

Machine Learning in Smart Mining: A Systematic Review of Applications, Algorithms, Benefits, and Challenges

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Abstract

Background: Smart mining is rapidly evolving through the integration of automation, advanced sensing technologies, and Machine Learning (ML). **Methods:** This Systematic Literature Review (SLR), based on 99 peer-reviewed studies published between 2021 and 2025 and synthesized following PRISMA 2020 guidelines, analyzes the current role of ML algorithms in the mining sector, focusing on their applications, algorithmic prevalence, benefits, and challenges. **Results:** Machine Learning algorithms are primarily applied to equipment failure prediction, ore classification, grade and flotation control, transportation optimization, and environmental monitoring. The most frequently adopted algorithms include Decision Tree-based models, Artificial Neural Networks, Deep Learning architectures, Support Vector Machines, K-means clustering, and Gradient Boosting methods, reflecting different trade-offs between interpretability, computational complexity, and predictive performance. Reported benefits include improved operational efficiency, cost reduction, enhanced predictive maintenance, improved decision-making, and increased safety and environmental performance. However, widespread adoption remains constrained by limited availability of high-quality data, data heterogeneity, high implementation costs, shortages of specialized personnel, algorithm interpretability issues, and cybersecurity risks. **Conclusions:** Overall, ML algorithms emerge as key enablers of intelligent and sustainable mining. The review highlights the need for explainable and robust algorithms, improved multimodal data integration, and large-scale real-world validation to support the next generation of smart mining systems.

Keywords: machine learning algorithms; smart mining; predictive maintenance; mineral processing; algorithm interpretability



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1. Introduction

The mining industry is undergoing a rapid digital transformation, driven by the need to improve process efficiency, reduce operational costs, enhance worker safety, and minimize environmental impacts. In this context, Machine Learning (ML) has emerged as one of the most influential technologies, enabling data-driven, adaptive, and predictive decision-making throughout the mining value chain.

Machine Learning, as a branch of artificial intelligence, allows computational models to learn patterns from data, generate predictions, and support complex decision processes without the need for explicit programming. This capability aligns well with the nature of

mining operations, which generate large volumes of heterogeneous geological, geochemical, geophysical, operational, and environmental data. Consequently, ML has been increasingly adopted to address long-standing challenges such as orebody characterization, process optimization, equipment health monitoring, anomaly detection, and risk management.

In light of these characteristics, Artificial Intelligence (AI), and particularly Machine Learning (ML), is playing an increasingly important role in addressing the mining industry's long-standing challenges, such as improving resource estimation, enhancing operational safety, and reducing environmental impacts [1]. One of the most impactful ML applications is the prediction of ore quality and spatial distribution, where supervised learning models can capture complex, nonlinear patterns in multi-source geological data—supporting more efficient extraction strategies. Moreover, ML-enabled automation contributes to occupational safety by detecting hazardous conditions, equipment failures, and operator anomalies before incidents occur. In parallel, ML supports sustainability efforts by optimizing energy consumption, improving waste management, and anticipating environmental impacts, which helps mining companies meet growing regulatory and societal expectations.

In addition, ref. [2] demonstrated that lightweight ML models can effectively detect small obstacles in unmanned mining trucks, enabling real-time decision-making under limited computational resources and highlighting practical applications of ML for autonomous mining operations.

Despite these advances, the adoption of ML in mining still faces several challenges. These include data quality issues, high variability in mining environments, difficulties in system integration, and the substantial investments required in digital infrastructure and workforce training. Furthermore, the adoption of ML in mining is constrained by workforce-related challenges, including the need for specialized training and the development of digital competencies.

These challenges are consistent with the findings of [1], who highlight resistance to change, high costs, limited digital infrastructure, and workforce displacement concerns as key barriers to large-scale AI/ML adoption in mining. Their study underscores the need for cross-sector collaboration and workforce upskilling to enable responsible and sustainable implementation of intelligent technologies.

However, despite the growing volume of research, there remains a lack of consolidated evidence regarding: (i) which applications are most prevalent, (ii) which ML techniques are being effectively implemented, (iii) what benefits are being realized, and (iv) what challenges persist for large-scale adoption. Existing reviews are often fragmented, narrow in scope, or focused on isolated subsystems within the mining process.

To address this gap, the present study conducts a Systematic Literature Review (SLR) to assess the current state of ML adoption in the mining sector, based on peer-reviewed scientific literature. While commercial or proprietary implementations may be underrepresented in academic sources, the SLR offers a transparent, structured, and reproducible methodology for analyzing published evidence. As a result, the findings reflect only the academic perspective and may not fully capture the extent of real-world industrial adoption. This review does not assess the degree of internal organizational involvement in ML system implementation (e.g., vendor-managed vs. in-house development), as such information is typically unavailable in peer-reviewed publications.

In line with these considerations, it is important to clarify the scope and limitations of the evidence analyzed. This review focuses exclusively on peer-reviewed, open-access academic publications from 2021 to 2025. As such, it does not consider commercial developments or industrial implementations that are not reported in the scientific literature. Moreover, it does not evaluate the organizational maturity or internal adoption levels of

the ML solutions described. These limitations should be considered when interpreting the findings, as they may not fully reflect the actual state of ML use in real-world mining environments.

2. Literature Review

The adoption of Artificial Intelligence (AI), including Machine Learning (ML), has increasingly contributed to the transformation of the mining industry [3]. Applications of this technology range from increasing the efficiency of mining operations to optimizing environmental sustainability and worker safety [4]. The following sections provide an analysis of the main developments and applications of ML in mining, based on the available literature.

2.1. Smart Mining

Smart mining refers to the digital transformation of mining operations through the integration of advanced technologies such as automation, IoT systems, real-time sensing, and artificial intelligence. As highlighted by [5], the adoption of digital and intelligent mining technologies is central to establishing human-centered, climate-smart mines, emphasizing not only operational efficiency but also environmental and social sustainability. Within this paradigm, ML plays a central role, as it enables the processing and interpretation of large volumes of operational, geological, and environmental data to support data-driven decision-making. This is exemplified by the study conducted at the Yanshan Iron Mine, where an integrated ML-based system using multi-source geoscientific data enabled precise orebody localization and real-time surface mineral monitoring, enhancing the decision-making process and extraction planning [6].

In addition, ref. [7] developed an automated pipeline using Deep Learning and Optical Character Recognition (OCR) to classify and structure boring logs from abandoned mines, providing reliable data for future ML analysis.

Machine Learning contributes to smart mining by improving predictive maintenance, optimizing equipment performance, improving ore grade control, and reducing safety risks through anomaly detection and automated monitoring. By leveraging these capabilities, smart mining not only increases operational efficiency and productivity but also supports more sustainable and safer mining practices, establishing ML as one of the foundational components of modern mining innovation.

2.2. Optimization of Mining Exploration

Mineral exploration is one of the most expensive and complex processes in the mining industry. Machine Learning has begun to play a fundamental role in this activity, as it can better predict the location of deposits of certain minerals. Integration of geospatial, geophysical, and geochemical data within ML models has improved the identification of areas with high potential for the development of a particular mineral deposit.

A focused review by [8] analyzes the evolution of ML techniques applied specifically to mineral prospectivity prediction, highlighting advances in spatial data integration, algorithm development, and predictive modeling. While their work centers on exploration targeting rather than broader decision-making processes, it offers a valuable methodological perspective on the role of ML in reducing uncertainty during early-stage exploration.

Algorithms such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM) are popular for identifying patterns and processing complex relationships in large volumes of data. An example would be the implementation of Deep Learning tactics for the interpretation of satellite images, which leads to improved detection of geological formations of interest. Similarly, the use of evolutionary algorithms could be applied to

optimize resource exploration strategies, leading to lower costs and improved exploration success rates.

2.3. Optimization of Mineral Extraction

Machine Learning (ML) plays a crucial role in optimizing mineral extraction by enabling automation, real-time decision-making, and process adaptation. One key application is the use of ML for mineral classification in processing plants, which enhances operational precision and reduces resource consumption.

Predictive algorithms are also employed to forecast variations in ore quality, allowing for the dynamic adjustment of crushing, grinding, and concentration parameters. In blasting operations, ML models can estimate material fragmentation and recommend optimal explosive charge configurations, contributing to lower energy usage and improved extraction performance. Additionally, ML supports logistics optimization by identifying efficient transportation routes for raw materials, minimizing downtime and maximizing throughput.

A practical example of this approach is the Yanshan Iron Mine, where artificial intelligence and integrated geoscientific datasets were used to refine orebody localization and streamline extraction planning. This resulted in a reduction of waste rock removal and significant improvements in the overall extraction efficiency [6].

2.4. Predictive Maintenance and Safety

One of the main benefits of ML technology in the mining field is the ability to anticipate equipment failures before they occur, using predictive maintenance models. By analyzing real-time sensor data using Recurrent Neural Networks (RNN) and classification algorithms, it is possible to determine when a machine or piece of equipment is about to fail, thereby reducing maintenance costs and downtime.

As noted in [3], digital technologies contribute to occupational safety in the mining industry. Regarding safety, mining is one of the most dangerous economic activities, and ML helps prevent accidents. Real-time ML-based monitoring systems analyze data from sensors, cameras, and other sources to detect abnormal behavior, unsafe working conditions, or structural failures in mines. Computer vision models are also used to independently detect the onset of problems such as landslides or facility failures, enabling rapid decisions to be made to reduce risk.

Furthermore, recent reviews highlight that the role of machine learning in mining extends beyond operational monitoring. As noted in [8], advanced ML models are increasingly used for large-scale mineral prediction and data-driven decision-making across the mining lifecycle, reinforcing the importance of AI in optimizing both safety and resource management.

2.5. Improvements in Energy Efficiency and Environmental Sustainability

Mining is an intensive energy and resource activity, which has raised concerns about its impact on the environment. Machine Learning has been a key tool for increasing energy efficiency in mining operations. Initially, optimization models and predictive analysis models help reduce energy consumption, while improving machinery utilization and load distribution. Energy demand prediction functions demonstrate more efficient use of electrical energy.

Similarly, we can address the environmental impact of mining in terms of waste and residues generated through ML, as process optimization models improve waste management and reduce the ecological footprint of operations. In addition, predictive model functions make it possible to predict the evolution of the behavior of pollutants and waste generated in a mine, facilitating the adoption of waste reduction and recycling strategies.

Furthermore, recent research shows that green mining research is expanding rapidly and increasingly integrates waste recycling, ecological restoration, and environmental monitoring throughout the mine lifecycle, highlighting the interdisciplinary nature of sustainable mining practices [9].

2.6. Challenges and Obstacles in the Implementation of ML in Mining

Despite the numerous contributions and advantages, the implementation of ML in mining presents several contingencies. The main obstacle is data management and quality. Mining generates very large volumes of data, but many of them are of poor quality for training robust models.

In addition, the lack of interoperability between systems, the heterogeneity of data across different stages of the mining process, and the limited number of professionals trained in artificial intelligence and ML represent important barriers to the integration of ML-based solutions. These difficulties are often compounded by insufficient technical infrastructure, particularly in smaller or less technologically advanced mining operations, where the deployment of complex ML systems is more challenging.

Beyond technical limitations, social and organizational factors also play a significant role. Previous studies have noted resistance to change and investment requirements as relevant challenges in the transition toward digital technologies in the mining sector [3]. Addressing these issues requires not only technological solutions but also organizational strategies focused on training, reskilling, and collaboration between industry and academia.

These challenges become even more pronounced in large-scale smart mining environments, where integrating ML with energy-critical, safety-constrained, and tightly coupled physical processes demands advanced uncertainty-aware frameworks and robust optimization models [10]. Furthermore, the high initial investment required for deploying ML technologies—although potentially recoverable over time—continues to limit their adoption, particularly in smaller markets and developing countries [9].

3. Materials and Methods

The PRISMA 2020 protocol was used to conduct the SLR, and this protocol also served to document it transparently. In this regard, the following research questions were proposed to determine and provide direction for the study, as shown in Table 1.

Table 1. Table of questions and motivation.

Research Questions	Motivation
Q01. What are the main applications of ML in mining process optimization?	Identify the areas in which ML techniques are being applied and what the most significant results are.
Q02. Which machine learning algorithms are most frequently used in smart mining, and what are their key algorithmic characteristics?	Determine the most widely used algorithms.
Q03. What are the main benefits of implementing ML in mining?	Analyze the improvements achieved through the use of these technologies.
Q04. What challenges do researchers and industry face in adopting ML in mining?	Identify the technical, operational, organizational, and regulatory barriers that limit the development and integration of ML-based solutions.

Various academic databases were considered for the bibliographic review; however, only those that guaranteed the quality and relevance of the sources according to the eligibility criteria were considered.

3.1. Eligibility Criteria

Eligibility criteria constitute a fundamental component in the development of a SLR, as they ensure the consistency, validity, and quality of the evidence analyzed. These criteria act as filters that define the scope of the review by determining which studies are relevant and should be considered for inclusion, and which should be excluded, thereby minimizing the risk of bias associated with irrelevant or low-quality literature.

Furthermore, they provide a clear and reproducible framework that facilitates the comparison of studies and the synthesis of findings. The inclusion and exclusion criteria were defined in accordance with the PRISMA 2020 guidelines to ensure the relevance, transparency, and methodological rigor of the selected studies.

In addition, only peer-reviewed Open Access journal articles were included. This restriction ensured unrestricted access to complete methodological details, allowed transparent verification of the screening and data-extraction procedures, and guaranteed consistent quality standards across all selected sources. While this criterion may have narrowed the scope of the evidence base, it contributed to a more rigorous and fully auditable review process, as summarized in Table 2.

Table 2. Selection of eligibility criteria for the SLR.

Inclusion Criteria	Exclusion Criteria
IC1: Open access articles	EC1: Hybrid or subscription access articles.
IC2: Articles published between 2021 and 2025	EC2: Articles published before 2021.
IC3: English-language articles	EC3: Articles written in a language other than English.
IC4: Articles with a valid DOI.	EC4: Articles with an invalid DOI.

Although the eligibility criteria listed in Table 2 focus primarily on accessibility, publication period, language, and DOI validity, this does not imply that methodologically weak studies were included without further evaluation. The assessment of research quality and risk of bias was not part of the initial eligibility filters because these aspects were addressed in a separate stage through an adapted checklist described in Section 3.6. This two-step approach is consistent with PRISMA: broad eligibility criteria ensure that all potentially relevant studies enter the screening pipeline, while methodological quality is assessed later to avoid prematurely excluding studies that may still offer valuable insights. During the risk-of-bias evaluation, studies presenting insufficient methodological detail, unclear data sources, inconsistencies between methods and results, or inadequate reporting were flagged and excluded from synthesis or considered with reduced weight. Therefore, even though quality-related criteria do not explicitly appear in Table 2, methodologically poor studies were not incorporated into the final analysis, ensuring that the synthesized evidence was both reliable and robust.

Regarding the restriction to Open Access publications (IC1), this criterion does not aim to exclude high-impact research but to ensure full transparency, verifiability, and reproducibility of the review process. Many subscription-based journals limit access to methodological details, supplementary data, or full-text content, which may hinder accurate screening, data extraction, and bias assessment. To mitigate the risk of publication bias, the search strategy deliberately included multidisciplinary and domain-leading databases (Scopus, IEEE, Springer, ScienceDirect), which index both open access and subscription journals. Thus, even if only open access articles were ultimately included, the initial retrieval captured the broader landscape of mining and ML research, allowing the review

to map trends and identify influential themes even when some individual subscription-only articles could not be incorporated into the final synthesis. This approach prioritizes methodological rigor and replicability while still ensuring broad coverage of the field.

The selection of the 2021–2025 time frame (IC2) was motivated by empirical trends observed during the initial scoping phase, where the volume of publications on ML applications in mining increased considerably after 2020 due to advances in sensor technologies, computing capabilities, and the growing adoption of Mining 4.0 practices. Earlier studies prior to 2021 were not disregarded as irrelevant; instead, they were reviewed during the exploratory stage and found to contribute primarily conceptual foundations or early-stage experiments with limited industrial deployment. Since the objective of this SLR is to analyze the current state of ML adoption, techniques, and challenges in modern mining, focusing on the most recent five-year window ensures that the synthesis reflects contemporary practices, datasets, and technological capabilities. Restricting the review to this period helps avoid diluting the analysis with outdated methods or pre-Industry 4.0 constraints, while still building upon the legacy insights identified during the scoping phase.

3.2. Information Sources

The information sources consulted were Scopus, Springer, Arxiv, MDPI, IEEE Xplore, and ScienceDirect. These databases were selected for their broad thematic coverage, academic reputation, and relevance in the fields of mining, engineering, and computer sciences. The main searches were conducted between January 2021 and July 2025; however, relevant studies published during the second half of 2025 that met the inclusion criteria were also incorporated.

3.3. Search Strategy

Although Table 3 shows that the search equations vary across databases, this does not compromise the comparability of results. The differences arise from the specific requirements, indexing structures, and search limitations of each database, which often prevent the direct replication of the same query string. To ensure both comprehensiveness and consistency, all equations were constructed from the same core set of keywords and conceptual categories namely smart mining, sustainable or intelligent mining, and ML and AI techniques. Each search string preserves these semantic components, adapting only the level of detail necessary to align with the search engine capabilities of each platform. Furthermore, the use of multiple synonyms, Boolean operators, and cross-referenced terminology ensures full coverage of the topic and minimizes the risk of missing relevant studies. Thus, despite the variations in structure, the search strategy remains methodologically robust, consistent, and comprehensive across all databases.

Table 3. Search equations for each academic database.

Database	Equation
Scopus	("smart mining" OR "intelligent mining" OR "mining 4.0" OR "sustainable mining" OR "data-driven mining") AND ("machine learning" OR "deep learning" OR "artificial intelligence" OR "predictive models" OR "data analysis")
Springer	("smart mining" OR "intelligent mining" OR "sustainable mining") AND ("machine learning" OR "artificial intelligence" OR "deep learning")

Table 3. Cont.

Database	Equation
IEEE	("mining industry" OR "smart mining" OR "sustainable mining") AND ("machine learning" OR "deep learning" OR "artificial intelligence")
Science Direct	("smart mining" OR "mining 4.0" OR "sustainable mining") AND ("machine learning" OR "artificial intelligence" OR "predictive modeling")
Arxiv	("smart mining" OR "sustainable mining") AND ("machine learning" OR "deep learning" OR "artificial intelligence")
MDPI	("sustainable mining" OR "smart mining" OR "intelligent mining") AND ("machine learning" OR "artificial intelligence" OR "deep learning")

3.4. Data Collection Process

For data collection, a standardized log was created in spreadsheet format. It was designed according to PRISMA 2020 guidelines and structured around the key elements of each publication (authorship, year, title, country, document type, relevance, and contributions to the variable analyzed). Each article identified the author of the current article, and all information collected from sources was rigorously analyzed beforehand. In the case of incomplete information, the reviewer of the article in question thoroughly analyzed the source's contribution to ensure the validity and consistency of the collected data. This guaranteed the traceability of the process, facilitating replication in future reviews.

3.5. Data Items

The extracted data was defined based on the results log and grouped into the following categories:

- Search metadata.
- Database searched.
- Search date to temporally delimit the results.
- Applied search equation, with Boolean operators and specific keywords.
- Total number of results obtained and number of relevant results selected after applying the eligibility criteria.
- Bibliographic information on the study.
- Lead authors and co-authors.
- Year of publication.
- Article title.
- DOI, ISBN, or ISSN.
- Access URL.
- Country of origin or primary institutional affiliation.
- Document type (research article, review, conference article, etc.).
- Assessment of relevance and contributions to the SLR.
- Analytical commentary on the relevance of the study in the context of smart mining and ML.
- Relevance to the SLR.
- Variable or area of contribution.

In this way, the log not only allowed for the collection of basic bibliographic data, but also for a structured assessment of the relevance of each publication, linking the studies to the research variables defined in the SLR.

3.6. Assessment of the Risk of Bias of the Study

This evaluation was conducted using a checklist adapted to applied ML research in mining. To this end, the clarity of the problem formulation, the quality and representativeness of the data used, the transparency in the description of the algorithm, the validity of the applied validation procedures, the possibility of reproducing the experiments and the identification of explicit limitations in each investigation were considered.

These criteria allowed for the establishment of a homogeneous framework for analysis and, in each case, were classified as compliant, non-compliant, or partially compliant.

3.7. Effect Measures

This was addressed using both technical performance indicators of the ML models and metrics of impact on mining processes.

The first group included accuracy, precision, recall, F1-score, AUC-ROC, mean square error, MAE, R^2 , computation times, and algorithmic complexity. The second group evaluated results related to the application context, such as improved operational efficiency, cost reduction, increased workplace safety, and contributions to environmental sustainability. In this way, it was possible to integrate technical and practical benefits, assessing not only the model's performance but also its relevance in real-life mining scenarios.

3.8. Synthesis Methods

The synthesis of the results was conducted in a qualitative, descriptive, and thematic manner due to the marked heterogeneity (variability or diversity among the included studies) of the approaches, algorithms, and datasets used. Although subgroup analysis was initially considered, it was not feasible because the heterogeneity extended beyond differences in application domains or ML technique types. The studies showed substantial variation in problem definitions, performance metrics, data characteristics, preprocessing strategies, and reporting formats, which prevented the formation of methodologically comparable subgroups. In several cases, essential methodological details were insufficiently reported, making any stratified comparison prone to bias or misleading conclusions. For this reason, a qualitative thematic synthesis was deemed more appropriate to identify meaningful patterns and methodological trends across the literature.

The information was subsequently coded and cross-referenced to identify patterns, methodological convergences, and unique cases. Finally, research gaps, recurring limitations, and potential lines of progress were highlighted.

3.9. Assessment of Reporting Bias

To reduce the risk of bias in the analysis of sources, cross-checking strategies were applied across databases, and the reference lists of key articles were manually reviewed to identify potentially omitted literature.

Likewise, duplicate documents were excluded, and the consistency between the abstracts, methodologies, and reported results was verified to detect inconsistencies that could affect the synthesis.

3.10. Certainty Assessment

In relation to this item, for each set of studies, aspects such as methodological quality, consistency between results obtained in similar contexts, the robustness of the data sources, and the relevance of the reported performance metrics in relation to the optimization of mining processes were analyzed.

4. Results

4.1. Study Selection

The use of the PRISMA flow diagram in this systematic review is essential to ensure transparency, traceability, and methodological rigor in the study selection process. In this regard, PRISMA is an internationally accepted standard that allows for the structured documentation of each stage of article screening, from initial identification to final inclusion. In the context of this article, the use of the PRISMA diagram (see Figure 1) made it possible to clearly visualize the flow of the studies retrieved, highlight the inclusion and exclusion criteria applied, ensure the replicability of the selection process, and demonstrate the rigor of the protocol by detailing the reasons for exclusion, thereby reinforcing the transparency and credibility of the study.

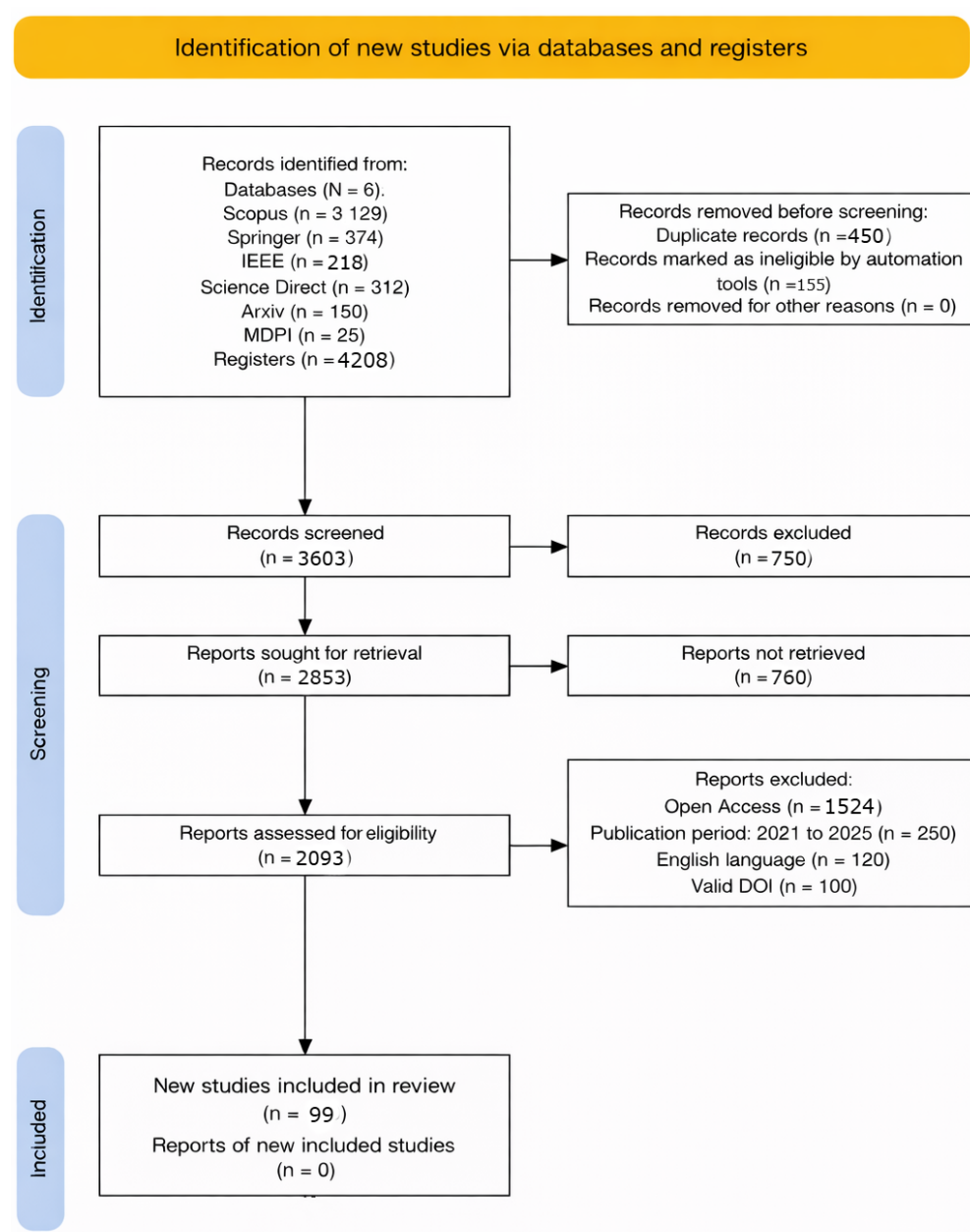


Figure 1. Flowchart for the application of eligibility criteria.

4.1.1. Identification

In this phase, a total of 4208 records were collected from six electronic databases: Scopus (n = 3129), Springer (n = 374), IEEE Xplore (n = 218), ScienceDirect (n = 312), arXiv (n = 150), and MDPI (n = 25). In addition, 450 duplicate records and 155 records classified as irrelevant were removed using automatic filtering tools during this phase, resulting in 3603 records for initial analysis.

4.1.2. Screening

Subsequently, titles and abstracts were examined, leading to the exclusion of 750 publications that did not meet the eligibility criteria. A full-text review of 2853 studies was conducted, leaving 2093 records. The inclusion and exclusion criteria were then applied to define the final SLR corpus. Specifically, 1524 records that were not open access, 250 articles published before 2021, 120 records written in a language other than English, and 100 records without a valid DOI at the time of the literature review were excluded.

4.1.3. Inclusion

Finally, in this phase, 99 articles that rigorously met the aforementioned criteria were included. During the final revision stage, one study was identified as retracted and was therefore excluded to ensure the integrity of the final corpus.

Table 4 presents a consolidated summary of the records analyzed from each database. It includes the number of pre-selected studies, the articles ultimately included and excluded based on the eligibility criteria, as well as the percentage contribution of each database to the final corpus. This unified view helps illustrate both the filtering process and the distribution of selected studies across different sources.

Table 4. Combined summary of database filtering and contribution to the final corpus.

Database	Pre-Criteria	Included	Excluded	Percentage
Scopus	3129	25	3104	25.25%
Springer	374	29	345	29.29%
IEEE	218	10	208	10.10%
Science Direct	312	11	301	11.11%
Arxiv	150	11	139	11.11%
MDPI	25	13	12	13.13%
Total	4208	99	4109	100%

4.2. Study Characteristics

This item constitutes a fundamental aspect for understanding the nature, scope, and consistency of the works selected in this systematic review. Through the analysis of the studies, we were able to identify the countries of origin, topics, contexts, and methodological specifics that were relevant to the field of smart mining and the application of ML techniques in mining process optimization.

In this sense, identifying the characteristics of the analyzed studies not only served to provide an overview to verify the rigor of the selection of records, but also provides key information for recognizing emerging trends. The summary table of the classification of the sources that comprise the SLR is presented below. Thus, Table 5 provides a structured and comparative view of the sources, constituting a relevant aspect for analyzing the prevailing trends and approaches in the literature on the subject.

Table 5. Summary table of the classification of SLR sources.

N	Database	Source
1	Scopus	[1–7,9–26]
2	Springer	[27–55]
3	IEEE	[56–65]
4	ScienceDirect	[66–76]
5	Arxiv	[77–87]
6	MDPI	[88–100]

With the aim of identifying the main concepts and trends that emerge from the analyzed literature, a word cloud was generated, summarizing the most frequently used terms in the articles selected for the systematic review. This visual representation facilitates understanding of the most relevant thematic axes and provides a quick overview of the topics related to SLR.

Figure 2 shows that terms such as “artificial intelligence,” “machine learning,” “smart mining,” “intelligent mining,” and “predictive modeling” appear more prominently, demonstrating the importance of these concepts in the corpus reviewed. Overall, the word cloud reflects how recent literature articulates mining with advanced analytical and predictive technologies.

**Figure 2.** Word cloud of the most relevant topics related to SLR.

Although word clouds are generally considered less rigorous than other forms of data visualization, their use in Figure 2 is justified as an exploratory tool to provide an intuitive and immediate overview of the dominant themes within the corpus. The objective of this figure is not to perform a quantitative analysis, but rather to offer a visual entry point that highlights the most recurrent concepts associated with ML and smart mining. To ensure methodological rigor, this visualization is complemented in subsequent sections with systematic analyses such as frequency counts, categorical grouping, and synthesis based on the research questions which more accurately capture thematic relationships. Therefore, the word cloud functions as a descriptive and accessible complement to the more detailed analytical procedures presented in the review.

Figure 3 shows that the number of SLR source records on the topic stands out in some countries, such as China (25), the United States (20), and Australia (12), which are the territories with the highest number of publications (see Figure 3). This demonstrates their role in generating scientific knowledge related to mining and emerging technologies. Significant contributions also come from Canada (10), Brazil (7), and India (5), while other countries have smaller shares (20).

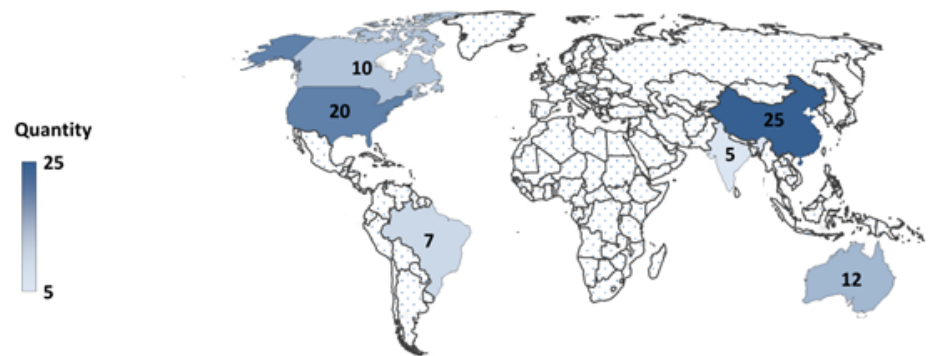


Figure 3. Geographic distribution of the studies analyzed in the SLR.

This geographic distribution reflects the potential for growth in scientific production in regions that are still underrepresented.

4.3. Risk of Bias in Studies

This other protocol item constitutes a key aspect of systematic reviews because it allows for the assessment of the validity and reliability of the findings obtained from the selected sources. In this sense, when analyzing the selected articles, various risks of bias were identified that must be considered when interpreting the findings. First, several studies report the use of limited or unrepresentative datasets, which may affect the generalization of ML models to other contexts. Second, some studies focused on the optimization of algorithms and performance metrics without delving into the external validity of the models or their practical applicability.

Likewise, limitations were identified regarding methodological variety, as there is a predominance of approaches based on DL and heuristic optimization, while other less explored analysis methods could provide complementary approaches. This predominance can generate a technological bias, favoring current trends without considering emerging methodological alternatives. These risks serve as a reminder of the need for future research to address these issues in order to reduce the potential for bias and strengthen the robustness of the literature on these topics.

4.4. Results of the Syntheses

The synthesis of the selected studies was structured according to the four research questions defined in this review. Each question addresses a key dimension of ML adoption in mining, including its main applications, the techniques most frequently employed, the benefits obtained, and the challenges that hinder broader implementation. To ensure a coherent presentation of the findings, the results are summarized and discussed in alignment with these research questions. This organization allows for a clearer understanding of how ML contributes to mining process optimization and where future research efforts should be directed. The following subsections present the outcomes associated with each question, supported by quantitative evidence extracted from the included studies and their corresponding graphical representations.

4.4.1. Q01. What Are the Main Applications of ML in Mining Process Optimization?

As illustrated in Figure 4 and derived from the systematic analysis of the reviewed studies, the identified ML applications were systematically categorized according to major operational domains within the mining value chain. This domain-based classification provides a structured overview of adoption patterns across equipment reliability, logistics optimization, occupational safety, and environmental monitoring. The following discussion is organized according to this classification framework.

The analysis reveals that the most frequently reported applications are failure prediction in mining equipment and prediction of critical equipment lifespan, followed by logistics and mineral transportation optimization, occupational safety monitoring, and environmental monitoring. These applications reflect the increasing integration of ML into mining operations, with a particular focus on enhancing operational efficiency, asset reliability, and environmental sustainability.

Failure prediction relies on real-time data collected from monitoring systems in mining operations. Algorithms such as decision trees, neural networks, and physics-informed models are used to detect patterns that precede hazardous events or system failures [41]. These applications help reduce unplanned downtime, improve operational planning, and lower overall operational costs through process optimization strategies [71].

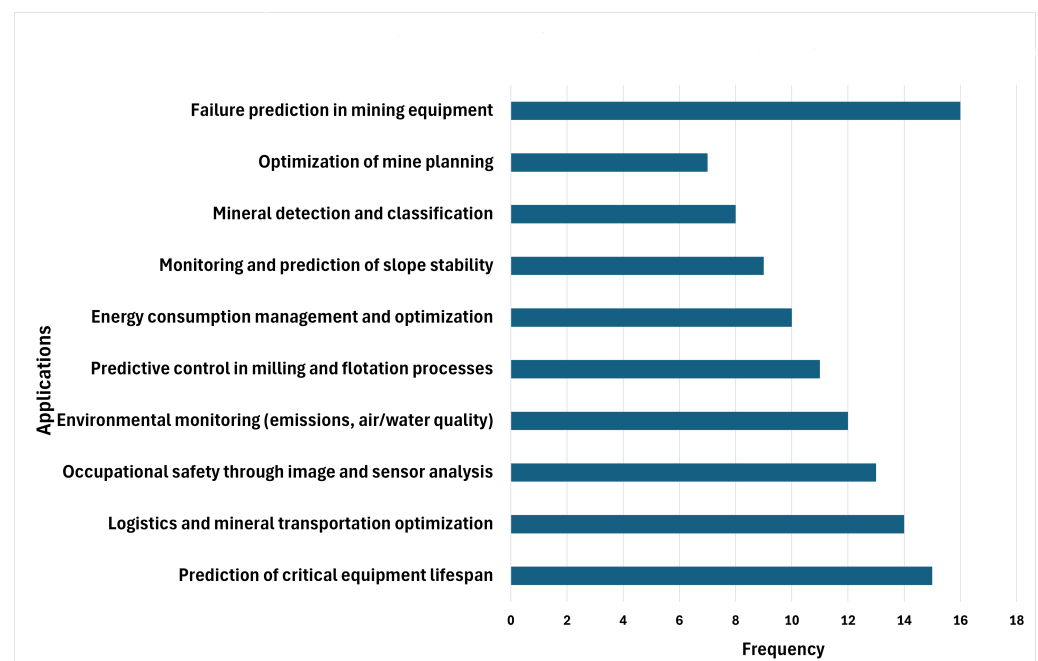


Figure 4. Main applications of ML in mining process optimization. (Q01).

In parallel, intelligent monitoring and reliability assessment focus on enhancing operational safety and performance in complex mining and tunnelling environments. Machine Learning and Deep Learning approaches that integrate multi-source sensing, high-resolution drilling data, and real-time monitoring are increasingly applied to support dynamic reliability optimization and automated rock mass quality assessment [35,75]. These data-driven strategies improve decision support, reduce manual intervention, and enhance overall system-level performance, particularly under challenging geological conditions.

Logistic optimization is another prominent application where advanced control and automation technologies are used to improve haulage performance and operational efficiency in mining operations. Evolutionary algorithms integrated with predictive control frameworks have demonstrated their effectiveness in enhancing trajectory tracking and vehicle performance in underground haulage systems [40]. In surface mining, the adoption of Autonomous Haulage Systems (AHS) has further contributed to improvements in safety, productivity, and operational efficiency [49].

In the area of occupational and operational safety, computer vision models are applied to analyze images and video streams to support real-time monitoring in mining environments. These approaches enable pedestrian detection, obstacle recognition, and enhanced situational awareness in both underground and open-pit operations [2,61]. Such solutions

contribute to accident prevention, improved safety management, and the generation of real-time alerts.

Environmental monitoring, while less frequent, is an expanding domain in mining applications. It includes air quality assessment, vegetation and land-cover analysis, and tailings storage facility surveillance. Machine Learning and Deep Learning models, including convolutional neural networks (CNNs), are applied in combination with satellite imagery, geospatial analysis techniques, and UAV-derived datasets to support predictive environmental assessment and sustainable management [70,101].

In addition to the predominant applications, the analysis identified a set of underrepresented areas with high potential for future research. These include mineral exploration and slope stability monitoring. In the latter case, recent review studies highlight the growing adoption of UAV-based monitoring combined with Machine Learning techniques for assessing slope stability and predicting geotechnical risks in open-pit mining operations [102,103].

Recent advances in geochemical anomaly detection and mineral prospectivity mapping demonstrate how domain-guided Deep Learning models and AI-driven mineral discovery frameworks can significantly enhance exploration accuracy and decision-making processes [104,105].

Overall, Figure 4 indicates that ML is predominantly applied in short- and medium-term operational tasks where real-time data is available. However, there remains significant opportunity to extend its use into long-term strategic decision-making, cross-process integration, and holistic predictive modeling across the entire mining value chain.

4.4.2. Q02. Which Machine Learning Algorithms Are Most Frequently Used in Smart Mining, and What Are Their Key Algorithmic Characteristics?

To address this question, a detailed analysis was conducted to identify the most frequently used Machine Learning (ML) techniques in smart mining and to examine the algorithmic trade-offs influencing their adoption. The identified algorithms were grouped into major methodological families, and the following discussion is organized according to this classification framework.

As shown in Figure 5, the most commonly applied ML techniques are Decision Trees (18 mentions), Neural Networks (16), and Deep Learning architectures (14). This distribution reflects a dual preference within the field: models offering high interpretability and low computational complexity, and models providing strong representational capacity to capture complex, nonlinear mining data patterns.

Decision Tree-based models are widely adopted in smart mining applications due to their structured learning process, ability to model nonlinear relationships, and relatively low computational complexity. Their interpretability and capacity to handle heterogeneous operational variables make them particularly suitable for productivity prediction and operational optimization tasks. In mining environments characterized by complex and data-intensive processes, tree-based algorithms have demonstrated strong predictive performance compared to baseline and linear models, supporting their practical deployment in real-world scenarios [106].

Neural Networks and Deep Learning architectures, in contrast, are primarily used in scenarios involving high-dimensional, heterogeneous, and sensor-rich datasets. Applications include image-based analysis and multivariate time-series forecasting for complex mining processes and environmental monitoring. These models offer superior feature extraction and nonlinear modeling capabilities, but they require larger datasets, higher computational resources, and often suffer from limited interpretability [35,78].

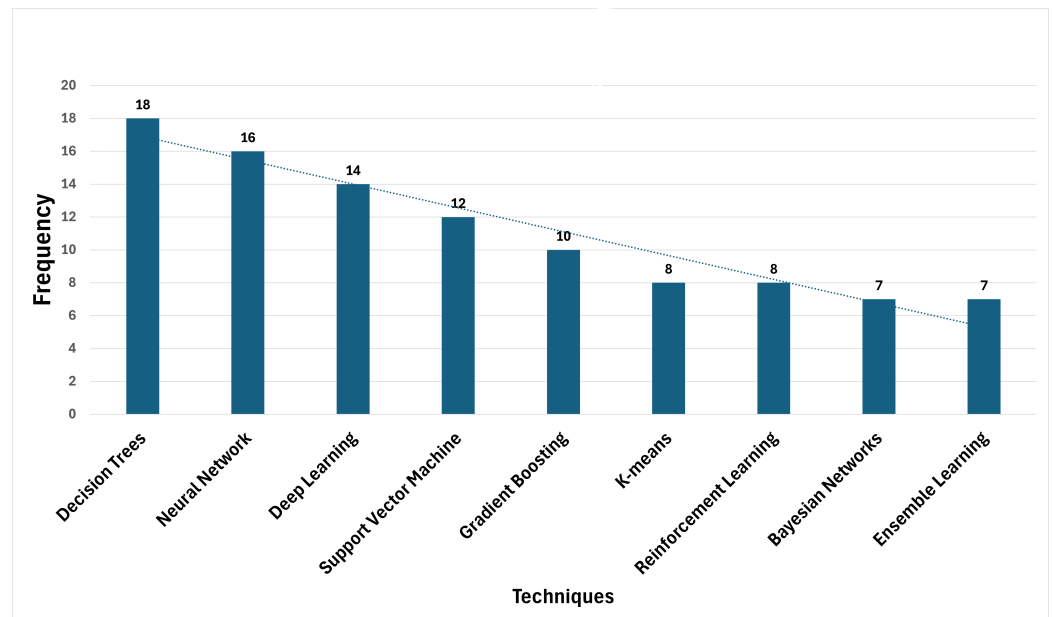


Figure 5. Most commonly used machine learning algorithms in smart mining.

A second tier of frequently reported algorithms includes Support Vector Machines (12 mentions), Gradient Boosting methods (10 mentions), and K-means clustering (8 mentions), as illustrated in Figure 5. These techniques provide a balanced trade-off between predictive accuracy, robustness to noise, and computational efficiency. In practical smart mining applications, they are commonly employed in productivity prediction, rock mass classification, clustering of operational patterns, and operational optimization tasks [75,106].

Less frequently reported, yet methodologically significant, are Reinforcement Learning (8 mentions), Bayesian Networks (7), and Ensemble Learning strategies (7). These approaches introduce capabilities such as sequential decision-making, probabilistic reasoning under uncertainty, and improved generalization through model aggregation. Their comparatively lower adoption may be attributed to higher implementation complexity, data scarcity in certain mining contexts, or integration challenges with legacy systems.

Overall, the findings indicate that algorithm selection in smart mining is influenced not only by predictive performance but also by contextual factors such as interpretability, computational cost, scalability, robustness to noisy industrial data, and ease of integration into existing operational workflows. These considerations are critical in mining environments characterized by dynamic conditions, safety constraints, and heterogeneous data streams.

4.4.3. Q03. What Are the Main Benefits of Implementing ML in Mining?

Figure 6 summarizes the distribution of the key benefits reported in the reviewed studies regarding the implementation of Machine Learning (ML) in the mining sector. The identified benefits were categorized according to their primary impact dimension, including operational efficiency, economic performance, maintenance optimization, safety enhancement, and sustainability-related improvements. The following discussion develops each impact dimension based on its relative prominence and supporting evidence from the literature.

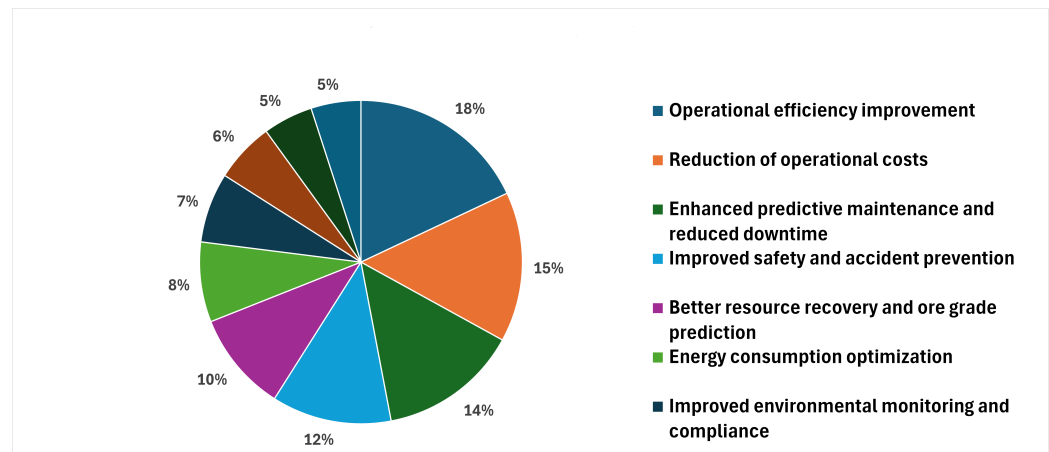


Figure 6. Main benefits of implementing ML in mining.

The most prominent advantage—operational efficiency improvement (18%)—reflects ML’s capacity to reduce process variability, optimize control parameters, and improve workflow stability across extraction, hauling, and processing stages. Predictive and data-driven decision models enable real-time adjustments that enhance throughput and system reliability [36].

Closely related are the reduction in operational costs (15%) and the improvement in predictive maintenance with reduced downtime (14%), as identified in the present review. These benefits highlight the strong economic impact of ML applications, particularly through early fault detection, optimized maintenance scheduling, and extended equipment lifespan. By minimizing unexpected failures and improving asset utilization, ML contributes directly to cost savings and production continuity. For instance, ML-based optimization models have demonstrated improved cost-effectiveness and operational performance in blasting operations [73].

Another significant benefit is improved safety and accident prevention (12%), largely enabled by computer vision systems and real-time detection technologies. These solutions enhance hazard identification, obstacle detection, and automated decision-making in mining operations, thereby strengthening risk management frameworks in hazardous mining environments [2].

Better resource recovery and ore grade prediction (10%) also represent key contributions. ML-based classification and regression models enhance geological interpretation and processing decisions, allowing more precise ore characterization and improved recovery strategies. This translates into higher extraction efficiency and better long-term resource planning.

Energy consumption optimization (8%) is particularly relevant in energy-intensive processes such as grinding, crushing, and mineral transportation. Predictive control systems and reinforcement learning models enable dynamic adjustment of operational parameters, reducing energy waste while maintaining production targets.

Finally, improved environmental monitoring and regulatory compliance (7%) demonstrate the growing role of ML in supporting sustainable mining practices. The integration of geospatial analytics and remote sensing techniques enhances the assessment of air quality, land-cover dynamics, and tailings dam conditions, thereby strengthening environmental risk mitigation and regulatory transparency [70,82].

Overall, the benefits presented in Figure 6 indicate that ML adoption in mining extends beyond productivity and cost reduction. It contributes to safer operations, improved environmental stewardship, and data-driven strategic decision-making—key pillars in the transition toward fully integrated smart mining systems.

4.4.4. Q04. What Challenges do Researchers and Industry Face in Adopting ML in Mining?

Figure 7 presents a radial chart summarizing the principal challenges identified across the reviewed studies. The numerical score assigned to each barrier corresponds to its frequency of occurrence in the analyzed literature and serves as a quantitative proxy for its relative prominence. These challenges affect both academic research and industrial implementation, revealing technical, economic, organizational, regulatory, and environmental constraints that limit the scalability and operationalization of ML-based solutions in operational mining environments.

To enhance methodological transparency, the chart integrates citation frequency with qualitative relevance reported in expert surveys and case studies. Barriers are grouped into structural categories and linked—where applicable—to their dominant impact domain (academic, industrial, or both). Regulatory and environmental factors are treated jointly due to their structural interdependence in mining operations. Based on this structured synthesis, the following subsections examine each barrier category in detail, discussing their specific implications and supporting evidence from the reviewed literature.

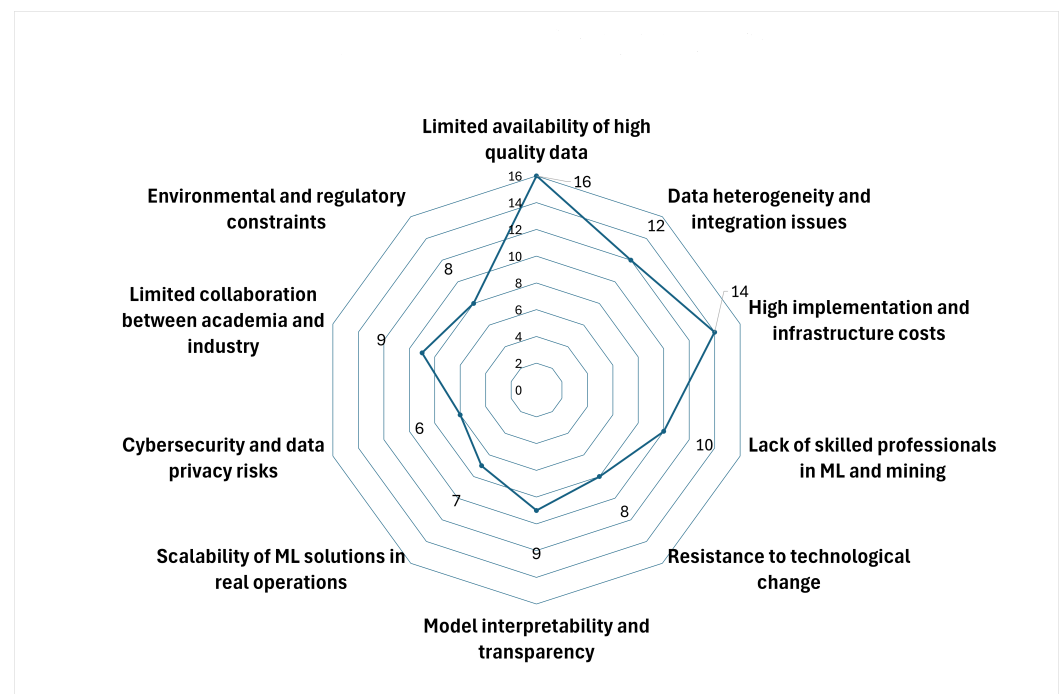


Figure 7. Main challenges in the adoption of ML in mining.

- **Limited availability of high-quality data:** The most frequently cited barrier concerns the scarcity of reliable, labeled, and standardized datasets. Inconsistent data collection practices, missing values, and poor sensor calibration directly undermine model accuracy and generalizability. The preparation and structured management of datasets are therefore critical enablers of successful ML deployment within digital transformation initiatives [44]. Moreover, increasing geological complexity and the integration of multi-source geological data introduce additional methodological challenges for large-scale mineral prediction tasks [8].
- **Data heterogeneity and integration problems:** Mining operations generate substantial volumes of heterogeneous, high-dimensional, and frequently unstructured data from multiple sources. The lack of harmonized analytical and operational mechanisms limits the effective coordination and integration of diverse mining systems [43]. Furthermore, research on digital twins and Industry 4.0-related technologies in mining

highlights ongoing technical challenges associated with technological integration and the broader process of digital transformation within the sector [62].

- **High implementation and infrastructure costs:** Deploying ML solutions often demands substantial investment in computational platforms, IoT sensors, data storage systems, and specialized software. Survey-based evidence indicates that economic constraints significantly influence AI adoption decisions in mining organizations [1]. Comparative analyses of autonomous haulage systems further emphasize the technological and economic barriers associated with large-scale digital transformation [49].
- **Lack of skilled professionals in ML and mining:** The shortage of professionals with competencies in both mining operations and data science constrains the effective development and deployment of intelligent systems [45]. Industry surveys indicate a growing demand for expertise in data science and autonomous technologies within the mining workforce. Furthermore, the increasing adoption of advanced digital technologies such as digital twins introduces additional competency requirements in mining organizations [62]. This skills gap slows innovation and weakens the alignment between algorithmic development and operational needs.
- **Resistance to technological change:** Resistance to technological change is particularly evident in traditional mining environments, where established operational routines, hierarchical structures, and contextual constraints may influence the adoption of digital and data-driven technologies. Although recent studies highlight the growing implementation of digital technologies in mining operations [3], empirical research specifically examining the sector identifies environmental and organizational barriers that can constrain technology adoption processes [107]. These structural and contextual factors shape the pace and effectiveness of digital and machine learning implementation in mining operations
- **Model interpretability and transparency:** The lack of interpretability in many ML models has raised increasing concerns as black-box approaches become widespread across industrial domains [47]. In mining contexts, where operational decisions may have significant safety and economic implications, limited explainability can reduce trust and acceptance among practitioners and decision-makers. Moreover, research on the application of ML in mineral processing emphasizes the importance of integrating domain knowledge and phenomenological models to enhance reliability and practical understanding in industrial environments [93].
- **Scalability and robustness of ML solutions:** Scaling ML models from controlled or site-specific studies to real-world mining operations is challenging, particularly in complex geological and high-stress environments that demand adaptive and dynamically reliable control systems [35]. Variations in geological, environmental, and operational conditions reduce model robustness and limit transferability across different mining contexts, especially in continuously changing and sensor-uncertain environments [60].
- **Cybersecurity and data privacy risks:** Increasing digitalization and system interconnectivity expose mining operations to cybersecurity threats and data protection risks. Cyber-physical systems in mining environments require enhanced resilience and protection against disruptions and cyber threats [34]. Broader Industry 5.0 frameworks further emphasize the need to address cyber-physical-social security and privacy challenges in highly interconnected industrial ecosystems [63].
- **Limited collaboration between academia and industry:** Insufficient knowledge transfer between researchers and practitioners reduces the practical applicability of proposed ML frameworks. Research on safe and intelligent mining highlights ongoing theoretical and technological challenges in translating advanced concepts into practical mining systems [22]. Moreover, studies on technology adoption in

mining identify organizational misalignment and weak collaboration mechanisms as barriers to innovation diffusion [107].

- **Environmental and regulatory constraints:** Environmental regulations and policy constraints may constrain experimentation and deployment of ML tools, especially in cases involving sensitive environmental data or emissions monitoring. As highlighted in recent studies on sustainable energy transition in mining, inconsistent regional decarbonization policies and the need for regulatory alignment introduce significant barriers to technological implementation in the sector [26,90]. These regulatory and environmental factors add further complexity to ML implementation in mining.

Taken together, the reviewed evidence indicates that barriers to ML adoption in mining are systemic and interdependent rather than isolated challenges. Technical limitations—particularly those related to data quality, integration, interpretability, and model robustness—interact with economic constraints, organizational structures, regulatory pressures, and workforce capabilities. This multidimensional landscape requires coordinated strategies that extend beyond algorithmic improvement to include institutional alignment, digital infrastructure development, and cross-sector collaboration.

Recent literature has also emphasized the role of data and model-related limitations in hindering the adoption of ML in geoscientific applications. The authors in [105] examine the use of Artificial Intelligence and Machine Learning in the exploration of critical minerals, highlighting their current limitations. The main challenges identified include the scarcity and low quality of geological data in many regions, the lack of model interpretability, geographic bias in training data, and difficulties in integrating expert knowledge and unstructured sources. The study concludes that the true value of ML in geosciences depends on its integration with human expert knowledge, proposing collaborative approaches as a way to overcome current barriers to the adoption of these technologies.

In summary, overcoming these barriers requires more than technological advancements alone. Effective implementation of ML in mining demands coordinated strategies that include infrastructure investment, workforce development, stronger collaboration between academia and industry, and regulatory frameworks that support responsible, transparent, and scalable ML solutions.

4.4.5. Characterization of Included Studies

After applying the inclusion and exclusion criteria described in the methodology, a total of 99 primary studies were selected for in-depth analysis.

In accordance with the PRISMA 2020 guidelines for reporting systematic reviews, Table 6 provides a structured summary of the included studies, categorized by their domain of application within smart mining.

This classification serves as a foundational overview of the current state of research and provides the basis for the in-depth synthesis of findings presented in the following subsections, organized according to the research questions Q01 to Q04.

However, it is important to note that most of the included studies do not explicitly report the maturity level of the ML solutions implemented. In particular, few papers clarify whether the systems described were conceptual models, pilot implementations, or fully deployed in operational mining environments. This lack of detail limits the ability to assess the actual scale of adoption across the literature. Future studies could address this gap by incorporating standardized indicators of technology readiness or implementation stages, which would enhance comparability and real-world relevance.

Table 6. Synthesis of reviewed studies by application domain in smart mining.

Application Domain	Main Problems Addressed	Predominant AI/ML Techniques	General Performance Trends	Main Limitations	References
Mineral Exploration & Geological Mapping	Low discovery rates, high exploration costs, orebody delineation uncertainty	CNNs, Random Forest, SVM, hybrid DL models	High classification accuracy (>85%)	Limited labeled datasets, poor regional generalization	[1–7,10–14,18,22,26,28,34,44,50,79]
Drilling, Blasting & Fragmentation Analysis	Inefficient blasting, poor fragmentation prediction, secondary breakage	CV + CNN, U-Net, YOLO, Mask R-CNN	Fragmentation prediction accuracy >90%	Dust, lighting variation, lack of standard datasets	[9,15,20,23,29,38,42,48,51,54,58,74,92]
Mine Operations & Equipment Automation	Low productivity, equipment downtime, unsafe manual operations	Reinforcement Learning, Deep RL, control-AI hybrids	Improved tracking and efficiency	Harsh environments, sensor reliability	[16,21,24,30,37,40,41,49,53,66,71,84,89]
Conveyor Belt & Transport Monitoring	Belt tear, misalignment, foreign object detection	YOLO, EfficientNet, TCN, CV detection	Detection accuracy >95%	Harsh lighting, real-time constraints	[17,25,31,39,43,51,57,60,75,92]
Mine Safety & Worker Monitoring	Fatigue, PPE non-compliance, accident risk	YOLO, LSSVM, pose estimation	Accuracy 90–98%	Privacy, poor underground visibility	[19,32,45,55,62,68,72,76,97]
Environmental Monitoring & Sustainability	CO ₂ , land degradation, tailings risk, illegal mining	CNN, remote sensing AI, geospatial ML	Detection performance >90%	Cloud cover, temporal limits	[27,33,36,46,56,59,63,70,77,81,82,85,90,94]
Mineral Processing & Metallurgy Optimization	Low recovery, unstable process control	ANN, hybrid ML + physics, predictive ML	Improved process stability	Data scarcity, poor sensors	[35,47,64,67,73,78,93]
Smart Mining Systems & Digital Twins	System integration, limited decision support	Digital twins, AI simulation, IoT-ML	Improved planning	High cost, low maturity	[42,43,87,88]
Data Infrastructure & Responsible AI	Energy consumption, bias, security	Efficient ML, XAI, Responsible AI	Reduced retraining energy	Few mining implementations	[86,91,95]
Cross-domain AI Applications	Economic forecasting, system-level AI strategy	Transformers, ensembles	High predictive performance	Indirect mining link	[96,98–100]

5. Discussion

The results of this SLR provide an integrated understanding of how ML is being applied, adopted, and expanded within the mining industry. Across the four research questions, consistent patterns emerge that highlight both the technological maturity of certain ML approaches and the structural limitations that still constrain their large-scale deployment. Beyond summarizing the findings, this discussion reflects on their broader implications for mining digitization, technological integration, and future research trajectories.

First, the synthesis of applications (Q01) indicates that ML in mining is predominantly oriented toward predictive and optimization-related tasks, emphasizing operational continuity and resource maximization. This predominance suggests that mining companies prioritize ML initiatives that offer immediate operational returns, such as equipment-life prediction, mineral classification, and predictive control in grinding and flotation. These findings align with the sector's emphasis on reducing downtime and maximizing throughput, reinforcing the notion that mining organizations tend to adopt ML where return-on-investment is more tangible. At the same time, the emergence of ML applications in environmental surveillance, tailing-dam monitoring, and safety analytics reflects a gradual shift toward sustainability-driven innovation, consistent with global regulatory pressures and ESG agendas.

Second, the analysis of algorithms (Q02) reveals that the current methodological landscape is shaped by the nature of mining data—heterogeneous, sensor-rich, and often high dimensional. The predominance of Decision Trees, Neural Networks, and DL architectures suggests that the field is transitioning from traditional statistical approaches toward more complex, data-driven methodologies. This trend indicates increasing computational capability in mining operations and growing confidence in ML systems. However, the limited use of ensemble learning, probabilistic modelling, or hybrid systems also points to a methodological stagnation that could be addressed by adopting more sophisticated approaches, particularly in contexts where uncertainty quantification and interpretability are critical.

Third, the benefits identified (Q03) show that ML contributes not only to operational efficiency and cost reduction, but also to safety, environmental management, and long-term sustainability. While the most frequently reported benefits—predictive maintenance, grade prediction, and process optimization—highlight the operational value of ML, the less explored advantages in energy optimization and safety monitoring indicate opportunities for further research. These areas are particularly relevant as mining companies face increasing pressure to decarbonize operations, reduce accidents, and demonstrate environmental compliance. Thus, the evidence suggests that ML can serve as a bridge between economic performance and responsible mining practices.

Finally, the analysis of challenges (Q04) reinforces that the widespread adoption of ML is constrained more by systemic than purely technological factors. Data availability and quality remain critical bottlenecks, especially in underground mines where sensor deployment is limited. Additionally, the lack of standardized data architectures across mining sites hinders model generalization and transferability—an issue amplified by the high variability of geological and operational conditions.

In addition, evidence suggests that the current academic literature provides limited insight into the organizational modes through which ML is adopted in mining. Most studies focus on technical performance or application feasibility, without distinguishing whether ML solutions are implemented as vendor-managed systems or developed and maintained internally by mining companies. This limitation restricts the ability to assess technological autonomy, long-term sustainability, and integration across operational workflows.

Based on the findings and limitations identified in this review, several directions for future research can be outlined. Future studies should extend beyond academic publications by incorporating industry reports, grey literature, patent databases, and empirical industrial case studies to better capture real-world ML adoption and deployment maturity. Additionally, the explicit classification of ML applications according to their maturity level—ranging from proof of concept to full industrial deployment—would improve the assessment of adoption readiness.

From a broader perspective, future assessments of ML adoption in mining should adopt a multi-dimensional framework—combining technical performance metrics with organizational, operational, and legal considerations. This includes evaluating the role of institutional actors, understanding lifecycle management strategies, assessing the legal frameworks surrounding model and data ownership, and identifying patterns of internal versus vendor-led system development. Such an integrative approach would enable a more realistic, actionable, and industry-aligned understanding of ML's evolving role in shaping the future of mining.

Building upon these directions, greater emphasis should be placed on evaluating the robustness of machine learning models under variable and harsh operational conditions, which are typical in mining environments—particularly in underground or remote settings. Likewise, the scalability of ML solutions across mining sites with diverse geological and

operational characteristics remains underexplored. Legal considerations should also be addressed, including data ownership, intellectual property rights over trained models, and legal responsibility in safety-critical decision-making systems. Addressing these aspects would improve the reliability, transferability, and accountability of ML implementations in real-world industrial contexts.

Overall, the integration of findings from Q01–Q04 indicates that although the mining industry recognizes the strategic value of ML and has progressed substantially in operational applications, its transition toward fully intelligent mining systems remains incomplete. Advancing this transition will require coordinated efforts to improve data governance, strengthen workforce capabilities, develop interpretable and robust ML solutions, and establish secure, scalable data-integration frameworks. Only through addressing these structural and organizational dimensions can mining operations evolve from isolated ML initiatives to interconnected systems capable of sustaining long-term operational efficiency, environmental responsibility, and enhanced safety across the mining value chain.

6. Conclusions

This systematic literature review provides a comprehensive assessment of the current state of Machine Learning (ML) adoption in the mining sector, based on 99 peer-reviewed studies published between 2021 and 2025. The findings indicate that ML has moved beyond purely experimental research and is progressively entering operational deployment across selected segments of the mining value chain.

Adoption is most advanced in operational domains such as predictive maintenance, ore characterization, logistics optimization, and process monitoring, where data availability is relatively high and performance improvements can be directly linked to economic outcomes. In these contexts, ML can be considered mature at the task or subsystem level.

However, adoption remains fragmented beyond these operational applications. Enterprise-wide integration, sustainability-oriented systems, and long-term strategic planning applications are comparatively underdeveloped. Although concepts such as digital twins and integrated decision-support ecosystems are emerging, fully validated system-level implementations remain limited in the reviewed literature.

The benefits of ML extend beyond productivity gains and cost reduction to include improvements in safety, energy efficiency, and environmental monitoring. Nevertheless, these broader dimensions remain less consolidated, suggesting that current integration is still primarily efficiency-driven rather than transformative at the organizational level.

Persistent structural barriers—including limited data quality and interoperability, high infrastructure costs, workforce skill gaps, cybersecurity concerns, and uncertainties regarding model robustness and interpretability—continue to constrain large-scale adoption. Furthermore, the absence of standardized reporting on implementation maturity levels (e.g., pilot vs. full deployment) makes benchmarking and comparative evaluation challenging.

Overall, the mining sector appears to be in a transitional phase of ML integration: applications are no longer confined to experimental contexts, yet fully integrated, enterprise-level intelligent mining systems remain under development. Achieving systemic adoption will require coordinated advances in data governance, organizational capability, regulatory alignment, and rigorous real-world validation. Addressing these dimensions will be essential for enabling ML to evolve from isolated operational tools into a foundational pillar of next-generation intelligent mining systems.

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