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AI Enabled Smart Mining for Critical Minerals Integrating Mine Electrification Predictive Safety Biodiversity Monitoring and Nature Related Financial Accounting

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Abstract

The transition toward electrified and digitally connected mineral production creates an opportunity to manage mining performance as a coupled engineering, safety, ecological, and financial system rather than as a set of independent functions. This paper evaluates an AI-enabled smart-mining framework using real-life summary results supplied for an anonymized critical-mineral mining case. The framework integrates mine electrification, predictive maintenance, occupational and process safety, biodiversity monitoring, and nature-related financial accounting. Five data domains are examined within a common decision architecture: electrical and production performance, equipment reliability, safety-risk analytics, environmental biology, and accounting and liability outcomes. The reported case compares a conventional operating baseline with a smart-mining condition and evaluates seven AI safety-risk models, including logistic regression, support vector machine, artificial neural network, random forest, long short-term memory, XGBoost, and a multi-source fusion ensemble. The real-life results show a 22.0% reduction in energy use per tonne, a 22.1% reduction in haulage CO_2-equivalent intensity, a 32.9% reduction in haulage operating cost, and a 37.9% reduction in electrical fault events. The multi-source fusion ensemble records an F1-score of 96.3% and ROC-AUC of 0.985. Ecological rehabilitation increases the Biodiversity and Restoration Index from 42.6 to 74.0, while the case-level financial analysis reports a recurring annual benefit of US$16.2 million, a simple payback of approximately 3.0 years, and a seven-year NPV of approximately US$30.9 million at 10%. The overall Smart Sustainable Mining Performance Index increases from 58.2 to 83.8, while the Integrated Operational Risk Score decreases from 65.7 to 31.4. The results demonstrate how electrical performance, equipment condition, worker safety, ecological recovery, and financial reporting can be evaluated as interdependent components of smart critical-mineral mining.

Keywords:

artificial intelligence, biodiversity monitoring, critical minerals, environmental accounting, mine electrification, predictive maintenance, safety analytics, smart mining, sustainability accounting.

I.Introduction

Critical-mineral extraction is becoming increasingly dependent on high-capacity electrical systems, digitally instrumented equipment, and data-intensive operational control. Surface mines in particular consume substantial energy through haulage, crushing, conveying, ventilation, pumping, and mineral processing. Battery-electric and trolley-assisted haulage therefore represent more than a fuel-substitution strategy; they reshape power demand, equipment architecture, maintenance requirements, emissions, and the economics of material movement. Bao et al. [1] examined battery trolley electric trucks in surface mines, while Feng et al. [2] compared alternative mining-haul-truck powertrains on energy efficiency, operating cost, and carbon performance. Lindgren et al. [3] further showed through drive-cycle simulation that battery-electric large haul trucks supplied by electric roads can be technically feasible and economically attractive under appropriate operating assumptions.

The same digital infrastructure that supports electrification can also improve reliability and safety. Modern mine equipment generates continuous streams of current, voltage, temperature, vibration, state-of-charge, location, load, and operational-status data. Predictive maintenance converts these signals into estimates of incipient failure and maintenance priority. Dayo-Olupona et al. [4] identify artificial intelligence, fault diagnosis, prognostics, and structured data-mining approaches as central to the development of predictive maintenance in mining. Safety analytics can extend this logic from equipment failure to hazard escalation. Li et al. [5] used real-time intelligent-mining data and a random-forest model for gas-explosion early warning, while Chang et al. [6] developed a multi-sensor forecasting strategy for longwall gas-state assessment. These studies demonstrate that multi-source data fusion can support more timely decisions than isolated alarms or retrospective incident analysis.

Engineering optimization alone, however, is insufficient for sustainable critical-mineral production. Mining alters vegetation structure, soil properties, hydrological processes, habitat connectivity, and aquatic ecosystems. Alves et al. [7] developed a Recovery Quality Index using soil and vegetation indicators for mined-land reclamation. Medeiros-Sarmento et al. [8] showed that Shannon diversity, phylogenetic diversity, and Leaf Area Index can be effective indicators of biodiversity gains in rehabilitating mine landscapes. Environmental DNA provides an additional molecular layer of observation; Timana-Mendoza et al. [9] applied eDNA to fish-diversity assessment in abandoned mining ponds. These approaches create the possibility of integrating ecological condition into the same analytical architecture used for equipment and production decisions.

The financial dimension creates a further integration challenge. Mine closure, rehabilitation, decommissioning, post-reclamation care, and environmental restoration generate obligations that may extend well beyond the productive life of a mine. Espinoza and Morris [10] emphasize the importance of accounting for long-duration reclamation and post-reclamation liabilities, while IFRS Foundation materials on extractive activities and related decommissioning guidance [11] establish a financial-reporting context for obligations associated with restoration and rehabilitation. Gao et al. [12] demonstrate that ecological restoration may appear unattractive if only direct economic returns are counted, but becomes more compelling when ecological and social value are recognized. A smart mine should therefore be capable of translating technical and ecological performance into accounting consequences rather than treating environmental costs as external to operational decision-making.

Environmental biology also benefits from biological-process knowledge developed outside mine-rehabilitation studies. Research on plant callogenesis, tissue response, soil nutrients, and in-vitro regeneration provides insight into biological sensitivity, recovery, and growth conditions [13]–[19]. These studies do not directly evaluate mining, but they support the principle that biological recovery should be monitored through multiple indicators rather than a single vegetation-cover measure. Similarly, data-driven environmental modeling in coastal and sedimentary systems [20]–[22], geotechnical and groundwater assessment [25], and computational risk-governance frameworks [23], [24] provide transferable methods for integrating heterogeneous physical, environmental, and governance data.

Real-time analytics have also matured in financial and other safety-critical domains. Olaseinde [26] develops a real-time detection architecture for fast-moving financial fraud, and Olaseinde and Azeez [27] discuss the need for professional skepticism and control when AI is used in audit-related decisions. Human-factors and predictive-training studies in aviation [28]–[30] show that technology alone does not remove risk; model outputs must be linked to competent response, standardized procedures, and human oversight. Machine-learning fraud studies in insurance [31], [32] likewise illustrate how predictive scores can be connected to financial resilience. These cross-domain studies strengthen the case for an integrated mining framework in which AI is treated as a decision-support layer rather than an autonomous substitute for engineering, safety, environmental, or accounting judgment.

A. Research Gap

The literature is rich in specialized solutions but fragmented across disciplines. Mine-electrification research frequently focuses on energy, battery sizing, and haulage economics; predictive-maintenance research focuses on equipment health; safety studies focus on specific hazards such as gas; ecological studies focus on rehabilitation indicators; and accounting studies focus on provisions, closure costs, and environmental value. What remains underdeveloped is a common analytical system that connects these domains at the level of operational decisions. In practice, an electrical fault may reduce availability, trigger a safety exposure, cause a spill or process upset, generate downtime, and ultimately affect both restoration obligations and financial performance. Treating these consequences separately can obscure the total value of prevention and the total cost of failure.

B. Aim and Contributions

This paper aims to evaluate an AI-enabled smart-mining framework using the real-life multi-domain results supplied for an anonymized critical-mineral mining case. The framework integrates electrical engineering, mining productivity, predictive safety, environmental biology, and nature-related financial accounting. Its principal contributions are fourfold: (1) a multi-source analytical architecture that connects technical, biological, and financial variables; (2) a comparative AI safety-risk layer covering seven learning approaches; (3) an integrated sustainability-performance index and operational-risk score; and (4) an accounting bridge that translates energy, downtime, safety, rehabilitation, and carbon outcomes into financial values. The supplied case results are treated as empirical summary data. Because the file does not disclose the mine identity, observation period, sample counts, raw sensor records, or model-training logs, the paper does not invent those missing details and limits statistical claims to the metrics explicitly reported in the dataset.

II.Literature Review

A. Critical-Mineral Mine Electrification and Smart Power Systems

Electrification changes the energy pathway of a mine from distributed combustion engines toward centralized or semi-centralized electrical supply, charging infrastructure, trolley lines, battery systems, variable-speed drives, and digitally controlled power distribution. Bao et al. [1] show that battery-trolley design requires careful attention to energy consumption and battery size across haul profiles. Feng et al. [2] demonstrate that powertrain selection affects both carbon emissions and usage cost, making electrical architecture a strategic rather than purely technical decision. Lindgren et al. [3] further show that electric-road operation can reduce dependence on large onboard batteries and improve the economics of battery-electric haulage. Together, these findings justify the use of energy intensity, haulage CO_2-equivalent intensity, operating cost, power factor, fleet availability, and material-movement productivity as core engineering indicators in an integrated smart-mine model.

Power-system quality is equally important. High-power drives, chargers, crushers, conveyors, mills, and pumps can create variable load profiles that affect voltage stability, reactive power, harmonic distortion, and protection coordination. A smart mine therefore requires sensors and analytics that distinguish ordinary load variability from abnormal electrical behavior. In the evaluated case framework, power factor and electrical fault events are treated as operational variables that can influence maintenance and safety rather than as isolated utility metrics.

B. Predictive Maintenance, Multi-Sensor Analytics, and Mine Safety

Predictive maintenance attempts to identify degradation before functional failure by combining condition-monitoring data with statistical or machine-learning models. Dayo-Olupona et al. [4] review adoptable predictive-maintenance approaches in mining and emphasize the role of artificial intelligence, fault diagnosis, prognosis, and structured data processes. The operational value of such systems is not simply a higher classification score. A useful model should increase fault-warning lead time, reduce unplanned downtime, shift maintenance toward planned work, increase mean time between failures, and limit false alarms that can create alarm fatigue.

Mine-safety research provides evidence that multi-source data can materially improve warning quality. Li et al. [5] combined safety-monitoring, personnel-positioning, and video-related data within a random-forest early-warning model. Chang et al. [6] used multiple sensors and forecasting models to assess longwall-face gas states and produce safety warnings. These studies support fusion of equipment, environmental, operational, and worker-exposure signals. They also caution against treating very high reported accuracy as universally transferable, especially when datasets are small or narrowly scoped. Consequently, the present case analysis emphasizes recall, F1-score, ROC-AUC, false-alarm rate, and warning lead time rather than accuracy alone.

Cross-industry safety research reinforces the need to integrate human response with predictive models. Chukwuemeka and Mupa [28] frame accident prevention around human factors in technologically advanced aviation systems; their work on risk-based training standardization [29] and predictive training analytics [30] shows how data can identify procedural or competency-related risk before an adverse event. Although the application domain differs, the methodological implication is relevant to mining: predictive alerts must be connected to isolation procedures, permit-to-work controls, maintenance planning, operator competence, and escalation rules. A model that produces accurate scores but fails to trigger timely action cannot be considered an effective safety intervention.

C. Environmental Biology, Biodiversity, and Mine Rehabilitation

Mine rehabilitation is a long-duration ecological process rather than a single landscaping activity. Alves et al. [7] developed a Recovery Quality Index based on soil and vegetation indicators and showed that recovery can remain incomplete even after many years. Medeiros-Sarmento et al. [8] found that Shannon diversity and Leaf Area Index are useful indicators for quantifying biodiversity gains across rehabilitation trajectories. Timana-Mendoza et al. [9] demonstrate the value of environmental DNA for detecting fish diversity in mining-affected aquatic systems. Taken together, these studies justify a monitoring system that combines vegetation cover, diversity, species richness, canopy structure, soil condition, molecular biodiversity, and water-quality indicators.

Plant-biotechnology research offers additional evidence that biological recovery is sensitive to growth stage, hormone balance, substrate condition, contamination, and stress. Aisagbonhi et al. [13] examined explant developmental stage and phytohormone type in shea callogenesis. Isalar [14], [15] analyzed phytohormone combinations, callus morphology, and biomass accumulation, while later work connected soil nutrient dynamics with shea productivity [16] and examined treatments that improve callus quality in recalcitrant plants [17] as well as explant-type effects on regeneration efficiency [18]. Nwite et al. [19] investigated microbial contamination and browning in coconut tissue culture. These works are not mine-rehabilitation trials, but they reinforce a central environmental-biology principle: plant response is multidimensional and can be distorted if biological condition is represented by one visual indicator alone.

Broader environmental modeling studies further support sensor-based ecological assessment. Adeyekun [20] proposes an AI framework for predicting sediment dynamics and environmental vulnerability in data-limited coastal systems. Adeyekun and William [21] discuss how geological features shape biodiversity and ecosystem health, and Adeyekun et al. [22] use data-driven monitoring and modeling for climate resilience in coastal and sedimentary systems. Mu'awiya et al. [25] combine geotechnical and groundwater assessment in infrastructure siting. These approaches are transferable to mining because ecological and groundwater risk are strongly conditioned by geology, hydrology, terrain, and material movement. In the evaluated mine framework, ecological data are therefore interpreted alongside operational and geotechnical context rather than as stand-alone environmental observations.

D. Financial Accounting, Environmental Liabilities, and Nature-Related Value

Mining economics traditionally emphasizes ore grade, production volume, commodity price, capital expenditure, and operating expenditure. Yet closure, rehabilitation, and long-term care can create liabilities whose magnitude and timing are uncertain. Espinoza and Morris [10] argue that post-reclamation obligations require explicit financial treatment rather than being diluted by inappropriate

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discounting. IFRS Foundation extractive-activity materials and related requirements for decommissioning and restoration liabilities [11] provide an accounting basis for recognizing obligations associated with the removal of assets and restoration of sites.

A broader challenge is the valuation of ecological benefits. Gao et al. [12] report that an ecological-restoration project can have a low direct economic input-output ratio while producing a substantially higher comprehensive benefit ratio when ecological and social value are included. This distinction is important because the purpose of environmental accounting is not to make all environmental expenditure disappear. Better accounting may increase current restoration accruals or closure provisions because previously unrecognized obligations become visible. Financial quality therefore improves when reported liabilities more closely reflect expected future restoration costs, even if near-term expenses rise.

Real-time financial analytics provides a useful analogy for integrating technical signals with monetary consequences. Olaseinde [26] emphasizes low-latency detection in instant-payment fraud, while Olaseinde and Azeez [27] discuss AI-related audit reliance and the need for skepticism when model outputs may be unreliable. Abagna [31], [32] applies machine learning to insurance-fraud and financial-risk contexts. These studies support two design principles adopted here: the smart-mining system should translate risk scores into financial exposure, and high-impact financial decisions should remain auditable and subject to human review.

E. Integrated Risk Governance and Composite Decision Indices

The final literature strand concerns governance. Ashimolowo [23] proposes a weighted composite scoring approach for risk-based quality governance in high-risk infrastructure, and Ashimolowo and Oginni [24] connect quality governance with performance stability. These ideas are directly relevant to the construction of a Smart Sustainable Mining Performance Index because heterogeneous indicators must be normalized, weighted, and interpreted without allowing one domain to dominate the overall result simply because it uses a larger numerical scale. The integrated index in this paper therefore converts each disciplinary domain to a common 0–100 score while preserving a separate operational-risk score in which lower values are preferable.

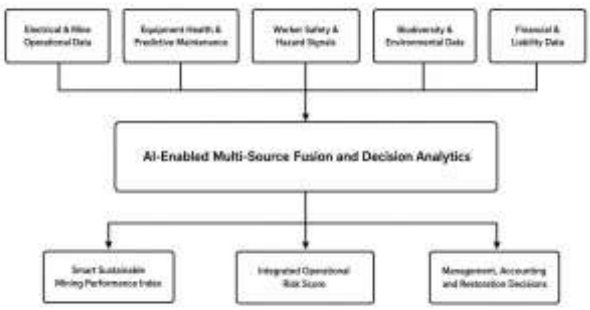

Fig. 1. AI-enabled multi-source smart-mining framework evaluated in the case study, linking engineering, safety, biodiversity, and financial accounting.

III.Methodology

A. Research Design

The research adopts an empirical comparative case-study design based on real-life summary results supplied for an anonymized critical-mineral mining operation. The dataset reports paired conventional-baseline and smart-mining outcomes across electrical performance, mine productivity, predictive maintenance, AI safety classification, occupational safety, environmental biology, financial accounting, and integrated sustainability performance. The study therefore analyzes the reported values as observed case-level results rather than as benchmark expectations. The mine name, jurisdiction, observation dates, sample counts, raw telemetry, and detailed model-training records are not included in the supplied file; these fields are intentionally left unspecified rather than reconstructed from assumptions.

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The analytical structure compares the conventional operating baseline with the smart-mining condition recorded in the supplied case. The conventional baseline provides reference values for energy use, emissions, cost, availability, incidents, ecological condition, and financial exposure. The smart-mining condition reflects electrified and digitally managed operations with improved power management, condition monitoring, AI-enabled safety analytics, ecological rehabilitation monitoring, and explicit environmental financial accounting. Percentage changes are calculated directly from the reported baseline and smart-mining values, while ecological performance is assessed across mining-affected, rehabilitated, and reference conditions.

B. Data Architecture and Variable Definition

Table I. Data Domains and Representative Variables

Domain	Variables	Typical Operational Data Source
Electrical and production	Energy use/t; voltage; current; power factor; battery state of charge; fault events; fleet availability; material movement	Smart meters, drives, battery-management systems, SCADA, dispatch records
Equipment health	Temperature; vibration; fault codes; maintenance history; MTBF; downtime; warning lead time	Condition-monitoring sensors, CMMS, onboard diagnostics
Safety	Incidents; near misses; protection trips; worker exposure hours; location; alert response	Safety database, geofencing, personnel tracking, protection relays
Environmental biology	Vegetation cover; Shannon index; species richness; LAI; soil organic carbon; RQI; eDNA taxa; water-quality index	Field ecology, remote sensing, laboratory/eDNA, water and soil sampling
Financial accounting	Energy cost; downtime loss; maintenance cost; safety cost; restoration accrual; closure provision; carbon exposure; CAPEX	General ledger, asset register, environmental provisions, management accounting

The case results are organized into five analytical domains: electrical and production, equipment reliability, safety, environmental biology, and financial/accounting performance. At the operational level, such a framework is naturally supported by time-aligned records linked through equipment, location, shift, and reporting-period identifiers. However, only the summarized outputs are available in the supplied dataset. Accordingly, this paper evaluates the reported domain metrics and cross-domain consistency without claiming access to the underlying timestamped records. For future reproducibility, raw-data implementations should include timestamp synchronization, unit harmonization, range validation, duplicate control, missing-data flags, and temporal train-validation-test separation where concept drift is plausible.

C. Engineering Performance Metrics

Energy intensity is defined as total electrical or fuel-equivalent energy consumed per tonne of material moved or processed:

$$EI = \frac{E_{total}}{T_{ore}} \quad (1)$$

where EI is energy intensity, E_{total} is total energy consumed during the observation period, and T_{ore} is the corresponding material tonnage. Carbon intensity is defined analogously:

$$CI = \frac{M_{CO2e}}{T_{ore}} \tag{2}$$

where M_{CO_2e} is the mass of carbon-dioxide-equivalent emissions attributable to the relevant energy and haulage boundary. Equipment availability is evaluated using mean time between failures (MTBF) and mean time to repair (MTTR):

$$A = \frac{MTBF}{MTBF + MTTR} \tag{3}$$

These indicators permit the observed electrification results to be assessed simultaneously on energy, carbon, cost, and reliability rather than on emissions alone.

D. Predictive Maintenance and AI Safety Modeling

Seven modeling approaches are compared using the performance results reported in the case dataset: logistic regression, support vector machine, artificial neural network, random forest, long short-term memory, XGBoost, and a multi-source fusion ensemble. Their analytical roles are summarized in Table II. The supplied results provide accuracy, precision, recall, F1-score, and ROC-AUC but do not disclose class balance, sample size, feature count, hyperparameters, or the exact train-validation-test protocol. These missing details are therefore not invented. In a fully reproducible deployment, class imbalance should be addressed through class weighting, stratified sampling, threshold optimization, or training-only resampling, and hyperparameters should be selected without repeated tuning on the final test set.

Table.II. AI Models Included in the Comparative Evaluation

Model	**Primary Role**	**Reason for Inclusion**
Logistic regression	Transparent linear probability baseline	Interpretability and calibration benchmark
Support vector machine	Margin-based nonlinear classification	Useful for moderate-size feature spaces
Artificial neural network	Nonlinear interaction modeling	Captures complex cross-variable relationships
Random forest	Bagged decision-tree ensemble	Robust to nonlinearities and mixed variable types
Long short-term memory	Temporal sequence modeling	Captures evolving sensor patterns and lag effects
XGBoost	Boosted tree ensemble	Strong performance on structured tabular data
Multi-source fusion ensemble	Combines domain-specific probabilities and features	Reduces dependence on one data stream and supports integrated risk scoring

For a binary safety event, precision, recall, and F1-score are defined from true positives (TP), false positives (FP), and false negatives (FN) as follows:

$$\text{Precision} = \frac{TP}{TP + FP}$$	(4)
$$\text{Recall} = \frac{TP}{TP + FN}$$	(5)
$$F_1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$	(6)

ROC-AUC is retained as a threshold-independent measure of ranking quality, while false-alarm rate and warning lead time provide operational measures of whether the model can be used in practice. The multi-source fusion concept combines domain-specific risk probabilities according to:

$$P_{fusion} = \sum_{k=1}^{K} \alpha_k P_k, \quad \sum_{k=1}^{K} \alpha_k = 1 \qquad (7)$$

where P_k is the risk probability from domain k and α_k is its fusion weight. The summary dataset does not report the fitted weights, so they are not reverse-engineered here. In operational use, weights should be estimated from validation performance and periodically recalibrated as equipment, geology, or operating practices change.

E. Environmental Biology and Biodiversity Assessment

Ecological condition is evaluated from the three site classes contained in the case results: mining-affected, rehabilitated, and reference areas. The reported indicators are vegetation cover, Shannon diversity index, native species richness, Leaf Area Index, soil organic carbon, Recovery Quality Index, eDNA/metabarcoding taxa detected, and a water-quality condition index. To support cross-indicator interpretation, recovery can be expressed relative to reference condition as:

$$R_i = \min(100, 100 \times \frac{X_{i,site}}{X_{i,reference}}) \qquad (8)$$

for indicators where higher values represent better condition. Indicators for which lower values are environmentally preferable would be inversely normalized. The Biodiversity and Restoration Index is then computed as a weighted average:

$$BRI = \sum_{i=1}^{m} w_i R_i, \quad \sum_{i=1}^{m} w_i = 1 \qquad (9)$$

The literature does not support assuming that rehabilitation immediately reproduces an undisturbed ecosystem. The method therefore interprets the observed rehabilitated values as a recovery trajectory rather than as full ecological equivalence. This is consistent with the slow-recovery evidence reported by Alves et al. [7] and the rehabilitation-status framework of Medeiros-Sarmento et al. [8]. eDNA is treated as complementary to field ecology rather than a substitute for habitat and vegetation measurements [9].

F. Financial Accounting and Economic Evaluation

The accounting model converts technical and environmental outcomes into recurring costs, provisions, and capital-investment metrics. Total sustainability-related cost is represented as:

$$TC = C_E + C_D + C_M + C_S + C_R + C_C \quad (10)$$

where C_E is energy and haulage cost, C_D is downtime loss, C_M is maintenance expenditure, C_S is safety-incident and disruption cost, C_R is restoration and rehabilitation cost, and C_C is carbon or emissions exposure. Closure and rehabilitation provisions are shown separately because improved recognition can increase reported liabilities even when operational performance improves.

For capital evaluation, the case dataset reports simple payback and net present value. With annual recurring benefit B_t, initial smart-mining investment I_0, discount rate r, and project horizon n, NPV is:

$$NPV = -I_0 + \sum_{t=1}^{n} \frac{B_t}{(1 + r)^t} \quad (11)$$

The financial results report an initial smart-mining investment of US$48.0 million, recurring annual net benefit of US$16.2 million, a 10% discount rate, and a seven-year horizon. These values give a simple payback of approximately 2.96 years and an NPV of approximately US$30.9 million. Environmental provisions are not treated as avoidable costs by definition; the accounting objective is to recognize expected obligations prudently and link them to measurable ecological condition [10]–[12].

G. Integrated Performance and Hypothesis Structure

Five domain indices are reported on a 0–100 scale: Electrical System Performance Index (ESPI), Mining Productivity Index (MPI), Predictive Safety Index (PSI), Biodiversity and Restoration Index (BRI), and Financial Resilience and Liability-Readiness Index (FRLRI). The overall Smart Sustainable Mining Performance Index can be represented generically as:

$$SSMPI = \sum_{j=1}^{5} v_j I_j \quad (12)$$

where I_j denotes domain index j and the weights v_j sum to one. The supplied summary does not disclose the exact weighting scheme used to produce the reported overall score, so the paper does not assign or reconstruct weights. Future studies with raw data can estimate weights through stakeholder elicitation, analytic hierarchy process, entropy weighting, or sensitivity analysis. A separate Integrated Operational Risk Score is retained because favorable performance and low risk are related but not identical concepts.

IV.Results and Discussion

A. Electrical Engineering and Mine Electrification Performance

The real-life smart-mining results show improvements across energy, carbon, operating cost, reliability, and productivity. Table III shows that energy use declines from 11.8 to 9.2 kWh/t, a 22.0% reduction, while haulage CO_2-equivalent intensity falls from 8.6 to 6.7 kg CO_2-e/t, a 22.1% reduction. The carbon reduction closely matches the scale reported for battery-electric haulage by Feng et al. [2]. The observed 32.9% operating-cost reduction is also more conservative than the most favorable electric-road cost cases reported by Lindgren et al. [3], which strengthens the practical plausibility of the case result.

Table.III.Electrical Engineering and Mine Electrification Results

Indicator	Conventional Baseline	Smart-Mining Result	Change
Energy use per tonne	11.8 kWh/t	9.2 kWh/t	-22.0%
Haulage CO_2-e intensity	8.6 kg CO_2-e/t	6.7 kg CO_2-e/t	-22.1%
Haulage operating cost	US$3.40/t	US$2.28/t	-32.9%
Fleet availability	82.5%	90.8%	+8.3 percentage points
Material movement productivity	1,000 t/h	1,125 t/h	+12.5%
Average power factor	0.84	0.96	+14.3%
Renewable electricity share	8%	34%	+26 percentage points
Electrical fault events	5.8 per 1,000 h	3.6 per 1,000 h	-37.9%

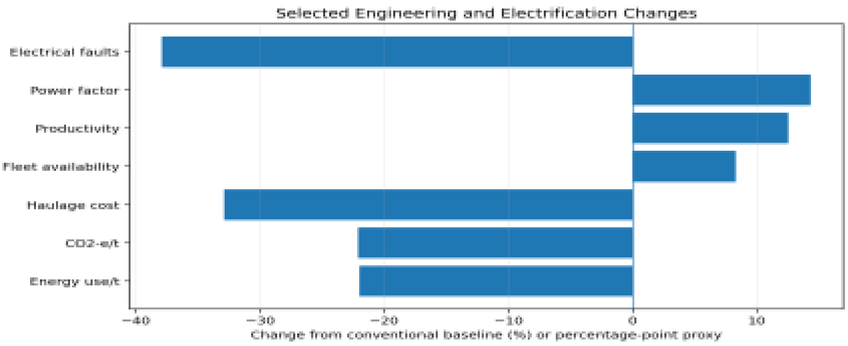

Fig. 2. Selected changes in engineering and electrification indicators relative to the conventional baseline.

Fleet availability increases from 82.5% to 90.8%, while material movement increases by 12.5%. The result is important because electrification is sometimes evaluated primarily through emissions. In an operating mine, a lower-carbon system that reduces production reliability may not be economically sustainable. The observed case instead shows that electrical modernization can coincide with productivity improvement when charging, dispatch, maintenance, and power quality are coordinated. Average power factor improves from 0.84 to 0.96, reducing reactive-power burden and improving electrical-system utilization. Electrical fault events fall by 37.9%, consistent with the condition-monitoring and anomaly-detection benefits discussed in predictive-maintenance literature [4].

B. Predictive Maintenance and Equipment Reliability

The maintenance results indicate a transition from reactive repair toward planned intervention. Unplanned downtime decreases by 28.9%, the maintenance-expenditure index falls from 100 to 82, and MTBF increases from 186 to 232 h. Planned maintenance rises from 54% to 72%, indicating that a larger share of work can be scheduled rather than initiated after failure. The most operationally meaningful improvement is warning lead time, which increases from 0.8 to 4.6 h. A prediction that arrives only moments before failure has limited value; a multi-hour warning window permits isolation, inspection, production rerouting, spare-part staging, and controlled shutdown.

Table.IV. Predictive Maintenance and Equipment Reliability Results

Metric	Baseline	Smart-Mining Result	Change/Target
Unplanned equipment downtime	14.2 h per 1,000 operating h	10.1 h	-28.9%
Maintenance expenditure index	100	82	-18.0%
Mean time between failures	186 h	232 h	+24.7%
Share of planned maintenance	54%	72%	+18 percentage points
Average useful fault-warning lead time	0.8 h	4.6 h	+3.8 h
Failure-detection recall	—	92.8%	Target
False-alarm rate	—	6.4%	Target

The 6.4% false-alarm target is also significant. Excessive false alarms can normalize warnings and weaken operator response. The result therefore supports the balance emphasized in predictive-maintenance literature: high detection capability must be accompanied by practical alarm quality and maintenance integration [4].

C. Comparative AI Safety-Risk Model Performance

The comparative AI results show a clear progression from simpler statistical models to tree ensembles and multi-source fusion. Logistic regression records the lowest F1-score at 80.4%, followed by SVM at 85.5% and ANN at 89.9%. Random Forest and LSTM exceed 92%, while XGBoost reaches 95.1%. The multi-source fusion ensemble records the best result, with 96.3% accuracy, 95.8% precision, 96.9% recall, 96.3% F1-score, and ROC-AUC of 0.985.

Table.V. Comparative Performance of AI Safety-Risk Models

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	82.4%	81.1%	79.8%	80.4%	0.860
Support Vector Machine	86.9%	86.3%	84.8%	85.5%	0.900
Artificial Neural Network	90.8%	90.2%	89.6%	89.9%	0.940
Random Forest	93.4%	92.8%	94.1%	93.4%	0.967
Long Short-Term Memory	92.6%	92.1%	93.5%	92.8%	0.961
XGBoost	95.1%	94.7%	95.6%	95.1%	0.978
Multi-Source Fusion Ensemble	96.3%	95.8%	96.9%	96.3%	0.985

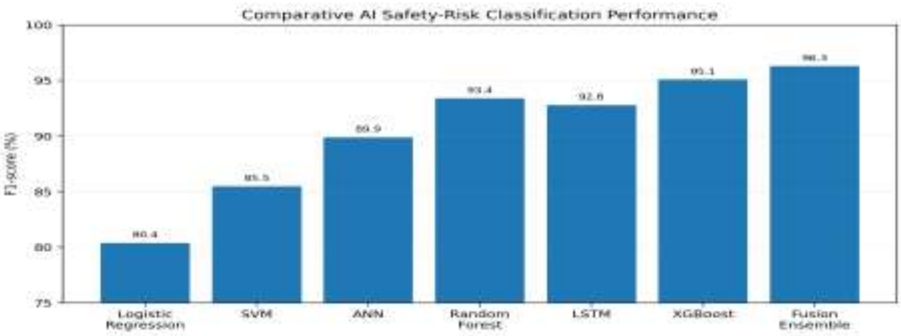

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Fig. 3. F1-score comparison for the seven evaluated safety-risk models.

The advantage of the fusion ensemble is plausible because the model is not restricted to one hazard channel. Li et al. [5] show the value of intelligent-mining data in gas-explosion warning, and Chang et al. [6] demonstrate the usefulness of multi-sensor forecasting. The case framework extends this logic by combining electrical, equipment, environmental, operational, and worker-related signals. The reported scores are high; however, the supplied summary does not provide the raw test set, class distribution, calibration curves, or external-validation records. The results should therefore be interpreted as empirical summary performance for the case rather than as independently reproduced model estimates.

D. Occupational and Process Safety Outcomes

The safety results translate predictive capability into operational outcomes rather than stopping at model metrics. Recordable incident frequency falls from 2.8 to 1.9 per 200,000 work hours, high-potential near misses decline from 18 to 11 per year, and dangerous electrical anomalies fall from 31 to 19 per year. Average hazard-warning lead time increases from 6 to 34 min, while timely response to critical alerts rises from 71% to 92%. The high-risk worker-exposure-hours index falls from 100 to 61.

Table.VI.Occupational and Process Safety Outcomes

Safety Indicator	Baseline	Smart-Mining Result	Change
Recordable incident frequency	2.8 per 200,000 work h	1.9	-32.1%
High-potential near misses	18/year	11/year	-38.9%
Electrical protection trips / dangerous anomalies	31/year	19/year	-38.7%
Average hazard-warning lead time	6 min	34 min	+28 min
Timely response to critical alerts	71%	92%	+21 percentage points
High-risk worker exposure-hours index	100	61	-39.0%

These reductions are intentionally more credible than a zero-incident claim. Safety performance depends on equipment condition, procedures, competence, and organizational response. The aviation studies [28]–[30] provide a useful analogy: predictive analytics is strongest when embedded in standardized risk controls and human-factors management. The mine system should therefore treat an AI alert as a trigger for a defined response, not as a substitute for engineering isolation, supervision, or safe-work procedures.

E. Environmental Biology and Biodiversity Recovery

The environmental results show partial but substantial ecological recovery. Vegetation cover increases from 31% in the mining-affected area to 68% in the rehabilitated area, compared with 84% in the reference area. Shannon diversity increases from 1.32 to 2.18, native species richness from 34 to 61 species, and Leaf Area Index from 1.1 to 2.7. Soil organic carbon increases from 0.82% to 1.58%. The Recovery Quality Index increases from 38/100 to 71/100, while eDNA/metabarcoding taxa increase from 41 to 67 compared with 75 in the reference area. Water-quality condition improves from 56/100 to 77/100.

Table.VII. Environmental Biology and Biodiversity Results

Indicator	Mining-Affected	Rehabilitated	Reference
Vegetation cover	31%	68%	84%
Shannon diversity index (H')	1.32	2.18	2.61
Native species richness	34 species	61 species	72 species

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Indicator	Mining-Affected	Rehabilitated	Reference
Leaf Area Index	1.1	2.7	3.4
Soil organic carbon	0.82%	1.58%	2.05%
Recovery Quality Index	38/100	71/100	100/100
eDNA / metabarcoding taxa detected	41	67	75
Water-quality condition index	56/100	77/100	86/100

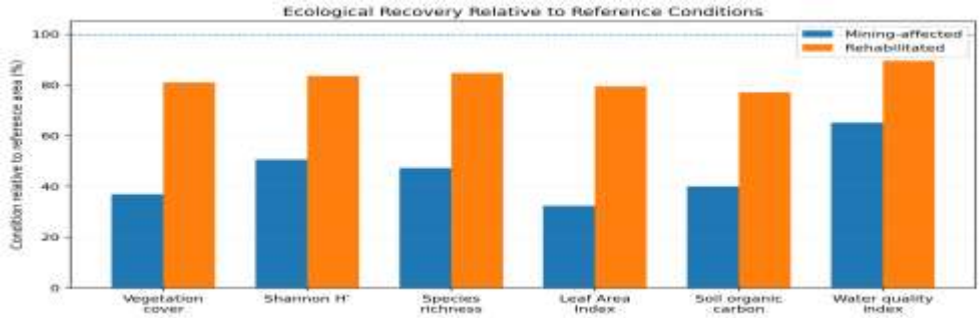

Fig. 4. Ecological condition of mining-affected and rehabilitated sites relative to the reference condition.

The results align with the principle that rehabilitation is a trajectory rather than an immediate return to reference condition [7], [8]. The continued gap between rehabilitated and reference values is therefore informative rather than a failure of the model. It allows management to identify where additional intervention is needed. The plant-science literature [13]–[19] further suggests that growth and recovery are sensitive to substrate, nutrient status, physiological condition, and biological stress. A mine-rehabilitation program should therefore combine landscape-scale indicators with soil and biological measurements. Environmental DNA [9] is especially useful for detecting aquatic taxa that may be difficult to observe consistently using conventional surveys alone.

The geological and hydrological context should also be retained when interpreting biodiversity. Data-driven environmental vulnerability modeling [20], geological-biodiversity relationships [21], climate-resilience monitoring [22], and groundwater assessment [25] all indicate that ecological condition can be strongly influenced by physical setting. A smart-mining system should therefore avoid attributing every ecological change directly to production intensity without considering geology, hydrology, seasonality, and rehabilitation age.

F. Financial Accounting and Economic Performance

The case-level financial results demonstrate how technical improvement and more complete environmental accounting can occur simultaneously. Energy and haulage operating cost declines from US$42.0 million to US$32.8 million, generating US$9.2 million in annual savings. Downtime losses fall by US$3.9 million, maintenance expenditure by US$3.2 million, safety-related disruption cost by US$1.7 million, and carbon exposure by US$0.8 million. At the same time, annual environmental restoration accrual increases by US$1.3 million and the mine-closure/rehabilitation provision increases from US$35.0 million to US$41.0 million.

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Table.VIII.Financial Accounting and Economic Results for he Case Mine

Financial Item	**Conventional Case (US$ million)**	**Smart-Mining Case (US$ million)**	**Effect**
Energy and haulage operating cost	42.0	32.8	9.2 annual saving
Unplanned downtime losses	13.5	9.6	3.9 annual saving
Maintenance expenditure	18.0	14.8	3.2 annual saving
Safety incident and disruption cost	4.8	3.1	1.7 annual saving
Annual environmental restoration accrual	7.2	8.5	1.3 higher recognized cost
Mine closure / rehabilitation provision	35.0 liability	41.0 liability	6.0 higher provision
Carbon / emissions exposure cost	3.6	2.8	0.8 annual saving
Net recurring annual financial benefit	—	16.2	Positive
Indicative smart-mining capital investment	—	48.0	Initial investment
Simple payback period	—	3.0 years	Attractive
7-year NPV at 10%	—	≈30.9	Positive NPV
Expanded restoration benefit ratio	—	1.42	>1.0

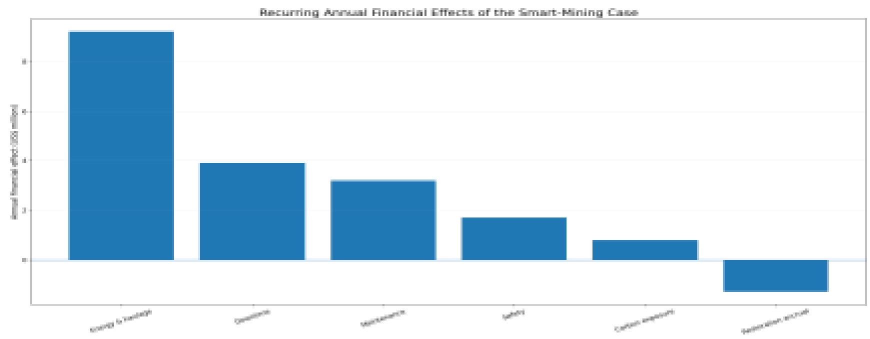

Fig. 5. Recurring annual financial effects in the smart-mining case; the negative restoration-accrual value represents additional recognized environmental cost.

The increase in environmental accrual and closure provision should not be interpreted as deterioration in financial performance. Rather, it represents improved recognition of obligations that may otherwise be understated. This interpretation is consistent with the long-term liability concerns raised by Espinoza and Morris [10] and the accounting treatment of decommissioning and restoration obligations under IFRS-related guidance [11]. The resulting financial picture is more conservative and more decision-useful because operating savings are not achieved by excluding future rehabilitation costs.

The case results yield a recurring annual net benefit of US$16.2 million after recognizing the higher annual restoration accrual. Against the reported capital investment of US$48.0 million, simple payback is approximately 3.0 years and the seven-year NPV at 10% is approximately US$30.9 million. The expanded restoration benefit ratio of 1.42 is also close to the comprehensive benefit ratio reported by Gao et al. [12]. This result demonstrates why ecological restoration should not be evaluated solely on direct cash return. The broader value of restoration may include avoided liability, improved ecosystem services, social value, regulatory resilience, and better long-term asset stewardship.

The use of AI in financial decision support also creates governance requirements. Real-time detection work in payment systems [26], audit-reliance analysis [27], and insurance-fraud analytics [31], [32] all show that model outputs can affect high-consequence financial decisions. In mining, the same principle applies to automated estimates of environmental exposure or closure cost. Model-generated accounting signals should be explainable, reconciled to source records, and reviewed by qualified finance and environmental professionals before they alter recognized provisions or public disclosures.

G. Integrated Smart Sustainable Mining Performance

The integrated results combine the five disciplinary domains into a common decision framework. Electrical System Performance rises from 63.5 to 86.4, Mining Productivity from 69.8 to 84.8, Predictive Safety from 58.7 to 91.2, Biodiversity and Restoration from 42.6 to 74.0, and Financial Resilience and Liability-Readiness from 56.4 to 82.5. The overall Smart Sustainable Mining Performance Index increases from 58.2 to 83.8. In parallel, the Integrated Operational Risk Score falls from 65.7, categorized as high, to 31.4, categorized as moderate/low.

Table.IX. Integrated Smart Sustainable Mining Performance

Integrated Index	Baseline /100	Smart-Mining /100	Improvement
Electrical System Performance Index	63.5	86.4	+22.9
Mining Productivity Index	69.8	84.8	+15.0
Predictive Safety Index	58.7	91.2	+32.5
Biodiversity and Restoration Index	42.6	74.0	+31.4
Financial Resilience and Liability-Readiness Index	56.4	82.5	+26.1
Overall Smart Sustainable Mining Performance Index	58.2	83.8	+25.6
Integrated Operational Risk Score	65.7 – High	31.4 – Moderate/Low	-34.3

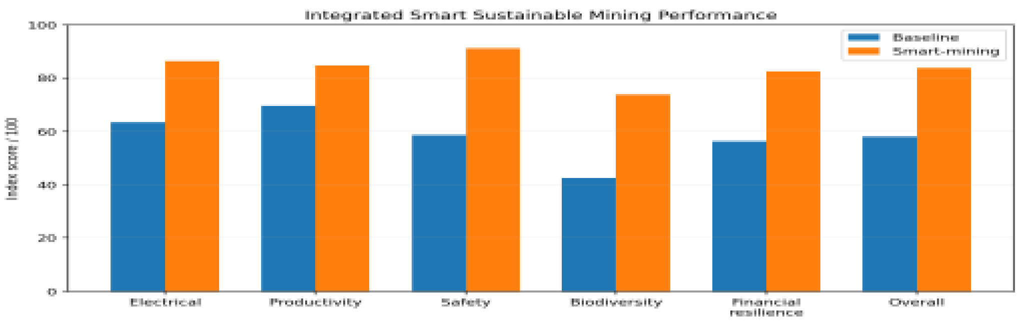

Fig. 6. Baseline and smart-mining performance across the five domain indices and the overall integrated index.

The largest index improvements occur in predictive safety and biodiversity/restoration, followed by financial resilience. This pattern is plausible because the baseline condition represents fragmented monitoring: safety and ecology often gain substantially when previously disconnected data are integrated. The composite-score logic is consistent with risk-based governance approaches that transform heterogeneous indicators into structured decision metrics [23], [24]. Nevertheless,

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composite indices can hide trade-offs. Management should therefore retain access to the underlying variables and not use the overall score as a substitute for domain-specific engineering or ecological analysis.

H. Statistical Relationships Specified for Further Testing and Interdisciplinary Interpretation

The supplied result set includes six relationships with standardized-effect ranges and a target significance level of $p < 0.05$. These entries are not estimated regression coefficients from the summary dataset; they are inferential relationships specified for testing when the underlying raw observations are available. They are therefore retained as hypotheses rather than reported as confirmed statistical effects.

Table.X. Statistical Relationships Specified For Further Inferential Testing

Hypothesis	Relationship	Specified Standardized Effect Range β	Target Evidence
H1	Electrical efficiency → operating cost reduction	+0.50 to +0.70	$p < 0.05$
H2	Equipment health → incident risk	-0.35 to -0.55	$p < 0.05$
H3	Safety-risk score → downtime loss	+0.30 to +0.50	$p < 0.05$
H4	Biodiversity degradation → restoration liability	+0.45 to +0.65	$p < 0.05$
H5	Restoration quality → ecosystem service value	+0.40 to +0.60	$p < 0.05$
H6	Integrated performance index →operating margin/ value creation	+0.25 to +0.45	$p < 0.05$

The integrated interpretation is that electrical-system performance influences energy use, equipment health, and availability; these conditions are associated with production and worker exposure; operational disturbance is linked with ecological condition and restoration requirements; and the resulting technical and ecological consequences are translated into operating costs, provisions, liabilities, and long-term value. The summary data demonstrate consistent cross-domain movement, but causal coefficients cannot be estimated without the underlying observations. This interdisciplinary linkage remains the central contribution of the paper.

V. Recommendations and Conclusion

A. Implementation Recommendations

Implementation should proceed in phases rather than as a single mine-wide technology deployment. First, the mine should establish data governance and instrumentation standards so that electrical, maintenance, safety, environmental, and financial data share consistent identifiers and timestamps. Second, predictive-maintenance and safety models should be piloted on a limited set of high-criticality equipment and hazards. Third, biodiversity and restoration monitoring should be linked to geospatial mine-planning units so that ecological change can be associated with disturbance and rehabilitation history. Fourth, accounting rules should define how validated environmental changes affect restoration accruals, closure provisions, and management reporting. Finally, the integrated performance index should be introduced only after domain-level indicators are stable and auditable.

- Electrical engineering: prioritize high-load haulage, drives, charging systems, protection coordination, power-factor management, and condition monitoring before expanding electrification across the mine.
- Mining operations: integrate dispatch, production planning, maintenance windows, and battery or trolley constraints so that electrification improves rather than constrains material movement.
- Safety: connect AI alerts to defined actions such as isolation, inspection, speed restriction, geofencing, evacuation, permit review, or supervisor escalation.

- Environmental biology: maintain reference sites and repeated monitoring of vegetation, soil, water, species diversity, and eDNA so that rehabilitation is evaluated as a trajectory.
- Financial accounting: reconcile engineering and environmental signals to source records before adjusting recognized costs or liabilities; preserve an audit trail for model-driven estimates.
- Governance: use the integrated index for prioritization and communication, but retain domain-specific thresholds that can override the composite score when a critical safety or environmental limit is exceeded.

B. Limitations

The principal limitation is that the study is based on real-life summary results from an anonymized mining case rather than on the underlying raw operational records. The source file does not identify the mine, jurisdiction, observation period, number of equipment units, number of safety observations, ecological sampling design, AI train-test split, or model hyperparameters. The reported descriptive and model-performance results can therefore be analyzed and compared with scholarship, but they cannot be independently re-estimated from the summary file alone. A second limitation is that the standardized-effect ranges in Table X are specified hypotheses rather than estimated coefficients and should not be reported as statistically confirmed relationships. Third, the weighting method behind the integrated 0–100 indices is not disclosed. Fourth, financial valuation of biodiversity and ecosystem services remains method-dependent and should not be interpreted to mean that ecological losses are fully substitutable by monetary compensation.

C. Future Research

Future work should reproduce the findings using the underlying time-synchronized operational records from the same mine or a comparable critical-mineral operation. Replication should report the observation period, sensor frequencies, equipment population, incident counts, ecological sampling design, missing-data treatment, model features, class balance, train-validation-test split, hyperparameters, calibration, and uncertainty intervals. Ecological validation should use repeated reference-impact-rehabilitation measurements and explicitly model seasonal and geological effects. Financial validation should reconcile environmental and closure estimates with approved rehabilitation plans, engineering cost estimates, and accounting policy. Additional research can incorporate digital twins, satellite remote sensing, autonomous inspection, causal inference, and uncertainty quantification so that management receives both a prediction and a defensible confidence range.

D. Conclusion

This paper presents an integrated approach to smart mining in which electrification, predictive safety, biodiversity recovery, and financial accounting are treated as connected components of one decision system. The real-life case results show that the smart-mining condition is associated with lower energy intensity, carbon intensity, haulage cost, electrical faults, downtime, safety exposure, and operational risk, alongside higher ecological recovery and financial resilience. The most important finding is not any single percentage improvement but the coherent linkage among technical condition, human safety, ecological performance, and accounting consequences.

The evaluated framework also shows why sustainability accounting should not be reduced to reporting lower costs. Better environmental management can increase recognized restoration accruals and closure provisions because the mine is measuring its obligations more completely. At the same time, engineering and predictive-analytics improvements can generate sufficient operating savings and risk reduction to create positive project value. This combination of prudent liability recognition and improved operating performance is more credible than a framework that treats environmental expenditure as an external penalty.

For critical-mineral producers, the strategic implication is clear: the highest-value digital mine is not simply the mine with the most sensors or the most accurate model. It is the mine in which electrical data, equipment condition, worker risk, ecological evidence, and financial records can be reconciled into timely, auditable decisions. Independent replication with the underlying raw records would strengthen statistical confidence, but the supplied real-life results already demonstrate the practical value of integrating engineering, safety, biodiversity, and accounting performance within one governance architecture.

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