# Towards a Digitally Enabled Intelligent Coal Mine Integrated Energy System: Evolution, Conceptualization, and Implementation

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**Abstract:** The consensus on energy-saving and low-carbon goals led to greater requirements for the sustainable development of coal mines (CMs) worldwide. Against the above backdrop, the concept of Coal Mine Integrated Energy System (CMIES), a promising solution for coping with the smartization and decarbonization issues in the future development of CMs, has been proposed. However, the complexities of CM structure and operations, the shortage of automation and intelligent control techniques, and the stringent operation criteria, lead to high energy consumption, inefficient resource utilization, and unsatisfactory renewable energy accommodation in the mining system. Here, research on the emerging digital technologies and their potential applications is reviewed to provide reference for enhancing energy efficiency and mitigating emissions in future CM energy systems. First, the evolution of mining energy production and consumption paradigms is summarized from the perspective of technological advancements. Subsequently, the need to develop digitally enabled CMIES through a combined economic-security-emission analysis is discussed. To overcome the obstacles hindering the digital transformation of CM energy systems, a hierarchical implementation framework for digitally enabled CMIES involving the value, physical, and information layers is proposed. Furthermore, an intelligent information system incorporating device sensing and intelligence technology, new information network, big data, and digital twin is designed, and specific application scenarios are presented. Finally, the challenges and opportunities for future development of digitally enabled CMIES are discussed based on the Strengths-Weaknesses-Opportunities-Threats (SWOT) analysis.

**Highlights**

- Evolution of coal mine energy production and consumption is analyzed.
- The strategy for mine integration energy system digital development is proposed.
- A three-tier hierarchical implementation framework for digitized CMIES is proposed.
- The directions for the application of digital technology in CMIES are presented.
- A SWOT analysis of digital coal mine energy development in the future is analyzed.

**Keywords:** coal mine integrated energy system; digitization technology; conceptual framework; decarbonization; application scenario.

# 1 Introduction

Many countries have the goal of global CO2 emission decline by 2050 [1]. The global reliance on coal is high, but negligent coal energy utilization and management have resulted in the emission of large amounts of excess carbon dioxide into the atmosphere, exacerbating the greenhouse effect. In the process of coal mining and production, the digging, washing, ventilation, and other processes are considerably energy consuming [2]. Coal-derived resources such as coal seam gas and gushing water are hardly utilized. Therefore, studying how to significantly increase the utilization rate of energy and coal-derived resources, enhance the governance of energy and coal mine (CM) safety, is the key to achieving sustainable CM development.

The conceptualization of the Coal Mine Integrated Energy System (CMIES) provides a promising solution to overcome the above challenges. Global integrated energy assessment shows that the integrated energy utilization has less cumulative emission than direct sectoral fossil fuel emissions and the total carbon budget [3]. The CMIES integrates the production, transmission, transformation, storage, and consumption of heterogeneous energy (e.g., coal, wind, solar, electricity, heat, and cold energy.) in CMs through energy conversion equipment including wind turbines (WTs), photovoltaics (PVs), combined cooling, heating and power units (CCHPs), gangue generators, water-source heat pumps (WSHPs), and energy storage to achieve efficient and clean energy management of CM. Meanwhile, CMIES has coal-derived energy sources that can be fully utilized. Coal seam gas and coal gangue can be used to generate electricity and heat through generator units, and the waste heat recovery of ventilation and gushing water can also be converted into high-grade heat energy, as shown in Figure 1.

In contrast with the typical integrated energy system, CMIES has the following unique characteristics: the process of coal production is accompanied by the production of coal-derived energy (e.g. gangue, gushing water, ventilation, and coal seam gas, etc.). These energy sources can be efficiently converted into electricity or heat, thereby improving energy efficiency while preventing the wastage caused by resource pollution. For example, mine gushing water is used to generate heat energy based on the consumption of electrical energy, which can produce more economic benefits with less energy purchases. However, CMIES have unique and rigid requirements for different types of energy. CM loads include living and production loads. Among the production loads, CM has stringent requirements with respect to reliability of equipment such as shaft insulation, underground lighting, and production equipment. In the living load, miners' 24-h bathing needs necessitate the continuity of the heating system. Therefore, the economic and energy efficiency of the system should be considered only after ensuring the safe production of CM.

Figure 1 Illustration of coal mine energy system

However, in practice, CMIES requires integrated coordination and automatic optimization of all parts of the energy system, which requires the support of digital technology. Numerous studies have focused on the application of digital technology in CM management. In Australia, Gudai-Darri used digital twin technology to manage the mine's digital assets [4]. Rio Tinto monitored processing data from the company's seven copper and coal operations around the world [5]. Li [6] showcased a comprehensive digitalization project in a Jiangxi CM, highlighting steps from network construction to software implementation and the resultant gains and challenges. Qiao [7] contrasted big-data-driven CM safety approaches with traditional safety theories, emphasizing the shift in understanding and methodologies. Miao [8] leveraged natural language processing and machine learning for hazard identification and safety management, markedly boosting CM safety and efficiency. Sadeghi [9] studied the application of wireless sensor networks integrated into underground mine safety and management. However, these studies primarily address safety and operational construction, with limited exploration of digital technology's potential in CM energy management.

Digital technologies are pivotal in advancing energy management within industries, leveraging digital twins, big data, and blockchain for enhanced data handling and real-time control [10]. Artificial intelligence (AI), Internet of Things (IoT), and blockchain integration play a crucial role in formulating smart energy strategies [11]. IoT technology is widely used in smart grid and smart energy storage. Seungkeun [12] studied how digital twins and extended reality technologies can contribute to the decarbonization and sustainability of building energy systems, while He [13] explored the application of digital twin technology for situational awareness of energy internet in smart cities. Egunjobi [14] addressed the challenge of seamless interoperability between blockchain and IoT and explored scalable blockchain-based energy applications. Wang [15] created a blockchain-based cloud platform for secure energy transactions and scheduling. Kumar [16] explored the synergy of blockchain, IoT, and cloud computing in energy systems, highlighting the efficiency gains in renewable energy integration through advanced control and data acquisition technologies.

Regarding the application of digital technology in coal mining, most of the existing reviews focus on the digital transformation of the coal mining face. Zhironkina [17] focused on the trend of deep digitization in the mining process and explored the development direction of coal mining enterprises towards Mining 5.0. Wang [18] outlined the practical cases of intelligent technology in China's coal mines, with a focus on the framework of intelligent coal mining system under 5G technology and the application of new mining. Liu [19] examined the latest progress of intelligent technology for underground mining of hard rock mines in drilling, blasting, transportation, hoisting, ventilation, support and filling, and pointed out the importance of intelligent unmanned mining for the safe production of coal mining enterprises. Zhang [20] studied the application of intelligent unmanned mining technology throughout the process of mining working face. The above literatures primarily discussed the feasibility and effects of digital technologies in mining in a fragmented manner. No study has provided a systematic framework for the implementation of a digitalized CM energy system.

The scientific gaps unsolved in existing literatures:

- Most existing studies on coal mine digitalization have mainly focused on the discussion of intelligent *mining production technologies* only (such as intelligent blasting technology [18], intelligent rock drilling [19], unmanned auxiliary transportation [20], etc.), while little attention was paid to the field of *coal mine energy systems*, especially concerning the effect of digital technologies to the energy efficiency of coal mines.
- Most of the existing literatures have only focused on the application of *one specific digital technology* in coal mines (e.g., big data in [8], wireless sensor networks in [9], etc.), and there is no *systematic framework* yet indicating how to develop a digitally enabled intelligent coal mine integrated energy system including *multiple digital technologies*.
- For most existing works, there is a lack of *multidimensional strategic analysis* validating the effectiveness of the proposed coal mine digitalization scheme.

Therefore, to more comprehensively elucidate how digital technology can promote the development of CM energy management, we propose in this study a digitally enabled three-layer CMIES framework, discuss the role of digital technology in supporting the economy, environmental protection, and safety of CMIES by analyzing the evolutionary process of the CM energy system and developmental needs, and outline the specific applications of the four types of new digital technologies in CMIES. The main contributions of this study are as follows:

- *Proposing a three-layer framework for implementing a digitally empowered coal mine integrated energy system.* This study reviews the evolution of coal mine energy production and consumption paradigms and leads to the concept of coal mine integrated energy system, highlighting the significance of transition to digitally empowered coal mine energy systems in achieving sustainable development of future coal mines. The proposed framework incorporates four aspects, namely, "accurate real-time state perception", "intelligent on-demand scheduling of equipment", "intelligent decision-making and cooperative control", and "interactive reproduction and intervention prediction", providing a complete roadmap to fulfill a digitally empowered coal mine integrated energy system.
- *Designing a new structure of intelligent information system for CMIES, considering the usage of multiple digital technologies.* This study elaborates on the typical application modes

of four types of CMIES digitalization technologies: equipment sensing and intelligentization technology, new information network technology, big data platform and application technology, and digital twin technology. The collaborative usage of these technologies promotes the clean, low-carbon, secure, efficient, and sustainable development of the CMIES.

- *Opportunities and challenges for the future development of digital-enabled CMIES are analyzed based on the SWOT analysis.* Depending on the SWOT approach, this paper analyzes the strengths, weaknesses, opportunities and threats of applying digital technologies to CMIES and proposes a strategy for the transition towards digitally enabled intelligent coal mines.

The remainder of this paper is organized as follows. Section 2 presents the evolution and analysis of the energy production and consumption patterns in CMs. Section 3 presents the conceptualization of the coupled physical-information-value layer of the CMIES. In Section 4, the various digitalization technologies that support the CMIES are described. Section 5 presents the strengths, weaknesses, opportunities, and threats of the digital development of CMIES and presents the development trends. Section 6 presents the conclusions of our study.

# 2 Evolution of CM energy systems

Energy systems in CMs have undergone varying degrees of evolution, with a gradual shift from rough-and-tumble production to a green and smart production model. Since the emergence of the concept of CMIES, a number of researchers existing studies have thoroughly investigated the sustainability of CM in terms of resource utilization, multi-energy coupling and safety management. In this section, literature on the development of CMIES is reviewed, and the need for and bottlenecks of applying digitalization technologies to CIMES discussed.

## 2.1 Evolution of energy production and consumption in CMs

Driven by social progress and scientific and technological innovations, the energy production and consumption patterns of the mining industry have undergone a remarkable transformation. Its evolution can be broadly divided into four stages: crude, intensive, integrated, and intelligent. Each stage represents a significant leap forward in mining technology and energy management, reflecting the industry's increasing focus on efficiency, environment, and sustainability. The characteristics of these four stages are detailed as follows:

(1) Crude

Historically, the coal mining industry prioritized rapid growth and extensive expansion, leading to inefficient and wasteful practices. Emphasizing quantity over quality and reliant on high inputs, the industry overlooked the potential of associated mineral resources due to limited technological capabilities and awareness. This approach resulted in significant resource wastage and energy-intensive operations, relying on external sources for electricity, heat, and water. The primary challenge was the industry's focus on maximizing production at the expense of energy efficiency, leading to supply-demand imbalances and heightened safety risks due to potential energy supply failures.

(2) Intensive

As society and the economy advanced, CMs moved away from their old ways of doing things to focus on intensive production. This meant that CMs began to process coal more thoroughly, tapping into a wider range of mineral resources and exploring new business areas. They also started using different types of energy, not just coal. The use of electricity, fuel oil, and water was maintained, but with a shift towards cleaner options such as electric or gas boilers to reduce pollution. CMs managed to lower the energy they needed for production by upgrading their equipment and adopting new, energy-saving technologies. Although these changes made energy use more balanced, a lot of work is needed to make operations more economical and environment friendly.

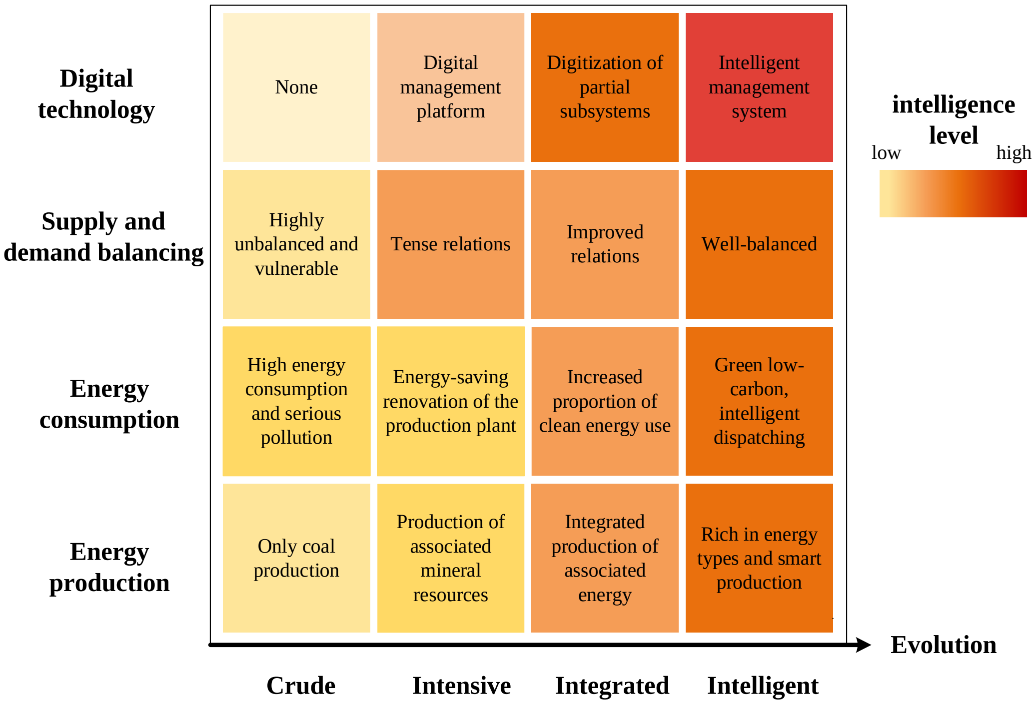
(3) Integrated

Over the last decade, as environmental protection became a priority, the coal industry embraced sustainable practices, including energy efficiency, green mining, and full resource utilization. A key innovation has been the adoption of energy cascade utilization strategies within coal mines, focusing on transforming waste into valuable resources. This approach is central to the development of CMIES, which not only recycle water and utilize the constant temperature of gushing water for heating and cooling but also convert by-products such as coal gangue and gas into electricity. These initiatives, part of a broader effort to optimize energy use and reduce emissions, highlight the industry's shift towards integrating renewable energies and enhancing system efficiencies. Although advances in CMIES show progress, challenges persist in system integration and information sharing, and green mining, humanistic care, and sustainable development does not receive enough attention.

(4) Intelligent

Despite the energy-efficient advancements in integrated CMs, challenges such as non-interoperable energy subsystems, inefficient production processes, and rising costs hinder safe and efficient operations. Digital transformation, leveraging IoT, cloud computing, and big data, are essential to addressing these issues, and promoting sustainable and safe mining. By optimizing energy use and production strategies through intelligent algorithms, CMs can achieve a balance between energy supply and demand, enhancing system stability and RES integration. This smart production mode not only improves monitoring and control but also ensures the safety and efficiency of mining operations.

Figure 2 summarizes the evolution of the intelligent level of the coal mine energy system across four dimensions: energy production, energy consumption, supply-demand balancing, and digitization technology. The horizontal axis represents the development stages of the energy systems, while the level of intelligence is depicted through a color gradient transitioning from yellow to red, symbolizing continuous improvement. The vertical axis reflects the four key indicators (characterizing dimensions) of the coal mine energy system.



| | Crude | Intensive | Integrated | Intelligent |
|---|---|---|---|---|
| **Digital technology** | None | Digital management platform | Digitization of partial subsystems | Intelligent management system |
| **Supply and demand balancing** | Highly unbalanced and vulnerable | Tense relations | Improved relations | Well-balanced |
| **Energy consumption** | High energy consumption and serious pollution | Energy-saving renovation of the production plant | Increased proportion of clean energy use | Green low-carbon, intelligent dispatching |
| **Energy production** | Only coal production | Production of associated mineral resources | Integrated production of associated energy | Rich in energy types and smart production |

Figure 2. Evolution of CM energy system in terms of intelligence level.

## 2.2 Introduction of CMIES

Energy significantly impacts CM efficiency and development, with future trends focusing on improving energy efficiency and clean resource use. CMIES introduce complexities due to diverse energy sources and operational challenges, including safety-critical loads and derived energy utilization. In the subsequent section, the current development of CMIES, including production optimization, resource utilization, and safety management, based on previous studies, is discussed.

### 2.2.1 Production optimization

Energy consumption in mining processes, notably in mining, ventilation, and washing, represents a significant portion of total usage, with inefficiencies arising from excessive focus on output and underutilization of by-products [21]. Research on energy-saving measures for CM equipment such as belt conveyors and ventilation systems has shown potential for reducing energy costs and enhancing CMIES economics. Studies have explored the optimization of conveyor efficiency and safety, with Zhao [22] modeling belt speed and coal flow rate matching, Mu [23] proposing energy dispatch strategies for conveyors and batteries, and Huang [24] suggesting a method for integrating energy and transport flows under uncertainty. Ventilation energy savings are also critical, with Babu [25], Sjöström [26], and Wu [27] focusing on optimizing airflow and reducing ventilator energy use. Additionally, addressing the high energy consumption of multi-level drainage systems, Liu [28] proposed an improved peak and valley avoidance strategy to realize the integration and linkage between the pumping stations of each mining level at multiple levels in response to the problems of frequent starting and stopping of pumps and the high cost of electricity in the traditional control method. Romero [29] introduced a model predictive control strategy to maintain the optimality during the operation period by taking into account the seasonal changes of mine drainage demand. Wang [30] proposed an optimization model to enhance gas concentration and energy efficiency in underground gas drainage systems, ensuring alignment between the drainage system and the targeted drainage objects. Additionally, automating coal washing plants and introducing waste heat recovery units can lead to significant energy savings and reduced consumption [31, 32]. In terms of multi-link cooperation, synergistic optimization of the coal miner and scraper conveyor operating speeds can achieve total energy savings of up to 10.9% [33]. Despite these individual efforts, a comprehensive approach toward CM energy efficiency, covering the full life cycle from production to consumption, has not been identified.

### 2.2.2 Resource utilization

The environmental impact of mining has prompted the exploration of comprehensive resource utilization in CMs to enhance efficiency, reduce emissions, and achieve sustainability. This approach has led to significant research in recycling and optimizing resource use in CMs.

Key studies have tackled various aspects of CM resource utilization. Li [34] proposed a method for recycling gushing water to prevent flooding and support comprehensive use. Zhang [35] focused on maximizing water resource utilization through innovative separation and purification processes. Menéndez [36] explored renewable heating from gushing water, contributing to sustainable energy solutions. For gas utilization, Liu [37] enhanced CM gas power generation efficiency, and Ma [38] investigated different power generation methods to optimize ventilation efficiency. Waste heat recovery efforts by Ghoreishi-Madiseh [39] and Al-Habaibeh [40] introduced new models and systems for energy recovery and management. RES storage and integration within CMs have also been explored. Baidya [41] proposed a zero-carbon heating model, integrating thermal energy storage for underground CMs. Comprehensive energy efficiency studies by Wang [42] and Cao [43] have laid the groundwork for life-cycle energy efficiency analysis and sustainable energy management in CMs. Despite these efforts, and models considering the utilization of RES [44-46], coalbed methane [47, 48], gas [49], and gushing water [50, 51] and aiming for low-carbon CM operations [52], the integration of these energy recycling strategies into a cohesive system that fully accounts for the ecological characteristics of CMIES warrants further exploration.

### 2.2.3 Security management

CMIES security is complex, encompassing production safety, energy reliability, and data confidentiality. Addressing security in the high-risk mining sector is essential. The traditional safety management mode focuses on improving the safety awareness of miners and citing advanced equipment and technology. Following the considerable changes in the production environment of coal mining enterprises, the traditional human-oriented CM safety management model can no longer meet the needs of CM safety development. Wang [53] used the digital twin five-dimensional model to construct a twin safety management model for CM gas accidents, which can make up for the shortcomings of the traditional CM safety management. Lalitha [54] used the IoT and AI to design a miner's protective helmet for monitoring the coal mine conditions and miners' health. Cheng [55] proposed a lightweight mashup middleware based on ZigBee wireless sensor networks to automate the remote monitoring and control of underground physical sensor devices. Li [56] proposed a solution to reconfigure the network of integrated energy systems under extreme disasters. Wu [57] optimized ventilation safety utilizing a steady wind inverter method. Zhang [58] developed a PKI-based security system focusing on certificate management and encryption. Zhong [59] examined information security in safety systems, suggesting technical and managerial improvements. Li [60] advanced hazard identification and risk assessment through quantitative models. Hao [61] employed text mining and Bayesian networks to identify safety risks from accident reports. These studies provide a comprehensive approach toward enhancing CMIES security, covering aspects from personnel management and system design to technological and digital innovations. Despite these advances, there is room for further exploration in energy security within CMs and a more integrated approach to digital security solutions to elevate security practices on a broader scale.

Given the above literature on CMIES energy production and consumption characteristics of the "three characteristics" of the analysis summarized, the existing CMIES has several obvious limitations:

- Energy consumption analysis and management for the entire production cycle of CMs is lacking, and energy consumption analysis is not systematic; therefore, a comprehensive analysis and unified optimization of energy cannot be achieved.
- Current energy-saving and consumption-reduction measures target only local aspects, achieving local optimization while overlooking global energy management.
- The CMIES recycling strategy is more traditional, and most reuse only a single associated energy source.
- Disregarding the distinct ecological nature of energy production and consumption in a CMIES, low-carbon demand is often overlooked when considering economic operations.
- The CMIES optimal operation scheme does not combine the specific process of CM production and disregards complex energy links and strong coupling energy flows.
- The close correlation between CM energy and production safety has not been fully considered, and the importance of whole-process CM safety management has been overlooked.

## 2.3 Digital supports in the CMIES

To address the diverse needs of mining areas and improve resource efficiency and environmental conditions, a clean and efficient energy supply tailored to specific demands is crucial. Key focus areas for CMIES include:

- Enhancing economic efficiency by integrating energy systems with industrial processes through network coupling and topology reconstruction, thereby increasing energy utilization and renewable energy integration.
- Environmental goals necessitate waste management from production to reduce ecological damage, optimizing energy processes, and improving energy efficiency through customized supply and demand interactions.

- Ensuring a secure energy supply involves adapting to geographical and production constraints, supporting diverse energy access, distribution, and consumption, and maintaining high-quality, safe energy use.

The development goals of CMIES extend beyond merely satisfying energy demands to fostering overall mine development, with digital technology playing a pivotal role. Digital advancements are transforming CMIES with sophisticated sensing and control technologies, creating a network for predictive analysis and efficient energy management. This approach optimizes equipment usage and renewable energy output, significantly enhancing operational efficiency and environmental sustainability. Furthermore, digitalization boosts CMIES security through disaster monitoring and data protection systems, ensuring comprehensive safety and supporting a low-carbon transition in mining operations.

- While CMs have made strides in digitalization, several key challenges persist evenly across regions.
- Current automation systems rely heavily on remote monitoring and control, lacking real-time operation perception and full autonomy.
- Systems are localized and compartmentalized, with mining software are often limited to basic visual resource displays without comprehensive management or design.
- Data collection and integration in the production process is limited by a mixed model of manual and automated capture, leading to delays, heavy workloads and questionable data accuracy.
- Utilization of collected data is primarily confined to report management and basic analysis, without deep mining or application through intelligent processing.

Digitally enabled CMIES should promote full circulation and use of data resources as a new type of production factor. This will open information barriers between different subjects, drive the interconnection and interaction of all links in the energy network to complement each other, enhance the upstream and downstream of the industrial chain and the efficiency of interindustry coordination and operation, and promote cross-industry synergies for the green and low-carbon development of energy with digital transformation.

# 3 Framework of digitally enabled CMIES

The CMIES is moving towards a new phase where digital and information technologies are embedded into CMs. However, with access to large-scale distributed renewable energy sources and the integration of innovative energy products, the limitations of each technology have been addressed. The CMIES is a new generation of energy networks that closely intertwines with various energy networks, including power grids, gas networks, heating and cooling networks, and associated energy networks, with higher digitalization characteristics, and is gradually ascending to the stage of history.

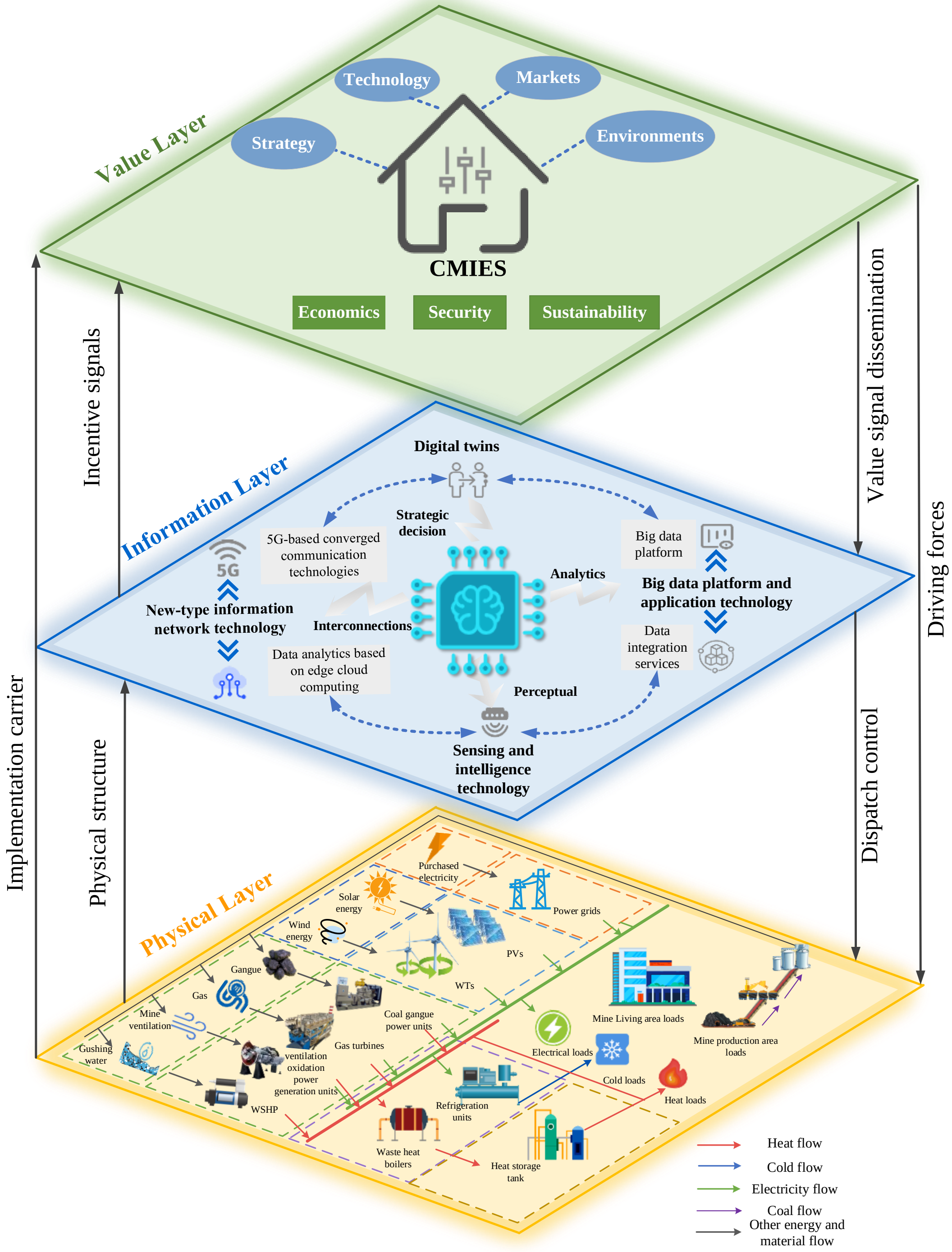


Figure 3 Three-layer framework for the implementation of a digitally enabled CMIES

Figure 3 presents the CMIES's digital architecture, divided into physical, information, and value layers, from equipment intelligence, domain-wide informatization, and decision-making accuracy. The energy flow of the physical layer influences the value layer's emphasis on economics, security, and environmental protection [62]. Directed by decision-makers' primary goals, value signals guide the information layer to manage and adjust the physical layer's operations through digital technologies [63]. This inter-layer feedback optimizes CMIES operations in real-time, showcasing a holistic approach that synergizes energy and information flows to align with strategic objectives. This architecture encapsulates a comprehensive strategy for enhancing CMIES efficiency and responsiveness to dynamic demands.

The physical layer is the topological architecture of the CMIES, which contains the energy supply equipment, energy conversion equipment, energy storage equipment, loads, and transmission networks in the CMIES, as well as mining equipment, transportation equipment, ventilation equipment, and coal storage silos in the CM production system. CM energy and production systems are intertwined with synergistic optimization. The CM production processes of mining, transportation, ventilation, drainage, gas extraction, and other links have a strong correlation; therefore, the optimization of coal flow transportation needs to have different links between the synergistic coupling of energy scheduling. This causes the CMIES to distinctly follow the coal flow transportation scheduling changes, and the energy use of coal flow transportation significantly affects the energy security of the CM.

The information layer is divided into information collection, transmission, and processing according to the different applications of various digital technologies. In the information collection stage, the physical parameters of the CMIES equipment, shaft air indicators, carbon emissions, and geology were monitored in real time by constructing a new type of sensing device. In the information transmission part, massive amounts of data are aggregated, fused, and quickly transmitted to the processing layer through 5G communication technology to ensure high reliability and ultra-low latency of data transmission. In the information processing part, a large amount of data collected is calculated and processed through edge cloud computing and other data analysis technologies, and the big data platform is used to realize visualization display and data integration, which makes the data of each energy system and production system of the CMIES united and coherent, and the energy and information flow are highly integrated. Therefore, the information layer forms an intelligent system with comprehensive perception, real-time interconnection, analysis, decision-making, autonomous learning, dynamic prediction, and cooperative control.

The value layer, as a top-level design, considers the value objectives of security, low-carbonization, and economy and aims to realize the multi-layer coupling mechanism and synergistic optimization of strategy, technology, and market environment under the "dual-carbon objective" of CMs. The value layer involves multiple subjects, including CM producers, CM employees, energy suppliers, and CM buyers, who cooperate and interact to determine the development of CMIES. The value layer is the lighthouse that determines the flow direction of the entire CMIES and is also the key bridge that connects the information and physical layers.

Overall, the CMIES aims to form an energy ecosystem with the ability to self-metabolize and new features of highly unified energy information value with intelligent equipment, multi-energy synergy, symmetric information, decentralized supply and demand, flat systems, and open transactions. Using digitalization, it promotes "information flow" to empower "energy flow" and realizes the goal of "value flow" for the security, economy, and environmental protection of CMIES [64].

# 4 Digital solutions enabling CMIES implementation

In recent years, the rapid development of digital technologies, such as sensing and intelligence technology, new information network technology based on 5G and edge cloud computing, big data platform and application technology, and digital twin technology, have provided fundamental support and development momentum for the informatization and intelligent development of CMIES. The digitally enabled CMIES is not a simple layering of various digital technologies, but a reasonable integration of digital technologies into all layers and links of the CMIES.

This intelligent system optimizes equipment usage and renewable energy integration, significantly improving operational efficiency and reducing environmental impact, which supports CMIES in achieving a clean and low-carbon transition. Additionally, disaster monitoring and data protection systems enhance mine safety by providing early warning and robust security measures, further supporting safe and resilient operations. Through predictive analysis and efficient energy management, the digitalized CMIES is able to minimize waste, maximize resource efficiency, and drive sustainable development within mining operations, aligning with goals for a low-carbon, safe, efficient, and sustainable future.

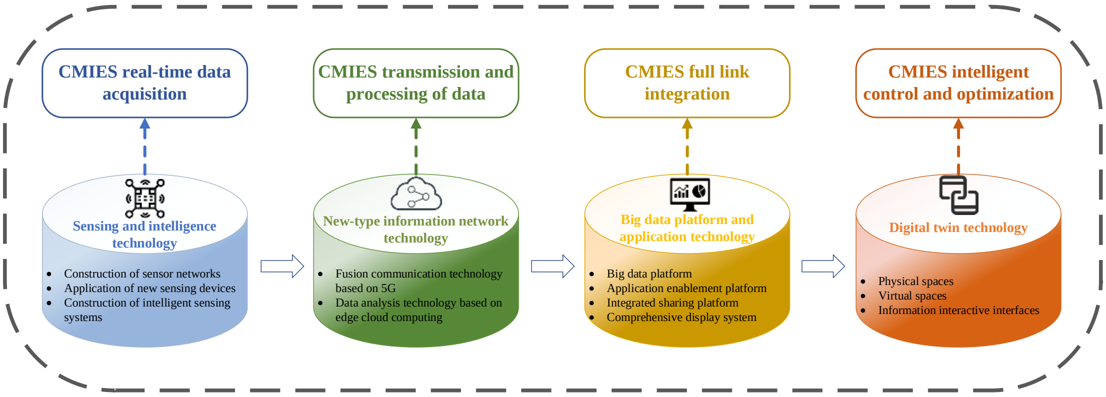


Figure 4 Core digital technologies for the implementation of CMIES

## 4.1 Sensing and intelligence technology in CMIES

In digitally enabled CMIES, reliable, stable, and extensive access to data and information is the foundation of all upper links [65]. The real-time accurate perception of the operating state of various equipment in the CM and the intelligence of equipment are the premise of the CMIES to realize intelligent, efficient, economic, and low-carbon production and operation [66], as well as the bottom pillar of digitally enabled CMIES. All types of sensors are terminals for data and information perception and collection in the CMIES. Therefore, deploying a large number of sensor nodes in CMs and continuously improving the accuracy and stability of sensing data in existing sensor systems. Meanwhile, there are distributed Micro-Electro-Mechanical Systems (MEMS) and other low-power consumption new sensor technologies [67], which should be adopted to broaden the perceptual boundary continuously to obtain more comprehensive detection data online for a long time. The intelligence level of the equipment must also be continuously improved. By further studying the knowledge representation and extraction technology of sensors [68], the intelligence level of sensors can be improved, and the sensor nodes can be equipped with online computing and network autonomy, which provide a strong basis for the intelligent equipment and collaborative control of the CMIES.

Wireless sensor networks refer to the networking of spatially dispersed and dedicated sensors that monitor and record the physical conditions of the environment and forward the collected data to a central location. Sensor networks are widely used in coal mines for air pollution monitoring, underground temperature and humidity measurement, pressure flow measurement, and seismic detection. A sensor network consists of a certain number of sensing nodes that communicate in a wireless multi-hop fashion. Typically, the nodes report their detection results to a small number of special nodes called sinks [69]. These sensor nodes recognize, compute, and collect environmental information and communicate the collected data to the control room based on some local statistical decision making process [70].

The enhancement of real-time equipment monitoring in CMs hinges on developing sensor networks and integrating new sensing technologies into CMIES. Recent advancements have seen telemetry, control technologies, and embedded computing applied to sensors, creating wireless networks for comprehensive underground data monitoring. Chen [71] leveraged ad hoc network features for efficient communication and sensing. Li [72] introduced a ZigBee-based system for collaborative data gathering from mining equipment, enhancing CMIES data accuracy. The Wits Mining Research Institute [73] deployed wireless networks for geotechnical monitoring, aiding in understanding underground deformations. Furthermore, the dense environment of CMs, filled with auxiliary systems such as ventilation and drainage, presents unique opportunities for utilizing wind, vibration, thermal, and electromagnetic energies through novel sensing devices. Yuan [74] developed a micro-energy model incorporating energy conversion structures for efficient sensing. To optimize sensing systems, data preprocessing, fusion, and intelligent analysis are crucial. Ali Gul [75] implemented a machine learning-based prediction system for sensor data, improving environmental monitoring. Duan [76] proposed efficient coding and optimization strategies for wireless sensor network management, significantly enhancing sensor reliability and stability in CMIES. Especially in coal transportation, the safety stability of transportation equipment needs to be detected by intelligent sensing devices and intelligent algorithms. Belt conveyors usually cause serious safety accidents due to conveyor belt tearing, misalignment or aging, Li [77] proposed an online detection method for longitudinal tearing failure of conveyor belt images based on improved SSR algorithm; Zhang [78] proposed a novel deep learning based conveyor belt deviation monitoring method; Yang [79] proposed a novel conveyor belt wear detection algorithm based on deep learning and machine vision techniques, and these methods greatly improve the intelligence and security of the coal transportation process.

These developments mark substantial progress in the accuracy and efficiency of CM operation monitoring. These technologies have significantly improved the stability and reliability of sensing devices in the CMIES perception layer. Figure 5 shows the representative scenarios of above technologies in CMIES.

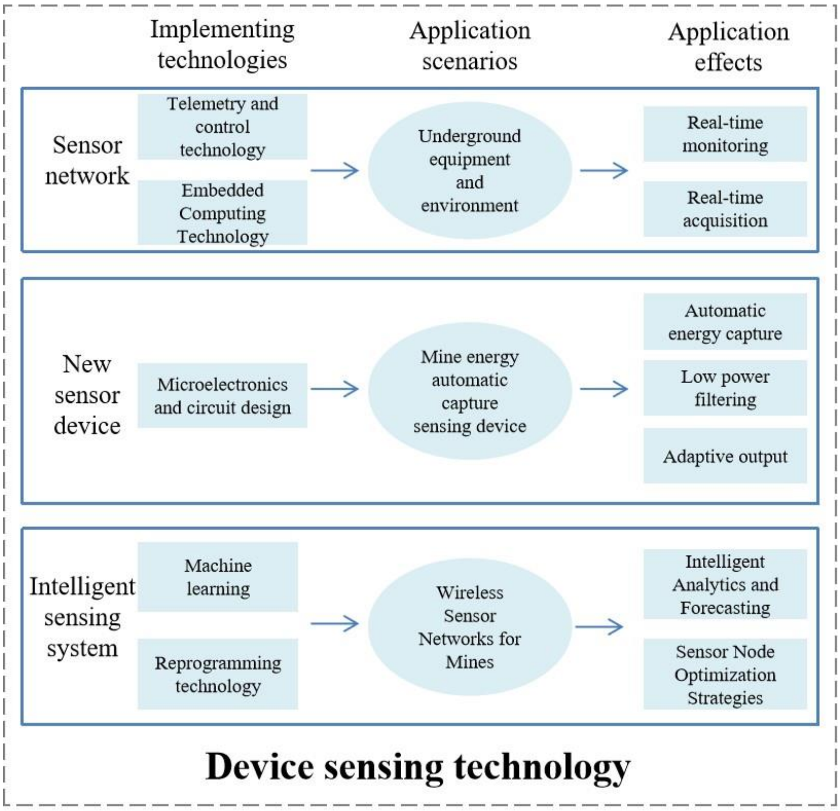


Figure 5 Representative scenarios for the application of device sensing technologies in CMIES

The optimization of the CMIES workflow and work efficiency is inextricably linked to the improvement of the intelligence level of the equipment in the CMIES. Intelligent equipment is primarily used in intelligent, fully mechanized mining faces, transportation faces, intelligent scheduling, and collaborative control of equipment. In the field of intelligently synthesized mining faces, Peng [80] proposed a two-end constraint algorithm based on control points for the inertial error dispersion problem that can accurately measure the running trajectory of a coal mining machine after it is used in the synthesized mining face. In the field of excavation working faces, Hu [81] accurately reconstructs a three-dimensional scene of the excavation face through three-dimensional laser scanning, depth vision, and SLAM technology. Combined with navigation technology and a geographic information system, a closed-loop control system for the digging pose and working parameters was established to realize the autonomous digging operation of the excavator. In the field of transportation, the unmanned technology of electric mining locomotives can avoid the problems of low productivity and high safety risk caused by manual driving. Yang [82] proposed a deep learning-based obstacle detection method for unmanned electric locomotives in underground coal mines, which makes the operation of locomotives safer and more stable. Zhang [83] established a multi-objective intelligent scheduling model for an unmanned car in an open-pit CM that matched the actual production of an open-pit CM. In the field of intelligent scheduling and collaborative control of equipment, paper [20, 84, 85] established the production process of the CM equipment system and the theoretical model of multimachine collaborative operation and proposed an intelligent scheduling and collaborative control scheme for a CM equipment system, which improved the working efficiency of the CM equipment system and reduced the CMIES energy consumption.

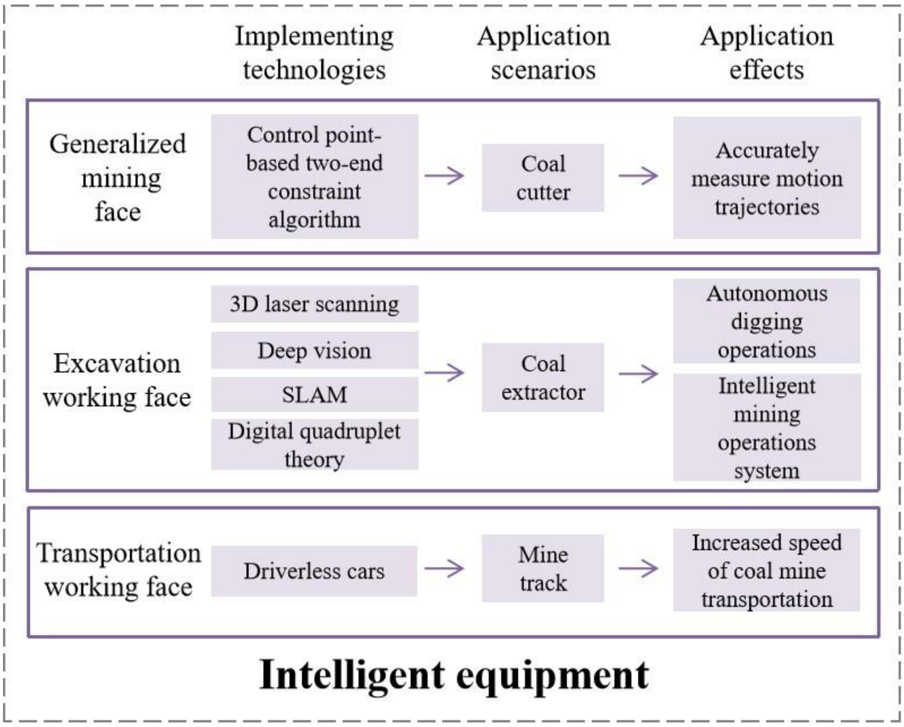


Figure 6 Representative scenarios for the application of intelligent technology in CMIES

## 4.2 New information network technology in CMIES

This new information network technology is based on 5G, edge clouds, and other advanced technologies to realize multifactor and multilink data transmission in CMs, which is the foundation and premise of the optimal operation of the control system. To guarantee the key businesses of the CMIES with high quality and to realize flexible access to multiple scenarios, a network of full connection, large broadband, unified bearing, and unified operation and maintenance needs to be established [86] to support the integration of multiple pieces of information and the linkage of the comprehensive energy system.

Traditional CMs utilize multiple industrial ring networks such as security and video monitoring, often relying on Gigabit Ethernet technology [87]. However, the bandwidth demands of CM underground production exceed what these networks can handle [88], leading to the construction of separate networks for different services, resulting in complexity, poor reliability, and limited data sharing. To overcome these limitations and support multi-scenario flexibility, a digitally enabled CMIES requires a novel information network architecture that leverages 5G and edge-cloud computing. Jiang [89] suggests integrating advanced technologies such as 5G private networks and WiFi6, alongside edge cloud computing, to enhance network capabilities. This approach enables comprehensive equipment data coverage, facilitates multi-information data sharing and interaction, and underpins intelligent CMIES operations, addressing the bandwidth and interoperability challenges of traditional setups.

### 4.2.1 Overall architecture of the new information network

The overall architecture of the new digitally enabled CMIES information network is shown in Figure 7. CMIES information fusion and system linkages are supported by building a fully covered and connected information network. The network architecture consisted of core switches, an underground production network, and an office network. 5G communication technology has been integrated into all aspects of production and office networks to achieve extensive access and reliable communication in various scenarios and functions. Meanwhile, the data analysis technology based on edge cloud computing provides data processing, analysis, and decision modes for the new information network architecture and connects the campus cloud to provide the cloud service of the entire network scheduling, which supports the local processing of computing power.

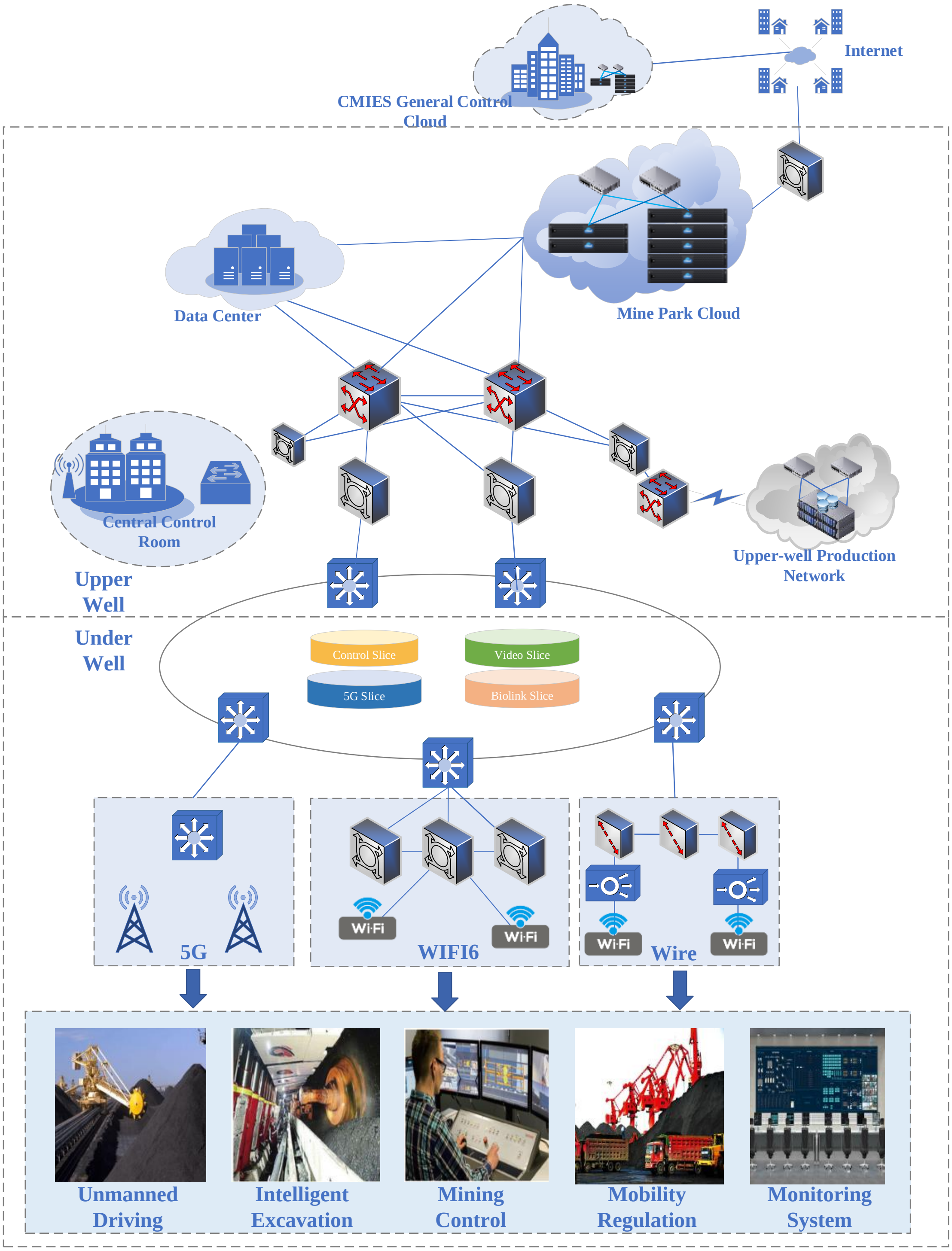


Figure 7 Overall architecture of a digitally-enabled CMIES information network.

The core switches connect each area. The backbone area is interconnected by 10 gigabits to realize high-speed data interaction and sharing among areas and to separate the control plane, monitoring plane, and data forwarding plane, achieving the highest reliability in the industry [90]. The production network of the CM ground and underground is the core area of CM production, whose backbone layer consists of backbone routers [91, 92]. The backbone ring network is constructed using 50GE/100GE links, which meet the increasing bandwidth demand of future CMIES services and carry all the traffic of the entire network. They also need to meet the unique environmental requirements of CMs, such as dust, moisture, and vibration resistance, while ensuring high reliability and low latency. In mining and underground production networks, network slicing is realized based on network function virtualization and software-defined network technology [93]. The network is divided into several virtual subnetworks that meet different requirements, such as control, video, 5G, and IoT. The different subnetworks do not interfere with each other and are logically independent, which can meet the difficult isolation and low-delay bearing requirements of underground personnel communication, sensor information collection, underground remote control, and other services, optimize service quality, and improve bearing capacity [94, 95]. On the access side of the production network, to meet the flexible access of underground mining, mining, transportation, monitoring, and other business scenarios, the wireless access of data information is realized by deploying 5G base stations and WiFi6 access points [96], creating an underground wireless network with large bandwidth, low delay, and high concurrency. Deploying a 10 Gigabit access router or switch provides both wired and wireless access to the CMIES isolation terminal [97]. The office network layers the network structure such that the layers are relatively independent, realize full information coverage of the CM office park, and realize trunk gigabit to the desktop.

### 4.2.2 Fusion communication technology based on 5G

Digitally enabled CMIES are inseparable from the efficient interconnection of data and information. The data characteristics and transmission requirements of different application scenarios vary significantly [98], and traditional technologies have difficulty meeting the needs of information differentiation and full coverage. The characteristics of 5G, including large bandwidth (particularly uplink bandwidth), low delay, wide connection, high reliability, edge computing, and slicing technology, have paved the way for intelligent data transmission in CMs [99].

The 5G technology has three business scenarios: enhanced mobile broadband (eMBB), ultra-reliable low-latency communications (urLLC), and massive machine-type communication (mMTC). All application scenarios can play an active role in the CMIES. The technical support capability of 5G technology for eMBB scenarios [100] can effectively meet the business requirements of large bandwidths, such as ultra-high-definition video transmission in CMs [101]. The technical support capability of 5G technology for the urLLC scenario [102] can effectively satisfy the communication requirements between intelligent devices in unmanned CMs, such as underground unmanned mining vehicles and excavators [103]. The technical support capability of 5G technology for mMTC scenes [104] can better support the sensor data acquisition requirements of the intelligent sensing layer [105]. This will effectively promote the process of CMIES digitalization and pave the way for "network communication" for the comprehensive opening of CMIES intelligent mining [106].

The coal mine 5G technology adopts the topology of high-speed fiber optic core network and 5G base station wireless network. The link channel established by the wireless network for large bandwidth backhaul to the 5G core network can provide multiple functional services such as large bandwidth backhaul, clock synchronization, and slicing service management and delivery [107]. On the issue of mine data sharing channel and safety data isolation, 5G technology adopts slice management technology to customize the network on demand. The dedicated networks are isolated from each other and interconnected end-to-end at the bottom. It provides dedicated channels and security solutions for the transmission needs of different scenarios [108].

Based on the technical support capabilities of each scenario, the CM 5G core network can be deployed in the CMIES to perform base station operation and management signaling, which realizes the independent operation of the base station in the park. Through integrated designs, reasonable collaboration can be achieved with public networks [86]. An independent private network is a mining-area-dedicated independent core network that supports 5G terminal access in CMs. It provides network-access services for private network users and terminal equipment [109]. The 5G private network deployed in the CMIES has some key features and advantages. First, full-service coverage planning was performed. Through various coverage technical schemes and business portraits, business modeling, industry professional planning, and other methods, CM full-scene planning is conducted to support full coverage of the mining business [110]. Second, the data cannot be out of the park; the core network of the CMIES sinks into the mining area, and the production data cannot be out of the mining area, which can ensure the security and confidentiality of the production data [90]. Furthermore, the network's reliability and availability continue to increase. By introducing an access router on the 5G terminal side and a dual-transmitter selection mechanism, a dual-link connection was established between the coal machine equipment and wireless network to reduce the occasional delay jitter caused by packet loss, making the remote control of the underground equipment more reliable [111]. Besides the above advantages, the uplink capacity of the communication network in the CMIES will also be enhanced, service connection failures can be automatically delimited while production is not interrupted, and the links are more secure and reliable.

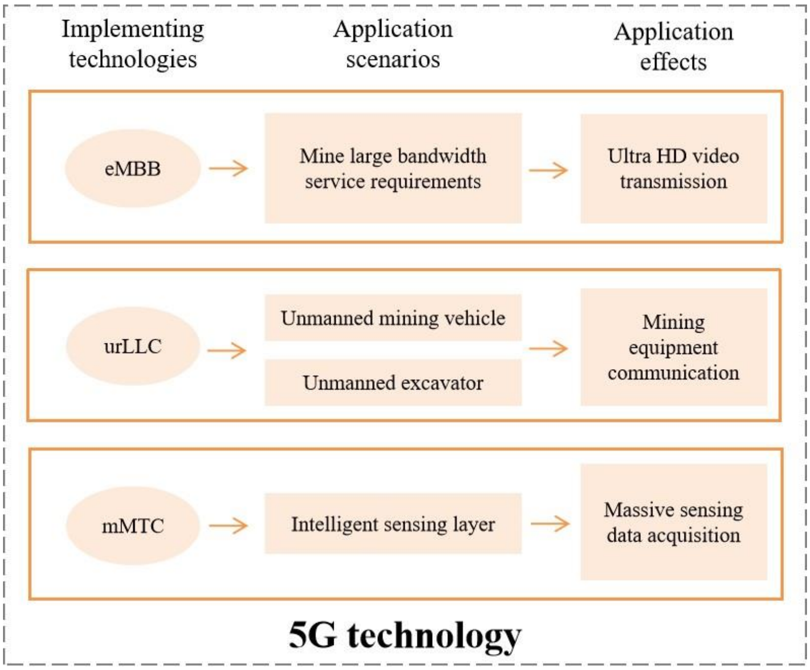


Figure 8 Representative scenarios for the application of 5G technology in CMIES

### 4.2.3 Data analysis technology based on edge cloud computing

Owing to the problems of excessive amount of data at the edge and privacy protection during massive data processing, cloud computing can no longer meet the time requirements and edge cloud computing emerges. Edge computing refers to enabling technologies that allow for the performance of computations at the edge of the network, on behalf of cloud services for downstream data and on behalf of IoT services for upstream data [112]. Edge cloud computing can significantly reduce latency and mobile energy consumption, fueling the development of 5G communications [113].

In the evolution of CMIES, the deployment of edge cloud computing is pivotal to managing the increasing data volume and bandwidth demand, mitigating risks of congestion that threaten system reliability and real-time control [114]. Tailored to the mining sector's unique challenges, edge cloud computing delivers low latency, high security, and adaptability, positioning it as an essential solution for on-site data processing [115]. This decentralized approach places computing and analytical capabilities at the network's edge, directly within the mining operations sphere, thus addressing latency and bandwidth issues while ensuring the dynamic and complex demands of modern coal mines are met for seamless, real-time operational control. Moreover, edge-side data become crucial in digitally enabled CMIES, with the key performance attributes of edge computing, such as convergence, real-time processing, and security, underpinning the implementation of an intelligent edge cloud platform. The integration and interoperability between edge and cloud data, alongside the real-time control of edge computing layer devices and secure multi-data interaction, emerge as vital areas of focus.

Object linking and embedding (OLE) for process control unified architecture (OPCUA) plays a critical role in achieving data convergence and interoperability within CMIES, offering a standardized, secure, and scalable infrastructure [116, 117]. Caiza [118] leverages OPCUA to create a human-machine interface that unifies messages across the production floor, enabling comprehensive coverage and interaction from device to cloud application layers. Pauker [119] outlines using OPCUA information models and unified modeling language for system analysis and design, supporting various programming languages and operating systems. This flexibility aids in the virtual representation of manufacturing systems, facilitating vertical system integration and addressing data silo challenges by enabling interoperability among diverse protocols and physical devices. OPCUA thus stands as a pivotal technology in CMIES, promoting seamless information flow and system efficiency.

Addressing the critical need for millisecond precision in operational technology (OT) data transmission within coal mines, to prevent issues such as equipment collisions, requires rethinking internal network protocols. Traditional Ethernet modifications for ultra-low latency often fall short in interoperability, scalability, and compatibility. Time-Sensitive Networking (TSN) emerges as a robust solution, offering real-time, efficient, and secure data transmission with minimal delay and jitter, and low data loss. TSN optimizes standard Ethernet through mechanisms such as time synchronization and data scheduling, ensuring the timely delivery of sensitive data. Lautenschlaeger [120] distinguishes OT from IT in time sensitivity, demonstrating TSN's capability to maintain defined delay limits and stable transmission through interoperability tests and field trials. When integrated with OPCUA, TSN extends real-time data collection directly to devices [121], enhancing production environment monitoring [122]. This synergy supports CMIES's evolving digital needs, including digital twin development. Current TSN switches from vendors achieve delays under 10 μs and synchronization accuracy of 20 ns [123, 124], promising to fulfill CMIES's extensive real-time requirements, marking a significant advancement in digital infrastructure for the mining industry.

The core of edge cloud computing platform security is ensuring robust boundary protection between edge and cloud environments [125]. With the challenge of evolving data encryption and access control technologies in CMIES, this security relies on one-way gate isolation transmission through physical isolation [126]. This method enables secure data exchanges between the edge and cloud via a "data ferry." Chadwick [127] introduces a five-level trust model using homomorphic encryption tailored for cloud-edge data sharing, particularly for confidential computer telephony integration data, ensuring its secure manipulation and analysis. Comprehensive security across all architectural layers is essential, with each layer demanding unique security measures [128]. Elevating security necessitates deploying strategies such as data backup, redundancy, and fault tolerance [129, 130], thereby reinforcing platform resilience. Continual refinement of these security mechanisms is vital for fulfilling the overarching security needs of the edge cloud computing architecture.

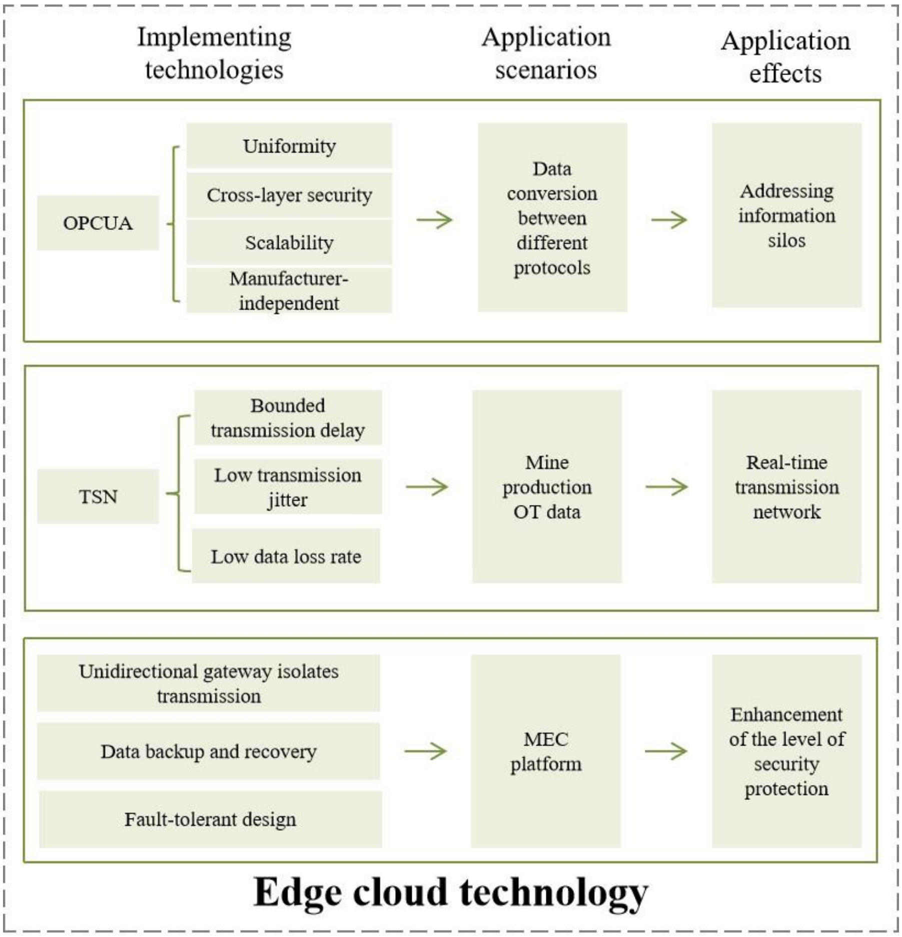


Figure 9 Representative scenarios for the application of edge cloud technology in CMIES

## 4.3 Big data platform and application technology in CMIES

The advent of smart devices and sensing technologies in CMIES has led to the generation of vast amounts of data from diverse sources [131]. Addressing the challenge of managing, analyzing, and utilizing this data necessitates the construction of a big-data platform [132]. Such a platform, grounded in big-data integration service technology, would facilitate data integration [133], governance [134], and sharing [135], to dismantle barriers within coal mine production and business operations [136]. This integrated approach allows data to be leveraged as an asset, enabling multi-scenario applications and connections that support intelligent application collaboration, optimize decision-making, enhance asset value, and foster value creation [137].

### 4.3.1 Big data platform in CMIES

The CMIES big data platform is a comprehensive application system that combines and fuses CM big data from various subsystems for analysis and display, and provides relevant technical support for the construction of CMIES through the analysis and mining of big data [138]. According to the characteristics of the CMIES big data and the real demand for construction, the mining big data analysis platform adopts a hierarchical design and is divided into five hierarchical structures, from bottom to top: data foundation, data aggregation, data storage, data analysis, and data value. Structure of big data analysis platform is shown in Figure 10.

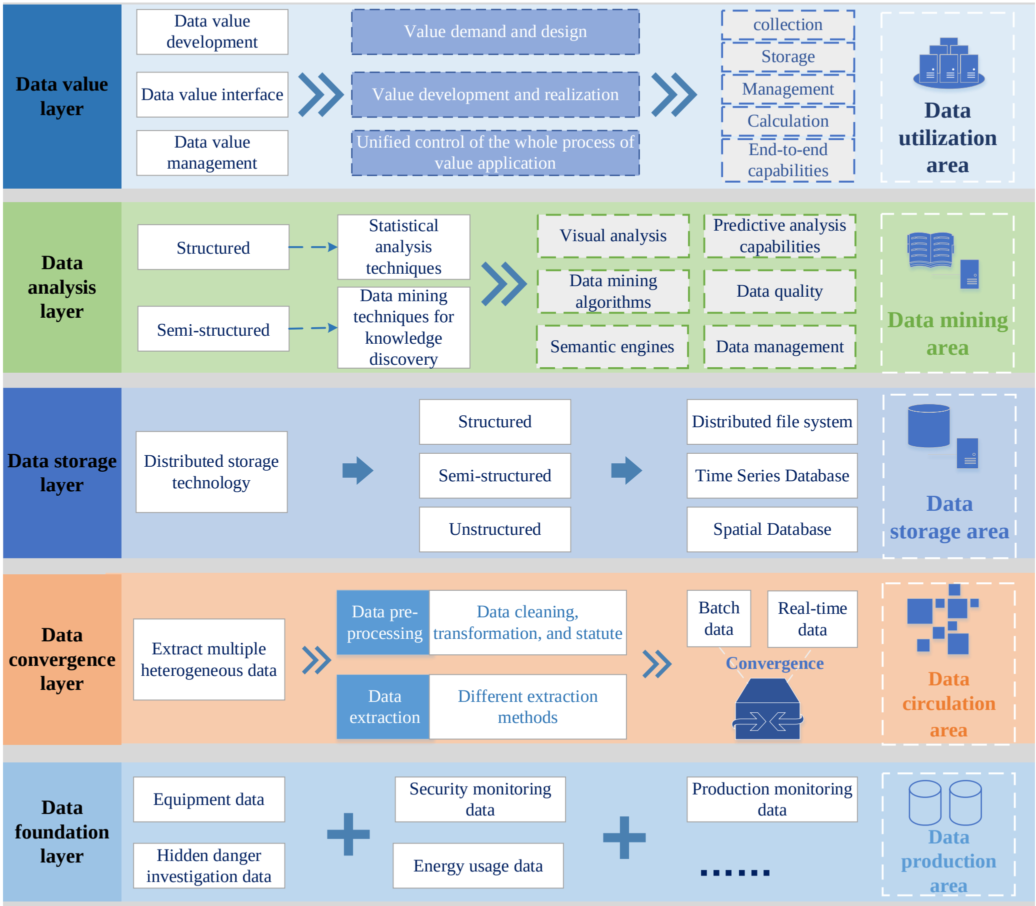


Figure 10 Illustration of big data analysis in CMIES

(1) Data-foundation layer

The data foundation layer is the area where the data are generated. The CM data is the cornerstone of the CMIES big data platform [139], including security monitoring data [140], energy usage data, production monitoring data [141], hidden danger investigation data [140], video monitoring data [142] and other data of various structure types.

(2) Data aggregation layer

The data aggregation layer is the area where the data flows. As CMIES big data are scattered in multiple information technologies and automation systems, extracting and converging these multisource heterogeneous data is an important process in CMIES big data platform construction [143, 144], specifically batch data convergence and real-time data convergence, which can extract multiple heterogeneous data sources from all types of business systems to the data storage layer through data extraction and data pre-processing. Data extraction design requires different extraction methods for various data sources after analysis [145]. Additionally, pre-processing is required because the extracted data are missing or unreasonable, resulting in an inability to store and analyze them [146]. In summary, the aggregation and extraction of data lay the foundation for subsequent data storage and analysis.

(3) Data storage layer

The data storage layer is the storage area for data and is a prerequisite for big data analytics. The business data in CMIES need to be stored after extraction and pre-processing, and because the aggregated data are quite massive and complex in structure, distributed storage technology needs to be used for data storage [147]. Considering the actual situation of the CM, the data can be stored as structured, semi-structured, and unstructured data [148] and then stored in a distributed file system [149], database, spatiotemporal database [150] and other storage systems based on the characteristics of the data, which can facilitate subsequent data processing and analysis.

(4) Data analysis layer

The data analysis layer is essential in constructing the CMIES big data platform, serving as the digitization linchpin. It employs statistical analysis for structured data and leverages machine learning and AI for mining unstructured data, facilitating knowledge discovery [151, 152]. This process is critical for interpreting vast volumes of coal mine data across varied business scenarios [153], incorporating techniques such as visual analysis, predictive analytics, and data quality management [154]. By applying big data analysis technology, with the redundancy and complementarity of CMIES panoramic data in space and time, it can realize a macro, real-time, continuous, and accurate grasp of the CMIES global situation, as well as a multi-level, multi-dimensional, and multi-modal accurate perception of CM local situations [155, 156].

(5) Data value layer

The data value layer is the area where the data are utilized. The data value layer specifically includes data value development, the data value interface, and data value management, which can realize unified control of the entire process of value demand and design, value development and realization, and value application [157]. In the data value layer, the functions of the remaining four layers can be combined to provide the CMIES with data collection, storage, management, calculation, and end-to-end capabilities [158], and the value of each layer of data can be used to process the business logic of each application, thus helping digitally enabled CMIES construction.

### 4.3.2 Data integration services in CMIES

Data integration involves combining data residing in different sources and providing users with a unified view of them. Data integration encourages collaboration between internal as well as external users. The data being integrated must be received from a heterogeneous database system and transformed to a single coherent data store that provides synchronous data across a network of files for clients. The data integration service focuses on application and data connectivity within the CMIES, adapts to a variety of common CMIES usage scenarios, and provides full connectivity for service integration, message integration, and data integration [139] to reach internal and external CMIES interoperability and multi-cloud interoperability. This technology integrates various subsystems of the CMIES [159] to break down data silos and achieve comprehensive control. The data integration service standardizes the accessed side-side data [160] and the data of each business scenario and provides a unified data interface, message interface, and back-end service interface to realize several services, such as application enablement, integration sharing, and comprehensive display of the big data platform.

In the CMIES, application enablement and integration are critical for enhancing efficiency and reducing redundancy. Utilizing application programming interfaces, CMIES can consolidate key capabilities such as 5G, big data platforms, and video surveillance [161], enabling smart applications and easing data sharing across subsystems [162, 163]. Integration facilitates the use of industrial protocols and gateways for diverse equipment data collection [164], while comprehensive displays offer holistic data visualization, situational predictions, and support for production planning [165-168]. Intelligent optimization in CMIES employs various algorithms for energy management, addressing uncertainties in renewable energy sources and optimizing operations. How to deal with the coordination and optimization among multiple energy sources [169] and the trading mechanism among integrated energy systems [170] are the key issues in promoting CMIES. For CMIES, Hu [171] introduced a multi-timescale strategy for system stability, Huang [172] developed a two-stage optimization method for robustness, and Dai [173] created a novel algorithm for global search performance in CMIES scheduling. Figure 11 shows the representative scenarios of the above technologies in CMIES.

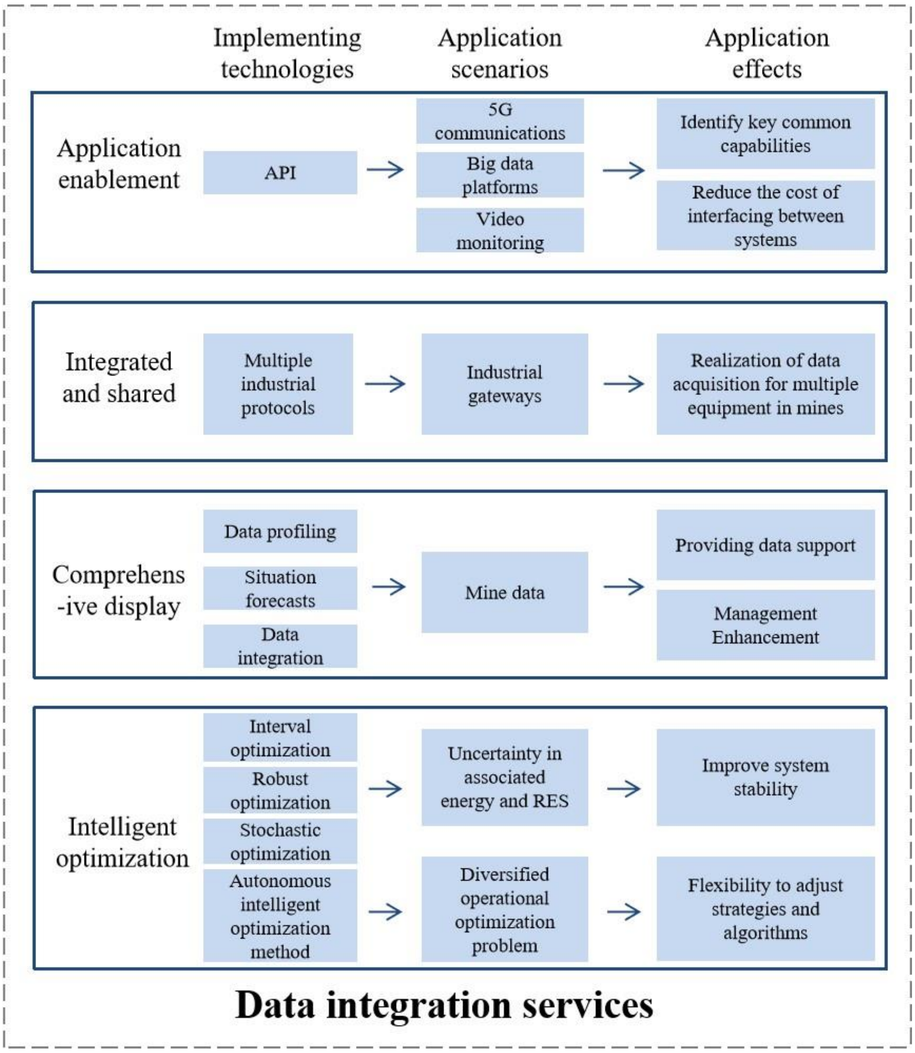


Figure 11 Representative scenarios for the application of data integration services in CMIES

## 4.4 Digital twin technology in CMIES

The accumulation of massive process data from sensor networks, smart devices, information networks, and big data platforms has laid the foundation for the CMIES to digitize its entire life cycle [174]. Digital twin technology can respond to production rules, track the evolution of the production process equipment environment, and interact intelligently with the production process is required to support the digital construction of a CMIES [175-177].

A digital twin accurately reflects the state of its physical counterpart by integrating historical data, real-time sensor data, and physical models. It consists of adaptive models that emulate the behavior of a physical system within a virtual environment, continuously updating itself with real-time data throughout its lifecycle. The digital twin not only replicates the physical system but also predicts failures and identifies opportunities for improvements, prescribing real-time actions to optimize or mitigate unexpected events by observing and evaluating the operating profile. By employing physical modeling, virtual modeling, connection modeling, data modeling, and service modeling, information-physical fusion is achieved, enhancing the reliability, flexibility, and predictability of production processes [178]. Implementing digital twin technology in CMIES enables the creation of a digital model, supporting intelligent control, fault prediction, and functionalities such as data synchronization, predictive analytics, thereby offering fresh perspectives on sustainable CMIES development [179].

For building the key technology of the digital twin CMIES model, we adopt the idea of "information-physical fusion" of the digital twin [180] and combine the three components of the digital twin given by Michael Grieves [181]: physical product in physical space, virtual product in virtual space, and data and information interaction interface between physical space and virtual space, to design the basic model of the CMIES digital twin. By establishing virtual simulation models of scenarios [182], equipment, and operational processes in the digital twin CMIES, the virtual-real mapping of each process in the CM was used to form an iterative and collaborative optimization mechanism of the virtual-real symbiosis [183]. Based on the collaborative optimization mechanism, it realizes the mapping feedback between the simulation of the CMIES information space and physical entities in the physical space [184], as well as the virtual-real interaction and data synchronization between the actual scene and the virtual simulation scene. Building a digital twin CMIES model can effectively correlate the digital twin-driven CMIES physical entities, virtual models, services, and data, which provides a way for each part to collaborate and interact [185], so that all parts can continuously interact and update, optimize, and iterate.

One of the key technologies of the CMIES digital twin involves creating a digital model that mirrors the physical entities of integrated mining equipment [186], enabling comprehensive depiction of the CMIES's mechanical, electrical, and hydraulic aspects [187]. Through the digital twin of the virtual energy system, the mechanical, electrical, and hydraulic characteristics of the CMIES are comprehensively described, and virtual mapping of each physical device is realized. Accordingly, it can be updated in real time to visualize the dynamic data of real and imaginary interactions in the CM [182], manage the entire life cycle of each piece of equipment [188], and effectively track changes in the operation status of equipment and facilities. Simultaneously, the digital twin also provides intelligent analytical tools to optimize the use and maintenance of equipment and facilities so that they are always under optimal operating conditions.

CMIES digital twin intelligent control technology can achieve integrity verification, iterative algorithm optimization, performance evaluation [189], and autonomous decision control for real-time state feedback and autonomous learning [190] through CMIES digital twin control system tuning and decision-making in control centers far from CMIES production sites. The realization of CMIES intelligent control based on digital twin needs to be based on the CMIES real-time state awareness layer, combined with workflow technology [191] and intelligent computing theory to drive the interaction between the collected real-time data of multiple production scenarios, each application system, and the digital twin model, and to simulate the behavior process. Intelligent control based on digital twins can solve the problem of optimal resource allocation and intelligent task scheduling in the production process of a CMIES and achieve a two-way flow of production information and feedback control information.

For CMIES equipment fault prediction technology, an intelligent control technique is used to analyze equipment disturbance factors and extract fault characteristics to model the fault process [192]. On this basis, deep learning is used to identify and predict the health of each type of equipment quality defect and the operational failure of the CMIES [193]. Driven by twin data based on synchronous mapping, real-time interaction, and accurate service between the physical and virtual devices of the CMIES, the collaborative operation of each scene is carried out in a panoramic immersion manner to help establish a perfect CMIES equipment operation plan for preventive maintenance and form a new model of CMIES health management. Figure 12 shows the representative scenarios of above technologies in CMIES.

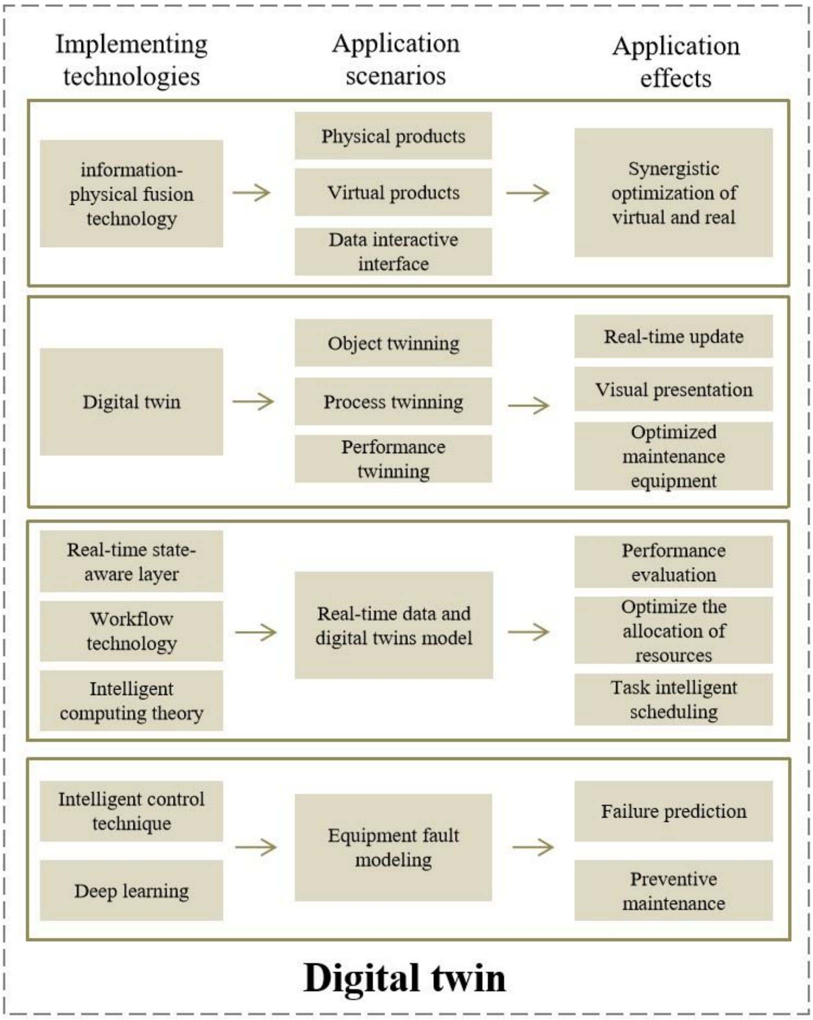


Figure 12 Representative scenarios for the application of digital twin technologies in CMIES

## 4.5 Quantitative comparison in the selected cases

Some domestic and international mines have pioneered digital transformation. This section quantitatively analyzes the changes in cost-effectiveness and production efficiency in three typical smart mines before and after transformation.

The smart mine established by Rio Tinto Iron Ore in Australia, which uses driverless drilling, is averaging nearly one-third more hours of operation and drilling an average of 10 percent more distance per hour. With the help of driverless vehicles, operating costs at the Pilbara mine are expected to be around 15 percent lower than at other mines [194].

China Jiang Jiahe coal mine constructed 5G 10 Gigabit ring network and data center, and built an intelligent control platform to complete the real-time comprehensive integration of the main production links (mining, excavation, machinery, transportation, ventilation, etc.), underground environment safety, personnel location and other information, and based on the 3D mine visualization display, fusion linkage, and cross-system synergistic control. It realizes remote control, reduces personnel and increases efficiency, and reduces the number of production personnel from 20 to 8 per shift in the normalized mining production process, which improves the work efficiency by 54% and reduces the electromechanical failure rate by 25% [195].

China Zhang Jiaxuan Coal Mine has developed a mine-wide cross-domain convergence intelligent integrated management and control platform based on the industrial Internet architecture, realizing the data connectivity between the upper and lower parts of the mine, and improving the comprehensive utilization rate of data by more than 50%. Based on 5G intelligent sensing and edge computing controllers for pressure, position and video, the company realizes automatic machine following, autonomous straightening, unmanned operation in the working face, 20% increase in the start-up rate of equipment, and 30% increase in the overall production efficiency. Breaking through the high-precision navigation technology of “laser-sensor” fusion for digging, the company has developed an intelligent fast digging system that can realize the highest daily footage of 120 meters [196].

# 5 CMIES future outlook

Section 4 presents a comprehensive overview of the digitization technologies underpinning CMIES, which are critical to its development. The technologies and methods proposed by these researchers are landmarks in the move towards digitally enabled CMIES. However, there are still a large number of challenges and barriers to achieving integrated and coordinated optimization of the equipment-information system. Certain applications have demonstrated the potential for CMIES to undergo digital transformation; however, further research is needed to identify its strengths and weaknesses. Utilizing the SWOT method as an effective strategic tool, this section analyzes the challenges and future trends associated with CMIES. SWOT methodology can identify internal factors (strengths and weaknesses) and external factors (opportunities and threats) that are favorable and unfavorable for achieving a specific objective or evaluating any type of business case, and has been applied in research areas such as renewable energy development [197], battery storage [198], asset management [199], digital transformation [200], etc..

## 5.1 SWOT analysis

(1) Strengths

1) Mine energy systems already have a degree of technological foundation:

Mine energy systems were developed to include certain levels of automated equipment, basic control systems, information management systems, and basic data analysis capabilities. These technological foundations provide a starting point for the digital transformation of CMIES, making technological upgrades and integration feasible.

2) The value of mine data can be substantial:

Mines have a large amount of production equipment operation monitoring, security and environmental monitoring, and energy utilization data, which contain huge value to be tapped. The use of digital technology can not only realize security risk warning, disaster prediction, and forecasting but also achieve synergy between various systems, unified and accurate scheduling, and improved energy efficiency.

3) Increased awareness of sustainable development and environmental protection in coal mining enterprises:

Due to the growing demand for low-carbon environmental protection, the transformation of coal mining enterprises has become particularly urgent. Consequently, coal mining enterprises are deeply aware of the importance of sustainable development and environmental protection. There is an urgent need for energy-saving modifications to internal processes and enhanced monitoring of equipment energy consumption and pollution emissions. This awareness has helped the CMIES adopt a more environmentally friendly and efficient digitalization strategy that ensures the environmental protection and sustainable development of mines while pursuing economic benefits.

(2) Weakness

1) The economics of digitization need to be improved:

Although digital technology can significantly improve the economic benefits of CMIES in the operation process, its high construction cost and rapidly changing technological updates have led to the need for large capital investments for equipment installation and upgrading. Sometimes, it is necessary to suspend production to install and retrofit equipment, which may cause a certain amount of disruption to coal production. This is the primary reason for the widespread use of digital technologies in CMIES.

2) The mining environment is harsh, and technology landing is difficult:

Mines are harsh environments with a wide range of facial depths. As the depth increased, the temperature of the working face increased, and the pressures of the rock and gas increased. Additionally, mines often contain flammable gases; therefore, underground communication equipment must be explosion-proof to prevent electromagnetic interference and explosions caused by sparks. These conditions pose challenges to the design of digital equipment. Moreover, mines contain nearly 100 subsystems, including basic application platforms, energy management systems, and mining operation systems. The compatibility between these systems at the data, network, business, and control levels is also a major challenge, which has led to the slow process of digitalization technology landing in CMIES.

3) Lack of workers dedicated to digital technology:

The novelty and complexity of digital technologies require a knowledge base to understand how they work and create value. Most mine workers who lack knowledge of this technology require specialized education and training to better adapt to the use of digital technology. Furthermore, fewer people in the mining industry specialize in digitization, which leads the industry to rely heavily on the support and services of information technology companies.

(3) Opportunities

1) Sustainable development and intelligent management requirements:

Global sustainability efforts are guiding the coal mining sector towards adopting greener, smarter practices. Initiatives such as the International Council on Mining and Metals' sustainable mining principles, the U.S. Environmental Protection Agency push for clean coal technologies, China's 14th Five-Year Plan focusing on green, smart mines, and India's policies on modernizing mines while minimizing environmental impact, all promote digitalization and automation in the industry. These measures are pivotal in driving the digital transformation of CMIES.

2) Promotion of market-based mechanisms:

The construction of electricity markets has opened new opportunities for mines to generate economic revenue. The application of digital technology enables the CMIES to monitor and analyze market price signals in real time, optimize the dispatch of the mine's energy system, and participate in the power market with maximum revenue. Simultaneously, the introduction of incentives, such as RES subsidies and carbon markets, has guided the CMIES to efficiently utilize renewable and derived energy sources to improve the overall economics of the mine.

3) Rapid development of digitization technologies:

Rapid advancements in digital technology have not only helped reduce overall technology costs but have also expanded its application areas and improved interactivity. These conditions are favorable for the digital transformation of CMIES and enable more mining companies to adopt advanced digital solutions that can enhance operational efficiency and security.

(4) Threat

1) Confidentiality of data from upstream and downstream enterprises:

Digital technologies must focus on key information from upstream and downstream companies, such as energy availability, price signals, and carbon emissions data, to optimize the CMIES process. If these enterprises impose strict confidentiality on their data, sharing and circulation may be hindered. In this case, the CMIES may face the challenge of integrating and analyzing data from the entire industrial chain, which in turn affects the efficiency of cooperation and speed of decision-making and leads to a slower response to market changes, thus affecting the economic development of the CMIES.

2) Market-based coal price volatility:

Coal prices are market-based, and an unstable economic environment may lead to volatility in coal prices, which in turn affects mining revenue and financial support for digital transformation. In the event of financial constraints, mines may need to reevaluate and prioritize aspects of their digital transformation, identify more cost-effective solutions, or postpone noncritical digital projects.

3) Policy and regulatory changes:

Uncertainty and frequent changes in government policies may create uncertainty in CMIES digital investments and planning, particularly regulations on data management, privacy, and cybersecurity, which can impede digital development.

## 5.2 Development trends

The SWOT analysis approach is used to create optimal strategies by aligning internal strengths and weaknesses with external opportunities and threats. Strengths-opportunities strategies use internal advantages to seize external opportunities, while strengths-threats strategies leverage strengths to counteract threats. Weaknesses-opportunities strategies focus on improving internal weaknesses by taking advantage of external opportunities, and weaknesses-threats strategies work on minimizing weaknesses to mitigate external threats. This structured approach helps organizations balance their resources and external factors to develop effective strategic plans. Based on the SWOT analysis, the development trend of CMIES is shown in Table 1.

Table 1. SWOT analysis of digital-enabled CMIES

| **SWOT analysis** | **Strengths (S)** | **Weaknesses (W)** |
|---|---|---|
|  | 1. CM energy systems already have a degree of technological foundation; | 4. The economics of digital construction need to be improved; |

| | | |
|---|---|---|
| | 2. The value of CM data is considerable;<br>3. Coal mining enterprises have increased their awareness of sustainable development and environmental protection. | 5. The harsh environment of the CM makes monitoring and collection difficult;<br>6. Insufficient training of digital talents in coal mining enterprises; |
| **Opportunities (O)**<br>1. Sustainable development, intelligent management needs;<br>2. Promotion of market mechanisms;<br>3. The rapid development of digital technology; | Promoting the intelligent transformation of CMIES to explore the potential value of internal data. | Promoting the CMIES key technology breakthroughs and realize technical solutions. |
| **Threats (T)**<br>1. Confidentiality of upstream and downstream business data;<br>2. Market-based coal price volatility;<br>3. Policy and regulatory changes. | Strengthening the construction of the CMIEIS ecosystem and realizing resource sharing. | Broadening CMIES marketed channels of revenue to reduce single market risk. |

(1) Promoting intelligent transformation of CMIES

Fully promote the intelligent transformation of CMs, promote the construction of intelligent CMs with 5G communication, advanced control technology, and intelligent analysis technology as the traction to accelerate the construction of unmanned CM production and energy loss reduction. Adequately explore the potential value of energy utilization, production and operation data within CMIES, to build an intelligent information system integrating perception, interconnection, analysis, decision-making, and prediction that supports the prediction of energy demand, optimization of production processes, and maximization of energy utilization efficiency.

(2) Strengthening the ecosystem in CMIES

Reinforce the cooperation and communication between upstream and downstream enterprises, and integrate various industries including manufacturing, mining, chemical, and electric power to build a mutually beneficial CMIES ecosystem. Through digital means and sharing to open up the flow of services, information, and capital among the nodes and subjects in the ecosystem, resource sharing, information exchange, and financial transactions in the ecosystem are made more efficient, transparent and convenient.

(3) Promoting key technological breakthroughs in CMIES

Promote developing communication and transmission systems that are adapted to the confined space of CMs. Research and develop CM monitoring equipment and communication equipment that are resistant to high temperatures, dustproof and explosion-proof. Formulate unified data collection technology standards for the coal mining industry, and design technical solutions for processing heterogeneous data from multiple systems. Promote the research of environmental management and resource reuse technologies for the mining area and the surrounding environment, to facilitate the sustainable development of CMs.

(4) Broadening of CMIES market-based revenue channels

Explore new markets and service areas to diversify revenue sources. Leverage the energy flexibility of CMIE, respond to government incentive and subsidy mechanisms, and participate in energy trading such as the power and carbon markets. Make full use of natural gas, CM water, and derivative mineral resources produced by the CMs to be used as raw materials or processed and sold outside. Provide upstream and downstream enterprises with services such as market analysis and risk assessment through the CMIES big data platform, thereby enriching CMIES' market-oriented revenue channels.

# 6 Conclusion

The arrival of Industry 5.0 will prompt the reform and innovation of the energy industry. The achievement of digital empowerment under the requirements of low-carbon environmental protection and sustainable development is a key challenge that must be addressed. The main contribution of this study is the establishment of an effective link between the development of digital technology applications and the theoretical study of CM energy management.

- This study summarizes the four stages of energy production and consumption patterns in CMs: crude, intensive, integrated, and intelligent phases, and proposes a digitally empowered CMIES framework consisting of physical, information and value layers.
- On the basis of establishing the physical topology of CM production process coupled with energy system in the physical layer, an intelligent information system is constructed with the information layer as the core.
- The process for implementing the said system to promote the digital transformation of CMIES with four types of core technologies: equipment sensing and intelligentization technology, new information network technology, big data platform and application technology, and digital twin technology, is proposed.
- The future development trend of digitally enabled CMIES is analyzed in terms of the internal and external environment.

CMIES undergoes digital transformation and is subjected to many unknown challenges in practical application and development. The digitally enabled CMIES framework proposed herein can provide a reference for achieving economic, low-carbon, and safe CM energy management as well as safeguarding CM security production, exploring the green potential of CM energy, and achieving sustainable development. The digitally-enabled CMIES is at an initial stage, and coal mining enterprises are advised to 1) implement the CMIES framework in phases; 2) prioritize the introduction of equipment sensing and intelligent technologies; 3) optimize the information network infrastructure; 4) pay attention to changes in external environments; and 5) promote the application of green technologies in the implementation process.

In this article, we have only discussed some of the cutting-edge digital technologies and more emerging digitization technologies, such as quantum computing, intelligent robots, etc. can be also investigated, which could be a direction for our future researches.

# CRediT authorship contribution statement

**Bo Zeng**: Writing – original draft, Validation, Methodology, Conceptualization, Funding acquisition. **Xinyu Yang**: Writing – original draft, Investigation, Visualization. **Pinduan Hu**: Writing – original draft, Investigation, Methodology. **Yuqing Wang**: Writing – review & editing,

Methodology, Supervision. **Houqi Dong**: Writing – review & editing, Validation. **Dunwei Gong**: Funding acquisition, Validation. **Xianming Ye**: Validation, Conceptualization.

# Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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