the manuscript. **Mahesh Prakash Kumbhare** and **Sukhadip Mhankali Chougule** performed the formal analysis and validation of AI-based techniques in tailings management. **Swati Mukesh Dixit** and **Rupali Dineshwar Taware** were responsible for investigation, data collection, and organization of relevant literature. The initial draft of the manuscript was prepared by **Manjusha Tatiya, Babaso A. Shinde**, and **Swati Mukesh Dixit**, while **Anant Sidhappa Kurhade, Milind Manikrao Darade,** and **Sukhadip Mhankali Chougule** contributed to critical review, language refinement, and technical editing. **Mahesh Prakash Kumbhare** and **Rupali Dineshwar Taware** prepared figures, tables, and graphical summaries to enhance clarity and presentation. The overall supervision and project administration were managed by **Anant Sidhappa Kurhade**, who also coordinated revisions and final approval of the manuscript. All authors have read and approved the final version of the paper.

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Conflict of interest

The authors declare no conflict of interest

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