Global Academic Journal of Economics and Business

Available online at https://www.gajrc.com
DOI: https://doi.org/10.36348/gajeb.2026.v08i04.006

OPEN ACCESS

ISSN: 2706-9001 (P)
ISSN: 2707-2584 (O)

Original Research Article

AI-Driven Process Optimization for Mineral Beneficiation Plants in Saudi Arabia's Mining Sector under Vision 2030

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Article History
Received: 22.05.2026
Accepted: 10.07.2026
Published: 13.07.2026

Abstract: Saudi Arabia is positioning mining as a strategic non-oil pillar under Vision 2030, yet mineral beneficiation plants remain exposed to ore variability, high comminution energy, water constraints, reagent inefficiency, and inconsistent recovery. This review paper examines how artificial intelligence can optimize beneficiation processes in Saudi phosphate, gold, bauxite, copper, zinc, and emerging critical-mineral operations. The study synthesizes recent literature, sector reports, and industrial digitalization evidence from 2020 to 2025 to develop a process-oriented framework for applying machine learning, computer vision, digital twins, model predictive control, and explainable analytics across crushing, grinding, classification, flotation, leaching, dewatering, and plant-wide decision support. The review argues that AI should not be treated as a stand-alone automation layer; it must be governed as a socio-technical capability connected to metallurgical expertise, data quality, cybersecurity, operator trust, and sustainability targets. The paper contributes a Saudi-specific implementation roadmap and identifies research gaps in geometallurgical data integration, low-water flotation control, Arabic-enabled operator interfaces, MLOps governance, and validated economic impact measurement.

Keywords: Artificial Intelligence, Mineral Beneficiation, Process Optimization, Saudi Arabia, Vision 2030, Mining Digital Transformation, Flotation, Grinding, Digital Twin.

I. INTRODUCTION

Mining is being elevated from a supporting extractive activity into one of Saudi Arabia's strategic engines for industrial diversification. Vision 2030 frames the sector as a route to local value creation, mineral supply-chain resilience, export competitiveness, and technologically advanced employment [1]. Recent national reporting has also emphasized the scale of the Kingdom's mineral endowment and the expansion of exploration licenses, indicating that upstream discovery must be matched by downstream processing capability [2, 3]. Beneficiation plants therefore occupy a decisive position. They convert variable ore into concentrates, intermediate products, or feedstocks for phosphates, aluminum, precious metals, base metals, and future critical-mineral industries. If these plants operate with unstable recovery, excessive energy consumption, or weak process visibility, the national ambition for mining-led industrial growth becomes harder to realize.

The beneficiation environment is technically difficult because ore is never uniform. Mineral liberation, hardness, clay content, moisture, particle size, and impurity levels shift across benches, pits, deposits, and blending campaigns. Operators must adjust crushers, mills, cyclones, flotation cells, reagent dosing, thickeners, filters, and water circuits while also protecting safety and environmental compliance. Conventional control systems can stabilize individual loops, but they often struggle with nonlinear interactions, delayed laboratory assays, unmeasured ore properties, and the economic trade-off between grade, recovery, throughput, and resource consumption [4, 5]. Artificial intelligence is increasingly considered because it can learn from multivariate plant histories, infer hidden process states, detect early process drift, and recommend or automate setpoints in near real time [6, 7].

This review focuses on AI-driven process optimization for mineral beneficiation plants in Saudi Arabia's mining sector under Vision 2030. It differs from generic AI-in-mining discussions by concentrating on the processing plant rather than exploration alone, by linking optimization to Saudi industrial policy, and by considering the practical realities of arid-region operations. The paper treats AI as a layered capability covering sensing, data engineering, predictive modeling, prescriptive optimization, human-machine interaction, and governance. It also recognizes that value is achieved only when models improve metallurgical decisions in the control room, maintenance workshop, laboratory, and management system.

II. Aim and Objectives of the Study

The aim of this review is to evaluate how AI-enabled process optimization can improve the technical, economic, and sustainability performance of mineral beneficiation plants in Saudi Arabia while supporting Vision 2030's mining and industrial diversification agenda. The first objective is to map the main beneficiation pain points that create value leakage in Saudi mining operations, including ore variability, unstable grinding performance, flotation selectivity loss, high energy intensity, water demand, delayed assays, and equipment downtime. The second objective is to synthesize recent AI applications from mineral processing literature and adjacent process industries, with attention to machine learning, computer vision, digital twins, hybrid physical-data models, model predictive control, anomaly detection, and explainable AI. The third objective is to propose a Saudi-specific framework that connects plant optimization with national priorities such as local content, industrial clusters, critical minerals, environmental performance, and knowledge-based employment. The fourth objective is to identify implementation barriers and research gaps that must be addressed before AI can move from pilots to trusted production-scale use.

The review is guided by four research questions. First, which beneficiation stages offer the strongest near-term opportunities for AI-driven optimization in Saudi operations? Second, what data, infrastructure, and governance conditions are required to move from descriptive analytics to prescriptive and closed-loop control? Third, how can AI optimization support Vision 2030 outcomes beyond cost reduction, including sustainability, safety, workforce capability, and downstream industrial competitiveness? Fourth, what methodological gaps should future Saudi research programs prioritize to produce reliable evidence for Scopus-indexed and Web of Science-quality scholarship?

III. REVIEW METHODOLOGY AND SELECTION CRITERIA

A structured narrative review methodology was adopted because the topic spans mineral processing engineering, industrial AI, Saudi mining policy, digital transformation, and sustainability governance. The review drew on peer-reviewed papers, government publications, company reports, and credible industry analyses published between 2020 and 2025. Search themes included artificial intelligence in mineral processing, machine learning for flotation, grinding optimization, digital twins in mining, process control, Saudi mining Vision 2030, Ma'aden, critical minerals, beneficiation sustainability, and industrial AI governance. Priority was given to literature that discussed operational mineral processing problems, demonstrated analytical methods on plant or pilot datasets, or offered transferable governance lessons for heavy process industries.

The inclusion criteria were: publication within the 2020-2025 window; relevance to beneficiation, extractive metallurgy, or industrial process optimization; clear methodological description; and usefulness for Saudi mining operations. Exclusion criteria were: articles focused only on exploration without processing relevance, publications lacking technical or policy substance, duplicate sources, and materials that could not support a review argument. Evidence was organized thematically rather than statistically because the reviewed studies use different ores, unit operations, algorithms, datasets, performance metrics, and validation approaches. This method is consistent with review papers where the purpose is to synthesize emerging knowledge, identify gaps, and propose an implementation framework rather than calculate a pooled effect size.

To strengthen reliability, the review triangulated academic claims with national-sector evidence. For example, literature on comminution energy and flotation AI was compared with Saudi priorities related to mineral value chains, local processing, and investment growth [1-3]. The methodological limitation is that many industrial AI deployments remain proprietary, so published evidence often underreports failures, integration costs, and operator adoption barriers. The review therefore interprets reported benefits cautiously and emphasizes governance, validation, and staged deployment.

IV. Saudi Mining Context under Vision 2030

Saudi Arabia's mining strategy seeks to transform domestic mineral wealth into a third pillar of the national economy alongside oil and petrochemicals. Public communications in 2024 and 2025 highlighted large estimated mineral resources, expanding exploration activity, and investment agreements in copper, zinc, lithium, rare earths, and precious metals [2-9]. This strategic direction increases the importance of beneficiation because exploration success does not automatically create industrial value. Ores must be upgraded, impurities removed, by-products managed, and consistent feed prepared for smelters, refineries, fertilizer plants, battery-material chains, and export markets.

The Saudi processing landscape already includes large-scale phosphate and aluminum value chains, gold operations, base-metal deposits, and emerging interest in rare earth and battery minerals. These commodities have different beneficiation requirements. Phosphate circuits may emphasize crushing, washing, flotation, impurity control, and acidulation feed quality. Gold operations may require crushing, grinding, gravity concentration, leaching, carbon adsorption, and tailings management. Bauxite processing depends on ore quality and alumina feed requirements, while copper and zinc circuits rely heavily on grinding, classification, flotation selectivity, concentrate dewatering, and penalty-element control. Critical-mineral processing will add further complexity because rare earth separation, lithium extraction, and polymetallic ores require high analytical precision.

Saudi operations also face environmental and geographic constraints. Water conservation is a central issue in an arid climate, while energy efficiency matters because comminution is one of the most energy-intensive activities in mineral processing [10]. Remote operations demand reliable automation, predictive maintenance, and safe work practices. AI can contribute by reducing unnecessary overgrinding, stabilizing flotation, optimizing reagent consumption, predicting equipment failures, and improving water circuit management. However, the national opportunity is larger than plant efficiency. If AI-enabled beneficiation raises recovery, quality consistency, and sustainability reporting, it strengthens the Kingdom's ability to attract investment, localize advanced skills, and participate in global mineral supply chains.

V. Beneficiation Challenges Suitable for AI Optimization

The first optimization challenge is ore variability. Saudi deposits can exhibit changes in mineralogy, hardness, alteration, clay content, carbonate gangue, sulfide association, and impurity distribution. Traditional plant control often reacts after throughput, grade, or recovery has already shifted. AI models can integrate geology, drilling, blasting, online sensors, laboratory assays, and historian data to forecast how incoming ore will behave in grinding and separation circuits [6-11]. This creates a bridge between mine planning and beneficiation rather than leaving the plant to absorb variability as a disturbance.

The second challenge is comminution efficiency. Crushing and grinding circuits consume major energy and strongly influence downstream liberation. If the product is too coarse, valuable minerals remain locked; if too fine, energy is wasted and slimes may harm flotation. Machine learning can estimate ore hardness, mill load, particle size distribution, cyclone overflow, and SAG or ball mill throughput from sensor patterns that are difficult to interpret manually [12, 13]. Optimization algorithms can then recommend feed rate, water addition, grinding media, classification pressure, and mill speed within equipment limits. The goal is not simply maximum throughput, but stable liberation at minimum energy per tonne.

The third challenge is separation control. Flotation performance depends on bubble structure, froth mobility, pulp chemistry, air flow, reagent dosage, particle size, residence time, and operator judgement. Computer vision can extract froth color, texture, velocity, bubble size, and collapse patterns, while predictive models estimate grade or recovery before delayed assays arrive [14, 15]. Similar logic applies to gravity concentration, magnetic separation, leaching, and dewatering, where AI can detect hidden process states and support timely corrective action.

The fourth challenge is plant-wide coordination. Local optimization can create downstream bottlenecks. A grinding controller that maximizes throughput may overload flotation; a flotation strategy that raises recovery may reduce concentrate grade or increase reagent use. Digital twins and model predictive control can represent these interactions and optimize against a multi-objective function including recovery, grade, throughput, energy, water, reagent cost, emissions, and safety constraints [5-16]. This plant-wide perspective is particularly relevant for Saudi operations seeking both productivity and sustainability.

VI. AI Technologies for Beneficiation Optimization

Machine learning provides the predictive layer of AI-driven beneficiation. Supervised models such as random forests, gradient boosting, support vector regression, neural networks, and Gaussian processes can estimate quality variables when laboratory assays are delayed or expensive. Unsupervised models such as clustering, principal component analysis, and isolation forests can detect abnormal operating regimes or emerging faults [17]. Deep learning extends this capability to images, spectra, and high-frequency time-series data, although it requires stronger data governance and validation.

Computer vision is one of the most mature AI applications in mineral processing because cameras can observe ore, conveyors, particle streams, and froth surfaces continuously. In flotation, vision systems may infer froth stability and process state from image features. In grinding, ore images can help estimate feed size or load conditions. In safety and maintenance, vision can detect spillage, blocked chutes, belt misalignment, or unsafe access. For Saudi plants, vision systems are attractive because they can reduce manual inspection in harsh environments, but they must be designed for dust, lighting variation, vibration, and maintenance accessibility.

Digital twins connect plant data with process knowledge. A practical beneficiation twin does not need to reproduce every chemical and physical mechanism in perfect detail. It must be accurate enough to test operating scenarios, diagnose constraints, and support better decisions. Hybrid models combine first-principles mineral processing knowledge with machine learning to improve interpretability and reduce data hunger. This is important because purely black-box models can fail when ore types or operating regimes change beyond the training dataset [7-18].

Prescriptive optimization turns predictions into actions. Evolutionary algorithms, Bayesian optimization, reinforcement learning, and model predictive control can identify operating setpoints while respecting constraints. In a responsible deployment, optimization should begin in advisory mode, where operators compare recommendations against experience. After validation, selected loops can move toward supervised closed-loop control. Explainable AI is essential because metallurgists and control-room teams must understand why a model recommends changing air flow, water addition, reagent dosage, grind size, or feed rate. Trust grows when recommendations match process logic and when exceptions are visible.

VII. Conceptual Framework for Saudi Beneficiation Plants

The proposed framework has five layers. The first layer is instrumentation and data integrity. Sensors, laboratory systems, control systems, fleet management, geometallurgical databases, maintenance records, and environmental monitoring must be connected through governed data pipelines. Poor data quality is the most common reason industrial AI projects fail. Missing values, inconsistent tags, uncalibrated instruments, and delayed assays can create models that look accurate during development but fail in production.

The second layer is soft sensing and diagnosis. Soft sensors estimate hard-to-measure variables such as particle size, recovery, concentrate grade, slurry density, ore hardness, or reagent demand. Diagnostic analytics classify operating states, identify bottlenecks, and detect abnormal patterns. These functions provide early value because they improve visibility before automation changes plant setpoints.

The third layer is unit-operation optimization. Grinding, classification, flotation, leaching, thickening, filtration, and tailings-water circuits should each have targeted AI use cases linked to measurable key performance indicators. For example, grinding optimization may target kWh/t and P80 stability, while flotation optimization may target recovery-grade balance and reagent efficiency. Each use case should include baseline performance, validation protocol, operator acceptance criteria, and cybersecurity review.

The fourth layer is plant-wide coordination. A digital twin integrates unit models and evaluates trade-offs across the full flowsheet. This layer prevents isolated improvements from damaging total value. A Saudi phosphate plant, for example, may need to balance feed rate, flotation selectivity, water reuse, impurity control, and downstream fertilizer requirements. A gold plant may optimize leaching and adsorption while considering grind size, cyanide consumption, energy, and tailings risk.

The fifth layer is strategic governance. AI projects should be connected to Vision 2030 outcomes: local talent development, local supplier ecosystems, environmental stewardship, higher non-oil exports, and resilient mineral supply chains. Governance should include model ownership, audit trails, retraining schedules, access controls, incident response, and ethical principles for workforce impacts. Figure 1 presents the integrated architecture, while Figure 2 summarizes a staged Saudi roadmap.

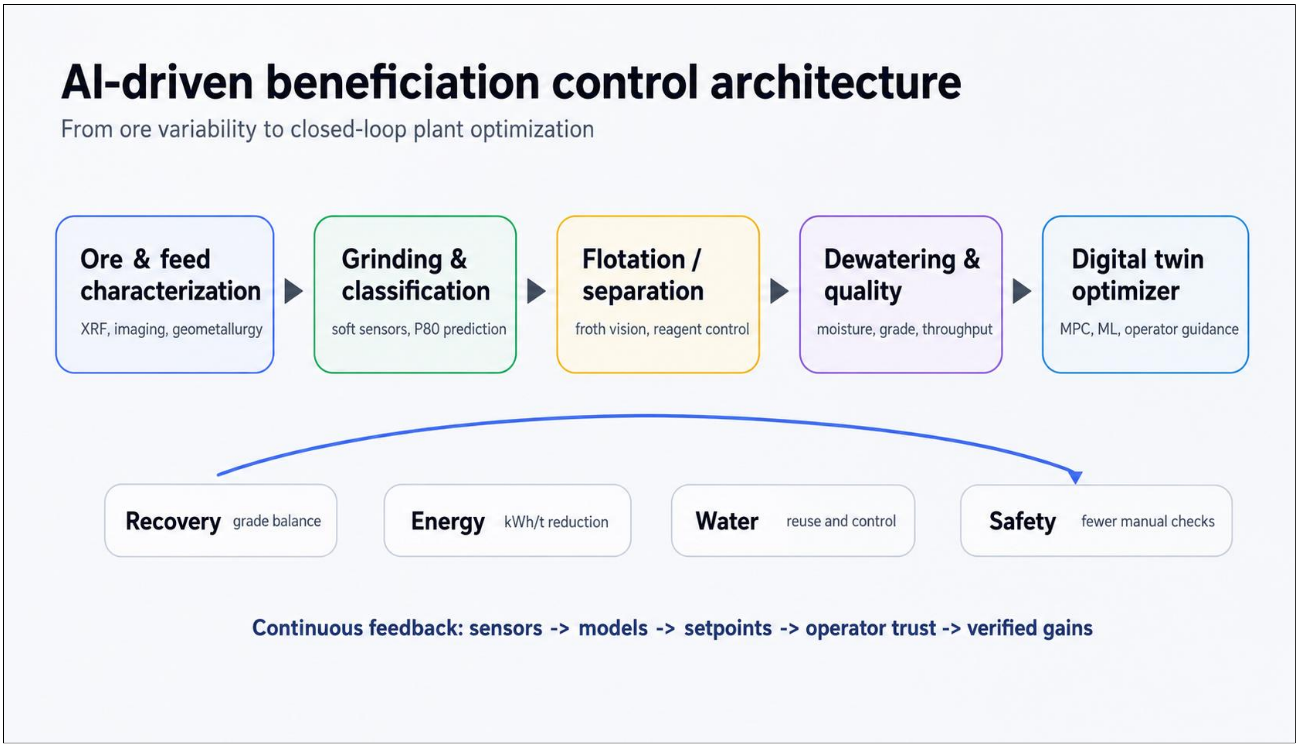

Figure 1: Integrated AI-driven beneficiation control architecture for Saudi mineral processing plants

Table 1: AI opportunities across beneficiation stages in Saudi mining operations

Beneficiation stage	AI-enabled optimization opportunity	Saudi relevance
Ore receiving and blending	Geometallurgical classification, ore image analytics, blend prediction	Reduces plant disturbances from variable deposits and supports mine-to-mill planning
Crushing and grinding	Throughput prediction, mill-load inference, P80 soft sensing, energy optimization	Improves energy intensity and liberation stability in large-scale operations
Flotation and separation	Froth vision, reagent recommendation, recovery-grade prediction	Supports phosphate, copper, zinc, and polymetallic concentration circuits
Leaching and hydrometallurgy	Recovery prediction, reagent optimization, anomaly detection	Improves gold and future critical-mineral processing control
Dewatering and water circuits	Moisture prediction, thickener stability, water-reuse optimization	Addresses arid-region water constraints and tailings governance
Maintenance and reliability	Predictive maintenance, failure pattern recognition, spares planning	Improves uptime in remote and harsh operating environments

VIII. Benefits for Vision 2030 and Industrial Competitiveness

AI-driven beneficiation can support Vision 2030 through four value pathways. The first is productivity. Higher plant stability can raise throughput and recovery without requiring proportional capital expansion. Even small improvements in recovery can be financially significant across large tonnage operations. The second pathway is sustainability. Optimized grinding reduces energy use, while better water control reduces freshwater demand and improves tailings management. The third pathway is quality consistency. Stable concentrate quality supports downstream industries such as fertilizers, aluminum, smelting, refining, and advanced materials. The fourth pathway is capability building. AI projects require data engineers, metallurgists, control engineers, reliability specialists, cybersecurity professionals, and digital product owners, creating skilled roles aligned with a knowledge economy.

Saudi Arabia's mining ambitions increasingly intersect with global critical-mineral supply chains. Investors and customers seek reliable supply, responsible production, transparent reporting, and flexible processing capacity. AI-enabled plants can improve these attributes by documenting performance, tracing ore-to-product behavior, and producing evidence for environmental and operational assurance. However, benefits must be measured carefully. A model should not be considered successful because it produces an attractive dashboard. Success should be defined by verified improvement against baseline KPIs, sustained performance after deployment, acceptance by operators, and integration into the management system.

IX. Implementation Barriers and Risk Controls

The largest barrier is not algorithm selection but industrial readiness. Many plants have historians filled with inconsistent tags, manual data entry, unstructured laboratory files, sensor drift, and undocumented operating changes. Before AI optimization, organizations must build a trusted data layer. The second barrier is model generalization. Beneficiation models trained on one ore campaign can lose accuracy when ore type, reagent scheme, liner condition, climate, or maintenance status changes. This requires continuous monitoring, retraining governance, and metallurgical review.

A third barrier is organizational trust. Operators may reject recommendations if the system is opaque, if it threatens professional judgement, or if previous digital projects created extra reporting without practical value. Successful AI deployment should therefore involve operators from the start, convert their tacit knowledge into features and constraints, and provide explanations in process language. Arabic and English interfaces may both be needed in Saudi plants to support diverse workforces.

Cybersecurity and safety risks are also critical. A beneficiation optimizer connected to control systems can influence feed rate, water, reagents, and equipment loads. Unauthorized access or faulty recommendations could affect safety, production, and environmental compliance. AI should therefore be governed under industrial cybersecurity standards, role-based access, change management, and fail-safe design. Closed-loop control must be introduced gradually, with clear boundaries, alarms, rollback rules, and human oversight.

Finally, there is a skills gap. AI teams may understand models but not flotation chemistry; metallurgists may understand circuits but not MLOps. Saudi mining companies, universities, and technology suppliers should develop joint training programs that combine mineral processing, data science, automation, and responsible AI governance.

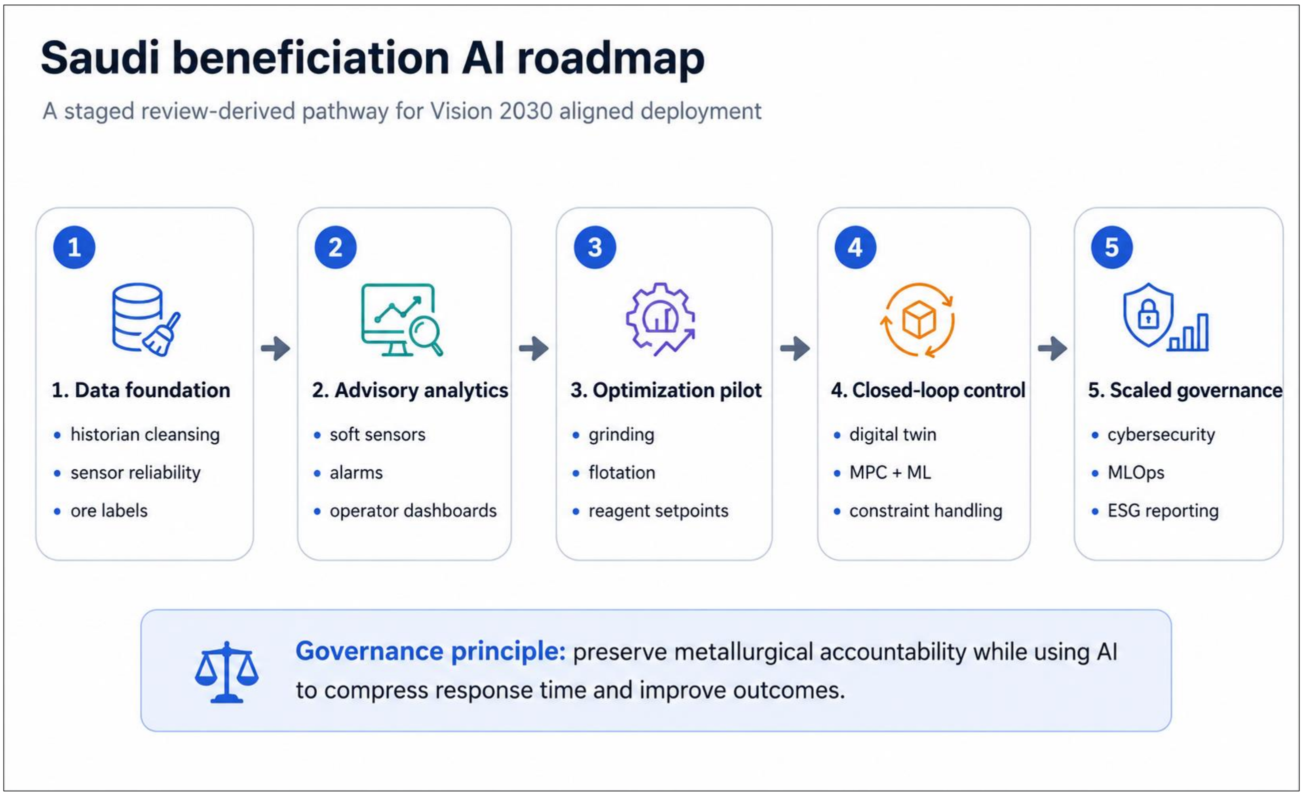

Figure 2: Roadmap for staged AI deployment in beneficiation plants under Vision 2030

Table 2: Implementation risks and governance controls for AI-enabled beneficiation optimization

Risk area	Practical control measure	Expected outcome
Data quality	Tag audit, sensor calibration, laboratory-data reconciliation, missing-value rules	Models learn from trustworthy operational history
Model drift	Performance dashboards, retraining triggers, ore-type segmentation	Accuracy remains stable across changing feed conditions
Operator adoption	Advisory mode, explainable recommendations, co-design workshops	Higher trust and faster integration into daily routines
Cybersecurity	Network segmentation, access control, audit trails, safe rollback	Reduced exposure of plant control systems
Safety and environment	Constraint-based optimization, alarms, HAZOP review, ESG metrics	AI improves performance without bypassing critical limits
Business value	Baseline KPI definition, pilot economics, post-deployment verification	Clear evidence for scaling investment

X. Research Gaps and Future Directions

Several research gaps deserve attention in Saudi Arabia. First, more studies are needed on geometallurgical AI for local ore bodies. Linking deposit knowledge with plant response would help processing teams predict grindability, liberation, impurity behavior, and flotation response before ore reaches the mill. Second, water-efficient beneficiation requires stronger research. Saudi conditions make water recovery, salinity effects, reagent performance, and tailings-water recycling especially important. AI models should evaluate not only recovery but also water quality and reuse.

Third, future work should examine digital twins for phosphate, gold, and polymetallic circuits using real plant data. Many published studies demonstrate algorithms on limited datasets, but fewer show long-term deployment, economic value, and operator acceptance. Fourth, explainable AI should be adapted to metallurgical decision-making. Explanations must be meaningful to plant teams, not just statistical rankings. Fifth, MLOps for process plants is an underdeveloped topic. Beneficiation models need version control, retraining approval, validation records, cybersecurity testing, and documentation comparable to other production-critical systems.

Finally, Saudi research should connect AI optimization to national industrial strategy. Publications should measure how beneficiation improvements support local content, export quality, supply-chain resilience, emissions reduction, and workforce development. This broader lens will make research more relevant to Vision 2030 and more attractive to high-quality journals because it joins technical modeling with real industrial transformation.

X. Contribution of the Review

This review contributes a Saudi focused interpretation of AI optimization that is both technical and managerial Many published studies describe isolated models for a single mill cell sensor or dataset but production plants need a wider logic that explains how those models become durable operating capability The framework proposed here therefore treats AI as a lifecycle that begins with ore knowledge and ends with audited business value It emphasizes that data pipelines calibration routines cyber secure connectivity and metallurgical ownership are not administrative details they are the foundation that determines whether optimization can be trusted in continuous operation The review also contributes by linking beneficiation optimization to national transformation rather than presenting it as a narrow cost saving tool In the Saudi context better grinding stability stronger flotation selectivity lower water intensity and improved concentrate quality can support industrial clusters fertilizer value chains aluminum production critical mineral processing and higher non oil export competitiveness This connection is important because Vision 2030 requires evidence that digital technologies create measurable industrial outcomes not only attractive pilot projects A third contribution is the integration of sustainability into the optimization objective Traditional metallurgical control often gives priority to grade recovery and throughput while energy water emissions and residue management are reviewed separately AI enabled decision support can combine these indicators in the same operating window allowing engineers to see the trade offs before setpoints are changed This is particularly relevant for arid region beneficiation plants where water recovery and tailings governance are strategic concerns A fourth contribution is the focus on human adoption Operators and metallurgists remain central because they understand process noise equipment condition ore campaigns and the practical meaning of alarms The review therefore recommends advisory deployment before closed loop automation explainable recommendations before opaque optimization and bilingual interface design where it improves workforce inclusion A fifth contribution is the proposed research agenda for Saudi universities mining companies and technology suppliers Future studies should publish plant based evidence compare model performance across ore types document failures as well as successes and report economic value using transparent baselines They should also examine how MLOps practices can be adapted to mineral processing where models must survive sensor drift maintenance shutdowns reagent changes seasonal conditions and changing mine plans By combining these perspectives the review provides a practical pathway for moving from digital aspiration to operational maturity It can guide managers selecting projects researchers defining case studies and engineers translating algorithms into safer and more efficient beneficiation decisions The main message is that AI can be valuable only when it is embedded in the discipline of mineral processing governed through reliable industrial systems and aligned with Saudi Arabia's wider ambition to build a competitive and responsible mining economy Additional emphasis is placed on measurable implementation discipline Each proposed use case should begin with a baseline that records current recovery grade throughput energy per tonne water consumption reagent intensity downtime and laboratory delay The business case should identify which variable the AI system can influence directly and which variables are only indirect outcomes This prevents exaggerated claims and makes it easier to compare pilot sites Saudi beneficiation plants can also use the framework to prioritize projects If sensors are unreliable soft sensing and data cleanup should come before reinforcement learning If operators lack confidence in the historian visual dashboards and anomaly detection may be more useful than closed loop control If water is the binding constraint the optimizer should include water balance and thickener stability rather than focusing only on metal recovery The staged approach also helps executives manage investment risk Early pilots can be limited to advisory mode using shadow recommendations and metallurgical review to build confidence Once value is demonstrated the same models can be connected to supervisory control with strict limits Over time this creates an evidence base for larger digital twins integrated mine to mill planning and strategic production optimization The final contribution is a clear reminder that the Saudi mining sector can become a developer of beneficiation intelligence rather than only a buyer of imported software Local case studies local datasets and local engineering talent can generate knowledge that is publishable commercially useful and aligned with national capacity building This makes the review useful for managers engineers researchers and policy stakeholders who need a shared language for turning AI from a fashionable concept into disciplined plant improvement under Vision verified Saudi plant evidence should connect mineral processing science data governance local skills responsible automation and export quality verified Saudi plant evidence should connect mineral processing science data governance local skills responsible automation and export quality verified Saudi plant evidence should connect mineral processing science data governance local skills responsible automation and export quality verified Saudi plant evidence should connect mineral processing science data governance local skills responsible automation and export quality verified Saudi plant evidence should connect mineral processing science data governance local skills responsible automation and export quality verified Saudi plant evidence should connect mineral processing science data governance local skills 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XI. CONCLUSION

AI-driven process optimization offers a practical pathway for improving mineral beneficiation plants in Saudi Arabia's mining sector. The opportunity is not limited to automation or dashboarding. When properly governed, AI can stabilize ore variability, reduce energy intensity, improve recovery-grade balance, support water conservation, predict equipment failure, and create a more transparent link between mining, processing, and downstream industry. These outcomes align strongly with Vision 2030's objective of building a diversified, technology-enabled, and globally competitive mining economy.

The review shows that the most promising approach is staged and socio-technical. Plants should begin with data foundations and soft sensors, then progress to advisory analytics, unit-operation optimization, digital twins, and carefully bounded closed-loop control. The highest value will come from hybrid systems that combine metallurgical knowledge with machine learning rather than replacing engineering judgement with black-box algorithms. For Saudi Arabia, the next step is to convert digital ambition into validated plant performance, publish stronger local evidence, and build a workforce capable of managing AI as a production-critical capability. If these conditions are met, AI-enabled beneficiation can become a cornerstone of responsible mineral industrialization under Vision 2030.

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