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Exploring digital twin systems in mining operations: A review

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ABSTRACT

Constant attempts have been made throughout human history to find solutions to complex issues. These attempts resulted in industrial revolutions and the transition from manual labor to machines and new technologies. The latest advancements in artificial intelligence (AI) are revolutionary. The use of these smart technologies in mining can lead to increased profitability, enhanced performance, improved safety, and better adherence to environmental regulations. In this paper, the applications of AI and digital twin systems in mining operations are reviewed, covering various components, including mineral exploration, drilling, blasting, loading, hauling, mineral processing, and environmental issues. Critical data inputs for each component are identified, and relevant tools and methods are discussed. These will facilitate the development of digital twin models with learning, simulation, prediction, and optimization capabilities. This study provides valuable insights into fully integrated digital twin mining systems, which will significantly improve mining efficiency and sustainability. Although innovative technologies, such as the Internet of Things (IoT) and other intelligent tools, are increasingly being used in the mining sector, many mining processes still depend on human oversight to deal with challenges, such as remote operations, geological variability, high investment costs, and a skills gap. There is, therefore, significant potential to enhance the use of sensors and IoT devices to support data collection for more integrated and powerful digital twin systems to drive further innovation and operational improvements across the mining value chain.

1. Introduction

Throughout history, humans have looked for feasible solutions for complex problems and ways of making routine tasks easier. As a result, specialists in diverse sectors have developed and implemented various tools and techniques. The simulation of processes is one of the most effective and powerful tools in this regard. According to Shannon, simulation is “the process of designing a model of a real system and conducting experiments with this model for either understanding the behaviour of the system or evaluating various strategies for the operation [1].” In the mining industry, digital twins have gained increasing popularity in recent years due to their potential to enhance operational efficiency, reduce costs, improve safety, and optimize resource extraction. The implementation of digital twins relies on various factors, such as increased adoption by companies, advancements in data analytics for more accurate predictions and better insights, integration with Internet of Things (IoT) devices, the use of cloud computing for handling large datasets and performing complex simulations, and customizing available digital twin platforms to meet specific mining needs.

The behaviors of a system can be explored through simulations if a numerical model representing the system is available. In the absence of a model to understand the behaviors of the system, the only viable alternative is to implement the system on a reduced scale, which could potentially result in significant costs and disruptions. Before creating or updating a system, simulations can help detect issues, bottlenecks, and design flaws. Simulation provides a means of evaluating various designs and operating principles before committing funds and time to a project. Simulations in this context are used to analyze the system dynamics, the evolution characteristics, and the component interactions. However, conventional analytical or static models only offer, at best, a basic level of understanding of a complex dynamic system [2]. As shown in Fig. 1, simulations provide a means of exploring a wide range of operational scenarios, enabling the derivation of the optimal operational strategy. In addition, they can be used for sensitivity analyses for different

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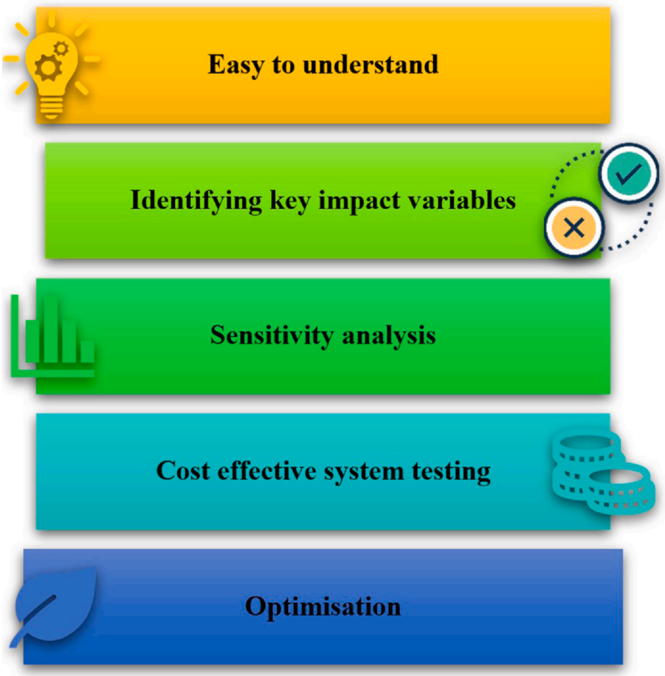


Fig. 1. Advantages of simulations.

variables, contributing to a thorough understanding of system dynamics and performance under different conditions.

For intricate systems, modeling and simulation facilitate the analysis of interactions between system components and their effects. This approach is becoming a way of tackling challenging real-world issues in biology, physics, economics, and others that involve many interconnected variables. The Monte Carlo approach, agent-based modeling, discrete event simulation, and dynamic modeling are currently the four key simulation techniques widely used in games, visual and audio synthesis methods, machine learning algorithms, processing kernels, and controller systems [3]. In addition, the mining industry also uses innovative technologies such as virtual reality (VR), augmented reality (AR), and mixed reality (MR), in which the four methodologies discussed earlier are deeply embedded [4–9].

Current simulation technologies have a long history, and industrial revolutions have played a significant role in their development. As briefly described below, there are four key industrial revolutions in human history.

1.1. Industry 1.0

The first industrial revolution (Industry 1.0) started in the 18th century and lasted until about 1840. Industry 1.0 is characterized by the extensive use of steam power and the mechanization of industry [10]. It signified the first major transition from traditional production methods and tools to a mechanical economy. The introduction of new machines significantly boosted worker productivity and enhanced the efficiency of production processes [11].

1.2. Industry 2.0

The second industrial revolution (Industry 2.0) occurred in the 19th century and ushered in industrial processes that used electrically powered machinery. These electrical machines were notably more efficient, easier to operate, and simpler to maintain than their steam-powered counterparts [12]. They also proved to be more cost-effective, requiring less labor and materials. A crucial element of Industry 2.0 was the enhancement of mass production methods. The application of steel and electrical energy in manufacturing was the main feature of this revolution [13].

1.3. Industry 3.0

The "Digital Revolution" or "First Computer Era" are other names for the third industrial revolution (Industry 3.0), which started in the second half of the 20th century. Partial automation techniques made possible by basic computers marked the start of the third industrial revolution [13]. Electronics and information technology (IT) were integrated into numerous production processes, increasing automation in the manufacturing process. As a result, this led to enhanced efficiency, faster production rates and, in some cases, the elimination of human labor in specific manufacturing processes [10].

1.4. Industry 4.0

The fourth industrial revolution, or Industry 4.0, is currently underway. This era is distinguished by the intelligent use of advanced information and communication technologies across various industries. Industrial systems have become fully automated, leveraging networks and IoT architecture. A hallmark of Industry 4.0 is the efficient networking of systems, known as "cyber-physical systems." Such a network enables the visualization, monitoring, and control of remote operations in an integration center, significantly improving efficiency, safety, management and, in some cases, costs. In addition, the growing focus on environmental and sustainability issues is also a significant component of the fourth industrial revolution [12,13]. A summary of Industry 1.0–4.0 is shown in Fig. 2.

In summary, the evolution of simulation technologies is mirrored by the advancement of industrial revolutions, each bringing transformative changes. There has been a long journey from the first industrial revolution (Industry 1.0) in the 18th century to the current Industry 4.0, characterized by advanced information and communication technologies, including the IoT and cyber-physical systems. The progression illustrates a pathway of continuous technological improvement, paving the way for further innovative solutions and more advancements in simulation technologies.

Digital twins can play a crucial role in the mining industry, yet their adoption in this sector lags behind other engineering fields like manufacturing and civil engineering. Despite their use in numerous projects and mining sites, the full potential of digital twins has not been realized within the industry. This paper aims to explore the opportunities for applying digital twins in the mining sector, ranging from exploration to downstream operations. Furthermore, this study will provide suggestions for implementing integrated systems to enhance productivity and efficiency in mining operations.

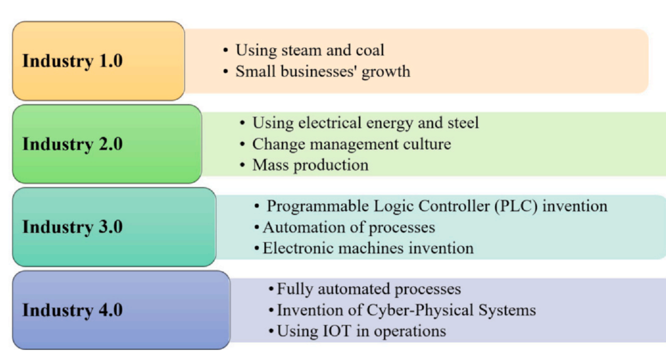


Fig. 2. Summary of Industry 1.0–4.0.

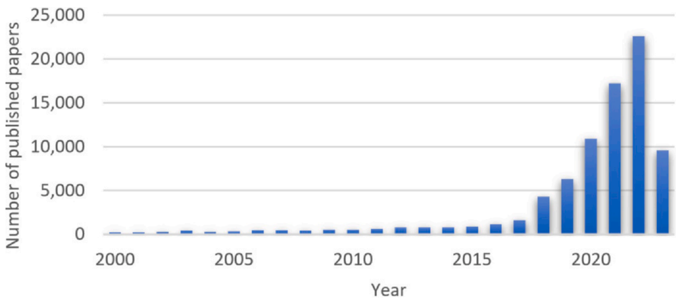


Fig. 3. Number of published papers in the field of AI.

2. Artificial intelligence

2.1. Background

The basic idea behind artificial intelligence (AI) is the automation of human thinking. Past civilizations had AI theories long before the Industrial Revolution [14,15]. However, the widespread practical use of AI began in World War II. The Bombe machine, developed by renowned British mathematician and computer scientist Alan Turing and his colleagues to crack the Enigma code, laid the groundwork for machine learning (ML). American computer scientist John McCarthy initially used the phrase "Artificial Intelligence" in 1956 at Dartmouth College, where it was later formally recognized as a field of study [16]. The programs that AI created in its early development stages were astounding. Its uses at the time included studying English, using algebra to solve word problems, and proving geometric theorems [17]. Over the past two decades, an ever-increasing number of scientists have conducted significant work in AI. As shown in Fig. 3, based on publicly available databases, there were only about ten published papers on AI in 2000, but the number jumped to 23,000 papers in 2022.

2.2. Applications of AI

As shown in Fig. 4, AI has been employed extensively in many different applications. For instance, with the assistance of AI, the medical system can better identify medical issues and improve the quality of healthcare systems [18–24]. AI-driven technological improvements have boosted manufacturing enterprises, enhancing their efficiency and reducing production costs [25–30]. Implementing AI technology in civil engineering has significantly improved the quality of buildings and their energy efficiency [31–38]. In the food industry, scientists use AI to help develop more healthy and nourishing food [39–42]. AI has benefited the fashion industry by allowing it to remain competitive and meet the ever-changing demands of consumers [43–48]. In recent years, new AI technologies have helped to increase the quantity and quality of crops in agriculture [49–54]. In sports, AI assists in making smarter decisions for athletes and sports teams by identifying their strengths and weaknesses [55–59]. The use of AI in the oil and gas industry has also been widespread during the last decade [60–65]. Finally, AI has impacted people's lives in many ways [66–70].

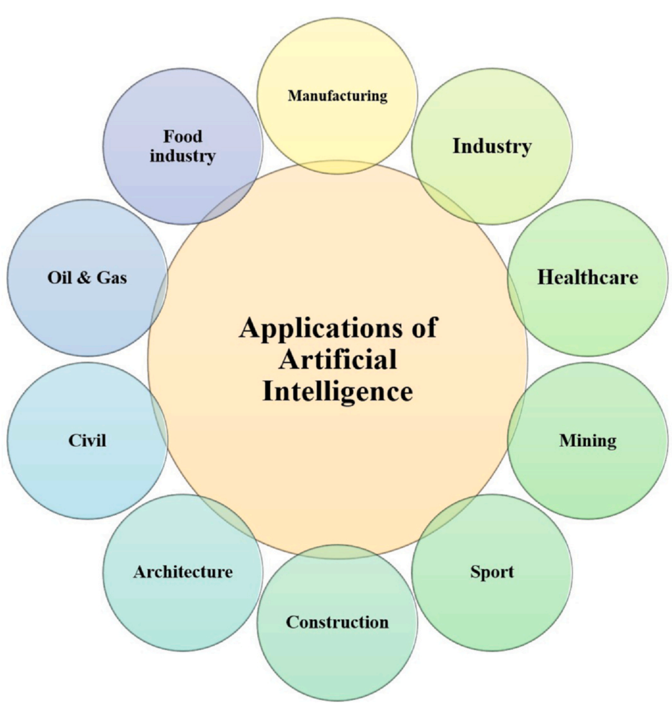


Fig. 4. Applications of AI in different industries.

2.3. Applications of AI in the mining industry

Traditional mining was typically characterized by high labor intensity, low productivity, high cost, and a poor safety record. Modern mining technologies using intelligent methods have significantly improved these aspects. One of the most significant advantages of using AI in mining is its ability to enhance efficiency, productivity, and safety.

With AI-powered systems, mining companies can optimize their operations by analyzing and integrating data from various sources, such as sensors, unmanned aerial vehicles (UAVs), and geological surveys. The data analytic outcomes can be used to identify potential risks and opportunities, streamline processes, and reduce costs. AI can improve safety in mines by detecting hazardous conditions and alerting workers accordingly. Overall, integrating AI in mining projects has revolutionized the industry by enabling faster and more accurate decision-making while reducing environmental impacts [71,72]. Table 1 lists the diverse applications of AI in mining operations, ranging from exploration and drilling to ore processing and safety management.

3. Digital twin

The power of AI and its impact on engineering applications has been covered in the previous section. As one of the most important applications of AI, the digital twin is becoming more integrated and critical in many engineering systems, including mining engineering. The basic implementation of a digital twin includes a virtual representation and the use of ML to build a functional model representing the real-world system, either based on physics or from historical and real-time data, to optimize the system's performance. In this context, digital twins operate as sophisticated virtual models, whereas AI technologies serve as the backbone of the models that enhance their functionalities and applications. This section explores the background of digital twin technology, its applications across various industries, and the implementation of a digital twin system within the mining sector.

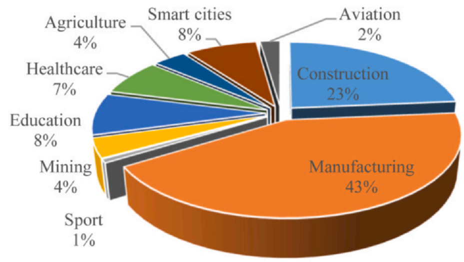
Digital twin systems are complex and multifaceted, integrating various technologies that enable the creation of a digital replica of physical assets. These systems typically consist of several core components, including sensors, data analytics, ML, communication technologies, and control mechanisms. ML studies were discussed in detail in the previous section. In this section, the other components of digital twin systems are discussed. The integration of digital twins into communication and control systems offers unparalleled opportunities for optimization, predictive maintenance, and real-time monitoring. These systems are crucial for synchronizing between the physical and digital worlds, ensuring that data flow seamlessly and actions taken in the virtual space can be effectively mirrored in the real world [139].

Effective communication systems are the backbone of digital twins. These systems encompass various technologies and protocols designed to facilitate data exchange between the physical asset and its digital counterpart [140,141]. Key components include:

Table 1
Applications of AI in mining engineering.

Areas of applications	Study	Task	Method
Exploration	Rigol-Sanchez *et al.* [73]	Mineral potential mapping	ANN
	Setyadi *et al.* [74]		FA
	Harris *et al.* [75]		ANN
	Brown *et al.* [76]		ANN
	Rodriguez-Galiano *et al.* [77]		RF, RT, SVM
	Sun *et al.* [78]		SVM, RF, ANN
	Xiong *et al.* [79]		DL
Mineral classification	Acosta *et al.* [80]	Drill-core mineral mapping	HS
	Rahman *et al.* [81]	Imaging and XRF association	RA
	Hood *et al.* [82]	Linking protolith rocks to altered equivalents	RF
	Díez-Pastor *et al.* [83]	Identification of rock originating	SVM, RR, DT, LR
	Kaplan *et al.* [84]	Ore grade estimation	KNN
	Chauhan *et al.* [85]	Processing of rock microtomography images	SVM
	Okada *et al.* [86]	Identification of mineral types	DL
Mine design & planning	Bangian *et al.* [87]	Optimum post-mining land use identification	FA, AHP
	Alipour *et al.* [88]	Production scheduling	GA
	Chicoisne *et al.* [89]	Mine production scheduling	IP
	Jélvez *et al.* [90]	Automated pushback selection	IP
	Jélvez *et al.* [91]	Constrained production scheduling	HA
	Guo *et al.* [92]	Forecasting mining capital cost	ANN
	Nourali *et al.* [93]	Mining capital cost estimation	RT
	Paduraru *et al.* [94]	Respond to new information in a mining complex	ANN
Equipment and fleet selection	Aghajani *et al.* [95]	Open pit mine equipment selection	FA
	Ortiz *et al.* [96]	Fleet selection and equipment sizing	Simulation
	Nobahar *et al.* [97]	Open pit mine equipment selection	DT, RF, SVM, XGB, KNN
Blasting	Faradonbeh *et al.* [98]	Predict flyrock in blasting operation	GP
	Monjezi *et al.* [99]	Prediction of backbreak in open-pit blasting	FA
	Shams *et al.* [100]	Prediction of rock fragmentation	FA
	Ghasemi *et al.* [101]	Predicting the flyrock distance	ANN, Fuzzy
	Hasanipanah *et al.* [102]	Forecasting blast-induced backbreak	FA
	Amiri *et al.* [103]	Predict blast-induced ground vibration and air overpressure	ANN, KNN
	Nguyen *et al.* [104]	Predict blast-induced peak particle velocity	XGB
	Nguyen *et al.* [105]	Prediction of blasting-induced fly-rock	SVM
	Sayyadi *et al.* [106]	Prediction of rock fragmentation	ANN
	Bahrami *et al.* [107]	Prediction of rock fragmentation	ANN
	Nobahar *et al.* [108]	Prediction of blast-induced flyrock, backbreak, and rock fragmentation	XGB, RF, KNN
Loading & hauling	Park *et al.* [109]	Simulation of truck loader haulage systems	GPSS
	Moradi Afrapoli *et al.* [110]	Dynamic truck dispatching	Simulation
	de Carvalho *et al.* [111]	Simulation of mine equipment systems	GA
Mineral processing	Ali *et al.* [112]	Predicting the flotation behavior	RF, ANN, ANFIS
	Jahedsaravani *et al.* [113]	Modeling of a batch flotation process	FA
	Nakhaei *et al.* [114]	Recovery and grade accurate prediction	ANN
	Ahmadzadeh *et al.* [115]	Useful life prediction of grinding mill liners	ANN
	Massinaei *et al.* [116]	Modeling of bubble surface area	ANN
	Karimi *et al.* [117]	Prediction of hydrocyclone performance	ANN
	Bonifazi *et al.* [118]	Characterization of flotation froth	IP
	Nayak *et al.* [119]	Monitoring the fill level of a ball mill	ANN
	Horn *et al.* [120]	Feature extraction in froth flotation sensing	CNN
	Pu *et al.* [121]	Froth flotation recovery prediction	DL
	Pu *et al.* [122]	Purities prediction in a froth flotation plant	DL
	Cook *et al.* [123]	Prediction of flotation efficiency	DL
Rock mechanics	Armaghani *et al.* [124]	Prediction of the strength and elasticity	ANN
	Shirani *et al.* [125]	Prediction of compressive strength	CART
	Majdi *et al.* [126]	Predicting the deformation modulus	GA
	Mahdevari *et al.* [127]	Stability prediction of gate roadways	ANN
	Xue *et al.* [128]	Deformation evaluation on surrounding rocks	PSO-LSSVM
	Bui *et al.* [129]	Prediction of slope failure in open-pit mines	GA
	Baghbani *et al.* [130]	Improved prediction of slope stability	CRRF, ANN
	Qi *et al.* [131]	Modeling for cemented paste backfill	RF, RT, XGB
	Lu *et al.* [132]	Estimating unconfined compressive strength of cemented paste backfill	ELR
Safety	Isleyen *et al.* [133]	Roof fall hazard detection	DL
	Badri *et al.* [134]	Risk management for underground mining	AHP
	Maxwell *et al.* [135]	Differentiating mine-reclaimed grasslands	GEOBIA
	Mukherjee *et al.* [136]	Detect opencast coal mine areas from Landsat 8	IP
	Luo *et al.* [137]	Mine landslide susceptibility assessment	SVM, ANN
	Bui *et al.* [138]	Land subsidence susceptibility mapping	BLR, SVM, LMT

Notes: ANN: Artificial Neural Networks, DL: Deep Learning, FA: Fuzzy Algorithm, AHP: Analytic Hierarchy Process, GP: Genetic Programming, IP: Integer Programming, HS: Hyperspectral, HA: Heuristic Aggregation, GA: Genetic Algorithm, CNN: Convolutional Neural Network, DT: Decision tree, RF: Random Forest, RR: Ridge Regression, SVM: Support Vector Machine, XGB: Extreme Gradient Boosting, ANFIS: Adaptive Neuro Fuzzy Inference System, KNN: K Nearest Neighbor, CRRF: Classification and Regression Random Forests, RA: Regression Algorithm, LR: Linear Regression, RT: Regression Trees, IP: Image Processing, GPSS: General Purpose Simulation System, CART: Classification and Regression Tree, PSO: Particle Swarm Optimization, LSSVM: Least-Squares Support Vector Machine, ELR: Energy-based Link Replacement, BLR: Beacon-Less Routing, LMT: Logistic Model Tree, GEOBIA: Geographic Object-Based Image Analysis.



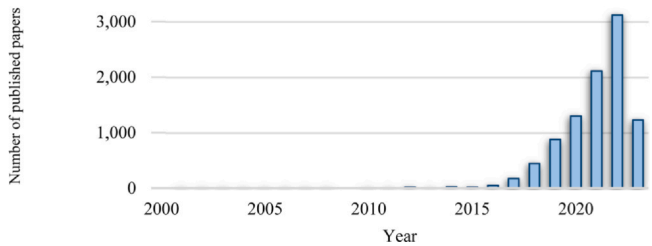


Fig. 5. Number of published papers on digital twins and their specific fields based on publications data.

(1) IoT sensors and devices: Internet of Things (IoT) sensors collect real-time data from physical assets. These sensors can monitor various parameters, such as temperature, pressure, vibration, and more. The data collected are transmitted to the digital twin for analysis and action.
(2) Edge computing: Edge computing involves processing data closer to where it is generated. This minimizes latency and bandwidth usage, making it possible for digital twins to operate in real time. Edge devices can perform preliminary data analyses and filter relevant data before sending them to the cloud or centralized servers.
(3) Cloud computing: Cloud platforms provide the infrastructure for storing and processing large volumes of data generated by digital twins. Cloud computing ensures scalability, flexibility, and the ability to integrate various data sources. It also supports advanced analytics and ML models that enhance the predictive capabilities of digital twins.
(4) Communication protocols: Several communication protocols are used to ensure seamless data transfer. These include MQTT (Message Queuing Telemetry Transport), OPC UA (Open Platform Communications Unified Architecture), and HTTP/HTTPS (Hypertext Transfer Protocol Secure). These protocols enable secure and efficient communication between IoT devices, edge systems, and cloud platforms.

Control systems within digital twins involve the mechanisms that allow the virtual model to influence the physical asset. These systems enable automation, real-time adjustments, and improved operational efficiency [142,143]. Key aspects include:

(1) Feedback loops: Digital twins use feedback loops to continuously monitor and adjust the performance of physical assets. Data from IoT sensors is analyzed in real time, and control commands are sent back to the physical system to optimize performance or prevent failures.
(2) Predictive maintenance: By analyzing historical and real-time data, digital twins can predict potential failures before they occur. Control systems can then schedule maintenance activities proactively, reducing downtime and maintenance costs.
(3) Simulation and optimization: Digital twins can simulate various operational scenarios and optimize processes based on the outcomes. For example, a digital twin in manufacturing can simulate production line adjustments to improve efficiency and reduce waste.
(4) Autonomous operations: Advanced control systems enable digital twins to perform autonomous operations. This is particularly relevant in industries such as autonomous vehicles, where the digital twin can make real-time decisions based on sensor data to navigate and operate safely.

3.1. History and background

The digital twin concept, first proposed by Grieves [144] in 2003, has since been applied to various aspects of spacecraft, health, and maintenance. National Aeronautics and Space Administration (NASA) defines a digital twin as a system-oriented aircraft that uses the best physical models, sensors, and historical data. It integrates multidisciplinary and multiscale probabilistic simulation processes and maps the state of its corresponding physical aircraft [145]. A digital twin refers to the full-element reconstruction and digital mapping of the processing status of a product's physical entity in the information space, enabling simulation, diagnosis, prediction, and control of the realization process of physical entities in real environments. Data modeling, application, and collection are the three fundamental facets of digital twins [146]. The number of research works published in this field over the past decade has demonstrated the significance of the digital twin and its undeniable influence on the progression of human development (see Fig. 5). The pie chart shows the spread of studies of digital twin technologies across different engineering applications. It is clear that manufacturing and construction are leading the way, with 43% and 23% of the studies, respectively. The mining sector lags far behind, with only 4% of the published research. This contrast highlights a significant gap in exploring and applying digital twin technology in mining operations. Considering that digital twins can optimize operations, improve safety, and enhance predictive maintenance in mining, this lack of research is a missed opportunity. Clearly, there is a pressing need to boost research efforts in the mining sector to fully leverage the digital twin technology so as to drive further innovation and efficiency in this crucial industry.

The digital twin technology has three levels, depending on the degree of data integration and communications between the physical and digital worlds. These three levels are commonly referred to as the digital model, digital shadow, and (full) digital twin. As shown in Fig. 6, a digital model is a representation of a real-life object, whether it is planned or already exists. It is created digitally without the automatic

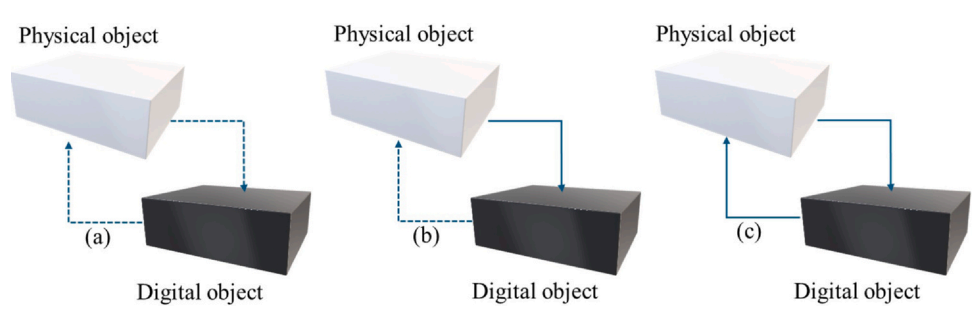


Fig. 6. Visualization of a digital model (a), digital shadow (b), and full digital twin (c).

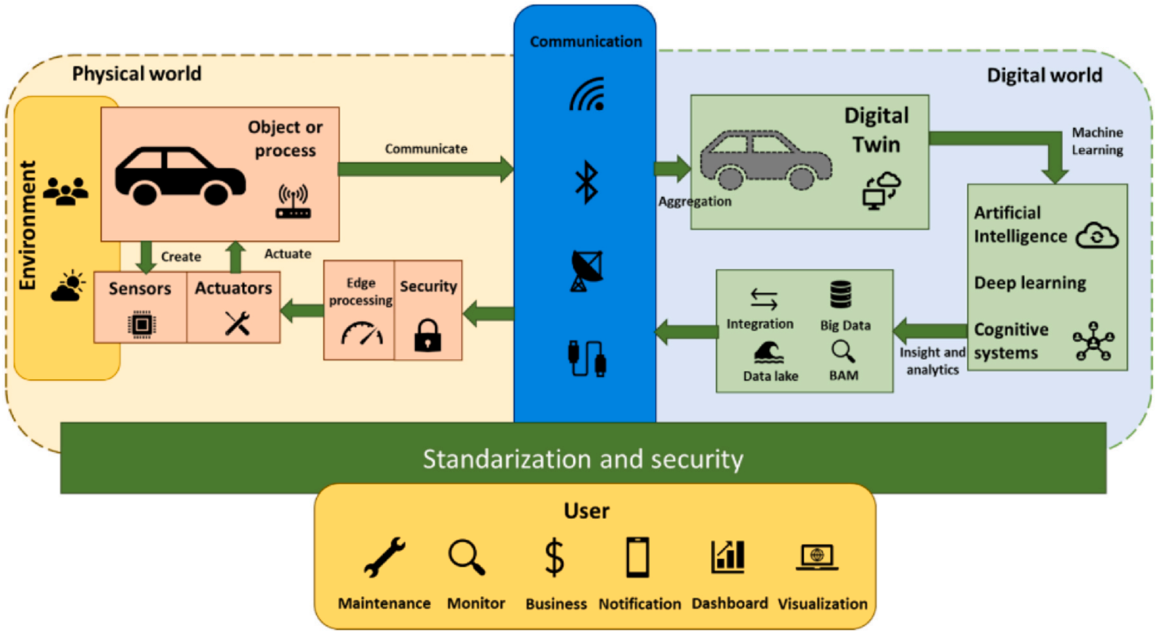


Fig. 7. Architecture of a digital twin model [147].

data communication between the digital and physical objects. If there is a one-way data flow from the physical object to the digital object, this combination is referred to as a digital shadow (Fig. 6(b)). If the data communications between an existing physical object and its digital representation are fully integrated bidirectionally, the system is a full digital twin (Fig. 6(c)) [142]. In designing a digital twin of a physical process, four key technologies that provide helpful insights are IoT, AI, extended reality (XR), and cloud storage/computing. In addition, depending on the type of application, a digital twin may use specific technologies [142]. Fig. 7 illustrates a digital twin architecture. As shown in Fig. 7, various objects, factors, and variables within the physical environment are monitored by sensors and other measurement tools, generating vast amounts of data. This database is then transmitted to the virtual environment through various communication channels, including Wi-Fi, Bluetooth, and cables. Innovative techniques, such as AI, deep learning, and cognitive systems, aggregate and process the raw data in the virtual space. The processed data are then sent to the cloud and subjected to big data analytics, enabling performance optimization and decision-making for the entire system.

By using the real-time status of the physical entities and processes, digital twins can be employed in industry to optimize operations and enhance safety. This technology has several critical applications, enabling experts to produce a more detailed and precise representation of the operations in real time. The top five advantages of digital twin technology are shown in Fig. 8.

3.2. *Applications of digital twins*

In numerous sectors, including healthcare, construction, and agriculture, the use of digital twins has significantly simplified and improved operations. In addition, digital twins are used in the military, aerospace, education, sports, and building smart cities and automotive industries to increase efficiency. Some instances of digital twin implementations for a variety of purposes are summarized in Table 2.

3.3. *Digital twin systems: from resources to downstream processes*

Industry 4.0 technology is impacting all industries across the globe, and it will bring a plethora of improvements when it comes to productivity, adaptability, and efficiency. As one of the most critical industries, mining encompasses several subsystems, and improving the performance of each of these subsystems can increase overall profitability, improve performance, and comply with environmental requirements [165–167]. A full digital twin system for mining projects should include a virtual model of the mine site, equipment, and processes from exploration to mineral processing (assuming a typical mine where the product is concentrated). The system uses sensors, IoT devices, and ML algorithms to monitor and optimize operations. The digital twin provides real-time data analytics, predictive maintenance, and scenario simulations to increase efficiency, reduce downtime, and ensure safety. The system is fully integrated with a central dashboard where operators and managers can monitor and control the entire mining operation. In this system, data collected from sensors and instruments can be transmitted to a control center through various methods, such as wired connections (ethernet) or wireless connections (Wi-Fi), Bluetooth, or cellular networks [168–171].

Data can be transferred using different protocols, such as MQTT or HTTP, to ensure their security and reliability during transmission, and the control center can receive the data in real time or periodically, depending on the application requirements. The data can then be processed and analyzed to make informed decisions, control processes, or trigger alerts based on predefined rules. In the digital twin system designation, irrelevant or redundant data should be eliminated to avoid confusion and ensure easy navigation through the system. On the other hand, data critical to the system's functionality should be recognized as necessary and retained in the system. These include data related to the physical objects or subsystems being simulated, such as their geometry, mechanical properties, and operating parameters. Other important data may include sensor data, performance metrics, and contextual information used to simulate real-world scenarios. Overall, it is vital to prioritize data elements that have significant impacts on the system's accuracy and performance. Fig. 9 provides a complete digital twin system, which is discussed in detail in the following sections.

3.3.1. *Exploration*

Mining exploration is a crucial step in discovering economic mineralization for mining operations. Geologists gather essential information on the location, quality, and quantity of minerals, which helps to ensure that mining projects are environmentally and economically responsible and feasible. In this process, it is essential to use

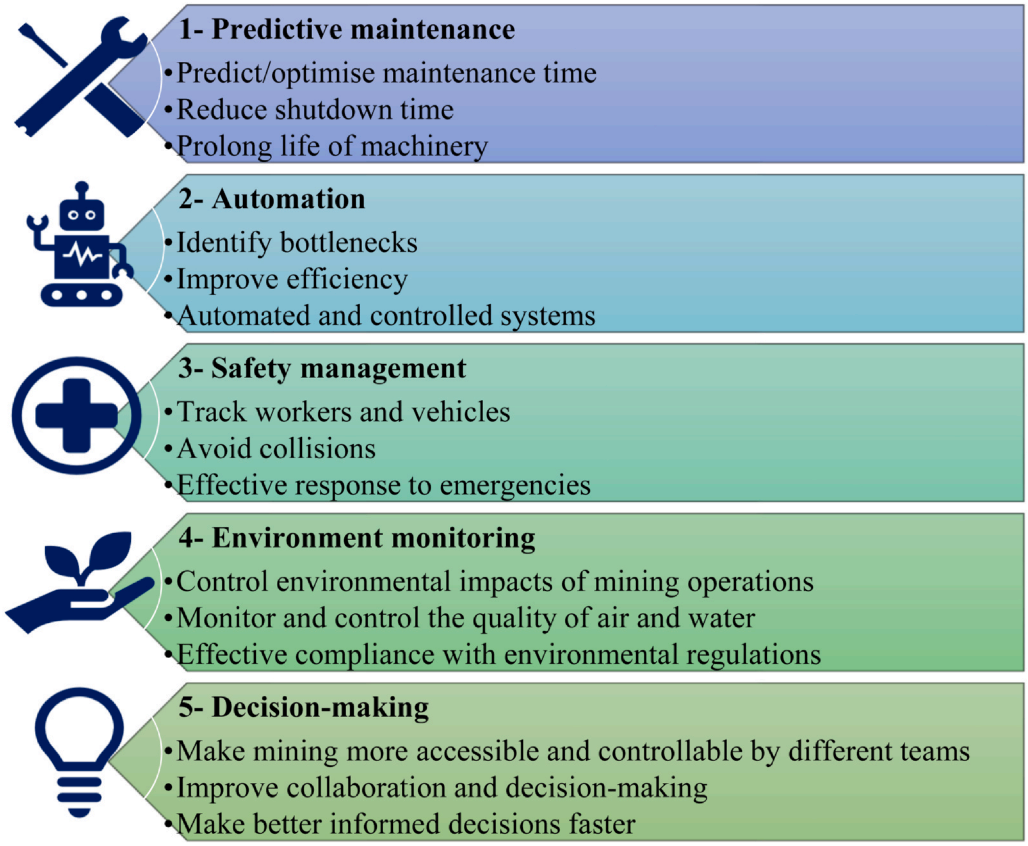


Fig. 8. Key advantages of digital twin implementation.

measures to improve the accuracy of mineral resource estimates and minimize the risks associated with the mining operation.

The latest methods and technologies have been increasingly used to help professionals in the exploration phase. Topographic modeling using UAV imagery is used in the mining industry, along with automated surface feature detection using ML algorithms to classify a complete detailed geological model [172]. Compared with a laser-scanned surface, the UAV results are less erratic around real-time kinematic (RTK) points, indicating that surfaces generated by photogrammetry can be a more straightforward and quicker alternative for mining reconciliation. In addition, convolutional neural networks (CNN) have demonstrated excellent performance on various visual tasks, including the classification of two-dimensional images [173–177]. Terrestrial light detection and ranging (LiDAR) data can be acquired from either static or mobile platforms [178]. With regard to data collection from core samples, hyperspectral (HS) imaging, an emerging technique in the mining industry, is increasingly being used to complement other analyses by rapidly characterizing large amounts

Table 2
Applications of digital twins in various fields.

Areas of applications	Study	Task	Method
Construction	Development of maintenance systems [148]	Bridge maintenance	3D digital twin model
	Geometric digital twins [149]	Building modeling	Slicing-based object fitting method
	Digital twinning of buildings [150]	Building modeling	Semi-automatic geometric
Healthcare	Improve the quality of patient care [151]	Patients' pathways in hospitals	HospiT'Win framework
	Monitoring the health of individuals [152]	Elderly healthcare services	Cloud-based framework
	Management of severe traumas [153]	Integration of agent	Agent-based digital twins
Manufacturing	Cyber-physical manufacturing [154]	Virtual machine tools	Sensor data and information fusion
	Synchronizing engineering models [155]	Manufacturing automation	Automation software-code
	Machinery fault diagnosis [156]	Smart manufacturing	Digital twin model of a rotor system
Smart cities	Solutions for urban challenges [157]	Urban planning	Urban digital twin
	Test different scenarios for future planning [158]	Urban planning	Urban digital twin
Agriculture	Plant development [159]	Planting	Multi-agent approach
	Simulate porker's feed consumption and weight growth [160]	Livestock farming	Creating a digital twin of a pig fattener
	Planning Agricultural Core Road Networks [161]	Agriculture planning	Digital twin of the cultivated landscape
Automotive	Minimize privacy risks [162]	Privacy enhancement	Digital twin demonstrator
	Predictive maintenance of an automobile brake system [163]	Predictive maintenance	Thingworx (IoT) platform
Aviation	Automate Fan-Blade reconditioning [164]	Aerospace maintenance	DoF robotic arm and digital twin
	Re-engineering aircraft structural life prediction [145]	Aerospace maintenance	Integrate computation of structural deflections
	Simulating helicopter dynamic systems [165]	Helicopter industries	Using multibody simulations

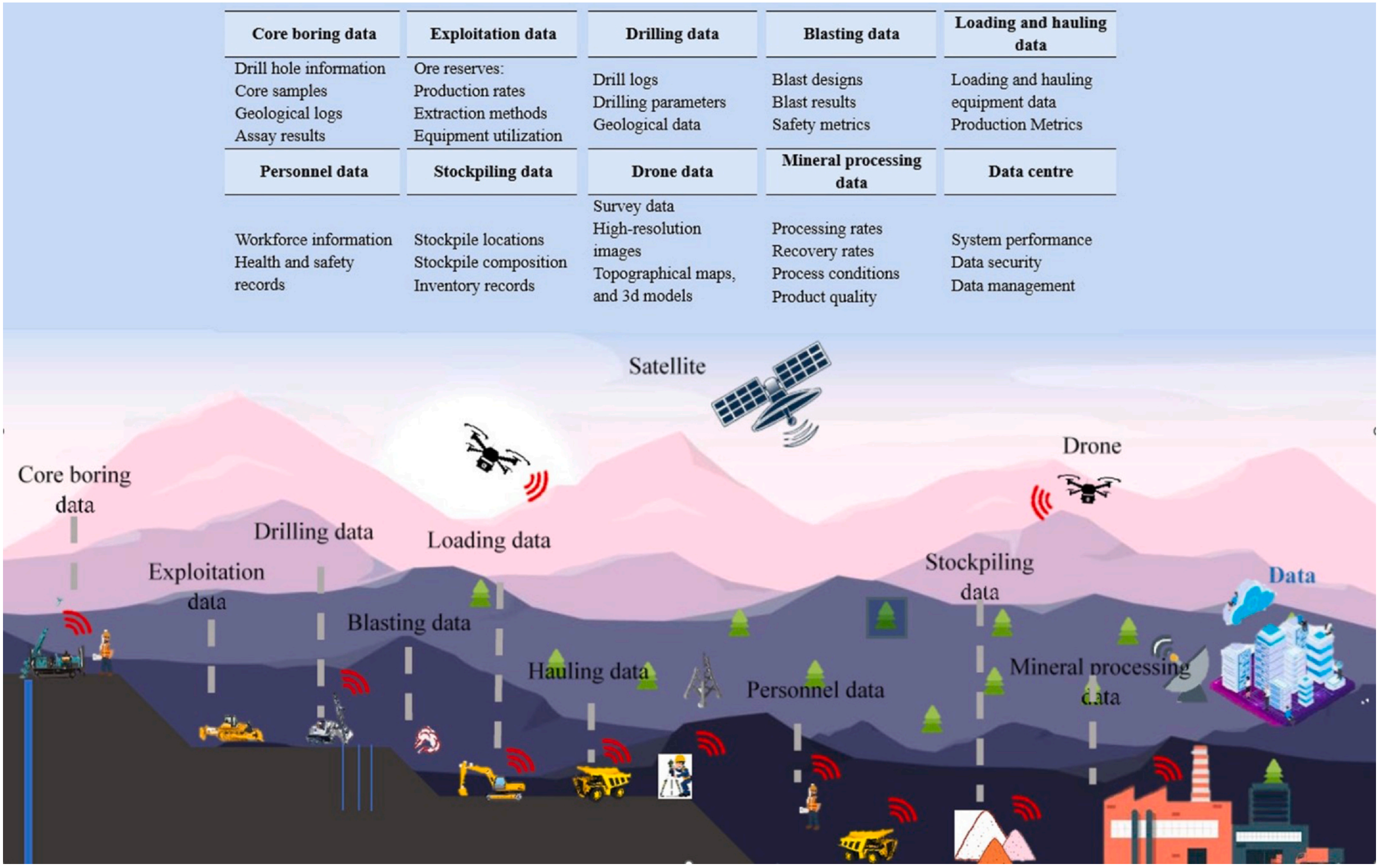


Fig. 9. Schematic view of a digital twin system.

of drill cores [80]. For coring operations, AI has also been used to analyze underperforming bits in exploration [179].

Over the past decade, remote sensing has played a vital role in mining exploration and mineral identification [180–183]. As an example, Fig. 10 shows that lithological and structural characteristics of a specific area can be identified using this methodology. Recent drilling technologies can be used to conduct downhole geophysics and collect real-time proxy data while drilling [184] to estimate mineral concentration and physical and geomechanical properties with fine spatial sampling. The data streams can be transmitted in real time to the cloud to enable data analytics and near real-time decision-making to achieve better outcomes [185].

However, achieving an operational full digital twin in exploration is very challenging, even with the progress made thus far. The techniques and tools discussed earlier play a significant role in advancing the development of a digital twin across various facets of the exploration process. These encompass optimizing resource estimation procedures, refining geological modeling approaches, enhancing exploration planning strategies, and expediting exploratory operational optimization procedures. Most of these models are at the level of a digital model (e.g., mineralization classification systems and resource modeling) or a digital shadow (e.g., LiDAR scanning and automatic core scanner). Despite the challenges encountered, advancements in these fields provide a solid foundation for geo-data scientists to continue refining and enhancing the digital twins tailored to unique applications.

3.3.2. *Production drilling*

Monitoring a production drilling operation is vital to ensure safety, efficiency, and productivity in mining operations. Various sensors are used to collect data related to drilling operations, such as depth, pressure, torque, and temperature. Different methods, such as acoustic sensing, vibration analysis, and electromagnetic imaging, are used for real-time monitoring of drilling performance, rock characteristics, and potential hazards. In addition, cameras, LiDARs, radars, and global positioning system (GPS) receivers are also used to enhance the accuracy, safety, and productivity of drilling operations. This information helps operators to optimize drilling parameters, adjust the drilling process, and prevent costly breakdowns. In addition, these data are considered some of the most critical inputs for a digital twin model for a mining operation [187–189]. Autonomous production drilling systems, together with autonomous trucks, are perhaps the closest to a full digital twin system in mining operations, particularly in open-pit environments. Even if an operator is involved in a remote operation, if the drills are fully autonomous, the operator's role is mainly for monitoring purposes. In this case, an operator can look after several operating drills simultaneously. Such a system is claimed to result in a 20% improvement in drilling performance and increased resource utilization [190–192].

3.3.3. *Blasting*

As integrated subsystems from mine to mill, drilling and blasting are critical components required to increase the efficiency of mining and downstream processes via the reduction in energy consumption [192]. The efficiency of mining operations can be particularly affected by the monitoring and adjustment of blasting parameters. By adjusting factors such as the type and amount of explosives, the timing of the blast, and the design of the blast pattern, the effectiveness of the blasting process and productivity can be improved. Ongoing real-time optimization of blasting activities adapted to *in-situ* conditions can help ensure that safety measures are followed and the environmental impacts (e.g., dust and fly rocks) are minimized.

Ideally, in an effective digital twin system, data including blasting energy, blasting vibration, explosive characteristics, seismic velocity, blasting design parameters, and outputs of blasting operations (e.g.,

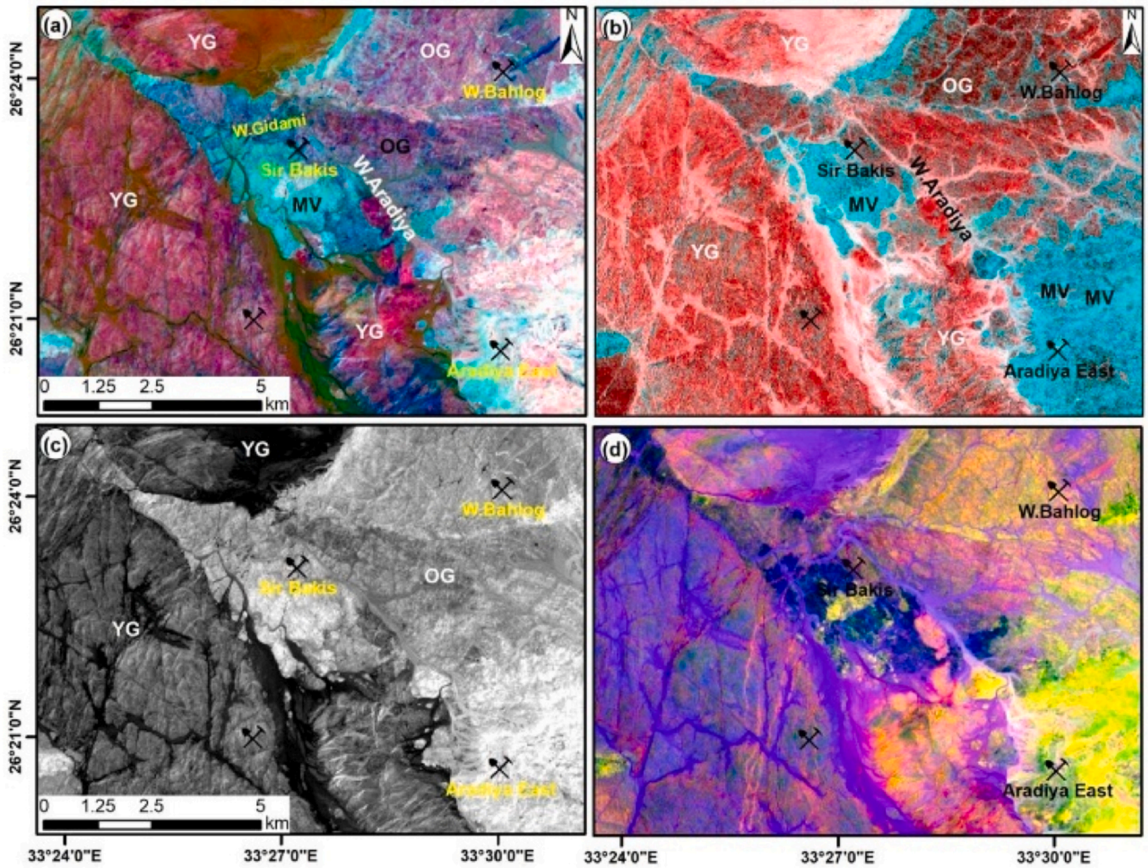


Fig. 10. Distinguishing lithological and structural features by remote sensing [186].

rock fragmentation, fly-rock, backbreak, and air blast) should continuously be collected and analyzed by various hardware and software, from which experts would be able to view blast results, produce reports, and optimize the operation to decrease costs and enhance efficiency. The latest proposed system creates a blasting vibration monitoring device that operates automatically. This system primarily consists of modules that enable engineers to achieve real-time transmission, automatic calculation, intelligent analysis of blasting vibration monitoring data, blasting-related parameters, and automatic alarms. These modules include data acquisition, transmission systems, client tracking control systems, and risk management platforms [193,194]. A network of remote blast monitoring stations, composed of distinct units, is part of the automated blast monitoring system. Engineers can designate one or more early warning units (EWUs) to serve as trigger sources for other units by using the dynamic triggering program integrated into each unit's software. These EWUs are often the ones closest to the explosion epicenter.

For surface blasting operations, UAV-based monitoring is widespread and is conducted in three stages: preblasting, during blasting, and postblasting. At the pre-blasting stage, pit walls are mapped to collect structural data to predict *in-situ* block size distribution and to develop as-built pit wall digital elevation models (DEM) to assess blast-induced damages. At the blasting stage, a high-speed camera monitors and analyzes blast initiation, blast sequencing, misfired holes, and stemming ejections. At the post-blast stage, the blasted rock pile (i.e., muck pile) is monitored to estimate fragmentation and assess muck pile configuration. Data collected from each stage can be analyzed using ML, DL, or CNN models (see Fig. 11), and finally, a digital twin model of the blasting process is created [195,196]. In the digital twin system, understanding rock fragmentation using computer-aided methods, such as image analysis [197–199].

For explosive charging, there are automatic hole charging technologies [201]. The robot charger can be remotely controlled, safely charging the bored holes without the need for human intervention.

The open-pit autonomous blast hole explosive charge technique is more developed than that for underground operations. For example ANFO (Ammonium Nitrate Fuel Oil) truck that is wirelessly connected to the operating center as part of a digital twin system for open-pit blasting operations, which is capable of sensing and monitoring, controlling, and automating blasting operations based on blast design and sensed terrain and blast hole information [202].

3.3.4. Loading and hauling

Although the entire mining value chain does not yet have a fully integrated digital twin system, several subcomponents have made significant advancements in the use of digital twin technologies. Open-pit fleet management and dispatching systems are examples of this application. At some mining sites, fully autonomous loaders and trucks are operational, equipped with sensors and IoT devices and integrated into a full digital twin system located in a remote operation center. Some of these sensors and devices are listed in Table 3, and they provide the fundamental data collection and communications in the digital twin system. As an actual example, haulage trucks are equipped with sensors and intelligent systems for automatic operations [203,204].

As an essential input for a digital twin system, hauling and loading data collected by innovative procedures can be processed by data analytics in real time. For example, a third-person view of remote machinery operations, such as loaders and haulage trucks, using fixed or mobile cameras is commonly used to relay the haulage system information to control centers [205].

Sensing the position and orientation of vehicles is another critical issue for automating mining processes. For haulage trucks, the issue is

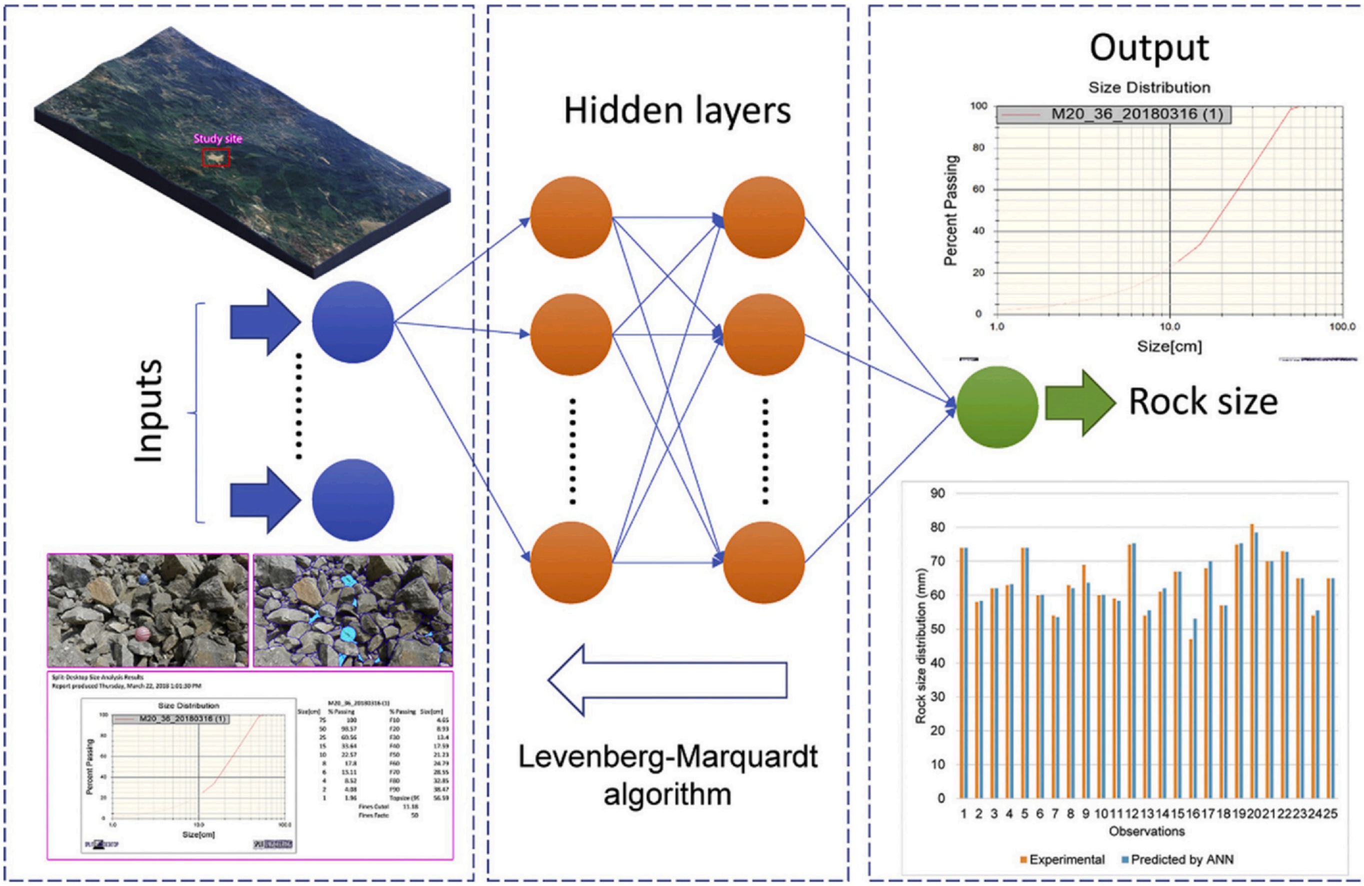


Fig. 11. Rock fragmentation size distribution analysis using an image processing technique [200].

Table 3
Sensors and IoT devices used for loading and hauling equipment.

Sensors	IoT devices
Engine sensors (temperature sensor, pressure sensor, fuel level sensor) Vehicle health monitoring sensors (tire pressure sensor, brake condition sensor, battery status sensor) Collision avoidance sensors Environmental sensors (air quality sensor, dust level sensor, temperature sensor) Operational sensors (inclinometer, weight distribution sensors, lighting sensors, payload monitoring sensors)	GPS (global positioning system) Cameras GPRS (General Packet Radio Service) /Wi-Fi communication Antennas Monitors Communication radios

addressed by a combined stereo camera and two LiDAR sensors to determine the three-dimensional (3D) position of the truck's cargo box and to analyze its loading space [206,207]. For operational safety, a collision detection/response system called the Hazama Intelligent Vehicle Automatic Control System (HIVACS) has been developed to prevent vehicle collisions in heavy construction sites [208,209]. For loaders, automatic recognition algorithms have been developed based on the feature extraction of working parameters to recognize the state of the loading cycle of electric shovels [210]. Approaches using deep learning for detecting missing teeth in mining shovels have also been implemented. This innovative method has several advantages over conventional methods, including real-time monitoring capabilities and the ability to identify broken or fallen teeth promptly. Its implementation has significant potential for improving mine production efficiency. In these systems, images captured from a camera mounted on the rope of the shovel are sent to the digital twin system and analyzed by AI using deep learning and image processing [211–213].

Fleet management systems for loading and hauling have improved significantly in open-pit mines over the past few decades. The technology was first developed in 1990 by Komatsu and was later developed further by other pioneering equipment manufacturers and solution providers, such as Hitachi, Caterpillar, ASI mining, and Modular Mining [214]. By using these technologies, fully autonomous dump trucks equipped with an autonomous haulage system (AHS) can be efficiently dispatched using autonomous haulage instructions from fleet management systems. In some cases, semiautonomous shovels that are remotely controlled by the operator and designed to improve safety and productivity can also be integrated into the digital twin system.

Overwatering roads can cause slippery driving conditions, but the new technology prevents overwatering, hence improving the safety and efficiency of the hauling operation. For underground operations, efforts have been made to create autonomous underground loading and hauling systems by the LHD (Load, Haul, Dump) systems [215]. A production shaft is also commonly used in underground mines and provides a means of transporting ore to the surface. A digital twin model of the production shaft incorporates the dynamics of the electric drive and the mechanical parts of the mine hoist, such as the electric motor control system with speed and current controllers to calculate the linear speed of the cage, the cage position, and the rotation speeds of the drum and pulleys [216]. In addition, sensors are also integrated into the digital twin system to monitor the health of the hoist and related parts to ensure the safety of the operation [217].

3.3.5. Conveyor belts

Conveyor belts are another component of a digital twin system of a mining process. Collected data from these belts could be significant for ore identification, ore tracking, ore sorting, and general maintenance.

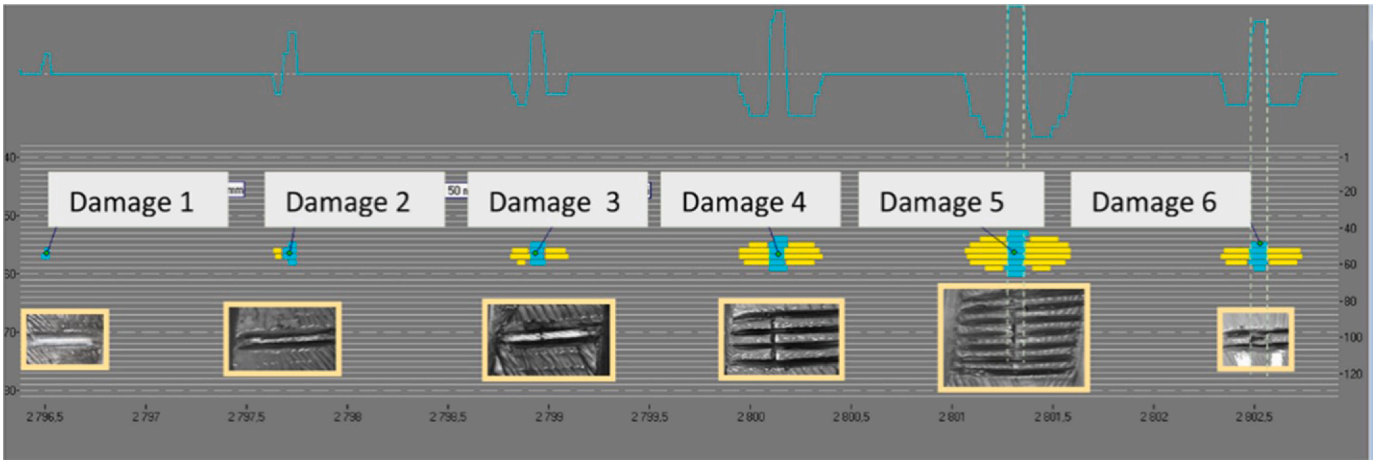


Fig. 12. Identification of damage on conveyor belt [221].

By using these sensors to continuously monitor the performance and condition of the conveyor belts (see Fig. 12), potential issues that can impact the mining operation and productivity can be detected in advance, leading to an increase in the lifetime of the belts and a reduction in downtime [218–220].

Online ore analysis technology can also be used to optimize the performance of the conveyor belts, ensuring that they are operating at their maximum capacity [222–225]. A recent development of the digital twin technology takes live data measurements and provides real-time feedback on the compatibility of the operating conditions of every major belt conveyor component, which can increase efficiency and energy savings, reduce unplanned downtime, and extend component service life [226]. Sensors are increasingly being employed to analyze ore composition as it is transported, allowing for ore sorting and rejection of wastes before the milling circuit, hence resulting in more efficient processing [227].

3.3.6. Mineral processing

In mineral processing, by creating a virtual replica (i.e., digital twin) of a processing plant, operators can simulate and optimize various processes before implementing them in real life. This allows for more efficient and cost-effective operations. Using the digital twin technology, operators can monitor and analyze real-time data, identify bottlenecks, and improve efficiency, leading to reduced downtime, increasing productivity, and improving overall performance. As shown in Fig. 13, various stages of mineral processing are equipped with different sensors, which are enabled by the latest developments in machine vision technology, as well as innovative monitoring and controlling techniques. Significant data can be collected in these subsystems to enable AI machine training [228].

Various online techniques for monitoring the performance and condition of hydrocyclones have been proposed. In recent years, the subject has gained significant interest as depleting ore grades impose a high demand on the performance of hydrocyclones in mineral processing [229]. As listed in Table 4, the digital solutions used to design a digital twin model of mineral processing include machine vision, information management systems, sensors, smart equipment, ML techniques, process control systems, robotic cells, and IoT technologies [230].

In a crushing circuit, a digital twin system based on dynamic simulation technology for feed hoppers, belt feeders, jaw crushers, cone crushers, and vibrating screens can deliver a complete set of operational variables for control system optimization [242]. In the grinding circuit, a digital twin system with advanced process control has been implemented to help ensure an optimal operation strategy [243]. As for the entire plant, a type of digital twin system has been constructed to develop an intelligent decision-making system based on interactive visualization [244,245]. However, there is still a significant gap between the current proposed systems and the full digital twin system for the entire mineral processing plant.

3.3.7. Personnel

Personnel monitoring can be conducted in various ways, including time-tracking software, performance metrics, and regular manager

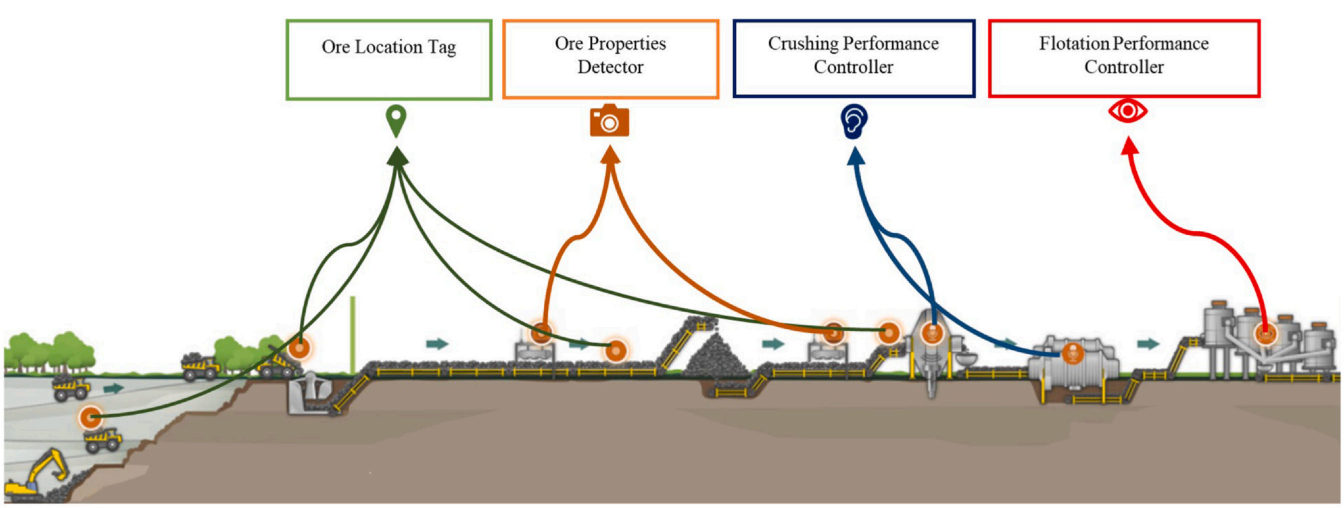


Fig. 13. Innovative sensors and detectors in mineral processing.

Table 4
Digital techniques used to build a digital twin model in mineral processing.

Subfield	Reference
Robotic cells	[231,232]
Sensors and smart instrumentations in the crushing and grinding circuits	[233]
Sensors and smart instrumentations in the flotation circuit	[234–236]
Sensors and smart instrumentations for tailings management	[237–240]
Machine vision	[41,240,241]

check-ins. By monitoring their employees, companies can identify areas that require improvements and provide timely feedback and support. This can improve work safety and increase efficiency, as employees can better understand expectations and work toward meeting them. However, it is important to balance monitoring with trust and autonomy, as excessive monitoring can have negative consequences [246].

There are systems and devices that can effectively analyze semantic information contained in images and automatically extract workers' unsafe behavior, enabling the control center to visualize unsafe acts in real time and further identify patterns of behavior that could jeopardize safety outcomes [247,248]. These systems can uniquely identify each employee and monitor their availability at a specific time. In addition, emotional assessment can be performed based on facial recognition technology. Cameras installed in the workplace can capture employees' facial expressions, which can then be analyzed to infer emotional states, such as happiness, stress, or fatigue [249]. A digital twin system can then better optimize the efficiency of each employee's workflow, investigate their satisfaction levels, and confirm fair treatment [250].

3.3.8. UAV-based data

UAVs have become increasingly used in the mining industry because of their ability to provide detailed and accurate site data. They can be equipped with a variety of sensors and cameras to capture images and data that would be difficult or impossible to obtain using traditional methods. They can also access difficult mining areas, such as mined cavities and drives, which are not accessible by conventional monitoring/surveying methods. These data can then be used to create 3D models of the site, monitor the progress of mining operations, and identify potential safety hazards [251].

The use of UAVs in the mining industry can lead to significant improvements in efficiency. By providing real-time mine data, UAVs can help companies make more informed decisions about where to allocate resources and how to optimize their operations. UAVs can reduce the need for manual labor in certain tasks, such as inspecting and surveying mines, which are time-consuming and costly procedures. UAVs are commonly used to collect various data from surface and underground mining operations [252–255], geological and structural analysis via remote sensing [256–259], aerial geophysical surveys [260–263], topographic surveying in open-pit mines [264,265], analysis of rock slopes [266], analysis of working environments [267,268], monitoring of soil and water pollution [269–273], and monitoring of ecological restoration [274,275]. For the digital twin system, UAVs are used to create a dynamic flow of data, enabling it to provide a live, interactive model of the entire mining operation, which helps in monitoring, optimizing, and enhancing the overall efficiency and decision-making processes.

3.3.9. Mining environmental data

Environmental monitoring includes remote sensing and ground-based monitoring. Remote sensing involves the use of satellites and other aerial platforms to gather data on environmental conditions. Ground-based monitoring uses sensors placed on the ground or in bodies of water to measure various environmental factors, such as temperature, humidity, and water quality. Air quality monitoring is commonly implemented on mine sites and is a ground-based technique that involves the use of sensors that measure dust and pollutants in the air. These methods and sensors are essential for creating and maintaining a digital twin system for the environment and can be used for simulations, predictions, and decision-making. As dust pollution is currently one of the most serious environmental problems in open-pit mines, the prediction and tracking of changes in dust concentrations using the digital twin is important for assessing the real-time environmental impacts of mining. Recently, several cutting-edge technologies have been developed to help experts monitor pollutants on mine sites [276,277]. In particular, fiber-optic-based sensors are useful in sensing dust particles in hazardous environments, particularly in coal mines [278]. For dust concentrations around haul roads, sensors mounted on haulage trucks are used to collect pollution data needed for the digital twin system [279–282].

3.3.10. Digital twin simulators

Several simulators, including the Petra MAXTA digital twin [283], the Orica Integrated Extraction Simulator [284], MATLAB Simulink [285], and the Dassault Systèmes digital twin [286], have been developed to simulate mining operations, offering a deeper understanding of the mining system. These advanced tools allow experts to simulate various scenarios, analyze data, and optimize processes. By implementing these simulators, mining professionals can delve into complex mining system details, identify potential challenges, and develop strategies to enhance efficiency and productivity. In addition, some of these platforms can incorporate real-time monitoring and predictive analytics, empowering mining companies to make informed decisions and improve operational performance.

4. Discussion

Digital twin technology is a key element in the industrial transformations driven by Industry 4.0, enabling the design of dynamic and real-time digital representations of physical systems. While digital twin systems have seen extensive applications in fields such as manufacturing, healthcare, and civil engineering, their adoption in the mining sector is still in an early stage.

4.1. Current status of digital twins in mining

Currently, digital twin systems in mining are employed to create virtual models that simulate and optimize various mining processes. These models can represent mine sites, machinery, and operations, encompassing the entire mining lifecycle from exploration and extraction to processing and logistics. Digital twin systems leverage a combination of sensors, IoT devices, and advanced analytics to provide real-time data, enabling predictive maintenance, process optimization, and scenario simulations.

Despite these advancements, the application of digital twin systems in mining is limited to specific areas, such as predictive maintenance of equipment, optimization of drilling and blasting processes, and fleet monitoring. Full-scale integration across the entire mining value chain is rare. For instance, while there are sophisticated digital twin models for equipment such as grinding mills and haul trucks, these models often operate in silos without being integrated into a unified system that can provide a comprehensive view of the entire mining operation.

This limitation reduces the ability of digital twins to provide an understanding and optimization of the entire mining system.

4.2. Gaps in prior studies

Several gaps have been identified in prior studies of the implementation and use of digital twin systems in mining. Most research is focused on isolated aspects of the mining process. For example, while there is a considerable amount of work on digital twin applications for equipment monitoring and maintenance, there is a lack of studies that integrate these applications with broader operational perspectives. This fragmentation prevents the development of comprehensive digital twin systems that can enhance overall efficiency and productivity. In addition, there is a significant absence of standardization in digital twin frameworks and methodologies in mining. This lack of standardization leads to inconsistencies in how data are collected, processed, and used, making it challenging to develop interoperable systems that can work seamlessly across the distinct stages of mining operations. Many digital twin solutions in the mining sector are designed for specific cases and lack scalability. This limitation restricts the broader application of digital twin systems across different mining operations and geographies, inhibiting the ability to implement widespread improvements in efficiency and sustainability.

Integrating digital twin systems with existing legacy systems in mining operations is another significant technical challenge. Many mining operations rely on outdated infrastructure that is not conducive to the seamless integration of advanced digital technologies. This gap requires the development of innovative integration strategies and tools. In addition, effective data management remains a critical challenge as mining operations generate vast amounts of data, but the ability to collect, store, and analyze this data in real time is often limited. In addition, issues related to data quality, consistency, and security further complicate the deployment of effective digital twin solutions.

4.3. Prospects and next steps

To boost the application of digital twin systems in mining, several suggestions and prospects can be considered.

(1) Investment in Infrastructure. Mining companies should focus on investing in robust digital infrastructure that can operate under challenging conditions in remote areas. Collaboration with technology providers could benefit the development of better connectivity and reliable power supply solutions. In addition, leveraging advanced technologies, such as IoT and AI, can enhance operational efficiency and safety in these environments.
(2) Skill development programs. The industry needs to invest in training programs to upskill the existing workforce and attract new personnel with digital skills. Educational partnerships with universities and technical institutions can bridge the skills gap and foster innovations. Specifically, universities, particularly mining departments, play a crucial role in this initiative by adding specialized courses related to mine automation and innovative technologies. These courses should focus on equipping future mining engineers with essential skills, including AI, software development, and programming. By integrating these advanced topics into the curriculum, universities can ensure that graduates are well-prepared to meet the demands of modern mining operations and drive the industry forward through technological advancements.
(3) Pilot projects. By testing and refining the technologies used in digital twins, pilot projects can provide valuable insights before they are scaled up to full implementation, ensuring higher efficiency and effectiveness in the final deployment.
(4) Collaborative research and development (R&D). It is important to foster collaborative R&D between mining companies, technology firms, and research institutions to expedite the development of customized digital twin solutions that address specific challenges within the mining sector, ensuring more efficient and sustainable operations.
(5) Regulatory frameworks. There is a need to create regulatory frameworks that encourage and facilitate the adoption of digital technologies in mining, as this helps overcome hesitations related to investment. As technology continues to evolve, the implementation of digital twins is expected to play an increasingly pivotal role in shaping the future of mining. By addressing the challenges and actively pursuing recent technologies, the mining industry can unlock new efficiencies, optimize resource usage, and pave the way for a more sustainable and innovative future.
(6) Sustainability and environmental considerations. Digital twins can play a significant role in advancing sustainability goals in the mining sector. By adopting the technology to optimize resource usage, reduce waste, and minimize environmental impacts, digital twins can contribute to more sustainable mining practices. Future research should focus on developing digital twin solutions that not only enhance operational efficiency but also promote environmental sustainability.

5. Conclusions

In recent years, the mining sector has undergone a transformative shift toward digitalization, using advanced technologies to optimize efficiency, safety, and sustainability. Despite significant progress, there remains a notable gap between current implementations and fully integrated digital twin mine sites. Certain critical aspects of mining operations, such as fleet dispatching and the deployment of autonomous vehicles, have successfully implemented digital twin technologies, revolutionizing operations by enabling autonomous operation and enhancing productivity and safety. Similarly, the use of digital twin systems in production drilling has streamlined processes and improved accuracy and efficiency while minimizing downtime. These advancements underscore the potential of digital twins to drive innovation and efficiency in mining operations.

However, it is important to acknowledge that many areas of mining operations still require human intervention to ensure acceptable performance. Certain processes, such as ore extraction and processing, often rely on human oversight to ensure adherence to safety protocols and optimal performance. For several reasons, the mining industry has been slower to adopt digitalization compared with other sectors. First, mining often takes place in remote and harsh environments, making it difficult to install and maintain digital infrastructure. These locations can lack reliable internet connectivity and power supply, which are essential for digital technologies. In addition, the rugged terrain and extreme weather conditions pose further challenges for implementing and sustaining these systems. Another reason is the high level of uncertainty in the mining industry. Various factors, such as geological variability, fluctuating commodity prices, and unpredictable market demands, add complexity to mining operations. This makes it harder to apply digital solutions effectively. Moreover, the mining industry has traditionally been cautious about adopting new technologies due to the significant investment required and the long lifespan of existing equipment, which might not be compatible with new digital systems. There is also a skills gap, as many mining professionals lack the digital skills needed to implement and use these technologies effectively. The increasingly widespread deployment of sensors and IoT devices throughout mining operations has facilitated the collection of vast amounts of data, serving as a foundation for the development of digital twins. These systems enable real-time monitoring, predictive analytics, and proactive maintenance strategies, further enhancing operational efficiency, cost reduction, and safety.

While the journey toward realizing full digital twin mine sites is ongoing, the industry's commitment to digitalization remains steadfast. Efforts are being made to push the boundaries of digital twin use in mining operations, aiming to enhance operational visibility, efficiency, and decision-making across the entire mining value chain. As technology continues to evolve, the implementation of digital twins is expected to play an increasingly pivotal role in shaping the future of mining, unlocking new efficiencies, optimizing resource usage, and paving the way for a more sustainable industry.

In conclusion, the integration of digital twin systems into the mining sector provides substantial opportunities for enhanced efficiency, safety, and sustainability. By investing in robust digital infrastructure, developing targeted skill development programs, conducting pilot projects, fostering collaborative R&D, and installing supportive regulatory frameworks, the mining industry can overcome existing challenges and fully harness the potential of digital twins. As these technologies continue to grow, they will play an increasingly critical role in optimizing resource use, reducing environmental impact, and driving innovation. Embracing these technologies will not only drive the mining industry toward a more efficient and sustainable future but also ensure it remains competitive in an increasingly digitalized world.

CRediT authorship contribution statement

Pouya Nobahar: Conceptualization, Writing – original draft. **Chaoshui Xu:** Supervision, Writing – review & editing. **Peter Dowd:** Supervision, Writing – review & editing. **Roohollah Shirani Faradonbeh:** Writing – review & editing.

Declaration of Competing Interest

Chaoshui Xu is an editorial board member for this journal and was not involved in the editorial review or the decision to publish this article. 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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