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From Mineral Liberation to Metallurgical Recovery: The Role of Automated Mineralogy in Sulfide Ore Processing

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ABSTRACT

Original Research Article

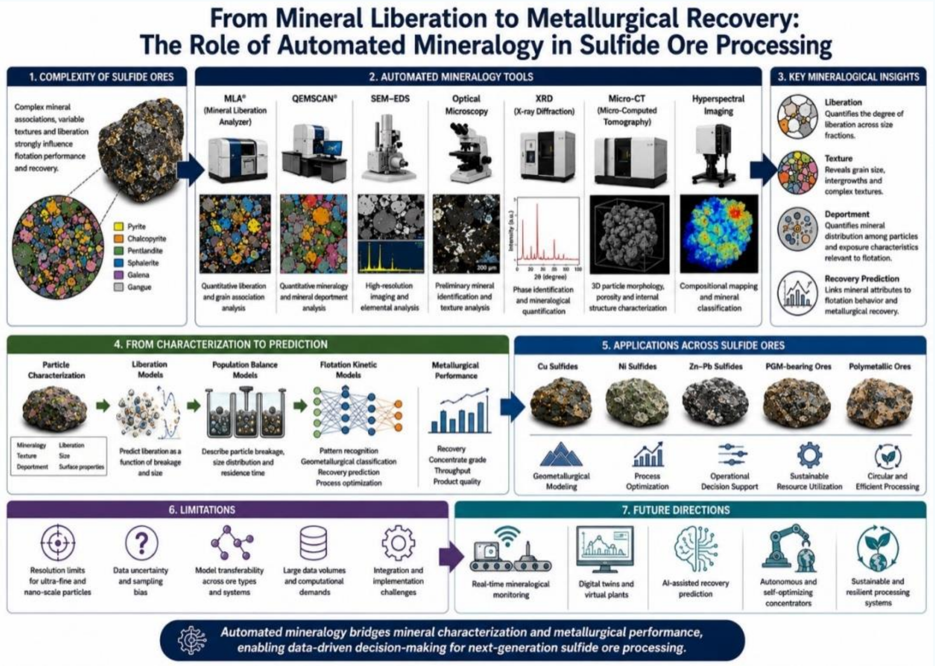
Sulfide ores are the primary source of nickel, copper, cobalt, platinum-group metals (PGMs), and several strategically important critical minerals. Yet their beneficiation remains challenging because of complex mineralogical associations, heterogeneous textures, variable liberation characteristics, and intricate mineral deportment patterns that strongly influence flotation performance and metallurgical recovery. Automated mineralogy has emerged as a transformative tool for quantitative ore characterization, providing detailed information on mineral composition, grain associations, particle texture, liberation, and exposure relationships. This review critically examines the role of automated mineralogy in sulfide ore processing and its contribution to linking mineral characterization with metallurgical performance prediction. Particular attention is given to the development and application of the Mineral Liberation Analyzer (MLA), QEMSCAN, SEM–EDS platforms, optical microscopy-based systems, X-ray micro-computed tomography (μCT), and hyperspectral imaging technologies. The review discusses how these techniques support quantitative liberation analysis, mineral deportment studies, flotation diagnostics, geometallurgical characterization, and recovery forecasting across a wide range of sulfide ore types. Recent advances in particle-based modeling are examined, highlighting the transition from conventional liberation metrics toward predictive frameworks that relate particle attributes directly to flotation behavior and metallurgical response. The integration of machine learning and artificial intelligence with automated mineralogical datasets is also evaluated, emphasizing emerging opportunities for recovery prediction, digital geometallurgy, process optimization, and decision support. Current limitations associated with spatial resolution, ultra-fine particle characterization, data uncertainty, model transferability, and industrial implementation are critically assessed. Future developments are expected to focus on real-time mineralogical monitoring, online process control, digital twins, AI-assisted recovery prediction, and autonomous concentrators. Automated mineralogy is increasingly evolving from a descriptive analytical technique into a predictive framework that supports next-generation mineral processing, geometallurgical modeling, and sustainable resource utilization.

Keywords: Automated Mineralogy, Sulfide Ores, Mineral Liberation, Flotation Recovery, Geometallurgy, Machine Learning.

Highlights

- Automated mineralogy provides quantitative links between ore characteristics and flotation performance.
- MLA, QEMSCAN, μCT, optical microscopy, and hyperspectral imaging enable advanced liberation and deportment analysis.
- Particle-based modeling and machine learning improve prediction of flotation recovery and metallurgical response.
- Future developments are expected to integrate real-time mineralogy, digital twins, and AI-assisted process optimization.

Graphical Abstract



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Introduction

Sulfide ores are the main source of key metals like copper, nickel, cobalt, and PGMs, vital for industry and energy transition. These metals are crucial for electrical grids, renewable tech, energy storage, catalysts, and manufacturing. As ore grades decline and deposits grow complex, recovering sulfide minerals efficiently is a major challenge for mining. Mineralogical characterization now plays a central role in process design, optimization, and decision-making (Becker, 2023; Frenzel et al., 2023; Butcher et al., 2023).

Mineral processing performance depends on ore characteristics like composition, grain size, mineral associations, alteration, texture, and liberation. These factors influence how particles respond in various processes. Understanding mineralogical controls is key to better resource use and reducing uncertainty. The increased use of mineralogical data in process engineering shows a broader shift to data-driven, ore-informed mining approaches (Becker, 2023; Frenzel et al., 2023; Butcher et al., 2023).

Mineralogical characterization is crucial beyond flotation, impacting hydrometallurgy, rare earths, beneficiation, titanium upgrades, refractory gold, and platinum extraction. Such constraints often shape process efficiency, flowsheet choice, and economics (Pereira, 2026e, 2026f).

Froth flotation is the primary method for concentrating sulfide minerals, but its success depends on ore characteristics. Recovery issues often stem from incomplete liberation, particle size, intergrowths, oxidation, alteration, gangue entrainment, and surface chemistry variations. These factors interact, complicating metallurgical predictions from chemical analyses.

The complexity of modern sulfide deposits increases the need for quantitative characterization tools. Many ores contain valuable minerals at fine grain sizes, spread across multiple mineral phases, or linked to alteration products that influence flotation. In copper, nickel, and PGM operations, mineral texture differences can cause major recovery variations even with stable head grades. Alteration can change mineral surfaces and flotation response, while pyrite and pyrrhotite behave variably depending on mineralogical and geological conditions (Can et al., 2021; Forbes et al., 2024). These factors reveal that liberation alone often can't explain processability and metallurgical performance (Pereira, 2026a, 2026b; Tonžetić, 2025).

Historically, mineralogical investigations relied heavily on optical microscopy and conventional petrographic methods. Although these techniques remain valuable, they are often labor-intensive and may not provide the statistical robustness required for modern process optimization. Advances in scanning electron microscopy, digital image analysis, spectroscopy, and automated classification algorithms have transformed mineral characterization over the past two decades. Automated mineralogy systems now enable rapid acquisition of quantitative information on mineral abundance, particle composition, grain size, mineral associations, liberation, and deportment across thousands of particles within a single dataset (Schulz et al., 2020; Schulz, 2020; Ali et al., 2023).

The most widely used automated mineralogy platforms include MLA, QEMSCAN, TIMA, and related SEM-based systems. These combine high-resolution imaging with energy-dispersive X-ray spectroscopy to produce representative mineralogical datasets. Recently, optical microscopy, machine vision, hyperspectral imaging, and X-ray micro-CT have broadened information for geometallurgy. These methods reveal mineral composition, three-dimensional particle structure, mineral exposure, texture, porosity, and internal grain relationships (Ali et al., 2023; De Castro et al., 2022, 2023; Krawczykowski & Kolodziej, 2021).

The availability of large mineralogical datasets has stimulated the development of new modeling approaches that directly link particle characteristics to metallurgical response. Traditional flotation models were largely based on empirical relationships and bulk kinetic parameters. In contrast, recent particle-based frameworks incorporate mineralogical attributes at the particle scale, enabling recovery predictions to be derived from measured liberation, texture, mineral associations, and surface-exposure characteristics. This represents a significant advance in the understanding of ore behavior because flotation ultimately occurs at the particle level rather than at the scale of bulk samples (Pereira et al., 2022, 2023).

Advances in machine learning and AI have opened new opportunities for processing complex mineralogical data. Predictive models estimate flotation kinetics, recovery, concentrate quality, and variability, integrating data from automated mineralogy, plant operations, and geology to optimize processes and inform decisions. Studies show machine learning can reveal relationships difficult for traditional stats, especially with multiple interacting variables (Huang et al., 2022; Gupta et al., 2022; Kabemba et al., 2025, 2026).

Despite these advances, the literature remains fragmented across different ore types, analytical platforms, modeling methodologies, and industrial applications. Studies are often focused on specific commodities, individual mineralogical techniques, or isolated modeling approaches. Consequently, a comprehensive evaluation of how automated mineralogy contributes to metallurgical recovery prediction across sulfide ore systems remains lacking (Pereira, 2026c, 2026d).

This review critically examines automated mineralogy in sulfide ore processing, focusing on quantitative liberation analysis, mineral deportment, flotation diagnostics, particle recovery modeling, machine learning, and geometallurgy. It discusses its evolution from a descriptive tool to a predictive framework that aids recovery forecasting, process optimization, and digital strategies.

Methodology

This study critically reviews the evolving role of automated mineralogy in sulfide ore processing, with a focus on mineral liberation, flotation, recovery prediction, particle modeling, machine learning, and geometallurgy. It combines a structured literature search with critical interpretation, guided by PRISMA 2020 principles (Page et al., 2021), balancing transparency with interpretative flexibility.

The literature survey used major scientific databases like Scopus, Web of Science, ScienceDirect, SpringerLink, Wiley Online Library, MDPI, Taylor & Francis Online, and Google Scholar. Searches from January to March 2026 involved keywords related to automated mineralogy, process mineralogy, mineral liberation, sulfide ores, flotation, geometallurgy, recovery prediction, particle-based modeling, machine learning, artificial intelligence, MLA, QEMSCAN, TIMA, SEM–EDS, hyperspectral imaging, and X-ray micro-computed tomography. Additional searches used terms for specific commodities such as nickel sulfides, copper sulfides, copper–cobalt ores, platinum-group deposits, lead–zinc ores, polymetallic sulfides, and refractory gold ores. References from key review papers and highly cited studies were also checked to identify relevant research missed by the main searches.

The review focused primarily on literature published between 2020 and 2026, reflecting the period during which substantial advances occurred in automated mineralogy, digital geometallurgy, predictive metallurgy, machine learning, and particle-based process simulation. Earlier publications were included when considered foundational to the development of analytical methodologies, mineralogical concepts, or modeling frameworks that continue to influence contemporary research and industrial practice.

Publications were screened based on relevance criteria. Studies were eligible if they covered topics like automated mineralogy techniques, mineral liberation, flotation diagnostics, process mineralogy, flotation modeling, AI in mineral processing, or sulfide ore characterization. Those solely on instrument development without processing relevance were excluded unless they aided mineralogical workflows. Various publication types were included if they offered significant or industrial insights.

The literature was organized into themes: one on sulfide ore mineralogy and characterization, another on automated mineralogy platforms and analysis, a third on mineral liberation, particle characterization, and flotation, a fourth on particle models and flotation simulations, a fifth on machine learning, AI, and predictive geometallurgy, and a final one on industrial applications, case studies, and digital tech. This structure highlights the growing role of mineralogy in metallurgical and geometallurgical workflows.

The evidence was classified by ore type, technique, and modeling. Ore categories included nickel sulfides, copper sulfides, copper–cobalt ores, platinum-group, polymetallic sulfides, lead–zinc deposits, refractory gold, and secondary resources like tailings. Techniques encompassed SEM-based mineralogy, microscopy, hyperspectral imaging, X-ray micro-CT, and other mineral methods. Modeling included liberation, flotation kinetics, particle simulations, machine learning, and geometallurgical approaches. This helped compare methods and their roles in understanding, predicting, and optimizing recovery.

The review emphasizes critical interpretation over quantitative aggregation. No meta-analysis or quantitative quality-scoring was used. Instead, studies were assessed based on relevance, rigor, industrial use, and insights into mineralogical and metallurgical relationships. Attention focused on those demonstrating practical automated mineralogy in flotation, recovery, and geometallurgical efforts.

To improve transparency, the literature selection process was documented through a PRISMA-inspired workflow. Figure 1 summarizes the identification, screening, eligibility assessment, and final inclusion of publications considered in the review. The workflow provides a structured overview of the literature selection process and facilitates reproducibility of the review methodology. However, the present study should be interpreted as a critical review informed by systematic-review principles rather than as a formal systematic review or meta-analysis (Page et al., 2021).

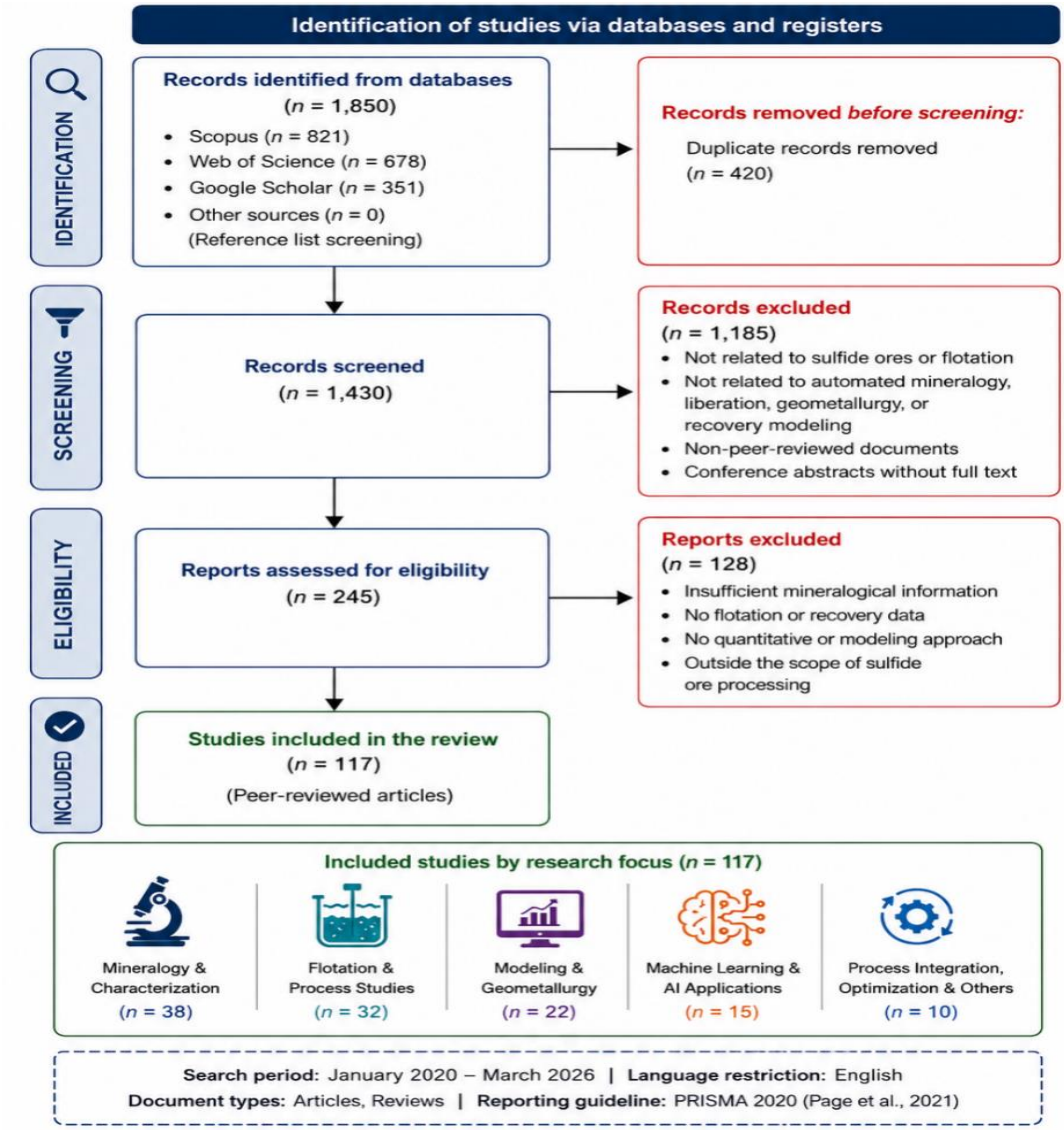


Figure 1. PRISMA-style flow diagram showing identification, screening, eligibility, and inclusion of references used in this review. Adapted from Page et al. (2021).

The resulting body of literature was subsequently synthesized through comparative and thematic analysis. Emphasis was placed on identifying major technological developments, methodological trends, recurring limitations, and future opportunities associated with automated mineralogy. Particular attention was given to the evolution of mineral liberation analysis, predictive flotation modeling, machine learning applications, and digital geometallurgical frameworks, all of which increasingly transform mineralogical data into actionable metallurgical knowledge (Becker, 2023; Butcher et al., 2023; Frenzel et al., 2023).

To facilitate interpretation and comparison among studies, the literature was classified according to database coverage, eligibility criteria, ore category, analytical technique, and modeling approach. The methodological framework adopted throughout the review is summarized in Table 1.

Table 1. Search strategy, databases, eligibility criteria, and thematic classification adopted in the review. Adapted from Page et al. (2021), Becker (2023), Frenzel et al. (2023), and Butcher et al. (2023).

Category	Description
Databases	Scopus, Web of Science, ScienceDirect, SpringerLink, Wiley, MDPI, Taylor & Francis, Google Scholar
Time period	2020–2026 (with selected foundational studies when required)
Main keywords	Automated mineralogy, MLA, QEMSCAN, TIMA, flotation, sulfide ores, liberation, geometallurgy, machine learning, recovery prediction
Inclusion criteria	Sulfide ore processing, mineral characterization, flotation performance, recovery prediction, process mineralogy, geometallurgy
Exclusion criteria	Studies unrelated to mineral processing or metallurgical performance
Ore categories	Ni sulfides, Cu sulfides, Cu–Co, Pb–Zn, PGM, refractory gold, polymetallic ores, tailings
Technique categories	MLA, QEMSCAN, TIMA, SEM–EDS, optical microscopy, µCT, hyperspectral imaging
Model categories	Liberation models, flotation kinetics, particle-based models, machine learning, geometallurgy

Several limitations should be acknowledged. Publication bias may favor successful industrial applications over unsuccessful implementations, terminology varies considerably among disciplines, and many industrial datasets remain proprietary and unavailable in the public domain. In addition, automated mineralogy technologies, digital geometallurgical platforms, and artificial intelligence tools continue to evolve rapidly, meaning that some emerging developments may not yet be fully represented in the published literature. These limitations are common in technology-focused review studies and should be considered when interpreting the conclusions presented herein (Page et al., 2021; Tonžetić, 2025).

Overall, the methodology adopted in this review combines systematic identification of relevant literature with critical evaluation of scientific and industrial developments. The resulting evidence base provides a comprehensive foundation for assessing how automated mineralogy contributes to sulfide ore characterization, flotation optimization, recovery prediction, process modeling, and the broader transition toward digital geometallurgy and autonomous mineral processing systems (De Castro et al., 2022; Pereira et al., 2023; Schulz et al., 2020).

Sulfide Ore Mineralogy and Metallurgical Response

Nickel Sulfide Ores

Nickel sulfide deposits are the main source of primary nickel essential for stainless steel, batteries, and energy technologies. Pentlandite is usually the main nickel mineral, but millerite, violarite, and other phases can also be significant depending on ore formation and alteration. Automated mineralogy shows nickel recovery depends on mineral associations, grain size, and liberation. Pentlandite often occurs with pyrrhotite and pyrite, causing complex flotation behavior and recovery issues when not fully liberated (Ayedzi et al., 2024; Dzvinamurungu et al., 2022).

Geometallurgical studies show mineralogical variability impacts concentrate quality and flotation. Mineralogical characterization is vital for ore blending and process optimization. Automated mineralogy aids in predicting metallurgical response in magmatic and volcanogenic sulfide deposits (Dzingai et al., 2021; Rincon et al., 2026).

Copper and Copper–Molybdenum Ores

Copper sulfide ores are among the most extensively studied applications of automated mineralogy. Chalcopyrite remains the dominant copper mineral in most deposits, although bornite, chalcocite, covellite, and secondary copper phases may contribute to ore variability. Recovery is strongly influenced by liberation, particle composition, and mineral associations. Numerous studies have demonstrated that flotation losses are frequently associated with composite particles containing copper sulfides locked within gangue minerals (Abdollahi et al., 2020; Tanaka et al., 2021).

Automated mineralogy has become particularly valuable for tailings diagnostics and process optimization. Investigations of copper concentrators have revealed significant quantities of unrecovered chalcopyrite remaining in flotation tailings due to incomplete liberation and unfavorable particle textures (Hu et al., 2021; Zhang et al., 2021). In copper–molybdenum operations, quantitative characterization of chalcopyrite and molybdenite distributions provides essential information for circuit optimization and concentrate quality control (Tumen-Ayush et al., 2025).

Pyrite, Pyrrhotite, and Iron Sulfides

Pyrite and pyrrhotite are among the most common sulfide minerals encountered in flotation circuits. Their behavior is highly variable and depends on mineral chemistry, crystal structure, oxidation state, and textural setting. In many deposits, pyrite acts as a gangue mineral; however, it may also host valuable trace metals or serve as an important carrier of gold and platinum group elements (Forbes et al., 2024).

Recent studies show pyrite flotation isn't only about surface chemistry. Texture, mineral associations, and grain shape also impact recovery and selectivity. Research on copper sulfides reveals pyrite's occurrence and texture influence concentrate quality and flotation rates (Can et al., 2021). Growing interest in recovering pyrite and extracting critical metals has increased the importance of process mineralogy in assessing pyrite resources (Eljoudiani et al., 2025; Escalante et al., 2026).

Platinum Group Metal Ores

Platinum group metal (PGM) deposits are characterized by extremely complex mineralogy and fine-grained valuable phases. Platinum and palladium commonly occur in multiple mineral species and frequently exhibit intricate associations with base-metal sulfides and chromite. Consequently, recovery is highly sensitive to liberation and mineral occurrence.

Automated mineralogy has significantly improved understanding of PGM deportment and flotation behavior. Studies on Platreef and UG2 ores demonstrate that particle exposure and mineral occurrence frequently control recovery more strongly than bulk grade alone (Carelse et al., 2022; Engelbrecht et al., 2022). Similar observations have been reported in tailings reprocessing studies, where substantial quantities of unrecovered PGMs were identified through quantitative mineralogical analysis (Baloyi et al., 2024; Notole et al., 2025).

Mineral Chemistry, Alteration, and Deportment

Mineral abundance and liberation alone rarely provide a complete description of metallurgical behavior. Although these parameters are fundamental for understanding flotation performance, numerous studies have demonstrated that mineral chemistry, alteration, and metal deportment frequently exert equally important influences on recovery, concentrate quality, and process selectivity. Variations in elemental composition can modify mineral surface properties, reagent adsorption mechanisms, electrochemical behavior, oxidation susceptibility, and flotation kinetics, ultimately affecting the response of individual minerals during beneficiation (Tiu et al., 2021, 2022).

Mineral chemistry plays a key role in complex sulfide systems, where minerals with similar optical or textural features may show different flotation behaviors due to compositional differences. For instance, iron substitution in sphalerite affects activation and flotation response, while trace elements in pyrite and pyrrhotite influence oxidation and reagent interactions. Geometallurgical studies reveal mineral chemistry can explain differences between similar ore zones that appear identical under standard mineralogical analysis. Integrating mineral chemistry with quantitative mineralogy enhances recovery prediction and process optimization (Layton-Matthews & McClenaghan, 2021; Tiu et al., 2023).

Alteration processes add complexity by modifying mineral assemblages and surface properties, affecting flotation. Secondary sulfides like chalcocite may respond differently than primary ones, and oxidation can boost or hinder recovery based on mineralogy. Recognizing these effects is crucial for accurate metallurgical and geometallurgical analysis.

Deportment analysis reveals how valuable metals are distributed among mineral phases and particles, affecting their recoverability. It often determines the practical recovery limits and guides process choices. Recent studies of silver sulfides, precious-metal ores, and polymetallic deposits highlight its role in assessing beneficiation and designing processes (Nourizenouz et al., 2026).

Before discussing analytical methods in automated mineralogy, review key sulfide minerals in flotation, their occurrences, deportment, and metallurgical implications. Table 2 details these for major sulfide commodities worldwide.

Table 2. Major sulfide minerals, associated commodities, deportment characteristics, and expected flotation implications. Adapted from Ayedzi et al. (2024), Abdollahi et al. (2020), Carelse et al. (2022), Tiu et al. (2022), and Forbes et al. (2024).

Mineral	Main Commodity	Typical Occurrence	Deportment Characteristics	Flotation Implications
Chalcopyrite	Cu	Disseminated, vein-hosted	Often locked with gangue	Requires adequate liberation
Bornite	Cu	Massive or disseminated	Usually favorable exposure	High floatability
Chalcocite	Cu	Secondary enrichment zones	Frequently liberated	Excellent recovery potential
Pentlandite	Ni	Associated with pyrrhotite	Complex intergrowths	Sensitive to texture
Millerite	Ni	Fine-grained occurrences	Variable liberation	Ore-specific response
Pyrite	Fe, Au carrier	Ubiquitous sulfide	May host Au and trace metals	Selectivity challenges
Pyrrhotite	Ni, PGM association	Magmatic sulfide systems	Variable magnetic behavior	Influences flotation selectivity
Galena	Pb	Polymetallic deposits	Usually coarse-grained	High flotation response
Sphalerite	Zn	Polymetallic deposits	Variable Fe substitution	Activator-dependent flotation
PGM minerals	Pt, Pd	Fine inclusions and intergrowths	Complex occurrence	Strongly texture-controlled

Table 2 highlights the mineralogical factors affecting flotation across sulfide ore systems. Copper sulfides such as chalcopyrite, bornite, and chalcocite are key minerals in many deposits, but their flotation behavior varies with occurrence, liberation, and gangue associations. Chalcopyrite often occurs in complex intergrowths that require proper liberation, whereas chalcocite generally yields better liberation and higher recovery potential.

Nickel sulfide systems pose challenges due to pentlandite that occurs in complex intergrowths with pyrrhotite and other sulfides. Flotation performance depends on texture, grain size, and mineral associations. Automated mineralogy helps quantify these factors, aiding ore blending and geometallurgical strategies to manage ore variability.

The table highlights the role of gangue and carrier minerals like pyrite and pyrrhotite. While not always the main target, they affect flotation selectivity and concentrate quality. Pyrite can contain gold and trace metals, and pyrrhotite is linked to nickel sulfides and platinum-group minerals. Their presence impacts recovery and processing.

Polymetallic systems featuring galena and sphalerite highlight the role of mineral chemistry. Galena floats well due to its coarse grains and floatability, whereas sphalerite requires activation and varies with composition. These show how mineral differences affect flotation.

Platinum-group mineral (PGM) systems are among the most complex flotation environments. PGM minerals often occur as fine inclusions, grain-boundary phases, or complex intergrowths with base-metal sulfides. Recovery depends more on texture, associations, and deportment than mineral abundance. Automated mineralogy is essential for assessing these factors and recovery limits.

Table 2 shows that liberation, mineral associations, chemistry, alteration, and deportment primarily govern flotation in sulfide ore systems. Although mineral assemblages vary among commodities, the principles governing their metallurgical behavior are similar. This highlights the value of automated mineralogy in quantifying these variables and converting mineralogical data into metallurgical insights. The next sections discuss techniques for quantitative characterization and their role in flotation diagnostics and recovery prediction.

Automated Mineralogy and Quantitative Liberation Analysis

SEM-Based Automated Mineralogy

Automated mineralogy is essential in modern process mineralogy, providing data on mineral composition, particle traits, liberation, and associations. Common systems such as SEM–EDS-based MLA, QEMSCAN, TIMA, and AMICS produce representative datasets and have become standard for flotation diagnostics, geometallurgy, and recovery prediction (Schulz et al., 2020; Schulz, 2020).

Although these systems differ in architecture and algorithms, their goal is to quantify mineral particles. MLA and QEMSCAN are the most industrially established, while TIMA and AMICS offer greater flexibility and faster acquisition. Studies show all four give reliable mineralogical data with proper calibration and mineral libraries (Ali et al., 2023; Tao et al., 2023).

The main benefit of SEM-based automated mineralogy is its ability to quantify liberation, exposure, and mineral associations in large particles, providing a better basis for flotation interpretation than bulk chemical analyses and aiding particle-based recovery models (Barton, 2020; Reed et al., 2025).

Optical Mineralogy and Image-Based Approaches

Advances in digital image analysis and computer vision have expanded automated optical mineralogy. While SEM-based systems are the standard for quantitative mineral characterization, automated optical approaches provide lower costs and higher throughput for certain applications.

Recent studies show optical mineralogy, combined with machine learning and image processing, effectively characterizes ore textures, mineral associations, and liberation patterns. Applied to nickel sulfide ores and geometallurgical classification, it aligns well with SEM methods while simplifying analysis (De Castro et al., 2022, 2023).

Deep learning and automated image classification enhance the reliability of optical mineralogy, aiding rapid, large-sample characterization (Koh et al., 2024).

Three-Dimensional Characterization by X-Ray Micro-Computed Tomography

Conventional automated mineralogy relies on 2D polished sections, which, while informative, may not fully capture the 3D structure of mineral particles.

X-ray micro-computed tomography (μCT) enables 3D analysis of particle shape, internal relations, porosity, and mineral connections, offering insights into liberation and flotation behavior (Guntoro et al., 2021a).

Recent studies show combining μCT with automated mineralogy enhances understanding of particle processes by reducing stereological bias in 3D datasets used in liberation, simulations, and geometallurgical models (Guntoro et al., 2021b; Buyse et al., 2023; Siddique et al., 2023; Erskine et al., 2023).

Although industrial implementation remains limited by cost and computational requirements, μCT is expected to play an increasingly important role in advanced process mineralogy.

Hyperspectral, FTIR, LIBS, and μ-XRF Applications

Sensor-based characterization technologies, like hyperspectral imaging, portable FTIR, LIBS, and μ-XRF, are vital complements to automated mineralogy, offering rapid, non-destructive analysis of mineral variability across large samples.

Hyperspectral imaging is valuable for drill-core characterization, ore sorting, and geometallurgical mapping. Using machine-learning algorithms, it supports mineral identification and predicts processing behavior at scales beyond SEM techniques (Tuşa et al., 2020; De La Rosa et al., 2021).

Portable FTIR systems have demonstrated utility for rapid characterization of alteration minerals and gangue assemblages in copper–cobalt deposits, while LIBS and μ-XRF technologies have expanded opportunities for high-throughput mineralogical screening and geometallurgical analysis (Dehaine et al., 2021a, 2021b; Viana et al., 2025).

These techniques do not replace automated mineralogy but provide complementary information that strengthens integrated characterization workflows.

Emerging and Non-Conventional Applications

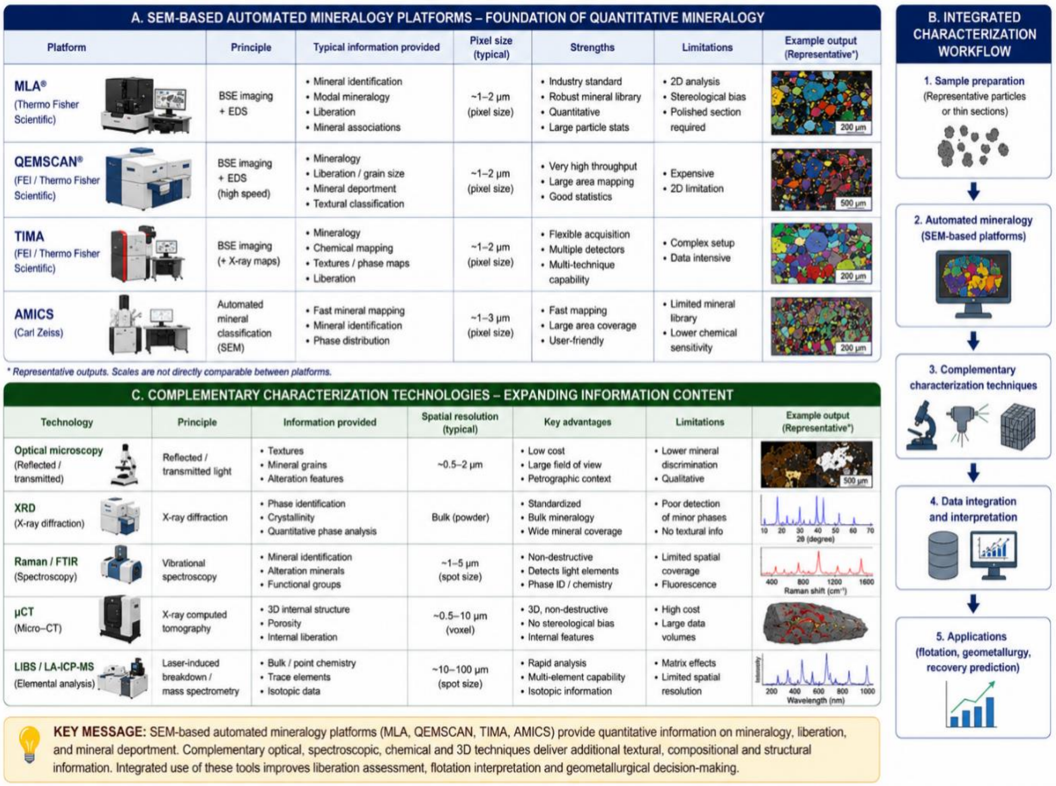
Automated mineralogy now addresses diverse scientific and industrial challenges beyond traditional flotation and mineralogy. Advances in imaging, computing, and data processing broaden its scope from ore characterization, liberation, and process optimization.

Recent studies have used automated mineralogy for atmospheric particles, environmental monitoring, mine emissions, carbon materials, industrial residues, and waste valorization. These systems quickly identify and quantify particles, revealing their composition, morphology, mineral associations, and sources.

Studies by Elmes et al. (2020) and Elmes (2021) demonstrated the use of automated mineralogy for airborne particulate matter, providing insights into sources, transport, and impacts. It has also been applied to graphite and carbon-rich systems for resource evaluation, beneficiation, and mineral association assessment (Lenoir, 2023).

These emerging applications show how automated mineralogy is becoming more flexible, with future developments likely surpassing traditional mineral processing. The integration of advanced imaging, AI, machine learning, and multisensor methods is turning automated mineralogy into a wider platform for detailed material analysis and data-driven decisions (Ali et al., 2023).

As automated mineralogy expands, integrating complementary techniques is key, as no single method can fully describe complex mineral systems. Modern process mineralogy uses workflows combining automated mineralogy with optical, spectroscopic, elemental, and 3D characterization methods. Figure 2 summarizes current platforms and techniques used in flotation and geometallurgy.



A. SEM-BASED AUTOMATED MINERALOGY PLATFORMS – FOUNDATION OF QUANTITATIVE MINERALOGY

Platform	Principle	Typical information provided	Pixel size (typical)	Strengths	Limitations	Example output (Representative*)
MLA® (Thermo Fisher Scientific)	BSE imaging + EDS	• Mineral identification • Modal mineralogy • Liberation • Mineral associations	~1–2 µm (pixel size)	• Industry standard • Robust mineral library • Quantitative • Large particle stats	• 2D analysis • Stereological bias • Polished section required	200 µm
QEMSCAN® (FEI / Thermo Fisher Scientific)	BSE imaging + EDS (high speed)	• Mineralogy • Liberation / grain size • Mineral deportment • Textural classification	~1–2 µm (pixel size)	• Very high throughput • Large area mapping • Good statistics	• Expensive • 2D limitation	500 µm
TIMA (FEI / Thermo Fisher Scientific)	BSE imaging (+ X-ray maps)	• Mineralogy • Chemical mapping • Textures / phase maps • Liberation	~1–2 µm (pixel size)	• Flexible acquisition • Multiple detectors • Multi-technique capability	• Complex setup • Data intensive	200 µm
AMICS (Carl Zeiss)	Automated mineral classification (SEM)	• Fast mineral mapping • Mineral identification • Phase distribution	~1–3 µm (pixel size)	• Fast mapping • Large area coverage • User-friendly	• Limited mineral library • Lower chemical sensitivity	200 µm

** Representative outputs. Scales are not directly comparable between platforms.*

B. INTEGRATED CHARACTERIZATION WORKFLOW

1. Sample preparation (Representative particles or thin sections)
2. Automated mineralogy (SEM-based platforms)
3. Complementary characterization techniques
4. Data integration and interpretation
5. Applications (flotation, geometallurgy, recovery prediction)

C. COMPLEMENTARY CHARACTERIZATION TECHNOLOGIES – EXPANDING INFORMATION CONTENT

Technology	Principle	Information provided	Spatial resolution (typical)	Key advantages	Limitations	Example output (Representative*)
Optical microscopy (Reflected / transmitted)	Reflected / transmitted light	• Textures • Mineral grains • Alteration features	~0.5–2 µm	• Low cost • Large field of view • Petrographic context	• Lower mineral discrimination • Qualitative	500 µm
XRD (X-ray diffraction)	X-ray diffraction	• Phase identification • Crystallinity • Quantitative phase analysis	Bulk (powder)	• Standardized • Bulk mineralogy • Wide mineral coverage	• Poor detection of minor phases • No textural info	10 20 30 40 50 60 70 2θ (degree)
Raman / FTIR (Spectroscopy)	Vibrational spectroscopy	• Mineral identification • Alteration minerals • Functional groups	~1–5 µm (spot size)	• Non-destructive • Detects light elements • Phase ID / chemistry	• Limited spatial coverage • Fluorescence	400 800 1200 1600 Raman shift (cm⁻¹)
µCT (Micro–CT)	X-ray computed tomography	• 3D internal structure • Porosity • Internal liberation	~0.5–10 µm (voxel)	• 3D, non-destructive • No stereological bias • Internal features	• High cost • Large data volumes	
LIBS / LA-ICP-MS (Elemental analysis)	Laser-induced breakdown / mass spectrometry	• Bulk / point chemistry • Trace elements • Isotopic data	~10–100 µm (spot size)	• Rapid analysis • Multi-element capability • Isotopic information	• Matrix effects • Limited spatial resolution	Intensity 200 400 600 800 1000 Wavelength (nm)

KEY MESSAGE: SEM-based automated mineralogy platforms (MLA, QEMSCAN, TIMA, AMICS) provide quantitative information on mineralogy, liberation, and mineral deportment. Complementary optical, spectroscopic, chemical and 3D techniques deliver additional textural, compositional and structural information. Integrated use of these tools improves liberation assessment, flotation interpretation and geometallurgical decision-making.

Figure 2. Main automated mineralogy platforms and complementary characterization technologies used in flotation studies.Adapted from Schulz et al. (2020), Ali et al. (2023), Tao et al. (2023), and Buyse et al. (2023).

Figure 2 shows how modern mineral characterization methods complement each other. SEM-based automated platforms like MLA, QEMSCAN, TIMA, and AMICS are still core to mineralogical studies because they offer direct data on mineral ID, liberation, associations, grain size, and textures. They are essential for flotation diagnostics, geometallurgy, and process optimization.

The figure highlights the rising importance of various analytical methods. Optical microscopy offers cost-effective insight into textures and mineral relations. Spectroscopic techniques like Raman, hyperspectral imaging, and LIBS provide compositional and mineral data over larger areas than SEM. 3D methods like micro-CT reveal internal structures, porosity, and mineral connections that 2D analyses can't show.

Integrating multiple characterization methods overcomes the limits of individual techniques. Combining automated mineralogy with spectroscopic, imaging, and 3D approaches offers a comprehensive view of ore variability, mineral occurrence, particle texture, and processing behavior. Since techniques give different mineralogical and textural data, a comparative assessment is needed. Table 3 summarizes the key information, strengths, and limitations of each method.

Table 3. Comparison of automated mineralogy and complementary characterization techniques used in sulfide ore processing. Adapted from Schulz et al. (2020), Ali et al. (2023), Tao et al. (2023), Buyse et al. (2023), and Viana et al. (2025).

Technique	Information Obtained	Dimensionality	Strengths	Limitations
MLA	Mineralogy, liberation, associations	2D	Industry standard	Stereological bias
QEMSCAN	Mineralogy, liberation, deportment	2D	High throughput	Cost
TIMA	Mineralogy and textures	2D	Flexible acquisition	Complex processing
AMICS	Automated mineral classification	2D	Fast mapping	Limited industrial database
Optical microscopy	Texture and mineral associations	2D	Low cost	Lower mineral discrimination
µCT	Internal particle structure	3D	No stereological bias	Cost and data volume
Hyperspectral imaging	Mineral mapping	2D/3D	Large-area coverage	Lower spatial resolution
LIBS	Elemental composition	Spot/Mapping	Rapid analysis	Limited mineral discrimination
µ-XRF	Elemental mapping	2D	Large-area scanning	Mineral inference required

Table 3 shows that no single technique offers all ore characterization data. SEM-based platforms like MLA, QEMSCAN, TIMA, and AMICS are most effective for mineral identification, liberation, and association studies. However, their 2D nature imposes stereological limitations that affect the interpretation of particle geometry and mineral exposure.

Complementary techniques fill mineralogical gaps. Optical microscopy offers quick, cost-effective textural insights, while micro-CT provides 3D structure, mineral connectivity, and porosity data. Hyperspectral imaging enables fast, large-area mineral mapping, and LIBS and μ-XRF provide elemental information that complements mineralogical data. Modern geometallurgy increasingly employs integrated workflows that combine these techniques for comprehensive ore property analysis.

While Table 3 compares the data types of different characterization techniques, practical use also depends on factors such as resolution, throughput, complexity, cost, and industry adoption. These influence the choice of analytical platforms for plant support, geometallurgy, flotation, and research. Table 4 compares key automated mineralogy and advanced technologies used in sulfide ore processing.

Table 4. Comparative assessment of major automated mineralogy platforms used in sulfide ore characterization.

Technique	Mineral Identification Accuracy	Spatial Resolution	Throughput	Relative Cost	Typical Applications	Industrial Adoption
MLA	High	High	High	Moderate	Liberation analysis, flotation studies, geometallurgy	Very High
QEMSCAN	Very High	Moderate–High	Very High	High	Large-scale ore characterization, geometallurgy	Very High
TIMA	Very High	High	High	High	Process mineralogy, liberation studies	Increasing
AMICS	High	High	Moderate	Moderate	Academic and industrial characterization	Increasing
Mineralogic	High	Variable	Moderate	Moderate	Customized mineralogical workflows	Moderate
Optical Microscopy	Moderate	Moderate	High	Low	Preliminary characterization	High
μCT	Very High (3D)	Very High	Low	Very High	Particle texture and 3D liberation studies	Limited
Hyperspectral Imaging	Moderate	Low–Moderate	Very High	Moderate	Ore sorting and geometallurgy	Increasing

No single automated mineralogy platform is universally best; selection depends on spatial resolution, throughput, complexity, goals, and costs. MLA and QEMSCAN are dominant in industrial flotation and geometallurgy for their high-throughput, robust data. TIMA is valued for its flexibility and resolution, μCT provides 3D data but is costly and slow, while hyperspectral imaging enables rapid large-scale characterization but lacks mineral detail compared to SEM systems. Thus, workflows increasingly combine techniques to leverage their strengths for better ore analysis, recovery, and process optimization.

Mineral Liberation, Texture, and Flotation Performance

Liberation and Mineral Exposure

Mineral liberation remains one of the most important descriptors of flotation performance because it determines the accessibility of valuable minerals to flotation reagents and bubble-particle attachment mechanisms. Numerous studies have demonstrated positive relationships between increasing liberation and increasing recovery across copper, nickel, platinum group metal, and polymetallic sulfide systems (Štirbanović et al., 2020; Vallejos et al., 2021).

However, modern automated mineralogy studies indicate that liberation alone rarely explains the full range of metallurgical responses observed in industrial operations. Particles classified as liberated may exhibit substantially different flotation behaviors due to differences in mineral exposure, surface accessibility, grain morphology, and mineral chemistry. Consequently, mineral exposure has emerged as a complementary descriptor that frequently provides stronger correlations with flotation response than liberation alone (Gupta et al., 2022; Huang et al., 2022).

Particle-based investigations further demonstrate that partially liberated particles can achieve high recovery when sufficient mineral surface is exposed to flotation reagents. Conversely, highly liberated particles may remain unrecovered because of oxidation, unfavorable surface conditions, or hydrodynamic limitations. These observations support the increasing use of integrated liberation–exposure metrics within flotation models (Runge et al., 2024).

Texture, Mineral Associations, and Particle Complexity

Ore texture exerts a fundamental influence on flotation behavior by governing mineral exposure, liberation pathways, and particle composition. Grain size distribution, mineral intergrowths, alteration features, and mineral associations collectively determine how particles respond to comminution and subsequent beneficiation.

Recent developments in automated mineralogy have enabled quantitative characterization of particle complexity and mineral associations. Studies have shown that particles with identical mineral proportions may exhibit significantly different flotation responses due to differences in grain arrangement and exposure characteristics. Consequently, texture has become an increasingly important component of geometallurgical characterization (Can et al., 2021; Forbes et al., 2024).

Quantitative texture metrics have further improved understanding of flotation variability. Chamlal et al. (2025) demonstrated that texture complexity can be incorporated into predictive frameworks, while Tungpalan et al. (2025) showed that microtextural characteristics influence flotation performance independently of conventional liberation measurements. Three-dimensional characterization studies similarly indicate that internal particle structure can strongly affect recoverability (Guntoro et al., 2021).

Particle Size Effects and Flotation Response

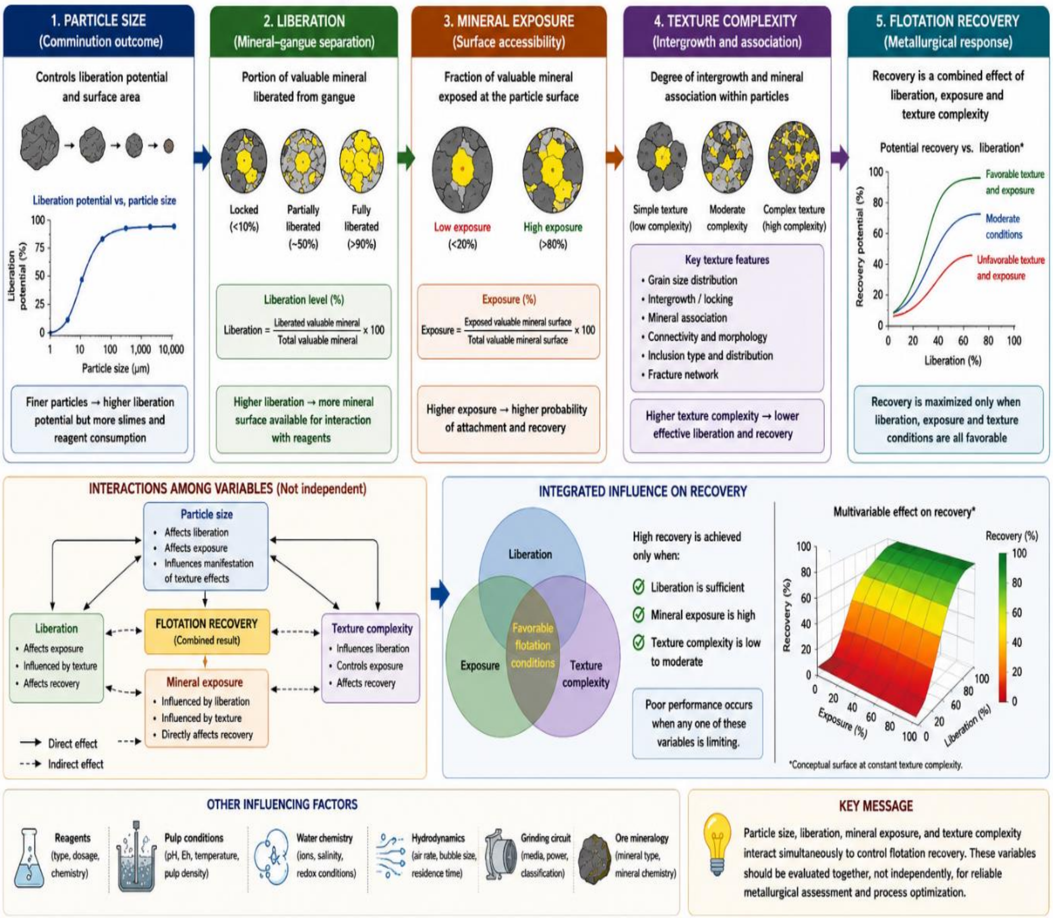
Particle size affects flotation by impacting liberation, collision, attachment, detachment, and transport within cells. Flotation recovery often follows a bell-shaped curve, with intermediate sizes usually delivering the best results. This illustrates the complex interaction between mineralogy and hydrodynamics, showing that size alone doesn't fully explain performance.

Coarse particles often suffer from poor liberation and higher detachment due to their mass and momentum, which destabilizes particle–bubble aggregates and increases detachment risk during flotation. Additionally, locked mineral assemblages from incomplete grinding further lower recovery. As a result, coarse-particle flotation methods are gaining attention for recovering partially liberated particles while reducing grinding energy (Taguta et al., 2023; Crompton et al., 2024).

Fine and ultrafine particles often contain unrecovered valuable minerals despite high liberation, with recovery losses linked to hydrodynamic effects such as reduced collision efficiency, attachment, and entrainment. Studies show that many losses can't be explained solely by mineralogy, underscoring the need to integrate flotation engineering with mineralogical analysis (Corin et al., 2021; Escalante et al., 2026).

The interaction between particle size and liberation highlights the need for integrated characterization. Automated mineralogy enables detailed flotation evaluation through size-by-liberation analysis, linking recovery directly to specific particle classes rather than bulk size. Studies show flotation losses often occur within certain size–liberation domains, emphasizing the importance of evaluating both simultaneously for performance diagnosis and process improvements (Vallejos et al., 2023a, 2023b; Frausto et al., 2021; Runge et al., 2024).

Figure 3 shows a framework linking particle size, mineral liberation, mineral exposure, texture complexity, and flotation recovery. It highlights that flotation performance results from multiple particle-scale factors, not just one.



$$\text{Liberation} = \frac{\text{Liberated valuable mineral}}{\text{Total valuable mineral}} \times 100$$

$$\text{Exposure} = \frac{\text{Exposed valuable mineral surface}}{\text{Total valuable mineral surface}} \times 100$$

Finer particles → higher liberation potential but more slimes and reagent consumption

Higher liberation → more mineral surface available for interaction with reagents

Higher exposure → higher probability of attachment and recovery

Higher texture complexity → lower effective liberation and recovery

Recovery is maximized only when liberation, exposure and texture conditions are all favorable

Poor performance occurs when any one of these variables is limiting.

Particle size, liberation, mineral exposure, and texture complexity interact simultaneously to control flotation recovery. These variables should be evaluated together, not independently, for reliable metallurgical assessment and process optimization.

Figure 3. Relationship among particle size, liberation, mineral exposure, texture complexity, and flotation recovery. Adapted from Vallejos et al. (2021), Guntoro et al. (2021), Yianatos et al. (2022), and Runge et al. (2024).

Figure 3 illustrates how particle size acts as a central variable controlling several mineralogical characteristics that ultimately influence flotation performance. As particle size decreases during comminution, mineral liberation generally increases because valuable minerals become progressively separated from gangue phases. However, the relationship is not linear, as the degree of liberation achieved depends strongly on ore texture, grain size distribution, and mineral associations. Consequently, particles of similar size may exhibit substantially different flotation responses depending on their internal mineralogical structure.

The figure further highlights the importance of mineral exposure, which represents the proportion of valuable mineral accessible at the particle surface. While liberation determines the degree of mineral separation within a particle, flotation is fundamentally a surface-driven process. Therefore, particles exhibiting similar liberation values may display significantly different flotation recoveries if their exposed mineral surface areas differ. Mineral exposure is increasingly recognized as one of the most important descriptors linking automated mineralogy to flotation performance.

Texture complexity provides an additional layer of control on flotation behavior. Ores characterized by fine-grained intergrowths, complex mineral associations, and heterogeneous textures often exhibit greater variability in liberation and exposure distributions. As a result, flotation recovery becomes increasingly difficult to predict using simple liberation-based approaches. Automated mineralogy enables quantitative characterization of these textural features, improving understanding of the mechanisms responsible for metallurgical variability.

The interaction diagram presented in Figure 3 demonstrates that particle size, liberation, mineral exposure, and texture complexity are highly interdependent variables. Changes in any one of these characteristics can influence the others and ultimately affect flotation response. Consequently, flotation performance should not be evaluated using individual descriptors independently but rather through integrated particle-based frameworks that consider the combined influence of multiple mineralogical attributes.

The figure also emphasizes the concept of favorable flotation conditions arising from the simultaneous occurrence of adequate liberation, sufficient mineral exposure, and manageable texture complexity. When these conditions are achieved, recovery probabilities increase substantially. Conversely, deficiencies in any of these parameters may result in recovery losses even when other descriptors appear favorable. This observation explains why flotation performance often varies among ores possessing similar mineral compositions but different textural characteristics.

Overall, Figure 3 demonstrates the transition from traditional liberation-based interpretations toward more comprehensive particle-scale approaches. By integrating particle size, liberation, mineral exposure, texture complexity, and flotation response within a single conceptual framework, automated mineralogy provides a more robust basis for flotation diagnostics, recovery forecasting, geometallurgical characterization, and process optimization.

Coarse and Fine Particle Flotation

Recovering coarse and fine particles remains a key challenge in sulfide flotation. Coarse-particle flotation tech offers potential to cut grinding energy while maintaining performance. Since comminution is energy-intensive, recovering coarser particles without extensive grinding has economic and environmental benefits. Automated mineralogy helps identify suitable coarse particles for flotation and diagnose recovery issues related to incomplete liberation, mineral associations, and textures (Taguta et al., 2023; Crompton et al., 2024).

Fine and ultrafine particles often contain unrecovered valuable minerals. Although these particles are sufficiently liberated, they are hard to recover due to low collision efficiency, attachment probability, and hydrodynamic issues. Studies show that recovery losses in fine fractions mainly stem from flotation challenges, not mineralogy alone. This highlights the need to combine mineralogical data with flotation engineering to enhance recovery of difficult particles (Corin et al., 2021; Escalante et al., 2026).

Understanding flotation of coarse and fine particles requires more than basic mineral liberation measurements. Modern automated mineralogy systems offer a range of quantitative descriptors that more accurately represent factors affecting flotation. Before exploring recovery models and prediction methods, Table 5 summarizes key liberation, exposure, and texture descriptors used in automated mineralogy.

Table 5. Principal liberation, exposure, and texture descriptors used in flotation characterization and recovery prediction. Adapted from Gupta et al. (2022), Huang et al. (2022), Guntoro et al. (2021), Chamlal et al. (2025), and Runge et al. (2024).

Descriptor	Definition	Relevance
Liberation (%)	Fraction of mineral exposed within particle	Primary flotation descriptor
Exposure (%)	Surface area available for reagent interaction	Directly affects floatability
Particle composition	Mineral proportions in individual particle	Recovery prediction
Mineral association	Relationship among minerals within particle	Selectivity evaluation
Texture complexity	Degree of mineral intergrowth	Recovery variability
Grain size	Individual mineral grain dimensions	Liberation behavior
Connectivity	Internal mineral continuity	Breakage and flotation behavior
Shape factor	Particle morphology descriptor	Hydrodynamic response
Porosity	Internal void structure	Reagent accessibility

Table 5 illustrates the evolution of flotation characterization from traditional liberation measurements to multidimensional, particle-based descriptions. Historically, mineral liberation was considered the primary variable controlling flotation performance because it determines the extent to which valuable minerals are physically separated from gangue phases. While liberation remains one of the most important descriptors, numerous studies have shown that flotation behavior cannot be explained solely by liberation measurements.

Mineral exposure is critical because flotation occurs at particle surfaces, not interiors. Two particles with similar liberation may behave differently in flotation if their surface mineral exposure varies. Therefore, exposure measurements more directly indicate floatability and are increasingly used in flotation models.

Particle composition and mineral association descriptors further expand the characterization framework by quantifying the distribution and relationships of minerals within individual particles. These variables are especially important in complex sulfide ores where valuable minerals occur in intricate intergrowths with gangue phases or other sulfides. Such information helps explain differences in flotation selectivity and concentrate quality that cannot be interpreted using liberation data alone.

Texture-related descriptors, including texture complexity, grain size, and mineral connectivity, provide additional insight into the geological and mineralogical factors controlling flotation performance. Texture complexity reflects the degree of mineral intergrowth within particles and is often associated with increased recovery variability. Grain size influences liberation behavior during comminution, whereas connectivity provides information regarding the continuity of mineral phases and their susceptibility to breakage and separation. Together, these descriptors improve understanding of how ore texture influences metallurgical response.

The table also highlights the growing importance of particle morphology descriptors such as shape factor and porosity. Particle shape can affect hydrodynamic behavior, particle–bubble interactions, and flotation kinetics, while porosity influences reagent accessibility and fluid penetration. Although historically less emphasized than liberation and mineralogy, these characteristics are increasingly incorporated into advanced flotation models and machine-learning frameworks.

Collectively, the descriptors summarized in Table 5 form the foundation of modern particle-based recovery models. By integrating information related to liberation, mineral exposure, mineral associations, texture complexity, particle morphology, and internal structure, automated mineralogy provides a comprehensive description of particle behavior that supports more accurate flotation prediction, geometallurgical characterization, and process optimization. This multidimensional characterization framework represents a major advance over traditional liberation analysis and forms the basis for the predictive methodologies discussed in the following sections.

Particle-Based and MLA-Based Flotation Modeling

From Automated Mineralogy to Recovery Prediction

The main contribution of automated mineralogy to modern mineral engineering is the ability to transform mineralogical data into quantitative predictions of metallurgical performance. Unlike traditional empirical models, which mainly use results from metallurgical tests, mineralogy-based models utilize particle characteristics such as mineralogical composition, degree of liberation, surface exposure, texture, and mineral associations to predict recovery and concentrate grade.

This approach recognizes that flotation is essentially a particulate-scale phenomenon. Thus, the overall performance of an operation corresponds to the collective response of populations of particles with different mineralogical characteristics. Recent studies demonstrate that particle-based models provide more realistic descriptions of metallurgical variability than conventional models based solely on average kinetic parameters (Gupta et al., 2022; Huang et al., 2022).

The advancement of geometallurgy has also increased interest in predictive models that convert mineralogical data into operational information. As a result, automated mineralogy has shifted from just a diagnostic tool to a source of quantitative variables used directly to predict recovery and process performance (Frenzel et al., 2023).

Particle-Based Flotation Models

Particle-based models are a major advancement in geometallurgy. They characterize each particle using data from MLA, QEMSCAN, TIMA, or similar techniques. Recovery is estimated by the flotation probability per particle. Pereira et al. (2021a, 2021b) showed that automated mineralogy data can combine with machine learning to determine particle-level flotation kinetics. This method was expanded to complex circuits and various mineral separation processes (Pereira et al., 2022, 2023).

The main advantage of these models is their ability to simultaneously incorporate mineralogical composition, surface exposure, texture, and particle size. Consequently, they more accurately reproduce the variability observed in complex deposits and enable assessment of metallurgical scenarios before conducting extensive experimental campaigns (Shackleton et al., 2024, 2025).

Recent applications in PGM deposits have shown that incorporating the mode of mineral occurrence significantly improves recovery predictions, especially when valuable minerals occur in complex textural associations (Kabemba et al., 2025, 2026; Doubra et al., 2023).023).

Recovery Simulators and Grade–Recovery Forecasting

The combination of automated mineralogy and mathematical modeling has enabled the development of flotation simulators that generate grade–recovery relationships directly from quantitative mineralogical information. Unlike conventional empirical approaches, these simulators utilize particle-scale descriptors derived from automated mineralogy to estimate the flotation behavior of individual particles or particle classes. Parameters such as particle size, mineral liberation, mineral exposure, texture complexity, and mineral associations can be incorporated into predictive frameworks that estimate flotation response before extensive metallurgical testing is conducted.

Among the available approaches, size-by-liberation models are among the most widely applied methodologies. These models classify particles according to size and liberation characteristics and subsequently assign flotation probabilities or recovery values to each particle class. By linking mineralogical attributes directly to metallurgical performance, size-by-liberation models have become important tools for flotation circuit design, process optimization, and geometallurgical characterization. Applications have been reported across a wide range of commodities, including copper, nickel, platinum-group metals (PGMs), and polymetallic sulfide systems (Vallejos et al., 2023a, 2023b; Yianatos et al., 2022).

Recent advances in computational methods and data analytics have improved the predictive capabilities of flotation simulators. The abundance of automated mineralogy datasets enables machine learning to identify complex relationships between mineralogical variables and outcomes. These methods often outperform traditional models, especially for deposits exhibiting high mineralogical variability, complex textures, and heterogeneous ore types (Gupta et al., 2022; Huang et al., 2022).

The conceptual workflow underlying modern flotation prediction systems is illustrated in Figure 4. The figure summarizes the progression from mineralogical characterization to flotation probability assignment and ultimately to recovery prediction and process forecasting.

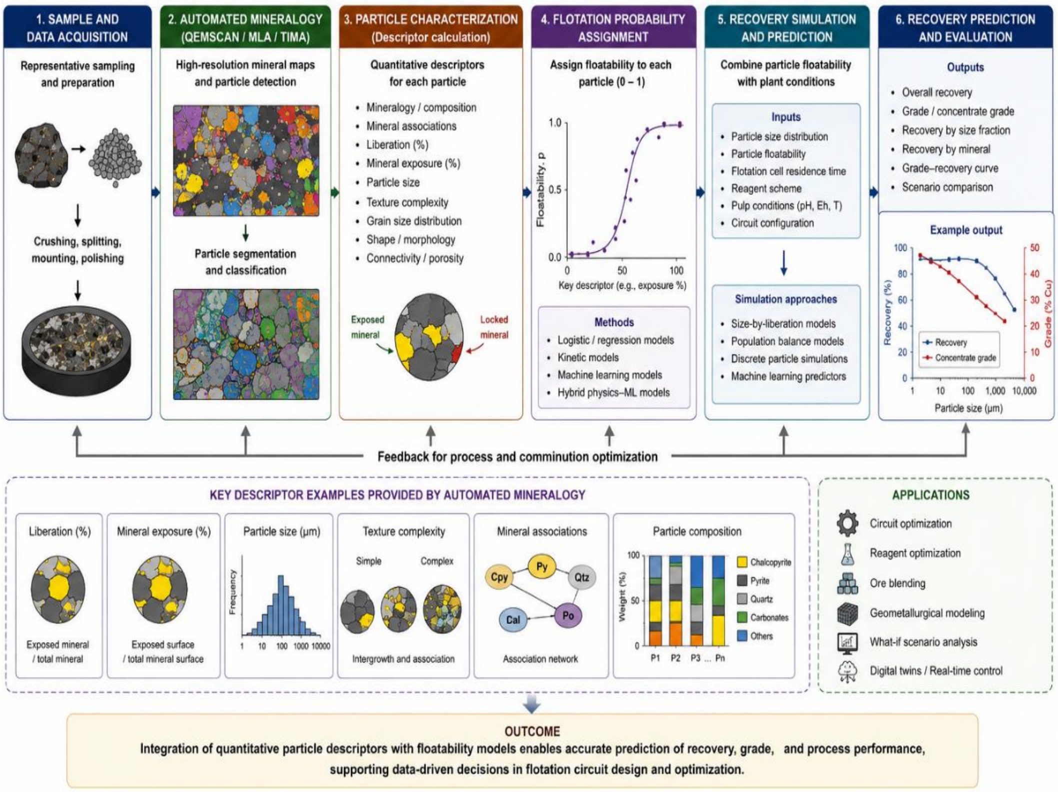


Figure 4. Workflow linking automated mineralogy, particle characterization, flotation probability assignment, and recovery prediction. Adapted from Pereira et al. (2021a, 2021b), Huang et al. (2022), Gupta et al. (2022), and Kabemba et al. (2026).

Figure 4 illustrates how automated mineralogy serves as the foundation for modern predictive flotation frameworks. The workflow begins with quantitative mineralogical characterization using automated mineralogy platforms such as MLA, QEMSCAN, TIMA, or AMICS, which generate detailed information on mineral composition, liberation, mineral exposure, particle-size distributions, texture complexity, grain size, and mineral associations. These measurements are subsequently transformed into particle-scale descriptors that provide a quantitative representation of the characteristics controlling flotation behavior.

The next stage involves assigning flotation probabilities to individual particles or particle classes based on their mineralogical attributes. Depending on the modeling approach employed, flotation probability may be estimated using empirical relationships, particle-based flotation models, kinetic models, or machine-learning algorithms. Mineral exposure and liberation are particularly important variables because they directly influence particle–bubble attachment and flotation recovery.

Once flotation probabilities are assigned, they can be used in recovery simulators to generate grade–recovery curves, predict concentrate quality, and evaluate process scenarios. These simulations offer insights into metallurgical performance of various ore types and help assess effects of grind size, reagent schemes, feed composition, or operating conditions. Consequently, recovery simulators are vital for flotation circuit optimization and geometallurgical forecasting.

The framework in Figure 4 emphasizes machine learning's expanding role in flotation prediction. By analyzing large mineralogical datasets and recognizing nonlinear relationships, these models enhance accuracy and support adaptive systems. This is especially useful in complex ore variability, where traditional models often fall short.

The integration of automated mineralogy, particle-scale characterization, flotation probability models, and machine-learning techniques is transforming flotation prediction from an empirical practice into a data-driven discipline. These advances support modern recovery simulators, digital geometallurgical platforms, and future digital twins for real-time process optimization and intelligent mineral processing.

Validation and Industrial Implementation

Although particle-based flotation models have demonstrated substantial predictive potential under laboratory and pilot-scale conditions, their industrial implementation remains an active area of research and development. The reliability of model predictions depends strongly on the quality, representativeness, and consistency of the mineralogical datasets used for calibration and validation. Furthermore, flotation circuits operating at industrial scale are influenced by complex interactions among particle properties, reagent chemistry, hydrodynamics, equipment design, and ore variability, many of which are difficult to reproduce using laboratory-scale datasets alone (Pérez-García et al., 2021).

One of the major challenges associated with industrial deployment is ensuring that mineralogical descriptors derived from automated mineralogy remain representative of the continuously changing feed characteristics encountered in operating concentrators. Variations in ore type, mineral associations, grain size distributions, and liberation characteristics can significantly affect flotation performance and may require periodic recalibration of predictive models. Consequently, successful implementation increasingly relies on the integration of mineralogical characterization, plant monitoring systems, geometallurgical databases, and advanced statistical methodologies.

Despite challenges, industrial applications are expanding rapidly. Automated mineralogy is now part of geometallurgical workflows, flotation optimization, mine-to-mill studies, and resource assessment. Research shows predictive mineralogy improves forecasting metallurgical recovery, concentrate quality, and process variability when combined with geological data, machine learning, and process simulation (McFadzean et al., 2024; Botha et al., 2025).

The evolution of flotation prediction methodologies has played a key role in enabling these industrial applications. Over the last two decades, flotation modeling has progressively evolved from empirical and population-based approaches toward integrated frameworks that incorporate particle-scale mineralogical information, machine learning, and digital process simulation. The principal modeling approaches currently used in flotation prediction are summarized in Table 6.

Table 6. Main flotation modeling approaches based on automated mineralogy and particle characterization. Adapted from Pereira et al. (2021a, 2021b), Yianatos et al. (2022), Gupta et al. (2022), Huang et al. (2022), and Kabemba et al. (2026).

Modeling Approach	Inputs	Outputs	Main Application
Size-by-liberation model	Size + liberation	Recovery	Circuit optimization
Exposure-based model	Exposure + mineralogy	Floatability	Recovery prediction
Particle-based model	Individual particle descriptors	Recovery probability	Geometallurgy
Kinetic model	Flotation test data	Rate constants	Process simulation
Machine-learning model	Mineralogical datasets	Recovery and grade	Predictive geometallurgy
Hybrid physics-AI model	Mineralogy + process data	Plant performance	Digital twins

Table 6 illustrates the diversity of modeling approaches currently available for linking mineralogical information to flotation performance. Early approaches, such as size-by-liberation models, focused primarily on the relationship between particle size, mineral liberation, and recovery. These models remain useful for evaluating grinding performance and identifying opportunities for circuit optimization but provide only a simplified representation of particle behavior during flotation.

Subsequent developments introduced exposure-based models that incorporate information regarding the proportion of valuable mineral exposed at the particle surface. Because flotation fundamentally depends on particle–bubble interactions occurring at exposed mineral surfaces, these models generally provide improved predictions of particle floatability and recovery. Exposure-based approaches have therefore become increasingly important in studies involving complex mineral textures and partially liberated particles.

More advanced particle-based models represent a significant step toward geometallurgical prediction. Rather than grouping particles into broad classes, these approaches treat individual particles as discrete entities characterized by attributes such as mineral composition, liberation, exposure, grain size, texture complexity, and morphology. This enables estimation of recovery probabilities at the particle level and provides a direct link between quantitative mineralogy and metallurgical performance. As a result, particle-based modeling has become a cornerstone of modern predictive geometallurgy.

Kinetic models continue to play an important role in flotation simulation by describing the rate at which particles are recovered under specific operating conditions. Although traditionally based on flotation test data, modern kinetic models increasingly incorporate mineralogical information to better represent differences in particle floatability and recovery behavior.

Recent advances in artificial intelligence have further expanded predictive capabilities through the application of machine-learning models. These approaches can identify complex nonlinear relationships between mineralogical descriptors and metallurgical responses, enabling prediction of recovery, concentrate grade, selectivity, and process performance directly from large mineralogical datasets. Their ability to handle high-dimensional data has made them particularly attractive for geometallurgical applications involving significant ore variability.

The most recent development is the emergence of hybrid physics–AI models that combine mechanistic process understanding with machine-learning methods. By integrating mineralogical information, process variables, operational databases, and flotation models, these approaches seek to improve prediction accuracy while maintaining physical interpretability. Such models are increasingly viewed as a key enabling technology for digital twins and future intelligent mineral processing systems.

Overall, Table 6 highlights the ongoing transition from traditional empirical flotation models toward integrated predictive frameworks that combine automated mineralogy, particle-scale characterization, geometallurgical modeling, artificial intelligence, and digital process simulation. This evolution reflects a broader transformation within the mineral processing industry toward data-driven decision-making, improved recovery forecasting, and ultimately the development of adaptive and autonomous concentrator operations.

Applications to PGM, Ni-Cu, Cu-Mo, Cu-Co, Pb-Zn, and Gold Ores

Platinum Group Metal and Nickel Sulfide Ores

Platinum group metal (PGM) and nickel sulfide deposits are among the most important applications of automated mineralogy because both systems exhibit strong mineralogical variability and complex flotation behavior. In PGM deposits, valuable minerals commonly occur as fine-grained phases associated with base-metal sulfides and chromite, making recovery highly dependent on mineral occurrence, liberation, and particle exposure (Carelse et al., 2022; Engelbrecht et al., 2022).

Automated mineralogy has significantly improved understanding of PGM deportment and flotation losses, particularly in tailings reprocessing studies where substantial quantities of unrecovered PGMs have been identified (Baloyi et al., 2024; Notole et al., 2025). Similar benefits have been reported in nickel sulfide systems, where mineralogical characterization supports geometallurgical domaining, ore blending, and recovery forecasting. Studies on magmatic and volcanogenic sulfide deposits demonstrate that mineral associations and textural variability strongly influence pentlandite recovery and concentrate quality (Dzingai et al., 2021; Dzvinamurungu et al., 2022; Ayedzi et al., 2024; Rincon et al., 2026).

Copper, Copper–Molybdenum, and Copper–Cobalt Ores

Copper flotation has generated some of the largest mineralogical datasets available for process mineralogy studies. Automated mineralogy is widely used to evaluate liberation performance, diagnose flotation losses, and support process optimization. Chalcopyrite recovery is strongly influenced by mineral associations, particle texture, and exposure characteristics, while flotation tailings frequently contain significant quantities of unrecovered copper sulfides locked within gangue minerals (Abdollahi et al., 2020; Hu et al., 2021; Zhang et al., 2021).

In copper–molybdenum systems, mineralogical characterization provides valuable information for evaluating chalcopyrite–molybdenite separation efficiency and concentrate quality (Tumen-Ayush et al., 2025). Similarly, studies of sediment-hosted copper–cobalt deposits demonstrate that quantitative mineralogy supports ore classification and metallurgical prediction by identifying mineralogical controls on flotation performance (Tijsseling et al., 2020; Dehaine et al., 2021a, 2021b, 2024; Fang et al., 2024; Amos-Judge et al., 2026).

Lead–Zinc and Polymetallic Sulfide Ores

Polymetallic sulfide deposits present additional complexity because several valuable minerals must be selectively recovered from the same ore. Automated mineralogy has become an important tool for evaluating mineral associations, liberation characteristics, and metallurgical losses in lead–zinc systems.

Investigations of galena- and sphalerite-bearing ores have demonstrated that variations in mineral chemistry, texture, and intergrowth relationships significantly affect flotation selectivity and concentrate quality. These findings highlight the value of integrating quantitative mineralogical data into flotation diagnostics and geometallurgical workflows (Tiu et al., 2021, 2022; Feng et al., 2022; Jo et al., 2024; Ying et al., 2025).

Gold, Refractory Sulfide Systems, and Secondary Resources

Gold-bearing sulfide ores represent another major area of application for automated mineralogy. Gold may occur as liberated particles, inclusions within sulfides, grain-boundary phases, or submicroscopic components hosted by pyrite and arsenopyrite. Consequently, detailed deportment analysis is often required to explain flotation performance, concentrate quality, and recovery losses (Costa et al., 2022).

The mineralogical complexity of refractory gold ores has made automated mineralogy an increasingly valuable tool for identifying the occurrence, distribution, and associations of gold-bearing phases. By quantifying liberation, mineral exposure, and mineral associations, automated mineralogy provides critical information to understand why certain gold particles remain unrecovered and to design more effective beneficiation strategies. Recent studies combining flotation testing, mineralogical characterization, and geometallurgical analysis have significantly improved understanding of refractory gold systems and supported the optimization of flotation, gravity concentration, and downstream extraction processes (Guner et al., 2023; Barbouchi et al., 2026; Simelane et al., 2026).

Beyond primary sulfide deposits, automated mineralogy is increasingly applied to tailings, slags, and other secondary resources. Historical processing operations often generated large volumes of residues containing significant quantities of unrecovered valuable minerals due to technological limitations, inadequate liberation, or suboptimal process conditions. Modern automated mineralogical investigations frequently reveal economically attractive opportunities for resource recovery and reprocessing by identifying residual metal-bearing phases and evaluating their recovery potential (Dadzie et al., 2025; Gürtekin & Aydar, 2023).

The broad applicability of automated mineralogy across different ore types and processing systems is illustrated in Figure 5, which summarizes representative applications spanning platinum-group metals, nickel, copper, polymetallic sulfides, refractory gold ores, and secondary resources.

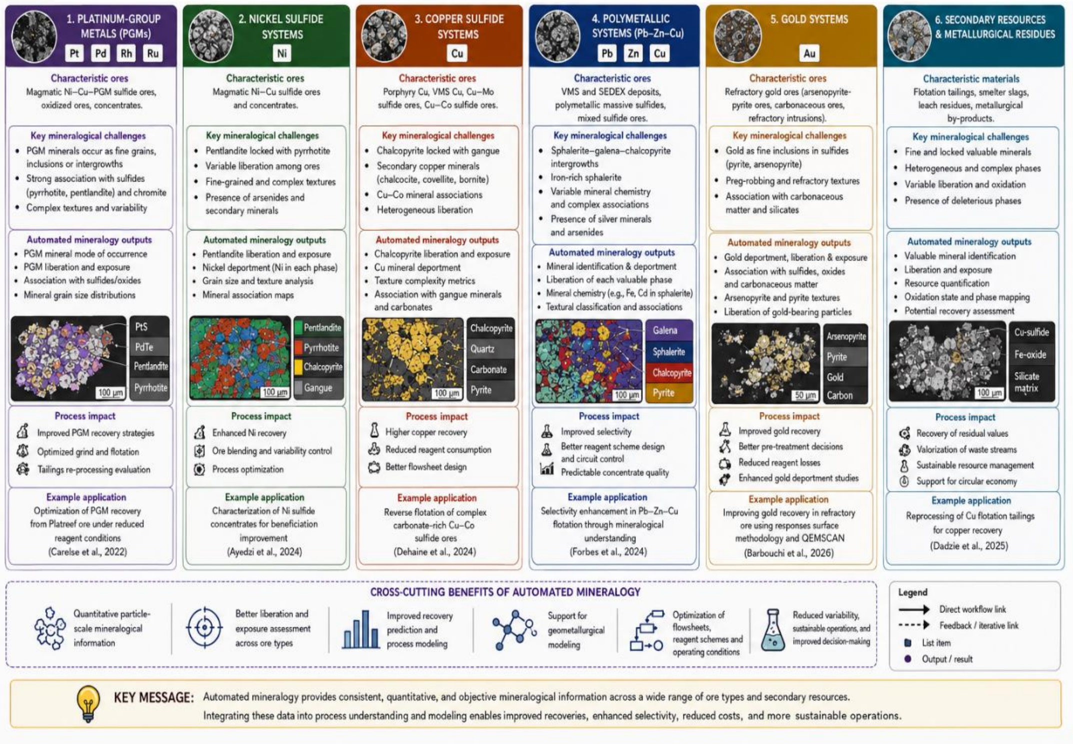


Figure 5. Representative applications of automated mineralogy across PGM, nickel, copper, polymetallic, gold, and secondary-resource processing systems. Adapted from Carelse et al. (2022), Ayedzi et al. (2024), Baloyi et al. (2024), Dehaine et al. (2024), and Barbouchi et al. (2026).

Figure 5 shows that, despite mineralogical differences and processing challenges among commodities, automated mineralogy offers valuable quantitative data for process optimization. In PGM systems, it identifies PGM mineral modes, evaluates liberation, and clarifies associations with sulfides and chromite. For nickel sulfide ores, analyzing pentlandite liberation, exposure, and relationships supports geometallurgical modeling and ore blending. Copper and polymetallic deposits benefit from quantitative assessments of chalcopyrite, sphalerite, galena, and gangue minerals, improving selectivity and recovery predictions.

The figure emphasizes automated mineralogy's role in refractory gold systems, where gold deportment studies reveal gold distribution among sulfides, gangue minerals, and carbonaceous phases. In secondary resources like flotation tailings and slags, it aids resource evaluation by identifying residual valuable minerals, assessing liberation, and estimating reprocessing potential. Overall, automated mineralogy now serves as a versatile platform supporting mineral processing, geometallurgy, resource management, and circular economy efforts.

To further illustrate the industrial relevance of these applications, Table 7 summarizes representative uses of automated mineralogy across major sulfide ore systems and secondary resources.

Table 7. Representative industrial applications of automated mineralogy in sulfide ore processing and recovery prediction. Adapted from Abdollahi et al. (2020), Carelse et al. (2022), Ayedzi et al. (2024), Baloyi et al. (2024), and Simelane et al. (2026).

Commodity	Main Objective	Typical Use
Copper	Recovery optimization	Liberation diagnostics
Copper–Molybdenum	Concentrate quality control	Mineral association analysis
Nickel	Ore blending and geometallurgy	Pentlandite deportment
PGM	Recovery improvement	Mode-of-occurrence studies
Lead–Zinc	Selectivity enhancement	Mineral chemistry evaluation
Gold	Refractory ore characterization	Deportment analysis
Tailings	Secondary resource evaluation	Recovery potential assessment
Slags	Metal recovery assessment	Resource characterization

Table 7 shows that automated mineralogy supports a wide range of objectives extending well beyond conventional mineral identification. In copper operations, liberation diagnostics and mineral association analyses are routinely used to optimize flotation performance and improve concentrate quality. Copper–molybdenum circuits rely on detailed characterization of mineral associations and locking relationships to control concentrate specifications and minimize penalty elements. In nickel operations, automated mineralogy provides valuable insights into pentlandite deportment and ore variability, supporting geometallurgical modeling and ore-blending strategies.

For PGM deposits, mode-of-occurrence studies and liberation assessments are vital to understanding recovery limits associated with fine mineral assemblages. Lead–zinc operations use mineral chemistry and textures to enhance flotation selectivity and concentrate quality. In refractory gold systems, deportment analysis offers insights into gold distribution and recoverability. Tailings and slags are also assessed as secondary resources, with automated mineralogy helping identify valuable minerals and evaluate reprocessing viability.

The adoption of particle-based geometallurgical methods strengthens these applications by linking mineralogy directly to metallurgical performance. Automated mineralogy is increasingly vital in workflows, aiding recovery forecasting, process optimization, resource evaluation, and strategic decisions across resource systems (Blannin et al., 2024; Becker, 2023).

Machine Learning, Artificial Intelligence, and Predictive Geometallurgy

Machine Learning for Recovery Prediction

The exponential growth of mineralogical databases has driven the application of machine learning in mining and mineral processing. Automated mineralogy systems generate large volumes of quantitative data related to mineralogical composition, liberation, exposure, texture, and mineral associations. Since these variables often exhibit nonlinear relationships with metallurgical recovery, machine learning algorithms have become attractive tools for predicting flotation performance.

Initial applications focused on predicting recovery and concentrate grade. Currently, models based on random forests, gradient boosting, artificial neural networks, and other advanced techniques are used to forecast flotation kinetics, metallurgical performance, and geometallurgical variability (Cook et al., 2020; Xu et al., 2025). Recent studies show that incorporating mineralogical variables significantly improves model robustness compared with approaches based solely on operational parameters (Chelgani et al., 2024). The integration of machine learning and automated mineralogy has also been applied to predict recovery in complex sulfide systems, enabling the identification of key mineralogical factors that control metallurgical performance (Jo et al., 2024; Koucham et al., 2024).024).

Artificial Intelligence for Mineral Recognition and Image Analysis

In addition to the forecast of recovery, artificial intelligence is transforming mineralogical identification and image analysis. Deep learning techniques have been used for automatic classification of optical images, electron micrographs, µ-XRF maps, and hyperspectral datasets. These methods enable the automation of steps traditionally dependent on specialized interpretation, reducing processing time and increasing analytical consistency. Recent applications have demonstrated high performance in mineral texture classification, recognition of individual minerals, and automatic particle segmentation (Koh et al., 2024; Viana et al., 2025). The combination of artificial intelligence with automated mineralogy tends to reduce analytical costs and increase characterization speed, especially in geometallurgical programs involving thousands of samples (Ali et al., 2023; Reed et al., 2025).025).

Predictive Geometallurgy and Ore Domain Modeling

Modern geometallurgy seeks to integrate geological, mineralogical, and metallurgical information into models that predict ore behavior throughout the entire production chain. In this context, automated mineralogy provides quantitative variables that can be used to define geometallurgical domains and predict process performance. Several studies have shown that incorporating parameters such as texture, liberation, and mineralogical composition significantly improves the prediction of recovery and concentrate quality (Lishchuk & Pettersson, 2021; Frenzel et al., 2023). The use of machine learning algorithms also enables the integration of information from multiple sources, including drilling, spectral sensors, operational data, and metallurgical results (Medina-Tasilla et al., 2024). Recent approaches have explored the combination of automated mineralogy and digital geometallurgical models, expanding the ability to predict performance in complex deposits. Work by Molifie et al. (2023) demonstrates that integrating multiple data domains can significantly improve geometallurgical characterization and recovery prediction.

Toward Digital Geometallurgy and Digital Twins

The convergence of automated mineralogy, artificial intelligence, machine learning, and geometallurgy is driving the development of integrated digital ecosystems for mining and mineral processing. These emerging systems aim to integrate geological, mineralogical, metallurgical, and operational data into unified platforms that generate predictive insights and support decision-making in near real time. As mineral processing operations become increasingly data-intensive, the ability to transform large mineralogical datasets into actionable knowledge is becoming a key competitive advantage.

The concept of digital geometallurgy represents a natural evolution of traditional geometallurgical approaches. Rather than relying exclusively on static geological and metallurgical models, digital geometallurgy integrates automated mineralogical characterization, machine-learning algorithms, spatial resource models, and process-performance databases to continuously update predictions of ore behavior. Such systems support mine planning, ore blending, recovery forecasting, and operational optimization by providing a more comprehensive understanding of ore variability and its metallurgical consequences (Frenzel et al., 2023; Butcher et al., 2023).

Recent advances in artificial intelligence have further accelerated this transition. Machine-learning models are increasingly capable of identifying complex relationships among mineralogical descriptors, process variables, and metallurgical responses. As a result, automated mineralogy is no longer viewed solely as a characterization tool but as a strategic source of quantitative information to feed predictive and prescriptive analytical frameworks.

To illustrate this technological evolution, Figure 6 presents a conceptual framework linking automated mineralogy, feature engineering, machine learning, geometallurgical domaining, and digital process prediction. The figure highlights the progressive transformation of mineralogical information into predictive knowledge and operational intelligence.

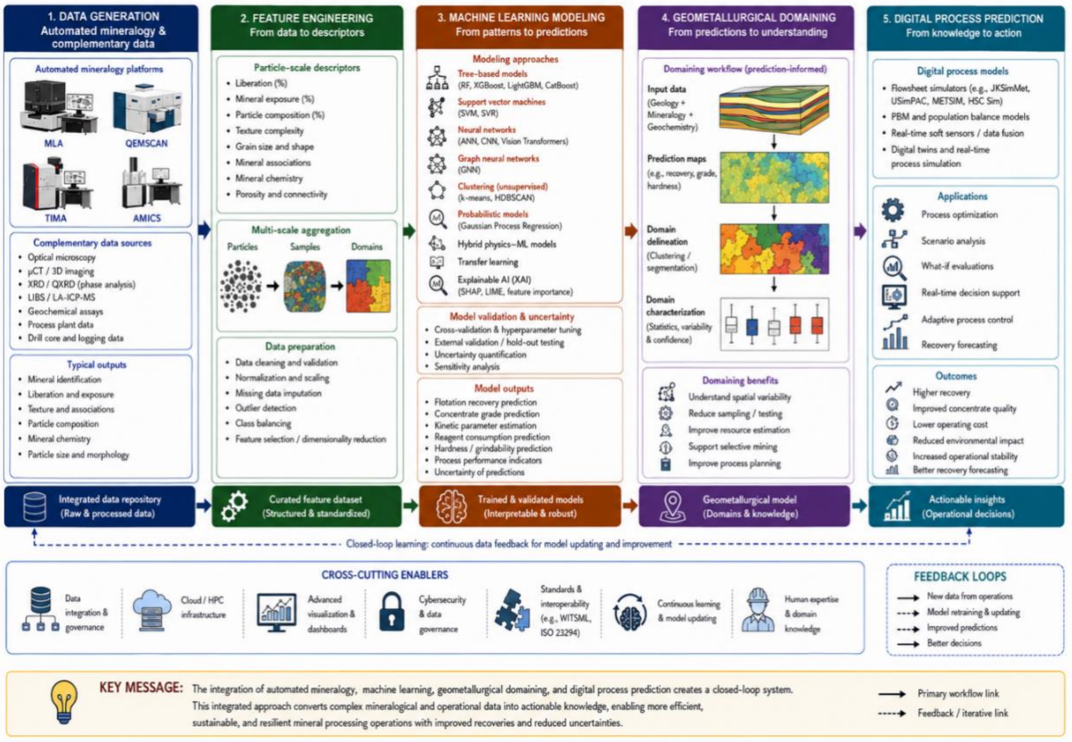


Figure 6. Integration of automated mineralogy, machine learning, geometallurgical domaining, and digital process prediction. Adapted from Frenzel et al. (2023), Medina-Tasilla et al. (2024), Molifie et al. (2023), Koucham et al. (2024), and Yang et al. (2026).

Figure 6 illustrates how quantitative mineralogical information generated by automated mineralogy and complementary analytical techniques can be converted into particle-scale descriptors, including liberation, mineral exposure, texture complexity, grain-size distribution, mineral associations, and chemical attributes. These descriptors form the basis for machine-learning and artificial-intelligence models capable of predicting flotation recovery, concentrate grade, reagent consumption, ore hardness, and other process-performance indicators. The resulting predictions can then be integrated into geometallurgical domaining workflows, allowing the identification of ore domains with similar metallurgical behavior and supporting improved mine planning and resource management.

The framework also demonstrates the growing role of digital process prediction and digital twins in modern concentrators. By combining mineralogical data, process simulations, real-time sensors, and machine-learning models, digital systems can continuously evaluate process performance, identify deviations from expected behavior, and recommend operational adjustments. This integration creates a feedback-driven environment in which mineralogical characterization, predictive modeling, and operational control become increasingly interconnected.

The practical implementation of these digital approaches relies heavily on artificial intelligence and machine learning. Table 8 summarizes representative applications that have emerged in recent years across mineral characterization, flotation prediction, and geometallurgical modeling.

Table 8. Representative applications of machine learning and artificial intelligence in automated mineralogy and predictive geometallurgy. Adapted from Cook et al. (2020), Chelgani et al. (2024), Koucham et al. (2024), Molifie et al. (2023), Xu et al. (2025), and Yang et al. (2026).

Application	Input Data	Output
Recovery prediction	Liberation, exposure, texture	Flotation recovery
Kinetic prediction	Mineralogy + process variables	Rate constants
Ore classification	Mineralogical descriptors	Ore domains
Texture recognition	Images and maps	Texture classes
Mineral identification	SEM/optical images	Mineral classes
Geometallurgical modeling	Geological + mineralogical data	Process performance
Digital twins	Integrated datasets	Real-time prediction
Explainable AI	Mineralogical variables	Driver identification

Table 8 demonstrates the breadth of applications currently being explored. Machine-learning models are increasingly used to predict flotation recovery and kinetic behavior directly from mineralogical descriptors, enabling more accurate estimation of metallurgical performance before large-scale testing. Similarly, mineralogical images and phase maps can be processed using advanced image-analysis algorithms to automatically identify mineral species, classify textures, and recognize complex mineral associations.

Artificial intelligence is also playing a growing role in geometallurgical modeling by classifying ore domains and predicting processing responses across different portions of an orebody. These capabilities support improved ore blending strategies, resource scheduling, and process optimization. Furthermore, explainable artificial intelligence (XAI) techniques are beginning to provide insights into the relative importance of mineralogical variables, helping researchers and practitioners understand the physical drivers behind model predictions and increasing confidence in data-driven decision-making.

At the highest level of integration, digital twins combine geological information, automated mineralogical characterization, operational databases, process simulations, and machine-learning models within a single dynamic environment. These systems continuously assimilate new information, update predictions, and support real-time optimization. Although still under active development, digital twins are widely regarded as a key enabling technology for future intelligent concentrators and autonomous mineral processing operations (Yang et al., 2026; Yenial-Arslan & Forbes, 2026).

Overall, the integration of automated mineralogy, artificial intelligence, and digital geometallurgy is transforming mineral processing from a largely empirical discipline into a predictive and knowledge-driven framework. As computational capabilities continue to advance and industrial datasets become increasingly accessible, these technologies are expected to play a central role in improving recovery, reducing operational variability, enhancing sustainability, and supporting the development of future autonomous mineral processing systems.

Advanced Flotation Technologies and Process Integration

Mineralogical Constraints in Modern Flotation Circuits

Conventional mechanical flotation cells remain the dominant technology for sulfide beneficiation, but their performance is strongly influenced by mineralogical factors such as liberation, particle-size distribution, mineral associations, and texture. Automated mineralogy has become an important diagnostic tool because it allows recovery losses to be linked directly to specific particle populations rather than inferred solely from metallurgical balances (Yianatos et al., 2020).

Studies across copper, nickel, and PGM operations show that unrecovered valuable minerals are frequently associated with composite particles, unfavorable textures, or poorly exposed mineral surfaces. By identifying these populations, automated mineralogy supports targeted optimization of grinding conditions, reagent schemes, and circuit configuration (Vallejos et al., 2023a; Botha et al., 2025).

Intensified Flotation and Process Optimization

The development of flotation columns, Jameson cells, coarse-particle flotation technologies, and other intensified flotation systems has increased the importance of quantitative mineralogical characterization. Automated mineralogy provides direct information on which particle classes benefit from alternative flotation technologies and helps explain differences in performance between conventional and intensified circuits (Corin et al., 2021; Taguta et al., 2023).

Because liberation is generated during comminution, flotation performance cannot be evaluated independently from grinding and classification. Integrated geometallurgical approaches increasingly combine mineralogical characterization with process simulation and optimization tools to improve recovery while minimizing energy consumption (Frausto et al., 2021; Runge et al., 2024).

Recent developments in digital process control further suggest that mineralogical information will become increasingly integrated into flotation optimization and operational decision-making (Arancibia-Bravo et al., 2022; Fang et al., 2024).

To illustrate the interactions among comminution, classification, mineralogical characterization, flotation, and process optimization, Figure 7 presents an integrated conceptual framework that depicts the information flow within a modern sulfide concentrator. The figure emphasizes how quantitative mineralogical information generated by automated mineralogy can be transformed into actionable process knowledge and subsequently incorporated into optimization and control strategies.

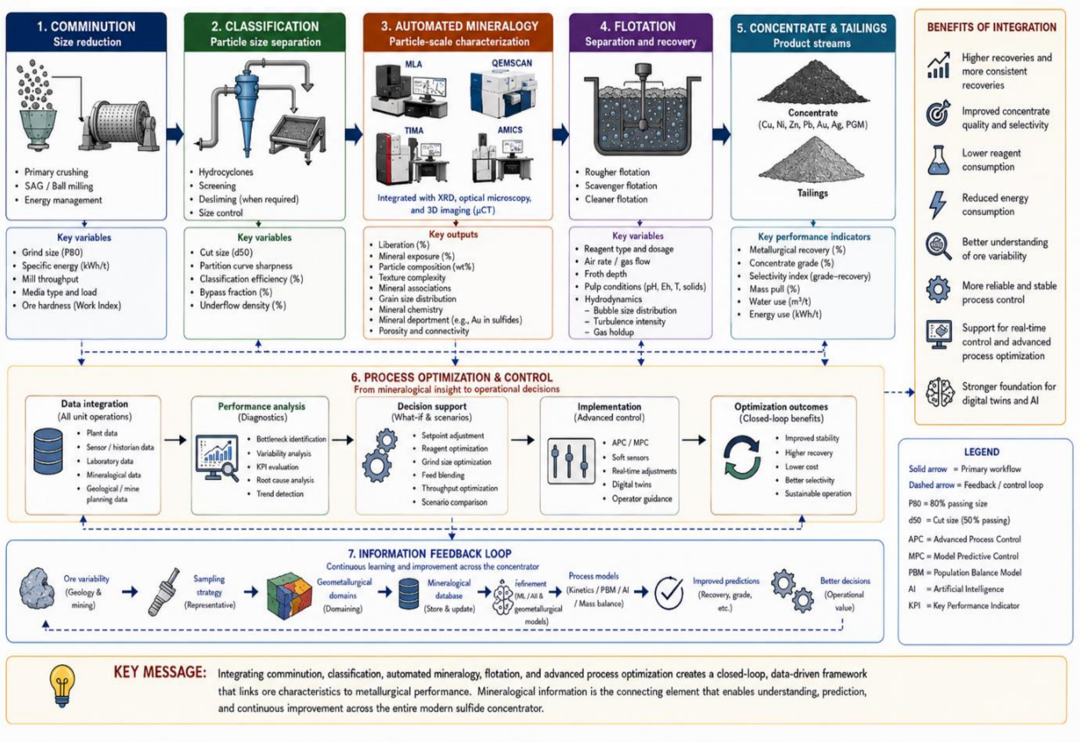


Figure 7. Integration of comminution, classification, automated mineralogy, flotation, and process optimization within modern sulfide concentrators. Adapted from Yianatos et al. (2020), Frausto et al. (2021), Runge et al. (2024), and Fang et al. (2024).

Figure 7 highlights the central role of mineralogical information in linking ore characterization with process optimization and metallurgical performance. The framework demonstrates that particle liberation, mineral exposure, texture complexity, mineral associations, and particle-size distributions generated through automated mineralogy provide critical inputs for understanding flotation behavior and process variability. These mineralogical descriptors can be integrated with operational data from comminution, classification, and flotation circuits to support diagnostics, process simulation, and optimization activities.

The figure shows data-driven concentrator management strategies where mineralogical info is key to process control. By integrating plant data, sensors, labs, and mineralogy datasets, operators can find bottlenecks, optimize grind size and reagents, improve flotation, and stabilize circuits. These methods support soft sensors, predictive models, and MPC systems that adapt to ore changes.

The framework emphasizes a feedback loop connecting geological variability, mineralogy, process performance, and decision-making. This structure allows ongoing model refinement, better geometallurgical understanding, and more accurate recovery forecasts. Automated mineralogy is shifting from a characterization tool to a strategic part of digital concentrators, supplying data for process optimization, digital twins, and autonomous systems.

Current Limitations and Future Research Needs

Analytical and Modeling Limitations

Despite major advances, automated mineralogy continues to face challenges related to analytical resolution, mineral classification uncertainty, stereological bias, and data integration. Fine-grained sulfides, PGM minerals, and submicroscopic gold-bearing phases may occur at scales that approach the resolution limits of conventional SEM-based systems, thereby affecting liberation estimates and recovery predictions (Barton, 2020; Escalante et al., 2026).

Additional uncertainties arise from mineral identification procedures, mineral libraries, sample preparation methods, and differences among analytical platforms. As automated mineralogy becomes increasingly integrated with predictive models, standardization of workflows and harmonization of datasets will become increasingly important (Siddique et al., 2023; Reed et al., 2025).

Furthermore, growing evidence indicates that liberation alone is insufficient to explain flotation performance. Future predictive frameworks will need to integrate mineral exposure, texture, mineral chemistry, particle morphology, and process conditions to improve forecasting accuracy (Tonžetić, 2025; Chamlal et al., 2025).

Future Perspectives: Digital Geometallurgy and Autonomous Processing

The future of automated mineralogy depends on advances in digitalization, AI, machine learning, geometallurgy, and real-time monitoring. Growing high-resolution datasets and improved computing are transforming it from a descriptive tool into a key part of decision-support systems, creating predictive frameworks that link ore traits to metallurgical performance across scales (Frenzel et al., 2023).

The long-term vision extends beyond lab mineralogy to fully integrated digital geometallurgical platforms that combine mineralogical data, geological models, plant data, process simulations, and machine learning for adaptive mining decisions. As sensing tech, digital twins, and autonomous systems advance, automated mineralogy will become crucial for future intelligent concentrators (Medina-Tasilla et al., 2024; Yang et al., 2026).

Despite opportunities, many technical, methodological, and operational challenges hinder the implementation of automated mineralogy in predictive geometallurgy. Recognizing these limitations and setting future research priorities are crucial for developing next-gen mineral processing systems.

Figure 8 summarizes key limitations in automated mineralogy, liberation analysis, and flotation recovery prediction, along with their consequences and potential mitigation strategies for future improvements.

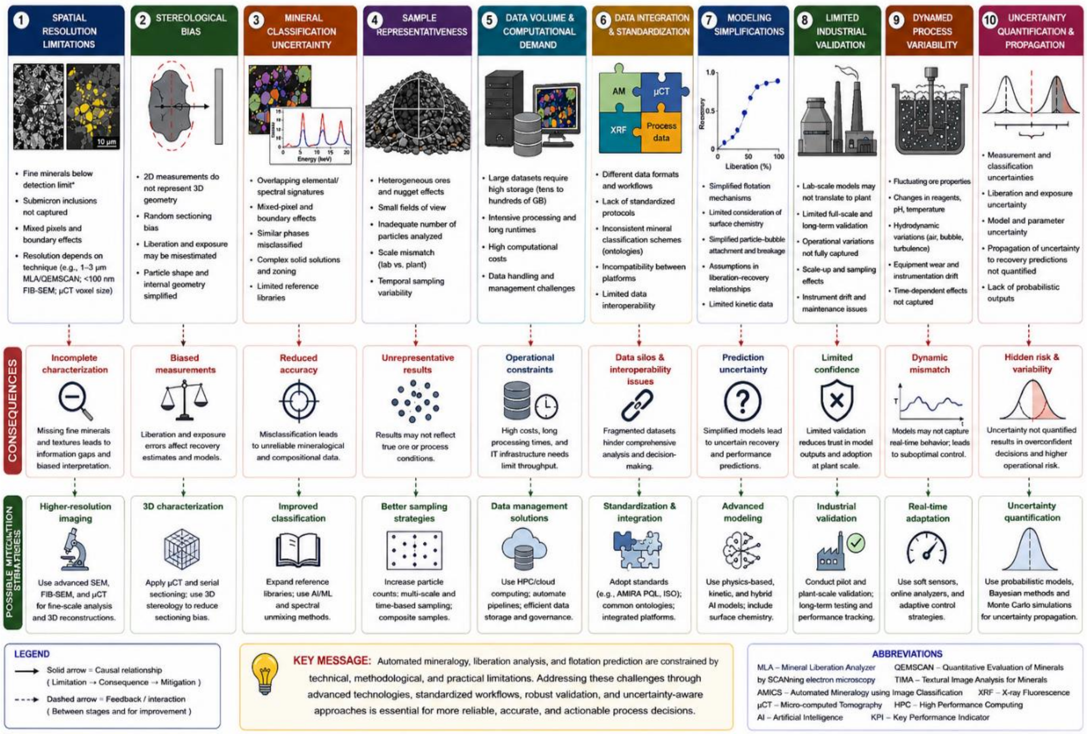


Figure 8. Principal limitations affecting automated mineralogy, liberation analysis, and flotation prediction. Adapted from Barton (2020), Siddique et al. (2023), Tonžetić (2025), and Reed et al. (2025).

Figure 8 shows uncertainties in automated mineralogical characterization, including resolution limits, stereological biases, classification issues, sample representativeness, and data integration challenges. Advances in 3D techniques, mineral libraries, sampling, workflows, hybrid models, and validation efforts can mitigate these problems. These developments are essential for improving the reliability and industrial use of mineralogy-based predictions.

Significant progress has advanced automated mineralogy into digital mining, evolving from a characterization tool to a core part of intelligent processing, as shown in the roadmap in Figure 9.

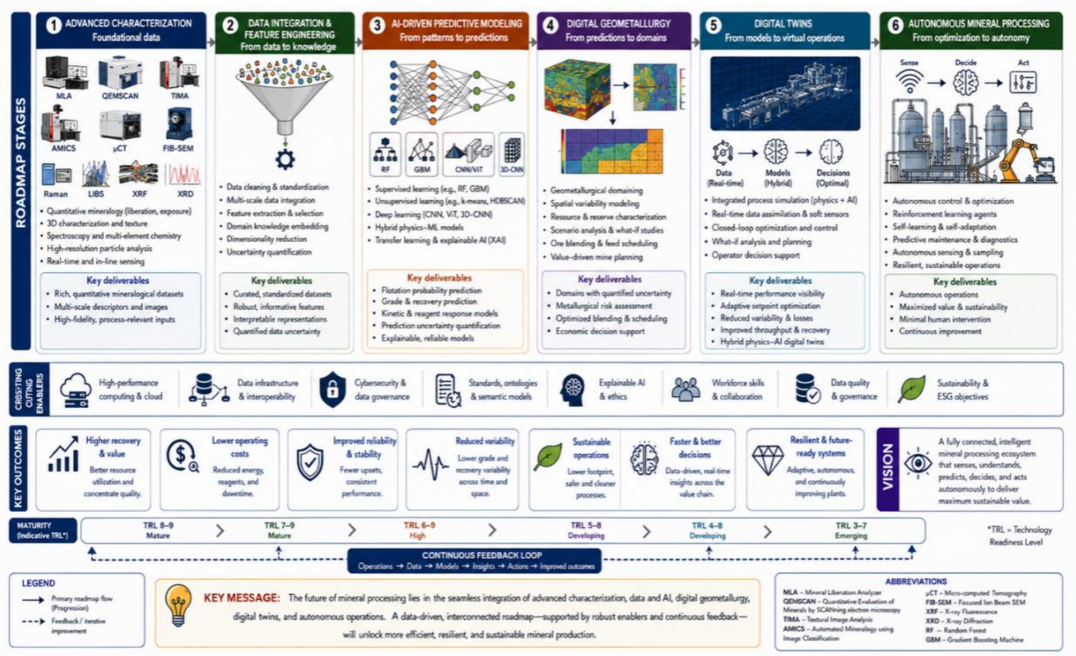


Figure 9. Future roadmap linking automated mineralogy, artificial intelligence, digital geometallurgy, digital twins, and autonomous mineral processing. Adapted from Frenzel et al. (2023), Medina-Tasilla et al. (2024), and Yang et al. (2026).

The roadmap in Figure 9 shows a progression from mineral characterization and data integration to machine-learning models, digital geometallurgical platforms, digital twins, and autonomous mineral processing systems. Automated mineralogy offers particle-scale data for feature engineering, modeling, and geometallurgical characterization. These are integrated into digital twins for real-time simulation, optimization, and decision support. The final stage uses autonomous systems with AI, adaptive control, predictive maintenance, and learning to enhance metallurgical performance, sustainability, and resilience.

Table 9 summarizes key limitations in automated mineralogy and outlines future research priorities, highlighting technological developments needed for next-generation digital geometallurgy and autonomous systems.

Table 9. Current limitations and future research priorities in automated mineralogy and flotation recovery prediction. Adapted from Barton (2020), Siddique et al. (2023), Tonžetić (2025), Reed et al. (2025), and Yang et al. (2026).

Limitation	Consequence	Future Priority
Spatial resolution limits	Incomplete characterization of fine minerals	Higher-resolution imaging
Stereological bias	Errors in liberation estimates	Expanded 3D characterization
Mineral classification uncertainty	Reduced prediction accuracy	Improved mineral libraries
Dataset incompatibility	Limited data integration	Standardized workflows
Limited online measurements	Delayed process response	Real-time mineralogy
Large data volumes	Computational challenges	Automated analytics
Restricted industrial validation	Uncertain transferability	Full-scale validation studies
Simplified flotation models	Incomplete process representation	Hybrid physics–AI approaches
Fragmented geometallurgical datasets	Reduced predictive capability	Integrated digital platforms

Table 9 indicates future progress depends on better instruments, data, models, and process integration. Key areas include high-res imaging, 3D characterization, improved mineral classification, standardized digital workflows, real-time monitoring, automated analysis, validation, and hybrid physics–AI models. The goal is to develop integrated digital platforms that combine geological, mineralogical, operational, and metallurgical data to build predictive systems.

Automated mineralogy is becoming essential in intelligent geometallurgical systems, supporting ore characterization, process prediction, optimization, and autonomous decisions amid digital growth. These advances improve resource efficiency, sustainability, and economic benefits.

Significant progress has been made in automated mineralogy, predictive metallurgy, and digital geometallurgy, but challenges remain. Their maturity levels and limitations hinder broader industrial use. Table 10 details their current status, limitations, and future development directions.

Table 10. Current status, major limitations, and future development directions of key technologies supporting automated mineralogy, predictive metallurgy, and digital geometallurgy. Adapted from Schulz et al. (2020), Becker (2023), Frenzel et al. (2023), Butcher et al. (2023), Medina-Tasilla et al. (2024), Tonžetić (2025), and Yang et al. (2026).

Area	Current Status	Main Limitation	Future Direction
MLA/QEMSCAN	Mature	2D bias	Integration with 3D data
µCT	Emerging	Cost	Faster acquisition
ML	Growing	Transferability	Explainable AI
Geometallurgy	Mature	Data integration	Digital twins
Recovery prediction	Promising	Generalization	Real-time prediction

Table 10 shows that the future of automated mineralogy relies more on integrating complementary technologies than on small improvements in individual platforms. Although these systems are mature and widely used, challenges remain in three-dimensional characterization, data integration, model transferability, and real-time decision support. The combination of advanced techniques, machine learning, digital twins, and predictive frameworks is expected to transform mineralogical data into actionable intelligence. These advances are crucial for developing more adaptive, efficient, and autonomous mineral processing systems.

Conclusions

Automated mineralogy is a key advancement in process mineralogy and geometallurgy, transforming how sulfide ores are characterized and used in metallurgical decisions. It has evolved from a descriptive tool to one offering quantitative data supporting flotation diagnostics, mineral deportment, recovery forecasting, geometallurgical domaining, and process optimization.

The reviewed literature shows mineral liberation is crucial for flotation but not enough to explain behavior in complex sulfides. Mineral exposure, texture, associations, alteration, and deportment also significantly affect flotation. As a result, process mineralogy shifts from focusing solely on liberation to integrated, multi-attribute particle-based approaches.

The review emphasizes that no single technique fully describes sulfide ore complexity. SEM platforms like MLA, QEMSCAN, TIMA, and AMICS are foundational, but complementary methods such as optical mineralogy, hyperspectral imaging, LIBS, µ-XRF, and X-ray micro-CT add valuable insights into particle structure, mineral variability, and heterogeneity. Future strategies will likely depend more on integrated multi-sensor, multi-scale workflows than on individual platforms.

Recent years have seen the rise of predictive mineralogy, driven by access to large mineral datasets. This has led to particle-based models, machine learning algorithms, and geometallurgical frameworks that connect mineralogy to metallurgical performance. These approaches shift from retrospective analysis to forecasting recovery, concentrate quality, process variability, and operational performance.

Despite advances, challenges remain. Automated mineralogy faces limitations like 2D measurement issues, stereological bias, characterization of ultra-fine particles, data standardization, platform interoperability, and transferability between deposits and plants. Many machine learning applications depend on site-specific data and often lack interpretability, hindering industrial adoption. Significant research is needed before autonomous mineralogical decision-making becomes practical.

The future of automated mineralogy will see greater integration with artificial intelligence, digital geometallurgy, sensor-based ore characterization, digital twins, and real-time monitoring systems. It is becoming a core part of digital mineral processing ecosystems, where geological, mineralogical, metallurgical, and operational data are constantly integrated to support adaptive control and predictive decisions.

Automated mineralogy primarily transforms mineralogical observations into actionable metallurgical knowledge, rather than merely generating quantitative data. Advances in characterization, modeling, machine learning, and digital integration will improve resource efficiency, reduce uncertainty, boost sustainability, and enable smarter, more autonomous mineral processing.

Declarations

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Conflicts of Interest

The author declares no conflicts of interest related to the subject matter of this work.

Data Availability Statement

No new experimental data were generated during this study. All information analyzed and discussed was obtained from publicly available scientific literature.

Author Contributions

Antonio Clareti Pereira was responsible for conceptualization, literature review, methodology design, analysis, interpretation, writing of the original draft, review, editing, and final approval of the manuscript.

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