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Mohammad. Najafi¹, Mohammad Ali. Keramati^{1*}, Hossein. Moinsad¹, Safiyeh. Mehri Nejad²

1 Department of Industrial Management, CT.C., Islamic Azad University, Tehran, Iran
2 Department of Financial Management, CT.C., Islamic Azad University, Tehran, Iran

Corresponding author email address:
keramati@iau.ac.ir

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Developing a Systemic Model of Intelligent Industrial Control Using a Grounded Theory Approach

ABSTRACT

The present study aimed to develop a systemic model of intelligent industrial control in ore mines using a grounded theory approach. In terms of purpose, the study was applied, and in terms of methodology, it was qualitative. The research population consisted of academic experts, managers, and specialists in mining, industrial control, automation, information technology, and artificial intelligence. Using purposive and snowball sampling, 15 participants were selected until theoretical saturation was reached. The data were collected through semi-structured interviews and analyzed according to the systematic grounded theory approach of Strauss and Corbin through open, axial, and selective coding. During the analysis process, 180 initial codes were extracted and, following refinement, organized into 144 final codes, 24 subcategories, and six main categories. The findings indicated that the final model comprised six dimensions: causal conditions, the central phenomenon, contextual conditions, intervening conditions, strategies, and consequences. Within the causal conditions, equipment deterioration, inadequate data infrastructure, operational risks, and the need for intelligent decision-making were identified as the most important influencing factors. The central phenomenon was a data-mining-based intelligent industrial control system, which develops within a context of technological infrastructure, organizational readiness, and specialized human resources and is influenced by intervening conditions such as economic constraints, technical challenges, legal requirements, and human factors. Strategies such as implementing intelligent monitoring systems, applying data mining and artificial intelligence, developing predictive maintenance, and establishing data governance were also identified as the principal actions required to realize this system. The implementation of these strategies leads to consequences such as increased operational productivity, enhanced safety, reduced maintenance costs, improved equipment reliability, higher-quality decision-making, and the realization of smart mining. By integrating technological, managerial, organizational, and environmental dimensions, the proposed model provides a comprehensive framework for designing and implementing intelligent industrial control systems in ore mines. It can serve as a roadmap for digital transformation, productivity enhancement, and sustainability improvement in the mining industry for managers, policymakers, and researchers.

Keywords: control system, intelligent industrial control, grounded theory

Introduction

The mining industry is undergoing a profound transformation as digital technologies increasingly reshape the planning, extraction, processing, maintenance, safety, and managerial control of mineral operations. Ore mines are complex sociotechnical environments in which heavy machinery, geological uncertainty, hazardous working conditions, geographically dispersed facilities, and highly interdependent production processes coexist. In such environments, even a minor disturbance in drilling, crushing, conveying, ventilation, or mineral-processing equipment can interrupt the entire production chain and generate substantial operational and financial losses. Conventional control arrangements, which often depend on isolated

equipment, fragmented databases, periodic inspections, and operator experience, are increasingly inadequate for managing this level of complexity. Consequently, the transition toward intelligent industrial control has become a strategic requirement for mines seeking to improve operational reliability, productivity, safety, and environmental performance. Recent developments in intelligent automation, industrial analytics, and autonomous control demonstrate that industrial organizations are moving from reactive supervision toward data-driven, adaptive, and predictive control architectures [1-3].

Industrial control systems traditionally include programmable logic controllers, supervisory control and data acquisition systems, distributed control systems, industrial communication networks, sensors, actuators, and human-machine interfaces. These technologies provide the fundamental infrastructure for monitoring operational variables and controlling industrial processes. However, traditional control systems are generally designed around predefined rules, fixed thresholds, and deterministic logic. Although such systems are effective under stable operating conditions, their performance may decline when processes become nonlinear, uncertain, dynamic, or affected by previously unobserved disturbances. Mining operations frequently exhibit all of these characteristics because equipment behavior is influenced by geological variation, fluctuating ore properties, changing environmental conditions, equipment deterioration, and variations in production demand. Intelligent industrial control extends conventional automation by integrating artificial intelligence, machine learning, data mining, real-time analytics, advanced sensing, and adaptive decision mechanisms into the control environment [4-6]. Through this integration, an industrial control system can move beyond merely reporting existing conditions and become capable of recognizing patterns, predicting failures, recommending actions, and continuously improving its responses.

The emergence of Industry 4.0 has accelerated the development of intelligent control systems by promoting the integration of cyber-physical systems, the Industrial Internet of Things, cloud computing, edge computing, digital twins, autonomous machines, and advanced analytics. Within this paradigm, equipment and processes are connected through digital networks that enable continuous data exchange between physical assets and computational systems. Smart sensors generate detailed information on temperature, vibration, pressure, speed, load, energy consumption, and equipment condition, while communication networks transfer these data to analytical and control platforms. The resulting data infrastructure supports continuous operational awareness and enables automated or semi-automated decision-making. Studies of digital transformation emphasize that the value of intelligent systems does not arise from individual technologies alone; rather, it depends on the coordinated integration of technological infrastructure, organizational capabilities, data resources, and managerial processes [7-9]. Therefore, the development of intelligent industrial control in mining must be viewed as a systemic transformation rather than as the isolated installation of new sensors or software.

One of the most important foundations of intelligent industrial control is the availability of accurate, timely, integrated, and contextually meaningful data. Mining organizations generate substantial quantities of data through equipment sensors, production records, maintenance reports, geological surveys, laboratory analyses, safety systems, and enterprise information systems. Nevertheless, the mere availability of data does not guarantee its effective use. Data may be incomplete, inconsistent, duplicated, manually recorded, stored in incompatible formats, or distributed across separate organizational units. Weak sensing infrastructure and poor data quality may undermine predictive models and produce inaccurate or misleading control recommendations. Accordingly, intelligent industrial control requires an integrated data architecture capable of collecting, cleaning, synchronizing, storing, processing, and governing operational data. Research on data-driven

organizations indicates that technological integration must be accompanied by clear data standards, defined ownership, access controls, quality-assurance procedures, and organizational mechanisms for converting data into actionable knowledge [10-12].

Data mining and machine learning constitute the analytical core of intelligent industrial control systems. Data-mining methods can identify hidden relationships among operational variables, detect abnormal performance patterns, classify equipment conditions, and reveal the factors associated with process inefficiency or failure. Machine-learning algorithms can learn from historical and real-time data to predict equipment breakdowns, estimate production outcomes, detect anomalies, and optimize operating parameters. Supervised-learning methods may be used when labeled examples of faults or operational states are available, whereas unsupervised-learning methods are valuable for detecting previously unknown patterns and anomalies. Reinforcement-learning approaches can also support adaptive control by enabling systems to learn optimal actions through interaction with the operating environment. The growing use of machine learning in industrial contexts reflects its capacity to process complex, high-dimensional, and nonlinear data that may not be adequately addressed by conventional statistical or rule-based techniques [13-15]. In mining, these capabilities are particularly valuable because production conditions change continuously and the cost of delayed or incorrect decisions can be substantial.

Predictive maintenance represents one of the most practical applications of intelligent industrial control in ore mines. Conventional maintenance approaches generally follow either reactive maintenance, in which repairs are performed after equipment failure, or preventive maintenance, in which components are replaced at predetermined intervals. Reactive maintenance can lead to unexpected shutdowns, secondary damage, safety hazards, and production losses, while preventive maintenance may result in unnecessary servicing and premature replacement of functional components. Predictive maintenance uses sensor data, equipment histories, condition-monitoring indicators, and analytical models to estimate the probability and timing of failure. This allows maintenance activities to be scheduled according to the actual condition of equipment rather than fixed intervals. Intelligent maintenance systems can prioritize critical assets, identify early signs of degradation, improve spare-parts planning, and reduce emergency stoppages [16-18]. For mining organizations that depend on crushers, conveyors, excavators, drilling systems, pumps, and processing equipment, predictive maintenance can significantly improve equipment availability and overall production continuity.

Real-time monitoring is another essential element of intelligent industrial control. In traditional systems, operational problems may remain undetected until they become visible to operators or cause a significant process deviation. By contrast, intelligent monitoring systems continuously assess equipment and process indicators and compare them with expected operating patterns. Anomaly-detection models can identify deviations that are too subtle or complex to be recognized through fixed thresholds. Early-warning systems can then notify operators, recommend corrective actions, or automatically adjust control parameters. The combination of real-time monitoring and intelligent analytics therefore reduces the interval between the emergence of a problem and the organizational response to it. Research on advanced monitoring and fault-diagnosis systems highlights the importance of integrating sensor networks, analytical models, and operational knowledge to improve the speed and accuracy of fault identification [19-21]. Such capabilities are particularly relevant in mines, where delayed responses may increase the risk of equipment damage, environmental incidents, or occupational accidents.

Safety is a central concern in the design of intelligent industrial control systems for mining. Mine workers are exposed to risks associated with machinery collisions, rock falls, dust, noise, toxic gases, equipment malfunction, unstable geological

conditions, and confined or remote operating environments. Intelligent sensing and control systems can support safety by monitoring hazardous areas, identifying abnormal equipment behavior, tracking environmental variables, and generating early warnings. Automated control can also reduce the need for workers to remain in high-risk locations. However, the introduction of intelligent systems does not automatically eliminate risk. New forms of technological dependency, automation error, algorithmic misclassification, communication failure, and overreliance on automated recommendations may emerge. Therefore, the safety benefits of intelligent control depend on system reliability, appropriate human oversight, validated analytical models, and clear procedures for responding to system warnings [22-24]. The design of intelligent industrial control must consequently integrate occupational safety, process safety, equipment safety, and human–system interaction.

The increasing connectivity of industrial control systems also creates serious cybersecurity challenges. Traditional industrial networks were often isolated from external information systems; however, contemporary intelligent control requires connectivity among sensors, operational technology, information technology, cloud platforms, remote-access tools, and external service providers. This connectivity expands the potential attack surface and exposes mining operations to unauthorized access, malware, data manipulation, ransomware, and disruption of control processes. A cyberattack on an industrial control system may affect not only information confidentiality but also equipment integrity, production continuity, worker safety, and environmental protection. Consequently, intelligent industrial control must incorporate network segmentation, identity and access management, secure communication, anomaly detection, incident response, and continuous vulnerability assessment. Studies of industrial cybersecurity emphasize that security must be embedded in system architecture and organizational practice rather than added after implementation [25-27]. This requirement is especially important in mines that depend on remote monitoring, interconnected equipment, and imported control technologies.

Although advanced algorithms can improve decision quality, their limited transparency may create barriers to organizational acceptance. Many high-performance artificial intelligence models operate as complex “black boxes,” making it difficult for managers, engineers, and operators to understand why a particular prediction or recommendation was produced. In safety-critical industrial environments, unexplained recommendations may be unacceptable because users must assess whether a decision is technically reasonable and consistent with operational experience. Explainable artificial intelligence addresses this problem by providing interpretable information regarding the variables, patterns, or rules that influenced model outputs. Explainability can increase user trust, facilitate model validation, support accountability, and help specialists identify biased or erroneous predictions. Nevertheless, explanations must be understandable to different users and must not oversimplify technically complex relationships. The literature on responsible and explainable artificial intelligence emphasizes that transparency, interpretability, robustness, and human oversight are essential for deploying AI in consequential operational environments [28-30].

Human and organizational capabilities are as important as technological infrastructure in determining the success of intelligent industrial control. Employees may resist intelligent systems because of uncertainty, concerns about job displacement, lack of digital skills, distrust of automated decisions, or insufficient involvement in system design. Operational personnel may also continue using informal or experience-based procedures when new systems are perceived as difficult, unreliable, or inconsistent with established workflows. Senior management commitment is therefore necessary to allocate resources, establish priorities, support training, and coordinate cooperation between mining, maintenance, automation,

information technology, safety, and data-analysis units. Organizational readiness includes not only technical competencies but also a culture that values data, experimentation, interdisciplinary cooperation, and continuous learning. Evidence from digital transformation research shows that organizations achieve better outcomes when technological adoption is supported by leadership, employee participation, capability development, and alignment with organizational strategy [31-33].

Economic considerations also influence the adoption of intelligent industrial control. Establishing sensor networks, upgrading legacy equipment, developing communication infrastructure, acquiring analytical platforms, employing specialists, and maintaining cybersecurity require substantial investment. Mining organizations may hesitate to adopt intelligent technologies when the return on investment is uncertain or when imported equipment and software are affected by price volatility and supply constraints. Furthermore, the benefits of intelligent control may be distributed across several areas, including reduced downtime, lower maintenance costs, improved safety, increased energy efficiency, and better production planning, making them difficult to evaluate through conventional financial indicators. A systemic assessment should therefore consider both direct and indirect benefits over the life cycle of the system. Studies of technology adoption and industrial modernization suggest that investment decisions are shaped by perceived usefulness, implementation cost, organizational scale, technical compatibility, and the availability of financial and institutional support [12, 27, 34].

The implementation of intelligent industrial control is also affected by regulatory, environmental, and governance requirements. Mining operations must comply with occupational safety standards, environmental regulations, equipment standards, data-protection requirements, and cybersecurity obligations. Intelligent systems may generate large quantities of sensitive operational data and may involve automated decisions with significant safety or economic consequences. Therefore, organizations must define responsibility for data collection, model development, system validation, decision approval, and incident management. Data governance is particularly important because inaccurate, inaccessible, or poorly secured data can undermine the entire control system. Effective governance clarifies data ownership, establishes quality standards, protects system integrity, and ensures that analytical outputs are used responsibly. Research concerning responsible industrial digitalization indicates that governance mechanisms must evolve alongside technological capabilities to maintain accountability and regulatory compliance [1, 18, 20].

Despite substantial advances in artificial intelligence, automation, industrial analytics, and smart mining, much of the existing literature examines individual technologies or narrowly defined applications. Some studies focus on fault detection, predictive maintenance, cybersecurity, process optimization, data mining, or explainability, while others emphasize organizational readiness or digital transformation. Although these contributions are valuable, the development of an intelligent industrial control system in mining requires the simultaneous consideration of causal pressures, technological and organizational contexts, implementation barriers, managerial strategies, and expected consequences. A fragmented approach may result in technically advanced systems that fail because of poor data quality, limited employee acceptance, inadequate integration, financial constraints, or weak governance. Accordingly, a comprehensive model is required to explain how the technological, managerial, organizational, human, economic, and regulatory dimensions interact in the specific context of ore mines [2, 3, 5].

Grounded theory provides an appropriate methodological basis for developing such a model because it enables theoretical categories and relationships to emerge systematically from the experiences of individuals directly involved in the phenomenon. Rather than imposing a predetermined framework, grounded theory facilitates the identification of the

conditions that generate a phenomenon, the context in which it develops, the factors that facilitate or constrain it, the strategies adopted by organizations, and the consequences that follow. This approach is particularly suitable for intelligent industrial control because the phenomenon involves emerging technologies, evolving organizational practices, and complex interactions among technical and managerial actors. Expert perspectives can reveal implementation issues that may not be evident in purely technical models, including informal work practices, coordination problems, resistance to change, resource limitations, and the practical requirements of maintaining intelligent systems [7, 9, 10].

A systemic model of intelligent industrial control can provide both theoretical and practical value. Theoretically, it can integrate previously fragmented concepts and clarify the relationships among the drivers, enabling conditions, barriers, strategies, and consequences of intelligent control. Practically, it can assist mine managers in prioritizing investments, sequencing implementation activities, developing human capabilities, establishing data governance, and evaluating expected outcomes. Such a model can also help policymakers and technology providers recognize that the transition toward smart mining depends on more than equipment acquisition. It requires sustained managerial support, stable policies, specialist knowledge, interdepartmental collaboration, secure infrastructure, and continuous organizational learning. The growing complexity of industrial digitalization therefore creates a need for context-sensitive models grounded in the experiences of mining and technology experts [6, 8, 11].

Accordingly, the aim of the present study was to develop a systemic model of intelligent industrial control in ore mines using a grounded theory approach.

Methodology

The present study was applied in terms of purpose and qualitative in terms of its research approach. It was conducted using the systematic grounded theory methodology developed by Strauss and Corbin (1998). The principal objective was to develop a systemic model of intelligent industrial control in ore mines based on data obtained from interviews with experts and specialists in the field. Grounded theory was selected as the appropriate methodology because of its capacity to extract concepts, explain relationships among categories, and develop a theoretical model grounded in empirical data. The research population included academic experts, ore-mine managers, industrial automation specialists, artificial intelligence experts, control engineers, industrial information technology specialists, and managers of mine maintenance departments. Sampling was conducted purposively using the snowball technique. The sampling process continued until theoretical saturation was achieved, and ultimately, 15 experts participated in the study. Data were collected through semi-structured interviews. Each interview lasted between 45 and 75 minutes, and all interviews were recorded, transcribed, and analyzed after informed consent had been obtained from the participants. To enhance the trustworthiness of the findings, the criteria of credibility, transferability, dependability, and confirmability were applied. Member checking, constant comparison of the data, and expert review were also employed to improve the accuracy of the analyses.

Findings and Results

Following the analysis of the expert interview transcripts, more than 180 initial codes were extracted during the first stage of open coding. These codes represented the experts' perspectives, experiences, and opinions regarding the factors influencing the design and implementation of intelligent industrial control systems in ore mines. Similar codes were

subsequently integrated and refined, resulting in 144 open codes organized into 24 subcategories. These categories formed the basis for developing the principal dimensions of the study's paradigmatic model.

Table 1

Coding Structure of the Intelligent Industrial Control System Model

No.	Paradigmatic Dimension	Subcategory	Codes Extracted from the Interviews
1	Causal conditions	Deterioration and instability of mining equipment	Frequent crusher failures; sudden conveyor shutdowns; deterioration of drilling machinery; reduced equipment reliability; increased equipment downtime; absence of real-time equipment monitoring
2	Causal conditions	Inadequate data and sensing infrastructure	Absence of intelligent sensors; manual data recording; fragmented information; inadequate communication between equipment and the control center; absence of an integrated database; data errors
3	Causal conditions	Operational and safety risks	Risk of collapse; machinery collisions; dust exposure; fluctuations in geological conditions; difficulty in process control; delayed identification of critical conditions
4	Causal conditions	Need for intelligent decision-making	Delayed responses to equipment failures; dependence on operator experience; inability to predict production stoppages; nonsystematic decision-making; absence of early-warning mechanisms; need for real-time optimization
5	Central phenomenon: intelligent industrial control system	Intelligent and real-time monitoring of mining processes	Real-time monitoring of extraction equipment; online monitoring of crushing lines; continuous tracking of machinery conditions; real-time supervision of operational indicators; instantaneous control of processing parameters; rapid detection of operational anomalies
6	Central phenomenon: intelligent industrial control system	Intelligent decision-making based on data mining	Analysis of operational data; prediction of equipment failures; extraction of performance patterns; generation of intelligent alerts; automated decision-making; data-based process optimization
7	Central phenomenon: intelligent industrial control system	Integration of control and information systems	Integration of programmable logic controllers and supervisory control and data acquisition systems; connection of equipment to a central database; synchronization of production and maintenance information; data exchange among operational units; centralized information management; development of an intelligent management dashboard
8	Central phenomenon: intelligent industrial control system	Continuous learning and improvement of the control system	Updating predictive models; learning from new data; continuous optimization of control algorithms; automatic adjustment of control parameters; improvement in decision-making accuracy; development of data-driven organizational knowledge
9	Contextual conditions	Information and communication technology infrastructure	Availability of a stable communication network within the mine; use of the Industrial Internet of Things; access to data-processing servers; adequate wireless network coverage; use of cloud and edge computing; integration of software infrastructure
10	Contextual conditions	Organizational readiness and digital culture	Senior management support for digital transformation; culture of accepting emerging technologies; employees' willingness to use intelligent systems; organizational learning; collaboration between operational and information technology units; positive attitudes toward data-driven management
11	Contextual conditions	Human resources and specialized knowledge	Access to industrial automation experts; availability of data-mining specialists; continuous employee training; data-analysis skills; operators' experience in industrial control; ability to work with intelligent systems
12	Contextual conditions	Mine operational infrastructure	Availability of mechanized extraction equipment; use of programmable logic controllers and supervisory control and data acquisition systems; implementation of equipment-monitoring systems; access to production and maintenance data; standardization of operational processes; capacity for continuous monitoring of mining equipment
13	Intervening conditions	Economic and investment constraints	High cost of intelligent equipment; budget limitations for system modernization; cost of maintaining digital infrastructure; long investment payback periods; fluctuations in the prices of imported equipment; limited financial resources for digital transformation projects
14	Intervening conditions	Technical and technological challenges	Incompatibility of legacy equipment with emerging technologies; poor sensor-data quality; disruptions in communication networks; limitations in real-time processing; complexity of system integration; dependence on foreign software and equipment
15	Intervening conditions	Legal, safety, and environmental requirements	Compliance with mining safety standards; regulatory requirements; environmental restrictions; cybersecurity requirements; compliance with industrial standards; legal limitations on the use of emerging technologies
16	Intervening conditions	Human and managerial factors	Employee resistance to change; shortage of specialized personnel; inadequate digital skills; absence of continuous training programs; insufficient managerial support for intelligent technologies; weak coordination between operational and information technology units
17	Strategies	Implementation of intelligent monitoring and control systems	Development of intelligent sensor networks; implementation of real-time monitoring systems; integration of programmable logic controllers and supervisory control and data acquisition systems; online monitoring of equipment conditions; development of intelligent management dashboards; use of early-warning systems
18	Strategies	Application of data mining and artificial intelligence in decision-making	Intelligent analysis of operational data; prediction of equipment failures; detection of operational anomalies; application of machine-learning algorithms; development of production forecasting models; decision-making based on data analysis
19	Strategies	Intelligent maintenance of equipment	Implementation of predictive maintenance; intelligent maintenance scheduling; prioritization of critical equipment; reduction of emergency shutdowns; monitoring of equipment health indicators; optimization of maintenance programs
20	Strategies	Development of data governance and organizational empowerment	Establishment of an integrated database; development of data-management standards; employee training in intelligent technologies; formation of data-analysis teams; strengthening collaboration between operational and information technology units; implementation of a data-driven continuous improvement system

21	Consequences	Improvement of mine productivity and operational performance	Increased extraction efficiency; reduced production-line downtime; increased production capacity; improved equipment productivity; optimized resource consumption; increased stability of production processes
22	Consequences	Improved safety and reduced operational risks	Reduction in occupational accidents; rapid identification of critical conditions; reduction in human error; increased equipment safety; intelligent hazard management; reduction in accident-related shutdowns
23	Consequences	Cost reduction and increased economic efficiency	Reduced maintenance costs; reduced energy costs; extended useful life of equipment; reduced production waste; optimization of maintenance expenditures; increased mine profitability
24	Consequences	Realization of smart mining and sustainable development	Increased digital maturity of the mine; data-driven decision-making; improved quality of managerial information; increased operational flexibility; enhanced organizational competitiveness; realization of digital transformation in mining

Causal Conditions

The findings obtained from the interviews indicated that the development of intelligent industrial control systems in ore mines is influenced by a set of causal factors. The experts maintained that equipment deterioration, the absence of adequate data-collection infrastructure, increasing operational risks, and the growing need for intelligent decision-making were the most important factors creating the need to implement intelligent industrial control systems. As a result of these factors, conventional control systems are no longer capable of responding effectively to the complexities of extraction and processing operations, making the transition toward data-mining- and artificial-intelligence-based technologies essential.

Equipment deterioration and instability were manifested in frequent crusher failures, unexpected conveyor shutdowns, deterioration of drilling machinery, reduced equipment reliability, prolonged equipment downtime, and the absence of real-time monitoring. These conditions increase the probability of unplanned production interruptions and reduce the operational stability of mining processes.

Inadequate data and sensing infrastructure included the absence of intelligent sensors, reliance on manual data recording, information fragmentation, weak communication between equipment and control centers, the absence of an integrated database, and data-quality errors. These limitations prevent the organization from obtaining accurate, timely, and integrated information for operational control.

Operational and safety risks included the possibility of mine collapse, machinery collisions, dust exposure, fluctuations in geological conditions, difficulty in controlling mining processes, and delays in detecting critical situations. Such risks increase the need for systems capable of continuous monitoring and rapid risk identification.

The need for intelligent decision-making was associated with delayed responses to equipment failures, dependence on operators' experiential knowledge, the inability to predict production stoppages, nonsystematic decision-making, the absence of early-warning systems, and the need for real-time process optimization. These factors highlight the limitations of conventional decision-making mechanisms in complex mining environments.

Central Phenomenon

The analysis of the interviews demonstrated that all extracted categories were organized around a central concept referred to as a data-mining-based intelligent industrial control system. Through real-time equipment monitoring, operational data analysis, integration of control systems, and continuous learning, this phenomenon enables intelligent decision-making and optimization of mining processes. The experts identified it as the central mechanism of digital transformation in mines.

Intelligent and real-time monitoring of mining processes involves the continuous observation of extraction equipment, online monitoring of crushing lines, continuous assessment of machinery conditions, real-time tracking of operational

indicators, instantaneous control of processing parameters, and rapid detection of operational anomalies. These capabilities enable the organization to identify deviations before they develop into major failures.

Data-mining-based intelligent decision-making includes the analysis of operational data, prediction of equipment failures, identification of performance patterns, generation of intelligent alerts, automated decision-making, and data-driven process optimization. This dimension transforms raw operational data into actionable managerial and technical knowledge.

The integration of control and information systems encompasses the integration of programmable logic controllers and supervisory control and data acquisition systems, connection of equipment to centralized databases, synchronization of production and maintenance information, data exchange among operational units, centralized information management, and the development of intelligent management dashboards. Such integration eliminates information silos and supports coordinated decision-making.

Continuous learning and improvement of the control system include updating predictive models, learning from newly generated data, continuously optimizing control algorithms, automatically modifying control parameters, improving decision-making accuracy, and developing data-driven organizational knowledge. This capability enables the system to adapt to changing operational and environmental conditions.

Contextual Conditions

Contextual conditions represent the organizational and technological foundations that facilitate the implementation of an intelligent industrial control system. According to the findings, the development of information technology infrastructure, organizational readiness, human resource capabilities, and appropriate operational infrastructure are among the most important conditions for the successful implementation of such a system. These factors enhance the organization's preparedness to adopt emerging technologies and effectively utilize intelligent systems.

Information and communication technology infrastructure includes a stable communication network within the mine, the use of the Industrial Internet of Things, access to data-processing servers, adequate wireless network coverage, the utilization of cloud and edge computing, and the integration of software platforms. These facilities provide the technical foundation required for collecting, transmitting, processing, and storing operational data.

Organizational readiness and digital culture include senior management support for digital transformation, an organizational culture receptive to emerging technologies, employees' willingness to use intelligent systems, organizational learning, collaboration between operational and information technology departments, and positive attitudes toward data-driven management. These elements reduce organizational resistance and facilitate technology adoption.

Human resources and specialized knowledge include access to industrial automation experts, the presence of data-mining specialists, continuous employee training, data-analysis skills, operators' experience in industrial control, and the ability to work with intelligent systems. Without these competencies, the technological infrastructure cannot be effectively employed.

Mine operational infrastructure includes mechanized extraction equipment, programmable logic controllers, supervisory control and data acquisition systems, equipment-monitoring systems, access to production and maintenance data, standardized operational processes, and the capacity for continuous monitoring of mining equipment. These elements provide the operational platform on which intelligent control technologies can be implemented.

Intervening Conditions

The results indicated that the implementation of an intelligent industrial control system is affected by factors that may either facilitate or constrain the execution of organizational strategies. The most important factors include economic limitations, technical challenges, legal and safety requirements, and human and managerial factors. Although these conditions do not directly create the central phenomenon, they substantially influence the quality and effectiveness of strategy implementation.

Economic and investment constraints include the high cost of intelligent equipment, budget limitations for system modernization, the cost of maintaining digital infrastructure, lengthy investment payback periods, fluctuations in the prices of imported equipment, and limited financial resources for digital transformation projects. These constraints may delay or restrict the scope of intelligent-control initiatives.

Technical and technological challenges include the incompatibility of legacy equipment with emerging technologies, low-quality sensor data, communication-network disruptions, limitations in real-time data processing, the complexity of system integration, and dependence on foreign equipment and software. These challenges may reduce system reliability and increase implementation complexity.

Legal, safety, and environmental requirements include compliance with mining safety standards, regulatory obligations, environmental restrictions, cybersecurity requirements, industrial standards, and legal limitations on the application of emerging technologies. The intelligent control system must therefore be designed in accordance with technical, legal, and environmental governance frameworks.

Human and managerial factors include employee resistance to change, shortages of specialized personnel, inadequate digital skills, the absence of continuous training programs, insufficient managerial support for intelligent technologies, and weak coordination between operational and information technology units. These factors may undermine the acceptance and effective use of intelligent systems.

Strategies

In response to the identified conditions, the experts proposed a set of implementation strategies. These strategies included the implementation of intelligent monitoring systems, the application of data mining and artificial intelligence, the development of predictive maintenance, and the establishment of data governance and organizational empowerment mechanisms. Implementing these strategies provides the conditions necessary to improve the efficiency of industrial control systems and reduce operational risks.

The implementation of intelligent monitoring and control systems includes developing intelligent sensor networks, establishing real-time monitoring systems, integrating programmable logic controllers with supervisory control and data acquisition systems, monitoring equipment conditions online, developing intelligent managerial dashboards, and employing early-warning systems. These actions improve operational visibility and accelerate responses to abnormal conditions.

The application of data mining and artificial intelligence in decision-making includes intelligent analysis of operational data, prediction of equipment failures, detection of operational anomalies, application of machine-learning algorithms, development of production forecasting models, and decision-making based on analytical data. These approaches enhance the accuracy, speed, and consistency of managerial and operational decisions.

The intelligent management of equipment maintenance includes implementing predictive maintenance, intelligently scheduling maintenance activities, prioritizing critical equipment, reducing emergency shutdowns, monitoring equipment health indicators, and optimizing maintenance programs. These strategies shift maintenance practices from reactive interventions toward predictive and condition-based management.

The development of data governance and organizational empowerment includes establishing an integrated database, formulating data-management standards, training employees in intelligent technologies, creating data-analysis teams, strengthening collaboration between operational and information technology units, and implementing a data-driven continuous improvement system. These actions ensure that data are reliable, accessible, secure, and effectively used in organizational decision-making.

Consequences

According to the findings, the implementation of the proposed strategies produces several consequences. The most important identified consequences include improved operational productivity, enhanced safety, reduced operating costs, increased economic efficiency, and the realization of smart mining. These consequences demonstrate that implementing an intelligent industrial control system not only improves technical performance but also provides the foundation for digital transformation and the sustainable development of mines.

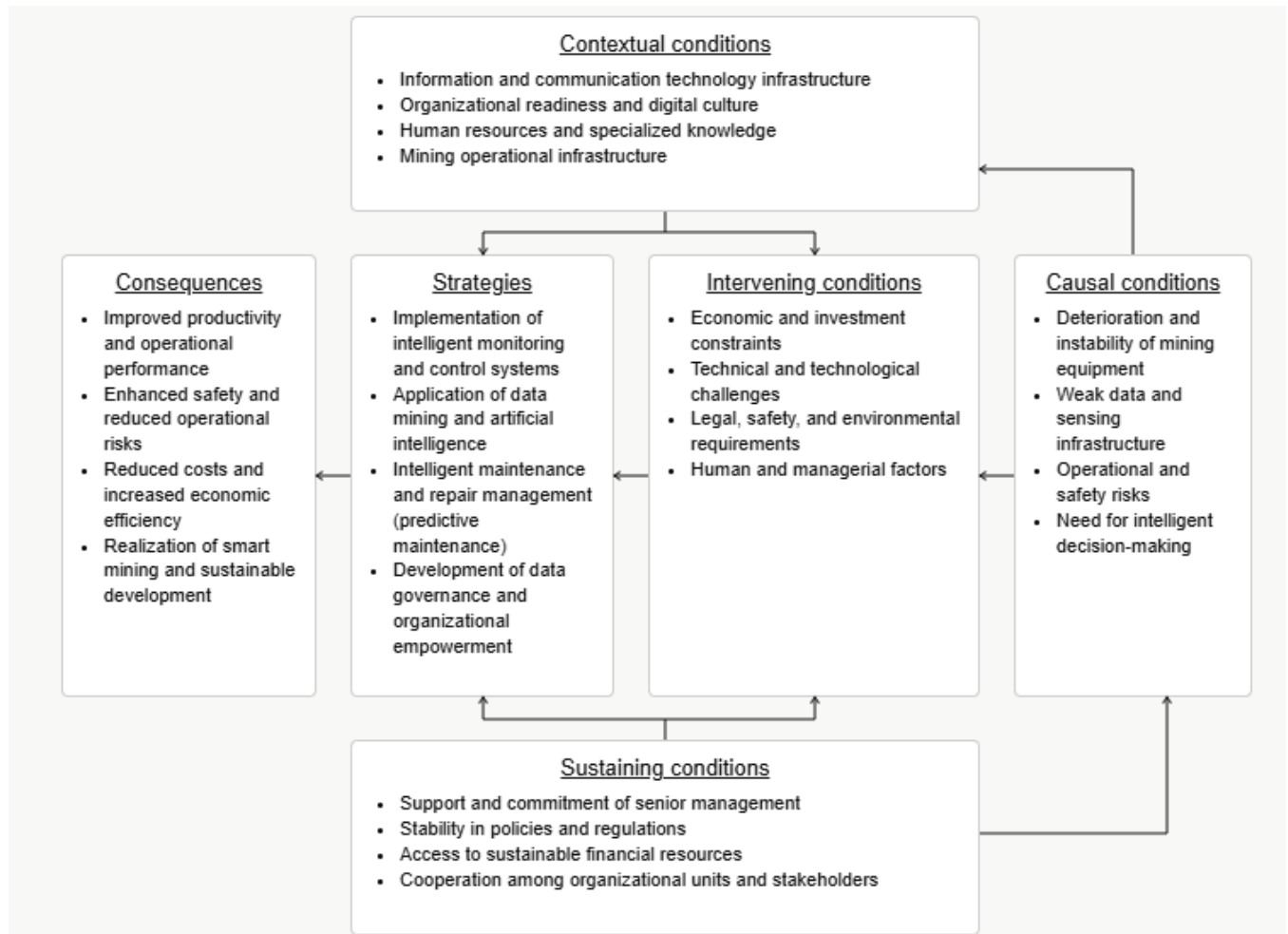
Improved mine productivity and operational performance include increased extraction efficiency, reduced production-line downtime, increased production capacity, improved equipment productivity, optimized resource consumption, and greater stability of production processes. These outcomes enhance the overall operational effectiveness of the mine.

Improved safety and reduced operational risks include fewer occupational accidents, rapid identification of critical conditions, reduced human error, improved equipment safety, intelligent hazard management, and fewer accident-related shutdowns. Intelligent control systems therefore strengthen both preventive safety and operational resilience.

Cost reduction and increased economic efficiency include lower maintenance and energy costs, extended equipment service life, reduced production waste, optimized maintenance expenditures, and increased mine profitability. These outcomes improve the financial justification for investment in intelligent industrial control technologies.

The realization of smart mining and sustainable development includes increased digital maturity, data-driven decision-making, improved quality of managerial information, greater operational flexibility, enhanced organizational competitiveness, and the realization of digital transformation in mining operations. These outcomes position intelligent industrial control as a strategic capability rather than merely a technical system.

During the final stage of the analysis, the relationships among the principal dimensions of the model were integrated, and the study's paradigmatic model was developed. The findings indicate that causal conditions, within the context of contextual conditions and under the influence of intervening conditions, lead to the emergence of a data-mining-based intelligent industrial control system. In response to these conditions, organizations adopt strategies that include intelligent monitoring, the development of data-mining capabilities, predictive maintenance, and data governance. These strategies ultimately lead to consequences such as increased productivity, improved safety, reduced costs, and the realization of smart mining. The model provides a coherent framework for explaining the relationships among the factors influencing the design and implementation of intelligent industrial control systems in ore mines and may serve as a basis for future research and managerial decision-making in the mining industry. The paradigmatic model of the study is presented in Figure 1.

Figure 1*Paradigmatic Model***Discussion and Conclusion**

The present study developed a systemic model of intelligent industrial control in ore mines through a grounded theory approach. The findings organized the phenomenon into six interrelated dimensions: causal conditions, the central phenomenon, contextual conditions, intervening conditions, strategies, and consequences. The causal conditions included the deterioration and instability of mining equipment, weaknesses in data and sensing infrastructure, operational and safety risks, and the growing need for intelligent decision-making. The central phenomenon was identified as a data-mining-based intelligent industrial control system characterized by real-time monitoring, intelligent decision-making, integration of control and information systems, and continuous learning. Contextual conditions consisted of information and communication technology infrastructure, organizational readiness and digital culture, specialized human resources, and suitable mining operational infrastructure. Intervening conditions included economic constraints, technical and technological challenges, legal and environmental requirements, and human and managerial factors. The principal strategies involved implementing intelligent monitoring systems, applying data mining and artificial intelligence, developing predictive maintenance, and strengthening data governance and organizational empowerment. Finally, the consequences included improved operational

productivity, enhanced safety, reduced costs, greater economic efficiency, and the realization of smart and sustainable mining.

The identification of equipment deterioration and operational instability as major causal conditions indicates that the transition toward intelligent industrial control is not merely driven by technological enthusiasm but by concrete operational deficiencies. Frequent equipment failures, unplanned shutdowns, reduced reliability, and prolonged downtime create substantial pressure on mining organizations to move beyond reactive forms of control. Conventional maintenance and monitoring systems are often unable to recognize complex degradation patterns before failure occurs, particularly when mining equipment operates under high loads, dust exposure, vibration, geological variability, and continuous production requirements. The present findings are consistent with studies emphasizing that intelligent industrial systems become necessary when conventional control architectures fail to manage uncertainty, nonlinear behavior, and dynamic operating conditions [1-3]. They also correspond with research demonstrating that predictive and data-driven systems can improve equipment reliability by identifying early signs of degradation and enabling timely intervention [16-18].

Weak data and sensing infrastructure also emerged as a fundamental causal condition. This finding demonstrates that intelligent control cannot be achieved without continuous access to accurate, integrated, and sufficiently granular operational data. Manual recording, fragmented databases, insufficient sensor coverage, and limited connectivity between equipment and control centers restrict the ability of organizations to detect patterns, estimate risk, and make timely decisions. This result supports the broader literature on Industry 4.0 and digital transformation, which identifies data availability and integration as prerequisites for intelligent automation [7-9]. It is also aligned with studies emphasizing that data quality, infrastructure interoperability, and organizational data capability determine whether analytical technologies can generate reliable operational value [10-12]. Therefore, the findings suggest that investment in artificial intelligence without simultaneous investment in sensing and data architecture is unlikely to produce sustainable results.

The identification of operational and safety risks as another causal condition reflects the hazardous nature of mining environments. Mining processes involve interaction among heavy equipment, unstable geological conditions, dust, noise, remote working areas, and complex processing systems. In such circumstances, delays in identifying abnormal conditions can lead to serious accidents, equipment damage, or production interruption. The present findings show that intelligent industrial control is expected to support not only productivity but also proactive risk identification and safety management. This interpretation is consistent with previous research demonstrating that intelligent monitoring, anomaly detection, and automated warning systems can strengthen occupational and process safety by detecting deviations before they escalate [22-24]. The result also supports studies showing that real-time analytical systems can improve the recognition of technical faults and critical operational conditions [19-21].

The need for intelligent decision-making was identified as the fourth causal condition. This finding indicates that dependence on operator experience and nonsystematic responses is insufficient in highly complex mining operations. Human experience remains valuable, but the volume, velocity, and complexity of operational data exceed the capacity of individual decision-makers to process all relevant information continuously. Intelligent systems can support managers and operators by extracting patterns, predicting failures, generating alerts, and recommending optimized control actions. This finding agrees with the literature on machine learning and industrial analytics, which shows that data-driven models can improve the consistency, speed, and precision of decisions in complex operational environments [13-15]. It is also consistent with research

indicating that artificial intelligence can extend conventional control systems from predefined responses toward adaptive and predictive decision-making [4-6].

The central phenomenon of the model was a data-mining-based intelligent industrial control system. This phenomenon integrated four core capabilities: real-time monitoring, intelligent decision-making, system integration, and continuous learning. The convergence of these capabilities suggests that intelligence in industrial control should not be reduced to a single algorithm or software application. Rather, it emerges from the interaction of sensing, communication, data management, analytics, automation, and organizational learning. This systemic interpretation is supported by studies that conceptualize intelligent industrial systems as integrated cyber-physical arrangements in which physical operations and computational intelligence continuously interact [1, 3, 4]. It also aligns with research emphasizing that digital transformation requires integration across technologies, operational processes, and managerial systems rather than isolated technological adoption [6-8].

Real-time monitoring was one of the principal dimensions of the central phenomenon. The importance of this capability lies in its ability to reduce the time interval between the emergence of a fault and the organizational response. Continuous monitoring of crushers, conveyors, drilling systems, and processing lines enables deviations to be detected before they result in major failures. Previous studies similarly indicate that intelligent monitoring systems improve situational awareness and provide the foundation for early-warning and fault-diagnosis mechanisms [19, 21, 23]. The present finding further suggests that real-time monitoring should be linked to analytical interpretation, because the mere collection of sensor readings does not ensure meaningful control. The system must distinguish normal variability from significant operational anomalies.

The intelligent decision-making dimension emphasized the use of data mining, predictive models, and automated recommendations. This result is consistent with research showing that machine-learning methods can detect nonlinear relationships, classify equipment conditions, forecast production outcomes, and identify anomalies that cannot be adequately captured through fixed thresholds [13, 29, 30]. However, the application of such models in mining also raises issues of interpretability and trust. Managers and operators need to understand the reasoning behind critical system recommendations, particularly when decisions affect safety or production continuity. This concern is supported by research on explainable artificial intelligence, which emphasizes transparency, interpretability, robustness, and human oversight in high-consequence environments [28-30]. Therefore, the intelligent control system proposed in the present study should be designed to complement expert judgment rather than replace it completely.

Integration of control and information systems was another core element of the central phenomenon. The integration of programmable logic controllers, supervisory control and data acquisition systems, maintenance records, production databases, and managerial dashboards enables the organization to create a unified view of operations. This reduces information silos and facilitates coordination among operational, maintenance, and information technology units. The finding is aligned with studies emphasizing interoperability and platform integration as central requirements for Industry 4.0 implementation [9-11]. It also reinforces the idea that technological intelligence depends on organizational connectivity; when production and maintenance information remain separated, predictive models cannot fully represent operational reality.

Continuous learning and system improvement constituted the fourth aspect of the central phenomenon. This finding highlights the dynamic nature of mining operations. Changes in ore characteristics, equipment condition, production

schedules, and environmental conditions mean that analytical models may lose accuracy over time. Continuous model updating, performance evaluation, and parameter refinement are therefore necessary. This result corresponds with research on adaptive and learning systems, which emphasizes that intelligent control should evolve as new data become available [2, 5, 13]. It also implies that organizational learning must accompany machine learning. Employees should review system outputs, interpret errors, and incorporate operational knowledge into future model development.

The contextual conditions identified in this study indicate that intelligent industrial control depends heavily on organizational preparedness. Information and communication technology infrastructure was the first contextual condition. Stable networks, Industrial Internet of Things technologies, data-processing servers, wireless coverage, and cloud or edge computing provide the technical foundation for real-time data transmission and analysis. This finding supports studies that identify digital connectivity and distributed computing as necessary for industrial intelligence [6, 31, 32]. The inclusion of edge computing is particularly relevant to mines, where communication interruptions or remote locations may make exclusive dependence on centralized cloud systems impractical.

Organizational readiness and digital culture also emerged as decisive contextual factors. Senior management support, employee willingness, organizational learning, and collaboration between operational and information technology departments influence whether intelligent systems are accepted and used effectively. This finding is consistent with studies showing that digital transformation is as much an organizational change process as a technological one [8, 31, 33]. Employee resistance may arise from fear of job displacement, distrust of automated decisions, inadequate training, or lack of participation in system development. Therefore, implementation should include communication, training, and participatory design.

The importance of specialized human resources further confirms that intelligent industrial control requires interdisciplinary knowledge. Automation engineers, data scientists, maintenance specialists, control engineers, and experienced operators must cooperate to design, interpret, and improve the system. This result agrees with research emphasizing digital competence and human capital as major determinants of successful technology adoption [10-12]. The finding also suggests that mining organizations should not treat intelligent systems as turnkey products that can operate independently of internal expertise.

The intervening conditions showed that implementation is shaped by economic, technical, regulatory, and human barriers. High costs, uncertain returns, legacy-equipment incompatibility, poor data quality, cybersecurity threats, and employee resistance may weaken the effectiveness of implementation strategies. The economic findings align with research indicating that investment cost, technical compatibility, organizational scale, and expected returns affect adoption decisions [12, 27, 34]. The technical findings are also supported by studies emphasizing interoperability challenges, dependence on external technologies, and limitations in processing industrial data in real time [6, 20, 32].

Cybersecurity requirements were included within the intervening legal and technical conditions. Increased connectivity among operational technologies, information systems, remote platforms, and cloud services exposes industrial control environments to cyber threats. This result is consistent with prior studies demonstrating that security vulnerabilities in intelligent industrial systems can affect production continuity, equipment integrity, and worker safety [25-27]. Therefore, cybersecurity should be incorporated into the system architecture from the beginning rather than treated as a supplementary feature.

The strategies identified in the study provide a practical pathway from the central phenomenon toward desired outcomes. The implementation of intelligent monitoring and control systems improves visibility, rapid detection, and operational responsiveness. The use of data mining and artificial intelligence supports prediction, anomaly detection, and optimized decision-making. Predictive maintenance reduces emergency shutdowns and extends equipment life, while data governance ensures that analytical decisions are based on accurate, secure, and accessible information. These strategies are strongly supported by previous studies on predictive maintenance, industrial data analytics, and intelligent automation [16-18]. Data governance and organizational empowerment also correspond with studies emphasizing the importance of management standards, employee capability, and cross-functional collaboration [9, 11, 33].

The consequences identified in the model included improved productivity, safety, cost efficiency, and progress toward smart and sustainable mining. These outcomes are logically connected to the proposed strategies. Real-time monitoring and predictive maintenance reduce unplanned downtime, while intelligent optimization increases production stability and resource efficiency. Early-warning systems and automated hazard detection improve safety, and improved equipment reliability reduces maintenance costs. These findings align with studies showing that intelligent industrial technologies can enhance operational efficiency, reduce failure-related losses, and improve organizational competitiveness [1-3]. The realization of smart mining also reflects broader digital transformation processes in which data-driven decision-making, automation, and organizational learning become embedded in routine operations [7, 8, 31].

Overall, the proposed model demonstrates that intelligent industrial control is a multidimensional organizational capability rather than a purely technical product. Its development begins with operational pressures and data limitations, but its success depends on technological infrastructure, organizational readiness, specialist knowledge, financial resources, governance mechanisms, and human acceptance. The model contributes to the existing literature by integrating these dimensions into a coherent framework specifically suited to ore-mining operations. It also explains how causal and contextual factors shape strategic responses and how these responses lead to technical, economic, safety, and sustainability outcomes.

This study had several limitations. First, the findings were based on interviews with 15 experts selected through purposive and snowball sampling, and the perspectives of these participants may not represent all mining organizations or industrial-control contexts. Second, the qualitative design focused on expert interpretations rather than direct measurement of system performance, implementation costs, or operational outcomes. Third, differences among mines in terms of size, mineral type, technological maturity, ownership structure, and geographical conditions may limit the transferability of the model. Fourth, the rapid development of artificial intelligence, industrial communication technologies, and cybersecurity requirements may cause some elements of the model to evolve over time. Finally, the study did not empirically test the causal relationships among the identified dimensions.

Future studies should quantitatively validate the proposed model using surveys and structural equation modeling with larger samples of mine managers, engineers, technology specialists, and operational employees. Comparative research could examine whether the model differs across open-pit and underground mines, different mineral industries, or organizations with different levels of digital maturity. Longitudinal studies should assess how intelligent-control capabilities develop over time and how they affect downtime, productivity, safety, energy consumption, and maintenance costs. Future research may also develop and test measurement instruments for each dimension of the model. Experimental and case-study research could evaluate specific technologies such as digital twins, edge-based anomaly detection, explainable artificial intelligence,

autonomous control, and predictive maintenance. Further studies should also examine employee trust, resistance to automation, cybersecurity preparedness, and the economic return on intelligent-control investments.

Mining organizations should begin implementation by assessing equipment criticality, data quality, sensor coverage, communication infrastructure, employee competencies, and cybersecurity maturity. Managers should avoid isolated technology purchases and instead develop a phased roadmap that links operational priorities with data architecture, system integration, predictive maintenance, and governance. Pilot projects should initially target high-risk or high-cost equipment for which intelligent monitoring can produce measurable benefits. Organizations should establish multidisciplinary teams composed of mining engineers, automation specialists, maintenance personnel, information technology experts, data analysts, and experienced operators. Continuous training, employee participation, transparent communication, and senior management commitment should accompany technological implementation. Clear standards should also be established for data ownership, data quality, model validation, system security, decision authority, and performance evaluation.

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Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants. Written consent was obtained from all participants in the study.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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