

Review

Artificial Intelligence in the Copper Mining Industry: A Systematic Mapping Review and Qualitative Synthesis

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Abstract

Artificial intelligence (AI) is increasingly being investigated to support decision-making and process improvement in copper mineral processing and extractive metallurgy; however, the available evidence remains fragmented across operational units, methods, sustainability dimensions, and geographical contexts. This systematic mapping review, complemented by qualitative cross-study synthesis, analysed publications from 2014 to 2025 retrieved from IEEE Xplore, Scopus, and Google Scholar. Of the 410 records identified before screening, 71 studies were classified according to four predefined research questions addressing copper-processing operations, AI domains, sustainability contributions, and geographical distribution. The findings show an uneven distribution of research across the processing flowsheet. Comminution and froth flotation received the greatest attention, whereas lixiviation, solvent extraction, electrowinning, and electrorefining were less represented. Machine learning was the dominant AI domain, particularly supervised approaches based on historical operational data; however, no algorithm was universally superior, as reported performance depended on the dataset, target variable, operational context, and validation procedure. Most studies focused on prediction, monitoring, fault diagnosis, and operational optimisation, while reinforcement learning, hybrid mechanistic–data-driven models, adaptive control, and sustained industrial deployment remained comparatively limited. Sustainability assessments emphasised operational and economic outcomes more frequently than social, ethical, circular-economy, and broader environmental implications. Geographical results reflected the locations assigned to the reviewed studies and industrial cases rather than regional AI maturity. The review identifies data availability, heterogeneous validation practices, model transferability, and limited evidence of sustained industrial deployment as recurring challenges. It proposes a staged research agenda to develop more reliable, transferable, and human-supervised AI applications across copper-processing operations.

Keywords: artificial intelligence; mineral processing; copper mining operations; systematic mapping review; qualitative synthesis; smart mining; sustainability



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1. Introduction

Given the impacts and challenges posed by climate change, decarbonization is critical to mitigation efforts [1]. The energy transition towards renewable energy sources is a crucial topic on the global agenda. In this context, the copper industry will play a pivotal role in electrification and electromobility. Copper has multiple industrial and technological applications, including electrical cables, electronic components, machinery, construction, and electric vehicles, all of which contribute to the decarbonization of transport [2]. Consequently, global demand for copper is expected to continue to increase in the coming years, rising from global mine copper production of 21,548 kMT in 2022 [3] to over 31,000 kMT annually. These projections highlight the need to optimise copper extraction and processing to maintain the industry's competitiveness and sustainability [4].

Copper mining faces several challenges that impact operational efficiency. Globally, ore grades are declining, and mineralogical associations are becoming increasingly complex, leading to higher operational costs with more complex extraction and processing procedures [5]. The copper mining industry also intensively uses water and energy, putting pressure on natural resources and contributing to the global carbon footprint. Productivity constraints, the slowdown in the start-up of new mining projects, and the need for comprehensive management of waste generated in mining operations all represent critical challenges that require new strategies to advance more sustainable mineral processing [6].

The integration of emerging technologies, especially artificial intelligence (AI), is opening up exciting possibilities for transforming the copper mining industry. AI-based methods have been proposed and evaluated for mine-design optimisation, equipment performance prediction, and resource management support, with reported potential to improve operational efficiency. Beyond that, AI-based analysis of real-time operational data may support safer mining operations by identifying hazardous conditions and providing early warnings of potential incidents [7]. AI-based optimisation may help reduce the environmental footprint of copper processing by enabling more efficient use of energy and water and identifying opportunities for waste reduction [8].

In addition, advanced sensor technologies and real-time monitoring systems are being deployed at various stages of the mining process, including milling and froth flotation [9]. These tools provide vital data that help mining teams make faster and better-informed decisions [10]. AI-driven systems continuously monitor equipment and process performance, spotting issues and predicting failures before they occur. This proactive approach to maintenance not only reduces unexpected downtime but also extends equipment life, thereby lowering operational costs.

Moreover, the industry is exploring innovative techniques such as in situ leaching, which extracts copper directly from the deposit using chemical solutions. This method avoids the need for traditional blasting and crushing, making the process less disruptive to the environment. Overall, the reviewed literature indicates that AI and machine-learning methods are being investigated across applications ranging from mine planning to equipment maintenance, with reported potential to improve operational efficiency, reduce costs, and enhance environmental performance.

Although interest in the use of artificial intelligence (AI) in the mining sector has grown, the current research on its impact and potential remains fragmented, making it difficult to obtain a clear picture of how AI is really transforming the industry [11]. AI technologies are advancing rapidly, and developments in machine learning algorithms, data processing capabilities, and connected sensors are opening new possibilities in copper mining [12,13]. However, a systematic mapping review is needed to identify how research is distributed across copper-processing operations, AI domains, sustainability dimensions, and geographical contexts, and to interpret the principal patterns and gaps across the field.

Accordingly, this review maps the areas in which AI has been most frequently investigated and complements this classification with a qualitative synthesis of the reported applications, methodological limitations, implementation challenges, and research needs [14].

Previous reviews have examined artificial intelligence, Industry 4.0, smart mining, sensing technologies, and digital transformation across the mining sector from broad technological, operational, or organisational perspectives [13,15–17]. However, these studies generally combine multiple commodities, mining stages, and digital technologies, which limits the visibility of how specific AI approaches are distributed across the operational units of copper mineral processing and extractive metallurgy. The present review addresses this more specific gap by integrating four analytical dimensions: the copper-processing operations in which AI has been investigated, the AI domains and methods reported, the sustainability dimensions considered, and the geographical distribution of the reviewed evidence. This work aims to conduct a process-specific review that examines how AI is being investigated across different stages of copper processing, while also assessing its reported implications for sustainability (economic, environmental, and social) and the geographical distribution of the reviewed studies. By integrating these dimensions, the review seeks to identify uneven patterns of research development across the copper-processing flowsheet and to reveal gaps that may remain obscured in broader reviews of mining digitalisation.

2. Background

This section provides an overview of the main operational units in copper processing and the Artificial Intelligence domains to give the reader a comprehensive understanding of the existing challenges. Other topics, such as regions and sustainability pillars (Economic, Environmental, Social), are self-explanatory and are therefore not discussed in detail here.

2.1. AI and Its Domains

The AI domains and subdomains used in this review were defined based on the AI High-Level Expert Group framework and the AI Watch taxonomy [18]. At the highest level, the classification distinguishes between reasoning and decision-making approaches and learning- and perception-based approaches. The AI Watch taxonomy extends this structure by incorporating transversal technological domains and ethical and societal considerations.

For the purposes of the systematic mapping review, the operational classification comprised reasoning, planning, learning, communication, perception, integration and interaction, AI services, and ethics and philosophy. These categories provided the analytical structure used to define the AI facet of the search strategy and to classify the included studies. The complete definitions, subdomains, and distinction between core and transversal categories are presented in Supplementary Note S1 and Table S1.

2.2. Operational Units in Copper Ore Processing

Copper ores are generally categorised into two main types, sulphide ores and oxide ores, each of which requires a distinct processing route for efficient copper extraction. For sulphide ores, the process begins with crushing the ore to reduce its particle size, making it more manageable for subsequent stages. The crushed ore is then ground in mills to achieve a fine particle size, increasing the surface area for the flotation process. During flotation, chemical reagents are added to the finely ground ore, causing the copper-containing particles to attach to air bubbles and form a froth, which is skimmed off as a concentrate. This concentrate is then thickened to remove excess water and filtered to produce a dry, manageable product. The dry concentrate is smelted to remove impurities; high temperatures separate copper from iron and sulphur, yielding a more refined metal.

Finally, additional refining techniques, such as electrorefining, are used to produce high-purity copper cathodes.

The processing of copper oxide ores begins similarly, with crushing and grinding the ore to facilitate subsequent chemical reactions. However, the main method for extracting copper from oxide ores is leaching, in which acidic or alkaline solutions dissolve the copper. Depending on the ore characteristics, either heap leaching or tank leaching is employed. The resulting copper-bearing solution is then treated with an organic solvent during the solvent extraction stage, which selectively binds copper ions, enabling their separation from the leach solution. The copper-laden solvent is subsequently subjected to electrowinning, in which an electric current causes copper to deposit onto stainless-steel cathodes, thereby producing high-purity copper cathodes.

For a visual summary of these two routes is shown in Figure 1. For additional background, readers may consult [19,20].

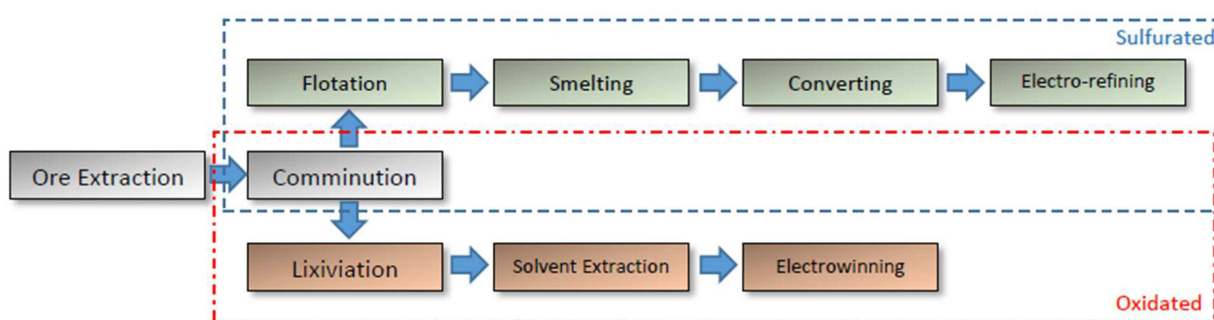


Figure 1. Processing routes for copper sulphide and copper oxide ores.

The pathways for copper ore processing vary by ore type. Copper sulphide ores, such as chalcopyrite (CuFeS_2) and bornite (Cu_5FeS_4), require a specific sequence of unit operations. First, the sulphide ore is crushed and ground to liberate the copper particles from the host rock. Froth flotation is then applied: the finely ground ore is mixed with water and chemical reagents (collectors, frothers, and modifiers) that enhance particle-bubble interaction and promote the formation of a copper concentrate. This concentrate is subsequently smelted and electrorefined, removing iron and other impurities and yielding copper with a purity above 99.99%. By contrast, oxidised copper ores, such as malachite ($\text{Cu}_2\text{CO}_3(\text{OH})_2$) and cuprite (Cu_2O), follow a different route. The oxidised ores are crushed and ground and then arranged in leaching heaps, which are irrigated with diluted sulphuric acid to dissolve the copper. The copper-rich solution is collected and subjected to solvent extraction and electrowinning (SX-EW) to recover metallic copper. Solvent extraction separates copper from the acidic solution, and electrowinning deposits it onto high-purity cathodes (99.99% copper) by applying electric current [21].

Based on this description, the facets that represent the copper mining process were defined as (1) comminution, which covers the grinding stages in both sulphide-ore and oxide-ore processing routes; (2) froth flotation; (3) smelting including fusion, converting, and refining; (4) electrowinning, or electroextraction, or electrorefining; (5) solvent extraction; and (6) lixiviation.

3. Research Methodology

This systematic mapping review, complemented by qualitative synthesis, followed the engineering-oriented methodology proposed by Torres-Carrión et al. [22], based on the approaches of Kitchenham and Bacca. The methodology is organised into three phases: planning the review, conducting the review, and reporting the results. In the present study, planning included identification of the review need, formulation of the research

questions (RQ1–RQ4), examination of related reviews, definition of the search strategy, and specification of the eligibility criteria. Conducting the review included study identification, screening, selection, classification, data extraction, descriptive mapping, and qualitative cross-study synthesis. Reporting was organised according to the four research questions. PRISMA principles were used as a reporting reference for the transparent presentation of study selection, while the engineering-oriented methodology constituted the primary review framework. Accordingly, the study was designed to map the distribution of the literature and qualitatively interpret cross-study patterns; it did not undertake a meta-analysis or formal evidence-weighted synthesis.

Figure 2 presents a schematic representation of the research methodology. The processes shown in the top row of the figure are linked to their primary outcomes in the bottom row: review scope, all papers, bibliometric analysis, relevant papers, and classification scheme. Although the bibliometric analysis is not the core of the methodology, it is included to provide a better understanding of topic trends. Each component is described in the following subsections in accordance with Figure 2.

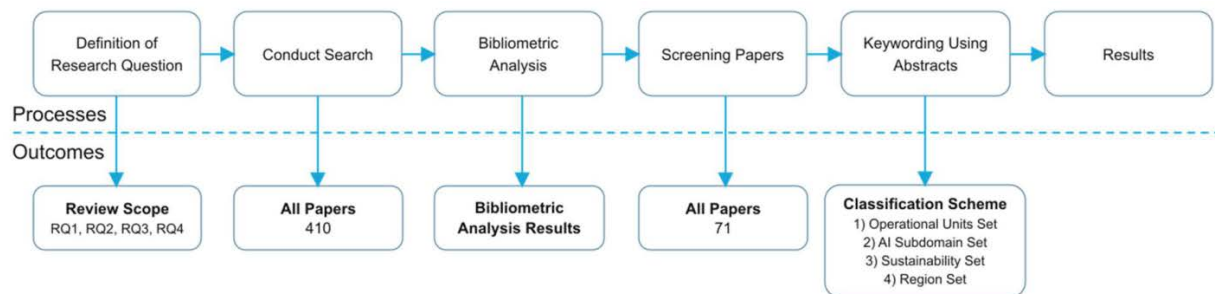


Figure 2. Systematic mapping approach.

3.1. Definition of Research Questions

The goal is defined as follows: “To provide an understanding of trends and status on the implementation of artificial intelligence in the copper mining industry”.

From this goal, the following research questions were derived:

RQ1—Which core operational units in the copper mining industry have incorporated, or have studied the incorporation of, artificial intelligence?

RQ2—Which are the main areas of artificial intelligence covered in the literature on copper mining?

RQ3—When artificial intelligence is incorporated into the mining sector, which sustainability pillars are discussed or evaluated?

RQ4—Which regions of the world show the greatest tendency to incorporate artificial intelligence into their copper mining processes?

For the purposes of RQ4, geographical tendency refers to the regional distribution of the studies and industrial cases represented in the reviewed corpus. These results should not be interpreted as a direct ranking of regional AI adoption or technological maturity.

3.2. Search Methodology

To assess the status of AI in the copper mining industry, a systematic approach was conducted. The process starts by defining the key pillars that shape the topic and using targeted keywords to conduct literature searches [23]. These keywords were used as markers, enabling efficient search across various platforms. Keywords and pillars were combined to address the research questions. More specifically, keyword selection was organised into groups to define the components of the search strings through a bottom-up approach. Query construction and keyword definition followed the PICOC methodology—

Population, Intervention, Comparison, Outcomes, and Context [24–26]. Each component is defined below:

Population: This refers to the specific group of individuals or subjects of interest in a study. In the context of this work, the population is the group of manuscripts from which research questions are formulated.

Intervention: The intervention refers to the approach or technique applied in an empirical study. In this review, it includes software methodologies, tools, technologies, or procedures. Different AI techniques that may be applied to specific procedures in the mining industry are therefore considered. This component is represented by the **AI domains**.

Comparison: The comparison component involves differentiating among methods, processes, or strategies. There are different AI techniques that can be applied to specific procedures in the mining industrial sector. To do that, a consideration of transversal components is included that, at the same time, can be further differentiated by the type of AI incorporated within them. These subsets were defined as **Deep Learning**, **Supervised**, and **Unsupervised** Machine learning-based components when machine learning components were considered. Machine learning can be categorised into supervised learning, where models are trained on labelled data to make predictions; unsupervised learning, where models identify patterns or groupings in unlabelled data without explicit instruction; and deep learning, a subset of machine learning that uses multi-layered neural networks to automatically learn and extract complex features from large datasets, applicable in both supervised and unsupervised contexts.

Outcomes: Since empirical approaches or comparisons are not considered, no specific outcomes are defined in this component.

Context: The context provides a comprehensive view of whether the study is conducted in academia or industry, the industrial segment, and the subject's incentives. Thus, the context imposes keywords to constrain the search, for example, using the words AI or artificial intelligence.

The keywords are grouped into three categories: copper operational units, AI subdomains, and context-based terms that helped to narrow the search.

For the first category, copper operational units, the terms were derived from the processes described above and shown in Figure 1. For the second category, the AI domains and subdomains were derived from the classification presented in Supplementary Note S1 and Table S1.

IEEE Xplore and Scopus were selected as the principal bibliographic databases because their coverage complements the interdisciplinary scope of this review. IEEE Xplore provides specialised access to journal articles and conference proceedings in artificial intelligence, automation, control systems, instrumentation, and computer engineering. In contrast, Scopus provides broader multidisciplinary coverage of engineering, mining, mineral processing, and extractive metallurgy. The combination of specialised and multidisciplinary databases is therefore well-suited to identifying studies at the intersection of AI and copper-processing operations [27].

Google Scholar was incorporated as a supplementary search source rather than as the sole or principal database. Its broader indexing of academic web content can complement structured bibliographic databases and has demonstrated substantial coverage of recent engineering literature; however, its dynamic ranking and limited reproducibility require that its results be interpreted with caution [27,28].

Together, the three sources retrieved 410 records before screening and provided a broad corpus spanning both the computational and process-engineering dimensions required to answer RQ1–RQ4. Nevertheless, the selection of databases constitutes a methodological boundary, since relevant studies indexed exclusively in other sources may not have been identified.

The time frame for the queries was from 2014 to 2025 to capture temporal trends. Only English publications were considered, and the analysis focused on journal articles, standards, and peer-reviewed conference publications.

Search terms were derived from the predefined conceptual categories of the review and expanded using related terminology and synonyms. The resulting Boolean structure combined copper-processing operations, AI domains and subdomains, and mining-context expressions. The search scripts were adapted to the syntax and capabilities of each database. This broad terminology was intended to maximise search sensitivity and accommodate variations in terminology across engineering and data-science publications, while final relevance was determined through the predefined eligibility and screening criteria.

The complete database-specific search expressions are provided in Supplementary Table S2. The expressions are reproduced exactly as executed, including the original terminology and Boolean structure adapted to each information source, to preserve methodological traceability and reproducibility. The term *Lixiviation* is retained in Supplementary Table S2 because it was used in the original search protocol; elsewhere in the manuscript, the standard English term *leaching* is used.

3.3. Bibliometric Analysis

Table 1 presents the findings before the screening phase, organised by the number of publications per year.

Table 1. Search results in IEEE, Scopus, and Google Scholar databases between 2014 and 2025.

Engine	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	Total	Perc.
IEEE	3	8	6	13	14	27	17	30	34	47	19	19	237	0.62%
Scopus	1	0	3	2	2	2	2	6	8	9	5	11	51	0.33%
GS	0	1	0	4	4	7	10	11	15	21	23	26	122	0.05%

The last two columns of the table show the total number of publications for the period analysed, labelled as Total, and the relative percentage of queries containing terms related to the copper-mining domain (i.e., the results obtained by removing “Artificial Intelligence” and all subsequent terms from the respective queries), labelled Perc.

As shown in the table, the IEEE and GS engines show a steady increase in publication activity. This consistent upward trend suggests a growing tendency in the subject covered here. Conversely, the Scopus database exhibited lower and less consistent search volumes, although it also displays an upward trend, especially between 2021 and 2022.

When the corresponding percentages are analysed, the proportion of publications within the copper-mining domain appears relatively low. The highest percentage (0.62%) is observed in IEEE, possibly because IEEE is more narrowly focused on technical aspects, particularly engineering and technology. In contrast, Scopus covers a wider range of subjects, including both technical and non-technical content.

3.4. Screening Papers

A systematic analysis was conducted on the collected dataset, with a primary focus on assessing the relevance of the titles to the previously identified key facets. In cases of uncertainty, a more detailed analysis was conducted based on the information provided in the abstracts. This evaluation followed a structured pipeline approach, as illustrated in Figure 3. The main purpose of this rigorous screening was to ensure that each manuscript addressed both AI-related topics and issues relevant to the copper mining industry. Manuscripts not directly focused on copper extraction were still considered when the operational unit under discussion could be clearly linked to copper processing.

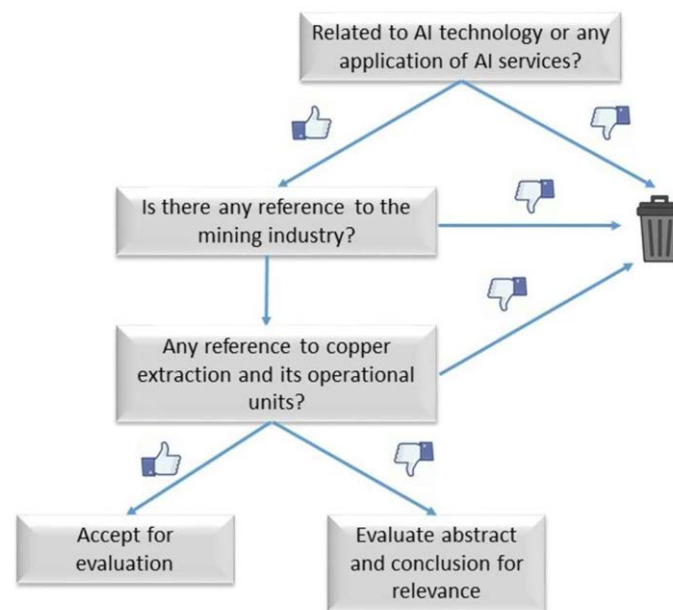


Figure 3. Screening process used to select papers based on keywords.

The screening process alone did not determine whether a manuscript made a substantial contribution to the research questions. Therefore, only manuscripts that could be linked to the defined facets were included in the analysis.

The inclusion criteria were as follows: (i) publications issued within the defined study period; (ii) documents written in English; (iii) peer-reviewed journal articles and peer-reviewed conference papers, with relevant technical standards considered separately when directly applicable to the review scope; (iv) studies addressing at least one of the predefined AI domains or subdomains; and (v) studies examining a copper-processing operation or an operational unit that could be directly associated with copper mineral processing or extractive metallurgy. Studies focused on other minerals were retained only when the process or technology investigated was clearly applicable to one of the operational units included in the review.

Database retrieval was not treated as automatic confirmation of peer-review status. In particular, because Google Scholar indexes multiple types of scholarly material, records retrieved through this source were checked against their original publication venue during eligibility assessment. Primary studies were retained only when they satisfied the same publication-type and peer-review requirements applied to records retrieved through IEEE Xplore and Scopus.

3.5. Keywording Using Abstracts

The predefined set of keywords served as the basis for the mapping and analysis processes in this study. However, during screening, additional terms were considered alongside the keywords associated with operational units and AI subsets. These included “Grinding” (as an aggregate term for comminution), “Leaching” (as an aggregate term for lixiviation), and “Refining”. The last of these was ultimately excluded because it was too general for the purposes of the analysis.

Figure 3 summarises the sequential application of these eligibility criteria. The screening procedure was designed to determine whether each publication could contribute evidence to at least one of the predefined facets and, consequently, to one or more of the research questions. Eligibility did not depend on whether the study reported a positive outcome for AI, but on its thematic correspondence with the scope of the review.

The review was conducted in predefined stages: database searching, study screening, eligibility assessment, data extraction, and thematic classification. The selected publications were subsequently organised according to the AI techniques employed, their application across copper-processing operations, their reported sustainability contributions, and their geographical distribution. This structure enabled the reviewed evidence to be synthesised in direct correspondence with RQ1–RQ4. Therefore, the research questions are addressed based on the studies included within the established scope and selection criteria. At the same time, the limitations of the search and classification processes are acknowledged in Section 4.6.

4. Results and Discussion

This section presents the findings of the systematic mapping review, organised according to RQ1–RQ4. The analysis combines descriptive mapping with qualitative cross-study synthesis, allowing the frequency and distribution of the identified topics to be examined alongside their operational relevance, reported AI methods and applications, levels of industrial implementation, recurring methodological limitations, and principal research gaps. Bibliometric analyses were also included to complement the interpretation of the mapped evidence.

The results are presented as bubble-grid maps showing the frequency, distribution, and overlap of specific topics across the included studies. This graphical format is consistent with the purpose of a systematic mapping review because it enables the reviewed evidence to be positioned across predefined categorical dimensions without implying a quantitative comparison of study quality or algorithmic performance. Bubble area is proportional to the number of identified occurrences, while bubble position represents the intersection between the categories shown on the corresponding axes. The values in the first row and last column indicate the overall frequency of the respective categories. Each figure includes only the manuscripts relevant to the facet under examination. Because a single publication may address multiple topics, the total number of occurrences shown in a figure may exceed the number of included manuscripts.

4.1. RQ1—Which Core Operational Units in the Copper Mining Industry Have Incorporated, or Have Studied the Incorporation of, Artificial Intelligence?

As shown in Figure 4, the level of attention given to AI differs across copper-mining operational units. Comminution received the greatest attention (34.51%), followed by froth flotation (32.74%), smelting (14.15%), and lixiviation (10.62%). By contrast, solvent extraction, electrowinning, electrorefining, electroextraction, and converting received the least attention.

These trends can be explained by considering the different processing paths.

Comminution is common to both sulphide-ore and oxide-ore processing pathways. Accordingly, it is unsurprising that this unit operation accounts for the largest number of studies. Moreover, grinding, or comminution, is one of the most expensive stages in mining because of its high energy demand, which can account for up to 50% of a mine's energy costs. For this reason, interest in improving its performance is particularly high. Recent work also reinforces this point by linking hydrocyclone overflow particle-size monitoring with energy-efficient comminution, showing that delayed particle-size information can lead to unnecessary overgrinding and reduced throughput [29].

In addition to its energy demand, the grinding process incurs substantial maintenance costs due to frequent wear and tear, further increasing overall expenditure.

From the analysis of the comminution literature, five main areas of application were identified: AI and machine learning for energy efficiency; enhanced fault diagnosis and

predictive maintenance; AI-driven process optimisation and control; integration of AI with Industry 4.0 and the internet of things (IoT); and future directions and challenges.

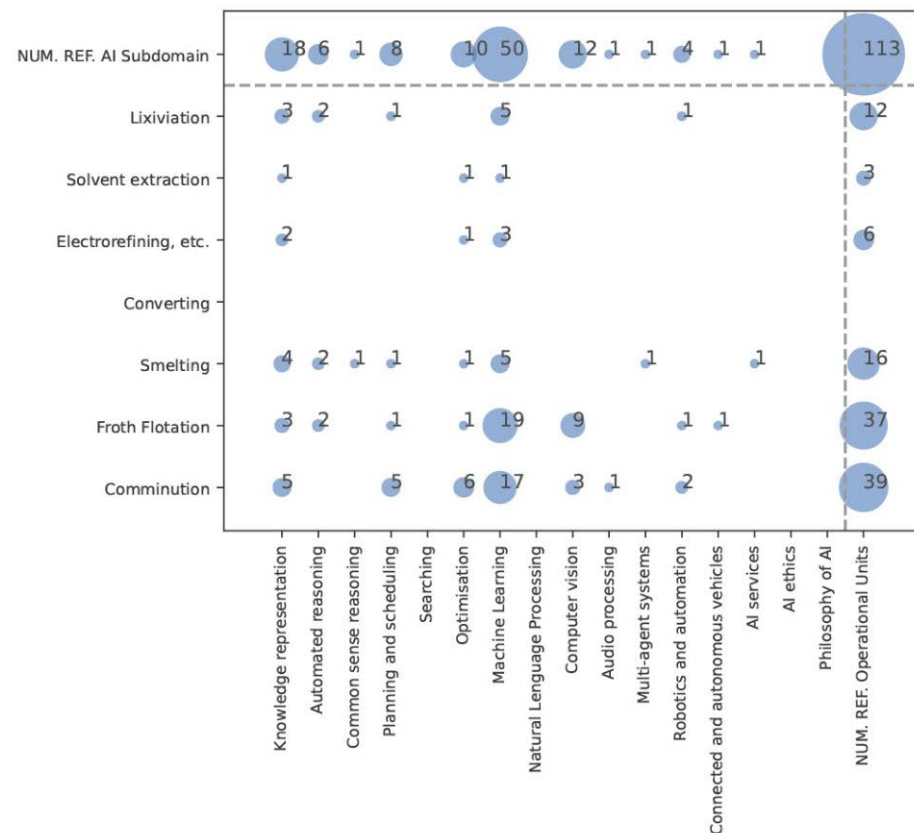


Figure 4. Bubble-grid map of the frequency and overlap of AI subdomains across copper-processing operational units. Bubble area is proportional to the number of identified occurrences.

AI and machine learning for energy efficiency are critical areas where these technologies are being applied to optimise energy use in comminution processes. Manuscript [30] highlights the use of machine-learning models, specifically Random Forest, to predict power consumption in grinding mills. This approach is important for optimising energy use and reducing costs in mining operations. Further discussion in [31,32] emphasises the importance of reducing energy consumption through AI integration. In addition, Pradip et al. [33] addresses strategies to improve comminution efficiency through AI-driven process optimisation, including fine-tuning operational parameters using data-driven insights.

Enhanced fault diagnosis and predictive maintenance also emerge as important areas of AI application. Manuscripts [34,35] explore the use of convolutional neural networks (CNNs) and transfer learning to improve fault diagnosis in rotating machinery. By converting time-domain signals into two-dimensional images, these models strengthen the diagnostic capabilities of AI systems and support predictive-maintenance strategies. Furthermore, [36] discusses advanced data segmentation and augmentation methods designed to improve the fault-diagnosis capabilities of deep neural networks (DNNs).

AI-driven process optimisation and control are illustrated through several applications. Manuscript [37] discusses the use of reinforcement learning combined with stochastic programming to optimise short-term production scheduling in mining complexes. This approach enables adaptive scheduling, which is valuable for managing the complexity of comminution processes in real time. In addition, Ref. [38] highlights the use of AI-driven genetic algorithms to simulate and optimise crushing plant configurations. This method balances production efficiency, product quality, and operating cost, reflecting AI's

growing role in improving the efficiency and output of comminution processes. Finally, Ref. [39] describes the use of clustering algorithms such as K-means and self-organising maps (SOMs) to identify operational regions within semi-autogenous grinding (SAG) mills, thereby supporting lower energy consumption and more desirable operating conditions.

The integration of AI with Industry 4.0 and IoT is increasingly being investigated to improve real-time process visibility and predictive capabilities in mining operations. Studies [30,40] discuss AI's role in enabling digital transformation, particularly through the integration of advanced analytics and real-time monitoring systems. Moreover, Refs. [33,41] examine the development of AI-enabled autonomous systems for comminution. These systems operate with minimal human intervention and continuously optimise performance based on real-time data, thereby improving both efficiency and safety while reducing human error.

The literature also discusses *future directions and challenges*. Studies [39,40] highlight the challenges of scaling AI technologies for real-time applications in comminution. Although deep learning models offer powerful solutions, their computational intensity poses challenges for real-time implementation. Future research is likely to focus on improving the scalability and efficiency of AI models to meet the demands of dynamic, complex mining environments.

The fact that **flotation** receives the second-highest level of coverage suggests that AI integration is focused primarily on the sulphide-ore processing pathway. The balance between sulphide and oxide ores varies significantly according to deposit type and location. However, most global copper production comes from sulphide ores, which are more abundant and have historically been preferred because of their higher copper content and more established processing routes. Globally, about 80% of copper ores are sulphides, with the remaining 20% being oxides [42]. Additionally, recent research [43] further confirms the growing use of embedded computer vision for real-time froth flotation monitoring, demonstrating that stability assessment can support faster process adjustments and improved operational performance.

Five main areas of application were identified from the analysis of the froth-flotation literature: AI and machine learning for process monitoring; dimensionality reduction and data analysis; real-time process optimisation and control; integration of AI with Industry 4.0; and future directions and challenges.

AI and machine learning for process monitoring play an important role in improving flotation monitoring. Study [44] evaluates hybrid machine-learning models to predict flotation performance and to support the identification of improved operating conditions. The proposed approach may assist operator decision-making, although its real-time industrial use should be distinguished from offline model evaluation. Study [45] examines how combining Fourier transform techniques with machine learning can more accurately and efficiently monitor mineral grades in froth flotation. In addition, Ref. [46] describes the use of machine-vision algorithms, such as mean-shift and watershed transforms, to estimate bubble-size distributions automatically in flotation froths, which is essential for maintaining stable operation and optimising performance.

Dimensionality reduction and data analysis are common AI-related processes, particularly when the aim is to simplify and interpret large and complex datasets. Study [47] shows how techniques such as principal component analysis (PCA) and t-distributed Stochastic Neighbour Embedding (t-SNE) can help manage and visualise the large volumes of data generated by flotation processes. These methods make it easier to focus on the most relevant factors, such as mineral concentration, and to optimise performance. The same study [47] also demonstrates how these techniques were used in an iron-mining case study to group and simplify data, identify key operating patterns, and improve monitoring. In addition, Ref. [48] uses PCA to analyse data from grinding circuits to control the P80 grind size,

which is crucial for achieving optimal flotation performance. Finally, Ref. [49] highlights the value of data-mining techniques for extracting actionable insights from large-scale flotation datasets, demonstrating the power of AI to turn complex information into insights.

AI-driven process optimisation and control are becoming increasingly important in flotation. For example, Ref. [50] explores how machine vision combined with AI can optimise flotation processes in real time. It describes an online analyser that predicts mineral concentrate grades by analysing froth images and process parameters, thereby improving control and efficiency. Study [51] examines the use of deep learning combined with traditional image-processing techniques to monitor and control flotation processes, demonstrating the accuracy and effectiveness of AI-driven approaches. In addition, Ref. [49] discusses the use of reinforcement learning to optimise reagent dosages in flotation, thereby illustrating AI's ability to adapt to complex process conditions in real time. Finally, Ref. [52] examines the use of fuzzy logic to control flotation circuits, offering a way to manage uncertainty in process conditions and to achieve more stable and optimised performance.

The integration of AI with Industry 4.0 is reshaping mining operations by providing enhanced real-time insights and predictive capabilities. Study [45] discusses how AI, combined with Industry 4.0 technologies such as the IoT, is driving digital transformation in mining. These technologies support the development of autonomous systems that use real-time data to optimise performance, leading to improvements in both efficiency and safety. Study [53] also explores this integration and addresses the challenges and future opportunities associated with implementing AI and Industry 4.0 in the mining industry. Then, these studies highlight the significant impact of AI on the modernisation of mining operations [54].

Future directions and challenges in applying AI to mining operations also emerge from the literature. Study [53] discusses the difficulty of scaling AI technologies for real-time use in froth flotation. It highlights the limitations of current computational models and the need for continuous retraining owing to variations in mineral resources, thereby underscoring the challenges of deploying AI effectively in real-time environments. Study [55] examines the use of polymeric depressants and machine learning to optimise flotation efficiency, suggesting that future research should focus on improving the scalability and efficiency of AI models for dynamic mining environments. Furthermore, Ali et al. [56] addresses the challenges of implementing AI for real-time flotation monitoring, particularly regarding ore variability and the need for robust, adaptable systems. Therefore, these studies underscore the importance of overcoming these challenges to realise the full potential of AI in mining.

When the sulphide-ore processing route is considered, the position of **smelting** as the third-most-studied unit becomes understandable. Nevertheless, its level of coverage remains of the same order of magnitude as that of the lixiviation process.

The analysis of the manuscripts reveals three key trends in smelting: technological advancements, process optimisation through data analytics, and environmental sustainability.

Technological Advancements: Significant progress has been made in adopting oxygen-enriched smelting, a method that enhances efficiency and sustainability by enabling higher temperatures and oxygen potentials. This is important for producing high-grade matte while reducing fuel consumption and emissions [57,58]. Moreover, machine learning and AI are increasingly utilised to model outcomes and optimise smelting parameters, thereby improving accuracy and enabling real-time adjustments to enhance efficiency [57,59].

Process optimisation through data analytics is improving smelting operations. Intelligent models analysing parameters such as copper content in slag and matte grade support improved process control by overcoming traditional delays in result analysis and enabling faster decision-making [57,60]. Machine learning also helps identify patterns among smelt-

ing variables, such as how blast volume and oxygen supply affect the distribution of hazardous elements [61,62].

Environmental performance and sustainability are critical concerns. Oxygen-enriched smelting reduces carbon emissions and enables more effective processing of low-grade ores, aligning with industrial sustainability goals [57,58]. The management of hazardous elements, such as arsenic and lead, is also emphasised, with strategies including increasing quartz input during refining to reduce environmental risks [61,62].

Finally, as mentioned above, **electrorefining**, **solvent extraction**, and **converting** exhibit the lowest levels of AI incorporation. Within electrorefining, electrowinning, and related processes, two main areas of application were identified: predictive modelling and machine-learning applications, and environmental impact and sustainability.

Predictive modelling and machine-learning applications use advanced data-driven techniques to forecast outcomes in electrorefining processes. For example, deep learning methods, particularly recurrent neural networks (RNNs) with attention mechanisms, have been explored for predicting cathodic rejection in copper electrorefining [63]. Similarly, neural networks and other machine-learning algorithms are becoming increasingly important for optimising process parameters and improving the accuracy of predictive models in electrowinning [33].

Environmental performance and sustainability focus on the environmental challenges associated with electrowinning and electrorefining, such as reducing greenhouse-gas emissions and making metal extraction more sustainable. AI-based methods may support the optimisation of specific electrowinning and electrorefining variables, including energy use, process stability, and waste-management decisions. Where reliable online measurements are available, AI-based systems may support process monitoring and operational decision-making, with potential benefits for resource efficiency and environmental performance. However, the reviewed evidence remains limited regarding sustained industrial deployment in these operations [61].

Overall, the distribution of studies across operational units reflects differences not only in publication volume but also in process relevance, data availability, and technological feasibility. Comminution and flotation receive the greatest research attention because they are central to copper processing, generate large volumes of continuously monitored operational data, and strongly influence energy consumption, recovery, and downstream performance. In these areas, AI has been applied mainly to prediction, process monitoring, fault diagnosis, and operational optimisation. By contrast, the lower representation of lixiviation, solvent extraction, electrowinning, and other hydrometallurgical stages may be associated with slower process dynamics, complex physicochemical interactions, and the limited availability of reliable online measurements and industrial datasets. Accordingly, RQ1 reveals an uneven development of AI research across the copper-processing flowsheet rather than merely a numerical ranking of unit operations [64–67].

4.2. RQ2—Which Are the Main Areas of Artificial Intelligence Covered in the Literature on Copper Mining?

As shown in Figure 5, the degree of attention paid to different AI topics varies across the operational units of copper mining. Machine learning has the highest application rate (42.03%), followed by computer vision (14.15%), knowledge representation (13.77%), and optimisation (7.8%). Other areas make only minor contributions and are discussed less frequently.

The machine learning analysis was conducted using the categories of supervised, unsupervised, and reinforcement learning. As observed in the literature, most manuscripts emphasise supervised learning techniques, which are widely used because of their effec-

tiveness in industrial applications. Manuscripts such as [34,35,44–46,50,53,67,68], among others, reflect this trend.

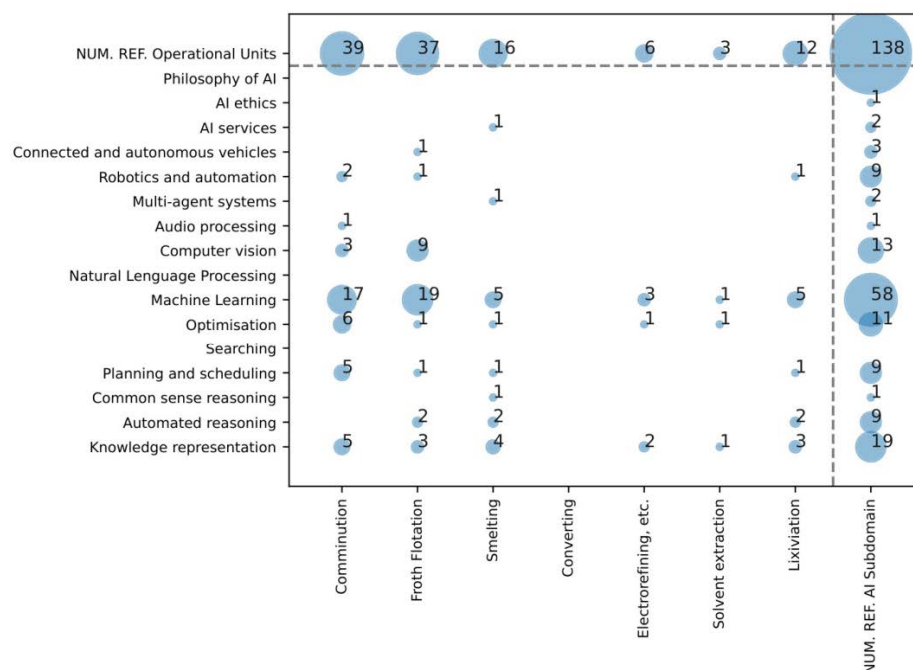


Figure 5. Bubble-grid map of the distribution and overlap of AI domains and learning approaches within the reviewed corpus. Bubble area is proportional to the number of identified occurrences.

In [51], supervised learning methods such as Random Forest, Support Vector Regression, and Extreme Gradient Boosting are evaluated for predicting outcomes in the flotation process, with Random Forest achieving the highest accuracy of 99.5%. This study reinforces the preference for robust and interpretable models in critical industrial applications, where accuracy is paramount.

Similarly, Ref. [32] discusses the application of supervised learning models to optimise SAG mill performance in mineral processing. The manuscript highlights the use of Gradient Boosting Machines, Random Forest, and Artificial Neural Networks, with the latter demonstrating superior performance in modelling complex systems.

Study [69] explores the use of ensemble learning techniques, particularly a combination of Nonlinear AutoRegressive Network with exogenous inputs Neural Network (NARX-NN) and Support Vector Regression, to predict grades in flotation processes. The use of stacking-based ensemble models in this context underscores the trend towards combining multiple supervised-learning models to improve predictive accuracy.

Unsupervised learning is also represented, though less frequently. Ref. [47] discusses the application of unsupervised learning techniques, such as K-means clustering and dimensionality reduction methods. The study demonstrates the effectiveness of these methods in identifying patterns and operational states without prior labelling, which is especially valuable in scenarios where labelled data is scarce or unavailable.

Furthermore, Ref. [49] employs semi-supervised generative adversarial networks (GANs) to assess performance in flotation processes. This approach combines a small amount of labelled data with a larger set of unlabelled data, offering a balance between the benefits of supervised and unsupervised learning in contexts where fully labelled datasets are not feasible.

Interestingly, none of the reviewed manuscripts explicitly explore reinforcement learning methods. This may suggest that, although reinforcement learning holds promise for

dynamic decision-making environments, its application to industrial mining processes and monitoring systems remains either underexplored or not yet mainstream.

The predominance of machine learning, particularly supervised learning, reflects the structure of the available evidence and the current emphasis on prediction and classification using historical operational data. Artificial neural networks, Random Forest, support vector methods, and gradient boosting algorithms are frequently applied because they can represent nonlinear relationships and predict recovery, product quality, equipment condition, and overall process performance. However, no single method emerges as universally superior, since reported performance depends on the dataset, operational unit, target variable, and validation procedure. The reviewed evidence therefore supports comparative, operation-specific model selection rather than the general adoption of a single algorithm across the copper-processing industry. Reinforcement learning and other adaptive approaches remain less represented because they require reliable process environments, real-time interaction, safe exploration, and stronger industrial validation. At the same time, the literature suggests a gradual shift from isolated predictive models toward ensemble methods, hybrid mechanistic–data-driven approaches, real-time monitoring, and closer integration between prediction and process optimisation. However, most studies still focus on model development and offline validation rather than sustained deployment under variable industrial conditions [46,64,67,70,71].

The reviewed literature suggests a gradual evolution in research emphasis. Earlier applications were predominantly based on isolated predictive models developed from historical process data. In contrast, more recent studies increasingly explore ensemble methods, hybrid mechanistic–data-driven approaches, real-time monitoring, and closer integration between prediction and process optimisation. Nevertheless, much of the evidence remains focused on model development and offline validation rather than sustained deployment under variable industrial conditions. Across the reviewed studies, reported model performance varies according to the characteristics of the dataset, operational unit, target variable, and validation procedure. Artificial neural networks, Random Forest, support-vector methods, and gradient-boosting algorithms frequently achieve strong predictive performance. Still, direct comparisons are limited when studies differ in sample size, input variables, train–test partitioning, evaluation metrics, and operating conditions. Consequently, the evidence does not support identifying a universally superior algorithm; instead, model selection should be based on operation-specific data characteristics, interpretability requirements, and validation under representative process conditions [70].

Technological maturity was interpreted qualitatively from the implementation context explicitly reported in the reviewed publications. The synthesis distinguishes among: (i) model development based on historical or simulated data; (ii) laboratory- or pilot-scale evaluation; (iii) individual applications evaluated under industrial conditions; and (iv) evidence of sustained industrial deployment. These categories are descriptive and should not be interpreted as formal Technology Readiness Levels. A numerical TRL classification was not assigned because the publications did not consistently report the information required to evaluate system integration, operational duration, scalability, robustness under changing process conditions, operator involvement, or sustained industrial validation. Inferring these attributes retrospectively would introduce unsupported precision. The reviewed evidence therefore supports a maturity-oriented qualitative interpretation but not a defensible numerical TRL assignment. Publication frequency should likewise not be interpreted as equivalent to industrial readiness [64,65].

Direct comparison of specific AI methods across the reviewed studies is constrained by substantial methodological heterogeneity. CNNs, tree-based algorithms, boosting methods, neural networks, and reinforcement-learning approaches were applied to different opera-

tional problems, datasets, target variables, preprocessing procedures, and validation settings. Therefore, reported performance metrics should not be interpreted as evidence that one algorithm is generally superior to another. The reviewed evidence instead supports operation-specific model selection based on data characteristics, prediction objectives, interpretability requirements, computational demands, and the intended level of industrial integration.

Future research Outlook: Two major research gaps emerge from the reviewed literature. First, AI applications remain underrepresented in hydrometallurgical operations compared with comminution and flotation, particularly in lixiviation, solvent extraction, and electrowinning. This gap is relevant because hydrometallurgical processes involve nonlinear interactions among mineralogy, solution chemistry, temperature, pH, residence time, and reagent concentrations. At the same time, several key variables are difficult to measure continuously under industrial conditions [64–66]. Although existing studies demonstrate the potential of machine learning to predict copper recovery and support hydrometallurgical process decisions, limited data availability, infrequent measurements, process variability, and difficulties in transferring models between operations continue to limit broader industrial implementation [11,64,67]. Second, reinforcement learning remains only marginally represented compared with supervised predictive models. Its potential lies in learning sequential operating policies for reagent addition, energy management, and adaptive process control; however, its application to industrial mineral-processing systems requires reliable process environments, safe exploration strategies, robust constraints, and continued human supervision. Consequently, short-term research should prioritise high-quality industrial datasets, soft sensors, and transparent benchmark models. Medium-term work should focus on hybrid mechanistic–data-driven models, digital process representations, and pilot-scale adaptive control. In the longer term, research may progress toward safely constrained and human-supervised autonomous optimisation across interconnected copper-processing operations [65,72].

4.3. RQ3—When Artificial Intelligence Is Incorporated into the Mining Sector, Which Sustainability Pillars Are Discussed or Evaluated?

Figures 6 and 7 show the results obtained when the sustainability pillars are analysed in relation to (1) the operational units identified as incorporating AI in the copper mining sector and (2) the AI tools used within those operational units. Numerical discrepancies may arise because a single manuscript can cover multiple topics, which may therefore overlap in the analysis.

As shown in the figures, economic efficiency is the aspect most frequently addressed in the screened literature, whereas only a small number of manuscripts consider environmental and social issues. With respect to the environmental dimension, the reviewed works were organised into three broad clusters: electrification and decarbonisation, technological advancement, and sustainability and waste management.

Electrification and decarbonisation emerge as significant trends across the mining industry, reflecting the sector's response to increasing environmental pressures and regulatory demands. The shift towards electrification, particularly through the adoption of battery-powered load-haul-dump (LHD) units and trucks, clearly indicates the industry's commitment to reducing greenhouse-gas emissions. This transition is intended not only to minimise the carbon footprint but also to improve operational efficiency in deeper and more challenging mining environments, where conventional diesel-powered machinery can exacerbate ventilation and heat-management problems. The adoption of electric vehicles therefore appears as both an environmental and an operational strategy aimed at enhancing sustainability while maintaining productivity [56,73].

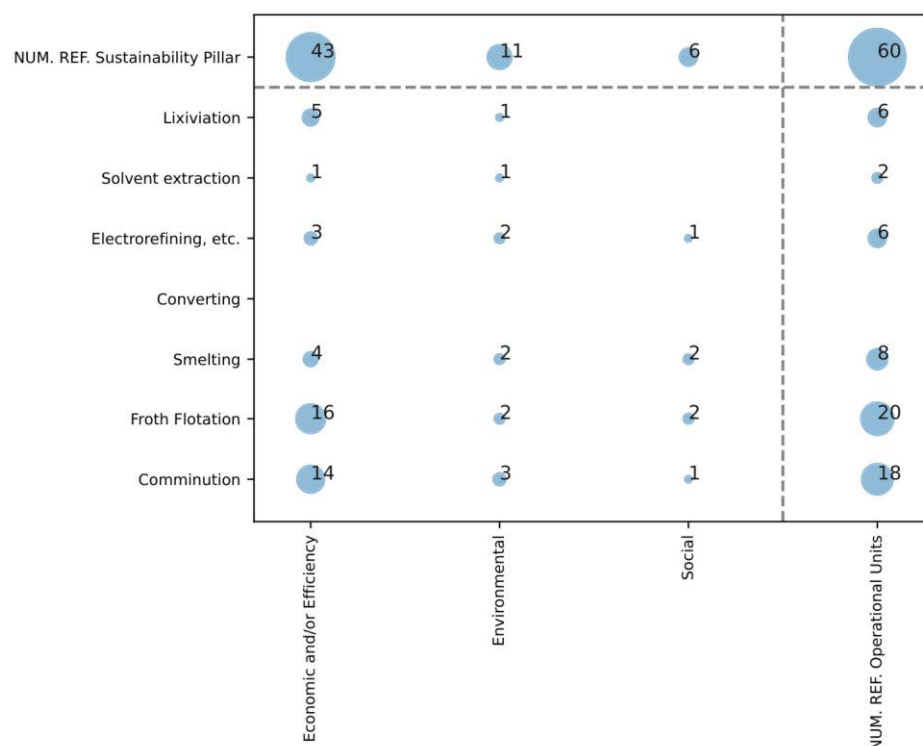


Figure 6. Bubble-grid map of the frequency and overlap of sustainability dimensions across copper-processing operational units. Bubble area is proportional to the number of identified occurrences.

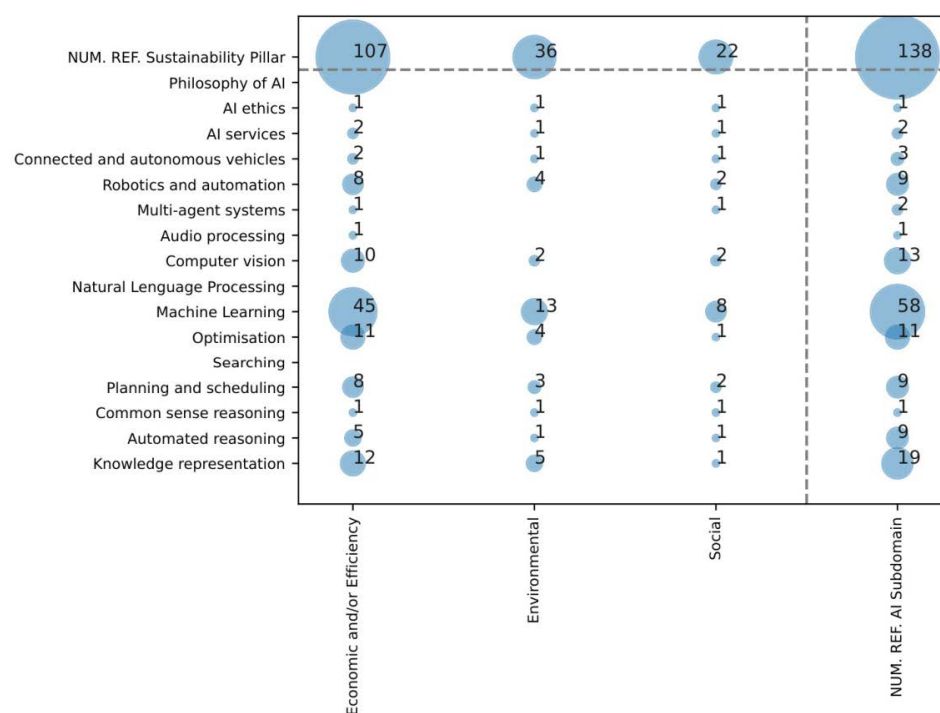


Figure 7. Bubble-grid map of the frequency and overlap of sustainability dimensions across AI domains and learning approaches. Bubble area is proportional to the number of identified occurrences.

Technological advancement encompasses a broad range of developments in the mining industry, including automation, invisible and selective mining methods, and urban and deep-sea mining. Through the integration of IoT, AI, and robotics, automation is transforming mining operations by increasing efficiency, reducing human exposure to hazardous conditions, and minimising environmental impacts through more precise re-

source extraction. Invisible and selective mining methods, such as in situ leaching (ISL), represent innovative approaches that can offer significant environmental advantages by minimising surface disturbance and waste generation. Urban mining, which recovers valuable materials from electronic waste, and deep-sea mining, which targets mineral-rich deposits on the ocean floor, are emerging as new frontiers. Both aim to meet the growing demand for critical minerals while addressing the environmental challenges associated with conventional mining. Together, these technological developments reflect a broader trend towards smarter, safer, and more sustainable mining operations [33,52,56,74–77].

Sustainability and waste management are recurring themes across the manuscripts, highlighting the industry's efforts to improve waste-management practices, enhance energy efficiency, and manage risk through advanced modelling. The adoption of improved waste-disposal methods, such as thickened and paste tailings, reflects the industry's commitment to minimising environmental harm. These practices not only improve water efficiency but also reduce the risk of environmental disasters such as tailings-dam failures. In addition, the focus on energy-efficient technologies reflects a broader effort to reduce the carbon footprint and improve the overall sustainability of mining operations. This emphasis is driven by both regulatory pressure and growing recognition within the industry of the need for long-term environmental stewardship. Moreover, the incorporation of stochastic modelling and risk-assessment techniques, such as Bayesian networks, provides tools for predicting outcomes and managing uncertainty in complex mining processes, thereby further supporting sustainable practices [37,67,73,78,79].

About the social pillar of sustainability, only a small number of manuscripts explicitly address it. The main themes identified include technological advancement and workforce implications, community engagement and social responsibility, and environmental justice and equity. Study [56] established that the adoption of artificial intelligence (AI), machine learning, and autonomous systems in the mining sector began roughly ten years ago, initially through the deployment of autonomous haul trucks. Nevertheless, the integration of these technologies has encountered a range of obstacles, including economic and financial constraints, technological limitations, and workforce and societal challenges. This highlights the need for mining companies to invest in upskilling and retraining so that workers can adapt to new technologies, transition into new roles, and avoid social disruption.

Another study [73] demonstrates that mining companies contributing to local development, considering meaningful engagement with local communities, is essential to prevent mining activities from negatively affecting the social dynamics of the regions where they take place. By guaranteeing that these communities share in the benefits generated by mining operations, companies can build trust and mitigate the risk of conflict.

Regarding environmental equity, another study [56] reported that the primary environmental issue associated with ISL is the containment of the leachate within the designated zone, thereby preventing contamination of surrounding groundwater resources. Furthermore, promoting environmental equity helps sustain long-term community support and the overall viability of mining operations.

Beyond operational efficiency and environmental performance, the incorporation of AI into copper-processing operations raises important social and ethical considerations. Automation may reduce workers' exposure to hazardous environments, but it can also modify occupational roles and increase the need for reskilling and continuous professional development [80,81]. In addition, the use of AI-supported decisions in safety-critical industrial processes requires human oversight, transparency, explainability, accountability, data protection, and mechanisms for identifying and mitigating algorithmic bias [80–82]. From a circular-economy perspective, AI and digital technologies can support predictive maintenance, extend equipment life, optimise the use of energy, water, and raw materials,

and improve the identification, sorting, recovery, and recirculation of valuable materials from process streams and mining waste [82,83]. However, these benefits should not be assumed automatically, because AI-enabled circularity may also involve ethical risks related to data control, unequal access to technology, and the environmental footprint of digital infrastructure [82]. The limited presence of these topics in the reviewed literature indicates that social sustainability, responsible AI governance, and circularity remain important areas for future research in copper processing.

The sustainability evidence is also uneven. Economic and operational benefits, including productivity, predictive maintenance, process stability, and reduced downtime, are reported more frequently than environmental or social outcomes. Environmental contributions are generally associated with energy efficiency, emissions reduction, resource optimisation, and waste management, whereas social sustainability and responsible AI governance receive limited attention. Consequently, the reviewed literature demonstrates a stronger capability to quantify operational performance than to assess broader environmental, workforce, ethical, and community impacts. The stronger representation of economic and operational sustainability can be attributed to the greater availability of measurable production indicators, such as throughput, recovery, energy consumption, downtime, and operating costs. These variables can be directly linked to AI predictions and optimisation results. Environmental and social outcomes are more difficult to assess because they require broader system boundaries, longer evaluation periods, and indicators that are not always integrated into industrial datasets. This helps explain why the reviewed literature reports efficiency and productivity benefits more frequently than workforce, ethical, community, or long-term environmental impacts.

4.4. RQ4—Which Regions of the World Show the Greatest Tendency to Incorporate Artificial Intelligence into Their Copper Mining Processes?

Unlike the previous analyses, no cross-analysis was conducted here; instead, the results are based on a direct count of the identified references.

About the regional distribution of studies on AI incorporation in copper-processing operations, three regions stand out: Asia (23 publications), South America (19 publications), and Africa (10 publications). These results suggest that the regions with stronger mining activity are also those most actively analysing or adopting AI within their processes. Contrary to what might be expected, Europe and North America have not directly contributed to the application of these technologies in copper mining, despite their strong technological development and AI capabilities.

The regional distribution identified in this review should be interpreted as the geographical representation of the studies included in the analysed corpus rather than as a direct measure of industrial AI adoption or regional technological capability. The comparatively high number of studies associated with Asia, South America, and Africa may partly reflect the concentration of mining and mineral-processing operations in these regions, which provide industrial cases and process-specific challenges for developing and assessing data-driven technologies. Nevertheless, the adoption of digital technologies in mining is not determined exclusively by the geographical availability of mineral resources. It also depends on operation-specific requirements, capital availability, digital infrastructure, access to industrial data, organisational capabilities, and collaboration among mining companies, technology providers, governments, and research institutions [15,84–86]. Previous studies have shown that mining companies must select digital technologies based on the specific needs and conditions of individual operations. At the same time, restricted access to industrial datasets and inadequate data infrastructure remain important barriers to AI development and deployment [15,85]. Therefore, the lower representation of Europe and North America in the results should not be interpreted as evidence of limited technological

contribution or lower AI capabilities. Technologies developed by companies, equipment suppliers, and research institutions located in these regions may be implemented or evaluated at mining operations situated elsewhere. Accordingly, the results indicate where the reviewed publications or case studies were geographically concentrated, but they do not constitute a comprehensive ranking of regional AI maturity or industrial adoption. The geographical concentration of the reviewed studies may partly reflect the location of major mining and mineral-processing operations, since access to industrial plants and process datasets facilitates the development and validation of AI applications. However, publication patterns are also influenced by research funding, industry-academia collaboration, data-access policies, and the way multinational studies are classified geographically. The regional distribution should therefore be interpreted as the location of the reviewed studies or case applications rather than as a direct measure of regional AI capability or industrial maturity [15,84,86].

Finally, Table 2 summarises the main findings for each research question.

Table 2. Summary of the main findings according to the research questions.

Research Question	Main Findings from the Reviewed Corpus	Cross-Study Interpretation	Principal Gap
RQ1. In which copper-processing operations is AI applied?	AI applications were concentrated mainly in the comminution and flotation stages. Leaching, solvent extraction, electrowinning, and electrorefining were less frequently represented.	Research activity was greater in operations with high industrial relevance, continuous data generation, and established monitoring variables. Hydrometallurgical processes presented more complex physicochemical dynamics and fewer online measurements.	Limited development and industrial validation of AI applications in hydrometallurgical operations.
RQ2. Which AI methods are used?	Machine learning was the dominant domain, particularly supervised approaches. Artificial neural networks, Random Forest, support vector methods, and ensemble models were repeatedly applied.	No method was universally superior. Reported performance depended on the dataset, operational unit, target variable, evaluation metric, and validation procedure.	Limited representation of reinforcement learning, hybrid models, adaptive control, and plant-wide optimisation.
RQ3. How is sustainability addressed?	The studies focused primarily on operational and economic outcomes, including recovery, productivity, energy use, maintenance, and downtime. Social, ethical, circularity, and broader environmental aspects were examined less frequently.	Outcomes that could be measured directly using operational variables were more commonly assessed than long-term or multidimensional sustainability impacts.	Insufficient integration of workforce, governance, community, circular-economy, and long-term environmental indicators.
RQ4. How are studies geographically distributed?	The reviewed publications and case studies were concentrated in Asia, South America, and Africa, with lower representation in Europe and North America.	The distribution reflected the location assigned to publications or industrial cases and should not be interpreted as a direct measure of regional AI capability or technological maturity.	Limited comparability due to differences in geographical classification and multinational research and technology development.

4.5. Future Research Roadmap

Based on the cross-study synthesis, future research can be organised into three successive stages. In the short term, efforts should prioritise access to reliable industrial datasets, transparent data-preprocessing and validation procedures, soft-sensor development, and reproducible benchmark models for specific copper-processing operations. These actions are necessary to improve comparability between studies and strengthen confidence in model performance under representative operating conditions.

In the medium term, research should advance toward hybrid mechanistic–data-driven models, transferability between operations, integration with digital process representations, and pilot-scale adaptive control. Particular attention should be given to hydrometallurgical stages, where complex physicochemical interactions and limited online measurements continue to restrict the development and implementation of AI-based systems.

In the longer term, research may progress toward safely constrained and human-supervised optimisation across interconnected copper-processing operations. This stage should integrate operational performance with interpretability, cybersecurity, workforce participation, responsible AI governance, environmental indicators, and circular-economy objectives. The proposed roadmap is not presented as a validated conceptual framework, but as a structured research agenda derived from the gaps, recurring limitations, and levels of technological development identified within the reviewed corpus. All this is summarised in Table 3.

Table 3. Research gaps, recurring limitations, and future research priorities.

Area	Gap or Limitation Identified	Short-Term Priority	Medium-Term Priority	Long-Term Direction
Industrial data	Restricted access, inconsistent quality, and limited reporting of preprocessing procedures.	Improve data quality, accessibility, documentation, and reproducible preprocessing.	Develop shared datasets and transferable data architectures.	Establish interoperable data ecosystems across processing operations.
Model validation	Heterogeneous metrics, validation strategies, and operating conditions restrict comparison between studies.	Standardise reporting and validation under representative conditions.	Conduct pilot-scale and cross-site validation.	Perform sustained validation in integrated industrial environments.
Hydrometallurgy	Leaching, solvent extraction, electrowinning, and electrorefining remain comparatively underrepresented.	Develop soft sensors and reliable process datasets.	Advance hybrid mechanistic–data-driven models.	Implement adaptive and integrated optimisation across hydrometallurgical circuits.
Advanced AI methods	Reinforcement learning and adaptive control are only marginally represented.	Develop constrained simulation and testing environments.	Evaluate human-supervised adaptive control at pilot scale.	Implement safely constrained autonomous optimisation.
Model transferability	Models are commonly developed for a specific plant, dataset, or operating condition.	Improve external validation and reporting of operational boundaries.	Develop transferable and domain-adaptation approaches.	Enable robust deployment across interconnected and variable operations.
Sustainability and governance	Social, ethical, circularity, and long-term environmental dimensions receive limited attention.	Define appropriate indicators and governance requirements.	Integrate these indicators into model assessment and decision support.	Align AI-based optimisation with environmental responsibility, workforce participation, and responsible governance.

4.6. Limitations of the Review

Although this review provides a structured synthesis addressing RQ1–RQ4, its findings should be interpreted in relation to the defined methodological scope. IEEE Xplore, Scopus, and Google Scholar were selected because their complementary coverage captures both the computational and process-engineering dimensions of the topic. IEEE Xplore provides specialised coverage of artificial intelligence, automation, instrumentation, and control, whereas Scopus offers broad multidisciplinary coverage of mining, mineral processing, metallurgy, and engineering. Google Scholar was used as a supplementary source to broaden retrieval beyond the two structured databases. As in any systematic mapping review, the selected information sources define the boundaries of the retrieved corpus. Transparent reporting of the databases, search expressions, eligibility criteria, and study-selection procedure therefore supports the traceability and evaluation of the review process [87].

The search strategy was based on predefined English-language terminology derived from the analytical categories of the study, including AI domains, copper-processing operations, and mining-context expressions. This approach ensured consistency between the research questions, search protocol, and classification framework. Studies using different terminology or published outside the defined language scope may provide complementary evidence, but the broad use of synonyms, related expressions, and supplementary searching was intended to maximise retrieval sensitivity within the established protocol. Classification by AI domain, operational unit, sustainability dimension, and geographical region was conducted according to predefined categories, with studies addressing multiple processes or technologies assigned to the corresponding analytical dimensions.

The reviewed corpus encompasses a heterogeneous range of engineering research, including data-driven model development, simulation, laboratory investigations, pilot-scale studies, and industrial applications. This diversity is valuable because it reflects the range of contexts in which AI is being investigated across copper processing. At the same time, differences in datasets, target variables, validation procedures, performance metrics, and operating conditions mean that reported model results are most appropriately interpreted within their specific study contexts. Accordingly, the review emphasises cross-study patterns, applications, methodological tendencies, and evidence gaps rather than constructing a direct quantitative ranking of algorithms. The geographical findings are interpreted in the same manner: they describe the regional distribution of the reviewed studies and industrial cases, while the discussion considers the operational and institutional factors that may contribute to these patterns.

The review did not apply a formal, design-specific critical-appraisal instrument or assign numerical Technology Readiness Levels. Baseline methodological credibility was supported through the inclusion of peer-reviewed journal articles and conference papers, predefined eligibility criteria, and contextual examination of the reported datasets, validation procedures, operating conditions, and implementation levels. These safeguards established a minimum threshold for inclusion but should not be considered equivalent to a formal study-quality or technological-readiness assessment.

Because the review encompasses heterogeneous engineering designs and does not consistently report the information required for uniform appraisal or TRL classification, retrospective numerical scoring could create false comparability and unsupported precision. The evidence was therefore interpreted qualitatively according to study design, validation context, and implementation level, distinguishing among model development, laboratory or pilot evaluation, individual industrial application, and sustained industrial deployment. The absence of formal quality appraisal and numerical TRL classification

remains a limitation. Future mapping reviews should prespecify design-specific appraisal and technological-readiness criteria during study selection and data extraction.

The scope of the review is intentionally centred on AI applications in copper mineral processing and extractive metallurgy. Within this defined domain, the synthesis provides direct and systematic responses to RQ1–RQ4 by identifying the principal operational areas investigated, the AI domains and methods reported, the sustainability dimensions considered, and the geographical distribution of the reviewed evidence. It also enables the identification of recurring methodological and industrial challenges and supports the formulation of a structured research agenda. Future updates may broaden this evidence base through additional databases, languages, and newly emerging AI applications while preserving the process-specific analytical framework developed in this study.

5. Conclusions

This systematic mapping review, complemented by qualitative synthesis, examined the application of artificial intelligence to copper mineral processing and extractive metallurgy across four predefined research questions. The review shows an uneven distribution of AI research across the processing flowsheet. Comminution and flotation are the most widely used applications, particularly in process monitoring, recovery prediction, operational optimisation, energy management, and equipment condition assessment. By contrast, hydrometallurgical stages such as leaching, solvent extraction, electrowinning, and electrorefining remain underrepresented, revealing important opportunities for further research and industrial validation.

Machine learning was the dominant AI domain, with supervised approaches most frequently applied, as the reviewed studies generally relied on historical operational data with measured inputs and known process outcomes. Artificial neural networks, Random Forest, support vector methods, and ensemble techniques were reported repeatedly; however, no single method emerged as universally superior. Model performance depended on the operational unit, data quality, dataset size, target variable, validation procedure, and industrial context. The evidence also indicates that most applications remain focused on prediction and offline model validation, while reinforcement learning, hybrid mechanistic–data-driven models, adaptive control, and integrated plant-wide optimisation are still in their early stages of development.

The sustainability analysis revealed a stronger emphasis on economic and operational outcomes, including productivity, recovery, energy efficiency, maintenance, and downtime reduction, than on social, ethical, circular-economy, and broader environmental implications. Although AI may contribute to more efficient resource use and improved process control, the reviewed literature provides more limited evidence on workforce transformation, human oversight, algorithmic accountability, data governance, community impacts, and the long-term environmental consequences of digitalisation. Likewise, the geographical distribution reflects the location of the publications and industrial cases included in this work. It should not be interpreted as a definitive ranking of regional technological capability or AI maturity.

Overall, the review answered RQ1–RQ4 within the methodological boundaries established by the search, screening, and classification process. The cross-study synthesis identified recurring challenges in access to high-quality industrial data, heterogeneous validation practices, model interpretability, limited transferability across operations, and insufficient evidence of sustained industrial deployment. Future research should therefore strengthen data quality, reporting, soft-sensing, and reproducible validation in the short term; advance hybrid and transferable models under representative operating conditions in the medium term; and, in the longer term, evaluate safely constrained and

human-supervised optimisation across interconnected copper-processing operations, while integrating operational performance with environmental responsibility, social sustainability, and responsible AI governance.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/pr14162540/s1>, Supplementary Note S1: AI taxonomy and operational definitions; Table S1: AI domains and subdomains used in the classification framework; and Supplementary Note S2: Table S2: complete database-specific search expressions used in IEEE Xplore, Scopus, and Google Scholar. Reference [88] is cited in Supplementary Materials.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AI HLEG	Artificial Intelligence High-Level Expert Group
CNN	Convolutional Neural Network
CV	Computer Vision
DNN	Deep Neural Network
GAN	Generative Adversarial Network
IEEE	Institute of Electrical and Electronics Engineers
IoT	Internet of Things
ISL	In Situ Lixiviation
LHD	Load-Haul-Dump
ML	Machine Learning
NARX-NN	Nonlinear AutoRegressive Network with eXogenous Inputs Neural Network
NLP	Natural Language Processing
PCA	Principal Component Analysis
PICOC	Population, Intervention, Comparison, Outcomes, Context
PaaS	Platform as a Service
RF	Random Forest
RNN	Recurrent Neural Network
RQ	Research Question
SaaS	Software as a Service

SAG	Semi-Autogenous Grinding
SOM	Self-Organizing Map
SVR	Support Vector Regression
SX-EW	Solvent Extraction–Electrowinning
t-SNE	t-distributed Stochastic Neighbour Embedding

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