Artificial Intelligence and Digitalization as a Response to New Challenges in Underground Mining

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Abstract: Underground mining faces unprecedented challenges requiring real-time information access at operational and strategic levels. Digitalization of mining processes and systematic implementation of artificial intelligence are fundamentally reshaping the industry's operational paradigm. Modern AI-driven solutions enable comprehensive real-time monitoring of equipment utilization and technical condition, transforming both tactical decision-making and long-term strategic planning. The integration of artificial intelligence with digital twins opens unprecedented opportunities for optimizing resource management and predicting technological outcomes with 85-95% accuracy. Contemporary mining demands intelligent tools that transcend historical data analysis, supporting dynamic management through automated reporting, predictive equipment reliability assessment, and continuous workplace condition monitoring. This paper synthesizes a decade of implementation projects and scientific research, presenting practical examples of AI applications across the mining value chain - from exploration and planning through production, transport, mineral processing, and metallurgical operations. The paper address key challenges in implementing AI across diverse operational scales, identify success factors, and provide recommendations for mining enterprises seeking to realize the transformative potential of artificial intelligence in underground operations.

1 INTRODUCTION

Monitoring and predicting hazards based on observation is not a modern invention. Nearly three thousand years before our era, the Egyptians constructed nilometers - specialized wells for measuring water levels in the Nile, which served to forecast river floods and plan agricultural activities and taxation systems. In Babylon, decisions regarding agricultural economy and tax collection were based on observations of celestial bodies, while Greek oracles were far more than mere "fortune-tellers" - they functionally served as early analytical agencies, interpreting signals from their environment. Similarly, the Incas utilized astronomy for agricultural planning; such practices - though in more disguised form - continue to appear in the background of decision-making processes in certain modern business cultures. Mining, from its earliest stages, adhered to this paradigm of "intuitive analytics." Until the early twentieth century, hazard detection relied on simple observations: rats fleeing a mine shaft signaled an impending collapse, while canaries functioned as living carbon monoxide sensors - a practice that continued into the twentieth century. Ore body recognition and hazard assessment often reduced to elementary methods: "divination," observation of water, its taste, color, or odor. All these were, in their time, attempts to extract decision-relevant information from severely limited environmental data. Only the development of statistics and probability theory in the nineteenth and twentieth centuries introduced systematic, quantitative analysis of risk and physical phenomena. In the latter half of the twentieth century, the first expert systems emerged - attempts to encode engineering knowledge as rules and simple heuristics. In mining, these were applied to hazard assessment and maintenance support, yet their susceptibility to errors, difficulty in updating, and brittleness when confronted with actual mine conditions limited their scope. Concurrently, classical machine learning methods developed, but only the deep learning breakthrough triggered a genuine transformation in project scale and ambition. The breakthrough associated with deep neural networks - including AlexNet's success in the ImageNet competition in 2012 - demonstrated that models could autonomously extract relevant features from data and surpass classical approaches based on manual feature selection and threshold setting [1]. A few years later, the first applications of these methods began penetrating industrial sectors adjacent to mining, and subsequently - though with some delay - underground mining operations themselves. Initially, these were pilots in predictive maintenance and production optimization, gradually expanding to more ambitious applications. Merely generations ago, the primary "warning system" in a mine was a small bird in a cage; today, we speak of deep neural networks, billions of measurement records, and digital twins of underground workings.

This paper aims to synthesize a decade of artificial intelligence application development in underground mining, with particular emphasis on deep mines and constraints arising from environmental and infrastructural conditions. The work integrates dispersed scientific research findings and industrial implementations, organizing them according to various underground mining applications. The paper also identifies key technical, organizational, and regulatory barriers limiting AI solution scalability in underground mining, and highlights research areas with greatest potential for practical impact.

2 WHY ANALYTICS IN MINING

Classical frameworks identify four industrial revolutions. The first was associated with mechanization and the harnessing of water and steam power, which in mining meant transitioning from exclusively manual tools to machines supporting dewatering, transport, and ore extraction. The second revolution - the era of fossil fuels and electrification - brought large-scale machinery, electric motors, lighting, and substantially increased mining scale. The third, computerized revolution, introduced electronics, programmable logic controllers (PLCs), and SCADA systems, enabling remote sensing of machine parameters, basic automation, and the first decision-support systems. We currently operate within the fourth industrial revolution - the era of Big Data, the Internet of Things, and intelligent machines [2], [3]. An "intelligent machine" is not merely an automated device. It is a system capable of independently collecting data from its environment, analyzing it, making decisions based on that analysis, and exchanging information with other machines and supervisory systems. A critical question thus emerges: what scales of data are we discussing in practice? Data generated by contemporary systems are orders of magnitude larger than ever before. An average smartphone generates approximately 2.5 GB of data daily; a modern personal vehicle, around 25 GB; an IoT system monitoring mining processes can produce 100 GB daily or more; and an autonomous haul truck may generate as much as 1,000 GB in a single day [4], [5]. For comparison: during the Apollo 13 mission in 1969, only several hundred megabytes of telemetry data were collected - equivalent to what a single industrial device can generate in a brief operational period today. Underground mining is a natural beneficiary and proving ground for Industry 4.0 solutions for several reasons [6]. First, it is inherently a high-risk environment where every opportunity to remove personnel from hazardous zones - through remote operation, autonomy, or better forecasting - carries direct safety implications. Second, modern deep mines generate enormous data streams from vibration sensors, seismic sensors, gas sensors, geodetic instruments, environmental monitoring systems, personnel and equipment locating systems, and technological process recorders. Third, increasing extraction depth, declining ore quality, and ESG requirements compel rising operational efficiency and process transparency, difficult to achieve through traditional management methods alone.

2.1 The Role of Humans

Significant concerns have emerged surrounding AI implementation in mining. Some workers perceive analytical systems as tools for job elimination, intensified surveillance, and "corporate policing" - much as electricity, steam engines, telephones, computers, and industrial robots were once feared. These concerns are understandable, but they need not - and should not - determine technology's development trajectory. Properly designed and implemented artificial intelligence in mining serves a different purpose: relieving workers from tedious reporting duties, providing faster and more precise information access, improving training processes (through simulations and digital twins), supporting decision-making through enhanced situational awareness, and introducing autonomy where human presence poses the greatest risk. This is analogous to a vehicle's backup camera: it does not replace the driver but significantly expands his field of vision and maneuver safety. However, the human factor remains critical. Engineers, operators, and mining experts must adapt AI solutions to the specific realities of each mine and subsequently monitor their performance under changing conditions. This underscores the growing importance of interdisciplinary Data Science teams within mining enterprises. Such teams should integrate expertise in mathematics and statistics, electronics and measurement systems, Big Data analytics, cybersecurity, GIS systems, and mining engineering. Their primary mission is not to create "artificial intelligence for its own sake" but to build concrete analytical tools supporting operational and decision-making processes at various management levels throughout the mine - from developing data analysis procedures, through diagnostic tools for key processes (transport, extraction, dewatering, ventilation), to specialized decision-support systems [4], [5].

2.2 The Role of Situational Analytics in Modern Mining Operations

Decision-making under uncertainty constitutes an integral component of extractive industry operations, where geological, environmental, and operational variables generate inherent risk. In contemporary practice, it is imperative to minimize intuitive decision-making or reliance upon catalog data alone, particularly when technology enabling detailed process monitoring is available. Consequently, continuous development and refinement of monitoring systems and specialized computational engineering, analytical, simulation, and optimization environments are critical to fully harness mining operations' potential. Such tools enable a strategic shift from reactive problem-solving toward proactive risk management and scenario-based planning [7]. Technological progress in this domain has been driven primarily by computer development and availability, increased computational power, and growing user interest from the mining sector. Early solutions, documented in the literature decades ago, concentrated on extraction planning and scheduling, with simulation models emerging concurrently. The development of specialized analytical environments spanned the period from the mid-1990s through approximately 2005, eventually becoming standard infrastructure components in major mining facilities. Since approximately 2013, specialized cyber-physical systems have assumed increasingly prominent roles, utilizing digital twins to manage transport processes and other critical operational areas - enabling near-real-time scenario analysis and substantially reducing decision uncertainty [8]-[10]. In the initial phase, many solutions relied upon simplified analytical models, fed with catalog data or averaged statistics, which - given the highly stochastic nature of mining processes (particularly haulage and extraction) - constrained their accuracy and operational utility. The critical qualitative shift emerged through access to real-time measured data and the ability to track ore flow through transport networks in both time and space, accounting for operational contexts. The breakthrough came with the introduction of extensive monitoring equipment arrays and the construction of broadband telecommunications networks utilizing fiber-optic technology - infrastructure that became practically accessible in underground mines only within the past decade. From that point forward, full, bidirectional information exchange between underground workings and surface facilities became feasible [7].

Acquiring merely a fraction of contemporary data volumes in earlier eras would have necessitated enormous quantities of manual measurements and required immeasurable human resources, while still failing to ensure comparable information quality and accessibility. Today, these data can be collected and processed in near-real-time through Operational Technology (OT), whose foundation in mining comprises SCADA-class systems and associated IoT platforms. These systems constitute the essential foundation for AI applications - spanning from predictive maintenance to advanced decision-support systems - because they enable model construction based upon actual operational conditions rather than hypothetical scenarios [9]-[12].

3 ADVANCING UNDERGROUND MINING OPERATIONS THOUGHT ARTIFICIAL INTELLIGENCE

Artificial intelligence is becoming one of the key pillars of the mining industry's transformation, spanning the entire mine life cycle-from geological exploration, through design and operation, to mineral processing, waste management, and reclamation. The term AI here encompasses classic machine learning methods (e.g., nonlinear regression, trees, random forests, SVM, boosting), deep neural networks (CNNs, RNNs, LSTMs, autoencoders), as well as heuristic optimization methods and decision support systems that combine data-driven models with expert knowledge. The common denominator across these applications is the ability to leverage growing reserves of data-operational, production, spatial, and economic-to forecast, optimize, and automate processes.

Figure 1: The main AI development priorities in the value chain.

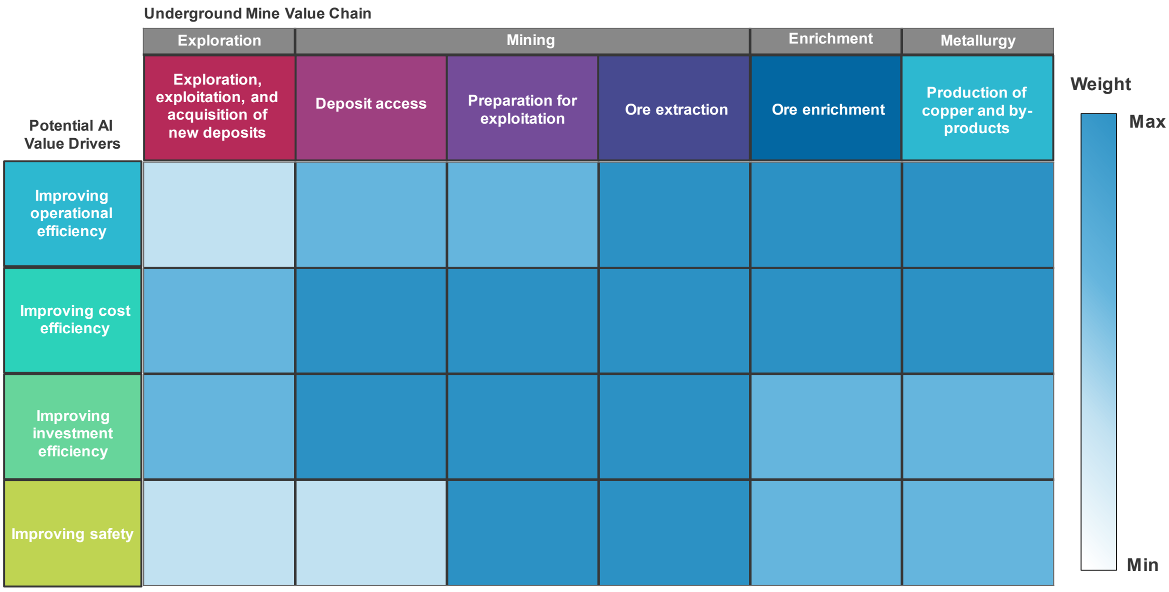

Figure 2. The main AI development priorities in the value chain.

AI applications in mining can be broadly categorized into several problem classes. The key areas of AI application within the technological process of underground mines, as identified in the literature, are presented in Figure 1.

During the exploration phase, the primary objective is to reduce geological uncertainty and the costs of deposit appraisal. Machine learning models are utilized to predict the occurrence of deposits based on complex input datasets, including geological maps, geophysical measurements, geochemical data, and satellite information. Deep neural networks are increasingly being used for facies classification, interpretation of geological images, and direct prediction of mineral quality parameters from drilling data or core scans. These types of models enable the construction of more realistic, probabilistic deposit models that subsequently feed into the design and economic evaluation stages [13]-[17]. At the design and planning stage of mine workings, AI assists in selecting exploitation methods, designing the layout of excavations, and scheduling development and extraction. Both multi-criteria decision support methods and optimization algorithms based on heuristics and metaheuristics are applied. The goal is to find a compromise between the project's economic value, safety, and the limitation of environmental impact. In a growing number of studies, these models are integrated with digital deposit models and simulations of material flow and safety parameters, effectively creating the foundation for "digital twins" of the mine [18]-[20]. In the exploitation phase, AI models that predict rock mass loads and deformations are crucial, supporting the selection of ground support and operational parameters. Also important are predictive maintenance systems that analyze signals from machinery (vibrations, currents, pressures) to detect faults in advance. Increasingly, data from machines, environmental sensors, and systems for locating people and equipment are aggregated on centralized analytical platforms, which provide operators with synthesized indicators and recommendations in near-real-time [21]-[23]. In mechanical processing and enrichment, AI primarily serves as the "brain" for advanced process control systems. Regression models and deep networks trained on historical data can predict recovery, concentrate quality, and process states, which in turn allows for the optimization of settings for flotation cells, mills, classifiers, or sorters. A growing number of implementations feature the integration of image analysis (e.g., of conveyor belt screenings, flotation froth) with classic process data, enabling the development of more sensitive and stable controllers. These applications translate into both improved technological indicators and reduced consumption of energy, media, and reagents [24]-[30]. AI in metallurgy is primarily applied for predictive maintenance of blast furnace refractory linings, where monitoring systems use thermocouple data and inverse heat conduction models to predict erosion profiles and remaining lining thickness. Neural networks, optimization algorithms, and advanced diagnostics enable real-time assessment of equipment condition, production process optimization across multiple variables, and early detection of potential failures. AI-driven safety and risk management systems analyze sensor data to forecast critical failures, recommend preventive maintenance strategies, and support operational decision-making, helping to reduce unplanned downtime, extend equipment life, and improve overall operational safety [31]-[34]. In the area of safety, health, and environmental monitoring, AI systems process data from networks of sensors distributed throughout the mining infrastructure. Classification and anomaly detection models are used to identify hazardous conditions in the mine atmosphere, analyze seismic and rock burst threats, detect endogenous fires, and recognize dangerous situations in camera footage [35]-[37]. A separate, rapidly developing group of applications involves the monitoring of complex facilities, such as waste dumps, spoil heaps, and tailings storage facilities, where AI analyzes data from inclinometers, piezometers, geodetic surveys, drones, and satellites to provide early detection of concerning changes. At the enterprise level, models based on production, economic, and environmental data support risk management, environmental footprint assessment, and the design of transformation pathways toward sustainable mining [38]-[42].

4 PERSPECTIVES, CHALLENGES AND NEW DIRECTIONS OF AI IN UNDERGROUND MINING

The transition from Mining 4.0 to Mining 5.0 represents an evolution from traditional digital systems toward integrated cyber-physical architectures that combine artificial intelligence, IoT, and autonomous collaborative robots. The Mining 5.0 model prioritizes human-centric production with strong emphasis on worker safety, ecosystem restoration, and green energy, which are all crucial directions for sustainable underground extraction. Many mining organizations are currently experimenting with digital twins, SLAM-based underground navigation, and neural networks for predicting equipment failures 24-48 hours in advance. Emerging technologies such as blockchain for value chain traceability, cloud-based data processing, and AI-driven optimization can improve operational performance by roughly 15-40% while simultaneously reducing operating costs [43]. The main AI development priorities in the value chain identified in the literature are presented in Figure 2.

The obstacles to implementing AI in underground mining can be grouped into four categories: operational, organizational, technical, and regulatory. Operational challenges include the sector's limited digital maturity, with about 70% of small and medium-sized mines still lacking even basic automation systems. Approximately 34% of mining companies worldwide identify insufficient AI skills and knowledge as a key barrier, while 29% point to the prohibitive cost of deploying such systems. Organizational challenges relate to workforce resistance, shortages of specialized staff, and the need for a fundamental shift in organizational culture. Technical challenges include difficulties integrating legacy ERP systems, ensuring cybersecurity (requiring significantly more intensive network monitoring underground), and overcoming the constraints of wireless communication in deep deposits. Regulatory and internal constraints involve legislation that still mandates paper documentation, limited access to machine data due to vendor lock-in, and the lack of standardized communication protocols across the industry. Studies indicate that the average time required to implement a fully integrated digital system is 3-5 years for large mines, reflecting process complexity and fragmented digitalization [43]-[46].

5 CONCLUSIONS

Artificial intelligence is fundamentally reshaping underground mining, transforming the industry from one based on intuition and experience into a technology-driven sector powered by advanced analytics, real-time monitoring, and automation. Over the past decade, research and industry deployments have proven that AI solutions reach a high degree of maturity in key domains-from resource exploration, through mine planning and operational monitoring, to workforce safety. The pace and effectiveness of AI adoption, however, depends on critical factors such as mine scale, spatial complexity, number of operational units, and existing process digitalization. Realizing the full potential of AI requires comprehensive, stepwise integration across all mining layers, enabling unified information architecture from exploration and planning, through extraction and haulage, to mineral processing and metallurgy.

Despite enormous opportunities-particularly in cost optimization, supply chain management, and workforce training-successful AI implementation is still challenged by operational, organizational, technical, and regulatory barriers. Key difficulties include a lack of digital maturity among small and medium mines, workforce skills gaps, high entry costs, and the need for deep organizational change. Effective AI transformation, therefore, demands strategic leadership, cultural evolution, modern IT infrastructure, and supportive regulatory frameworks. Systematic personnel training remains critical, as enterprises with well-trained teams see substantially higher returns on AI investment. The vision for mining's future is one where human expertise is leveraged by intelligent systems, shifting operators away from repetitive tasks toward strategic decision-making and continuous innovation.

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