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TOPICAL REVIEW

Exploring the Fusion Potentials of Data Visualization and Data Analytics in the Process of Mining Digitalization

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ABSTRACT Mining digitalisation have been receiving significant attention due to the utilisation of advanced technologies, such as IoT, automation, and sensing. However, maximising the potential value of collected data in the mining industry remains a challenge. Therefore, this paper aims to review timely concern topics to facilitate the fusion implementation in mining engineering. Specifically, this review covers recent popular topics, such as, data visualisation, data management, data analytics, data fusion, visual analytics, and mining digital twin construction. In this paper, we aim to draw a comprehensive picture about the fusion of data visualisation and analytics in the big data context, by examining the recent academic research related to these topics. Therefore, this paper reviews the visualisation domain by conventional classification, including scientific visualisation, information visualisation, and visual analytics, associated with the analysis of current digital twin development. Next, according to the challenges and issues related to visualisation development, this paper reviews the data management and data analytics domains as well. Incorporating with the fusion concept, machine learning-oriented fusion applications and potential scenarios in the mining industry have been discussed. In addition, based on the observation across various domains, this paper presents challenges and future potentials of data fusion in mining.

INDEX TERMS Mining digitalization, data management, data analytics, data visualization, data fusion.

I. INTRODUCTION

The mining industry is currently experiencing an intense digitalisation and transformation in mobile computing, cloud storage, data analytics, advanced process control, and the implementation of autonomous mining equipment [1], [2], [3], [4]. Advanced digital technologies such as the Internet of Things (IoT), sensing, and automation have revolutionised industries by improving production efficiency and safety. However, the massive amounts of data generated by these technologies have also created unprecedented challenges in managing, visualising, and analysing this data [2], [5], [6].

To date, due to the rapid advances in information and communication technology, the mining industry faces increasing challenges in managing, visualising, and analysing raw sensor data and other geological data [3], [7], [8], [9], [10]. Simultaneously, the integration of multiple datasets and the development of digital twin offer new opportunities to reveal potential mechanisms of geological hazards, which requires large amounts of cleaned data [11], [12]. Effective data management is critical for various data applications as it can improve efficiency and decision-making accuracy. Therefore, when conducting data management, it is of utmost importance to clarify data requirements across visualisation, analytics, and information-sharing schemes, including quality, quantity, attributes, and other relevant factors [13], [14], [15].

According to recent publications in the mining industry, visualisation and analytics are generally developed separately, resulting in different database, data exchange mechanism, and data exchange workflow [16], [17], [18], [19].

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From the visualisation perspective, it is generally developed by utilising 3R techniques, including virtual reality (VR), augmented reality (AR), and mixed reality (MR), and so-called extended reality (XR) [18], [20], [21]. However, due to the low data utilisation, visualisation-oriented mining education and training applications are still designed with simple interaction and are limited to solid 3D models [17], [22], [23], [24], [25], in which the solid model is manually generated from complex 2D DXF/DWG drawings. Given that, data-driven parametric modelling development receiving more attention in recent visualisation development [26], [27], [28], [29], [30], [31].

While artificial intelligence (AI) has been increasingly applied in various industry scenarios, data analytics in the mining industry still faces some intrinsic issues, such as data availability in processing, data quantity in analytics, and data quality in analytics and processing [32], [33], [34]. These issues can also impede the development of data fusion, making it challenging to achieve [2], [35], [36], [37], [38]. Given the four Vs of big data, including volume, velocity, variety, and veracity, the field of mining engineering faces significant challenges in managing and making sense of the vast amounts of data generated by various sources [39]. One solution to address these challenges is to leverage machine learning models, which can help with tasks such as rock status monitoring through image detection, semantic model training for survey exploration, and multi-dimensional data analytics considering spatial-temporal factors. By using machine learning algorithms, mining companies can better manage and analyse big data, improving their decision-making capabilities and gaining new insights into complex geological phenomena.

To that end, this paper aims at reviewing visualisation and analytics-based applications in engineering scenarios. The outcome can be referred to proceed data utilisation for knowledge discovery and risk management in the mining industry. In this regard, timely concern topics can be included, such as, mining digitalisation, data management, interactive data visualisation, digital twin, parametric model development, data fusion, data integration, etc.

II. BACKGROUND

A. MINING DIGITALISATION

Over the past decades, the mining industry has faced several challenges. Improving productivity to overcome natural factors such as decreasing ore grades, deeper deposits, and harder rock mass, combined with increasing environmental and social awareness, has boosted the industry to constantly work to enhance its processes along the whole value chain. In this context, innovation plays an irreplaceable role by providing suitable solutions to surpass these difficulties, ensuring continuity and sustainability in mining development [38], [40], [41]. In general, industry innovation is mostly driven by digital technologies, and mining engineering has been trying to brace the changes to improve efficiency, reduce cost, and meet the increasing social and environmental concerns among communities and authorities [2], [4], [42]. Nonetheless, it remains increasingly difficult for mining enterprises to decide which digital technologies are most relevant to their needs and individual mines, especially in such a technique explosion era [2].

Table 1 introduces some prevalence technologies adapted in mining engineering. The IoT/IIoT has led more wireless protocol data collection, resulting in various raw data has been collected and stored into database. It makes data collection, even real-time data collection possible in underground environment. Due to the specialised knowledge required for underground mining processes, 3R applications have been developed to address the need for effective visualisation and demonstration of mining information [23], [24], [43], [44], [45]. In contrast to conventional scientific visualisation, information visualisation places greater emphasis on 3D spatial visualisation. It makes users easier to understand the distribution of underground mining excavation and exploration. In this regards, taxonomy of the data visualisation has two branches. Scientific visualisation refers to the statistical and scientific data visualisation, which typically involves visualising physical data. Information visualisation is specifically designed to present 3D and spatial-temporal data in a virtual environment, allowing for more intuitive and interactive exploration of complex datasets [46]. Incorporating the ever-increasing data amounts, data management receives attention to facilitate the development of data analytics and visualisation. The challenges of developing an effective data management schema is the variety of mining data, which includes generic numerical data, drawings, images, complex surveys and report (text), and geological and geotechnical structures. As are result, data classification is normally the main task in the very beginning of a data management solution. However, as the confidential of data across mine sites, uniform data is normally hard to realise. The objective of data analytics in the mining industry is to discriminate and predict geological hazards. Advanced machine learning models are being developed to reveal complex geological mechanisms such as microseismic activity, rock mass response, and geological and geotechnical events. However, the success of these models relies on well-organised data sets, which is often hindered by data silos across information systems. In the realm of integration and information system development, various timely topics are emerging in the mining industry. One such topic is data fusion, which has gained considerable attention due to its potential for complex multi-source data analytics when integrated with data management and analytics. The aim of data fusion is to combine various datasets and uncover hidden connections, making it crucial for solving black box issues such as those encountered in underground mining activities. The topic of digital twin systems is gaining traction in many modern industries, including mining. It involves the real-time visualisation and interaction with a physical duplicate. Developing a digital twin system requires the integration of multiple state-of-the-art techniques such

TABLE 1. Advanced technologies and its development in the process of mining digitalisation.

Topics	Focus	Contribution	Future concerns
IoT/IIoT [47]–[53]	Efficient data collection by various sensors. Providing real-time data collection and transformation solutions across multiple scenarios.	Led in more wireless protocol data collection, resulting in various raw data has been collected and stored in a database.	Installing IoT devices in a complex underground environment, such as no power, high humidity, and high dust areas. Improving the efficiency among multiple data collection procedures, and enhancing the accuracy across various data exchange and transformation procedures. Bridging the procedures among data collection, data processing, and data analytics, so that contributing to the real-time data visualisation and analytics.
Data visualisation [17], [22], [24], [25], [31], [54]–[71]	3R application in training and education scenarios; Interactive information visualisation; Spatial-temporal data visualisation; Parametric visual model development.	Providing a comprehensive understanding of mining operations via interactive 3R applications. Leading BIM, point cloud, unmanned drone detection, and parametric modelling solutions into mining model reconstruction.	Providing a comprehensive understanding of mining operations via interactive 3R applications. Leading BIM, point cloud, unmanned drone detection, and parametric modelling solutions into mining model reconstruction.
Data management [19], [72]–[75]	Cloud service/database construction; Efficient data exchange and preliminary data cleaning; Data classification and standardisation.	Leading the cloud service, incorporating the web framework in information system development. Proposed data classification contributes to data management and analytics.	Proposing a uniform data diagram/structure in order to tackle the compatibility and scalability; Standardise the workflow of data exchange and transformation; Digitalising visual models and making it compatible with data management and analytics schemes; Proposing solutions for the analytics in terms of low data quality for ML training.
Data analytics [16], [73], [76]–[80]	Single factor analytics, such as rock mass rating, microseismic; Multi-factor analytics, such as rockburst, fall of ground; Semantic analytics, such as geo-hazard discrimination.	Enhancing the accuracy of geological events prediction. Improving the safety of working environment and the efficiency of management. Exploring the data fusion applications in mining operations.	Integrating multiple data sources in geohazard discrimination and prediction. Providing solutions for less sample ML training and application. Leading in multi-modality data analytics and management in order to discover more potential in complex underground environments. Improving the real-time capability of analytics in mining operations.
Timely concern topics (digital twin, data fusion, data security, visual analytics) [5], [73], [75], [81]–[83]	Integrating advanced technologies in a comprehensive system. Enhancing the real-time capability in visualisation and analytics. Improving data security and ensuring high efficiency in data management.	Providing potentials in mining information system construction. Optimising the mining procedures and enhancing the efficiency and safety of mining activities.	The development of a comprehensive mining digital twin prototype. Multi-modality data management and analytics framework in mining operations. Web-based information system with high compatibility and scalability to tackle the ever-increasing data.

as IoT for real-time data streaming, cloud services for data exchange and information sharing, and 3D interaction for bidirectional virtual-physical communication. As the development of digital twin systems progresses, data management and analytics become increasingly important. This includes data security and data fusion to ensure that data is managed effectively and insights can be gained from the large amounts of data generated by the system.

B. DATA VISUALIZATION

Visualisation is utilised to better understand the mining operations, especially for the underground mining. With the implementation of advanced technologies, we expect to get more insights into data analytics and management by data visualisation. For example, the patterns of complex geological and geotechnical structures can be revealed and involved into data analytics through the spatial and temporal perspectives [84], [85]. The revolution of mining data visualisation shown in Figure 1, which reveals its iteration from 2D to 4D (time series). This can also be recognised as scientific visualisation, information visualisation, and visual analytics separately [46]. Yet, due to different focuses of various visualisation schemes, all of them are playing essential roles across different sections. For example, 2D visualisation works for mining design, 3D visualisation is broadly developed in environment demonstration, and 4D visualisation is emerging as a critical role in data analytics. In addition, the interactive visualisation, involved in 3D and 4D visualisation, has been contributing to the development of digital twin and visual analytics. In order to realise automatic update of virtual environment, data-driven visualisation is receiving more attention. Hence, Building Information Modelling (BIM) and parametric modelling are becoming two typical data-driven visualisation solutions. They have been widely applied in civil and building engineering [20], [31], [87], as well as underground engineering [26], [88], [89], [90]. In a BIM

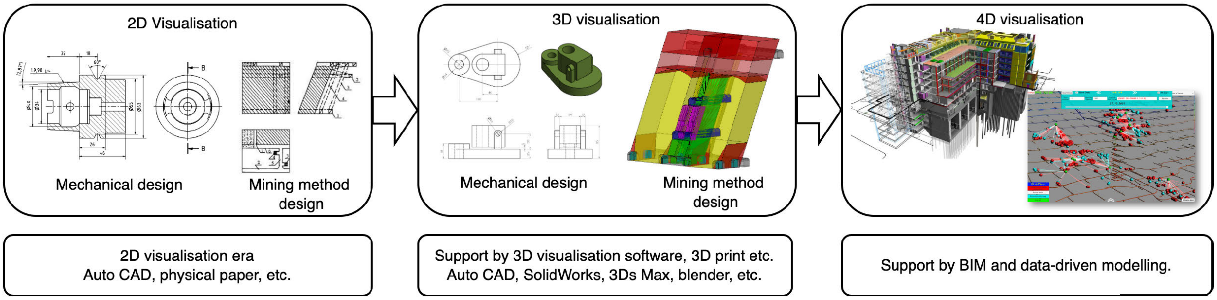


FIGURE 1. Visualisation revolution routine [86].

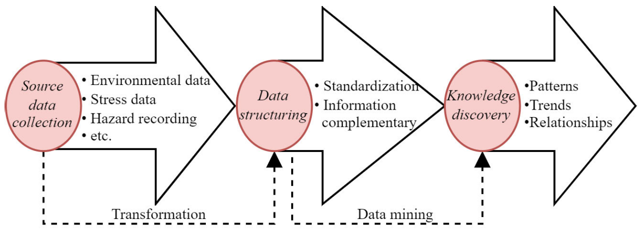


FIGURE 2. Application procedure of big data.

application, the visual model can update automatically with inputs. This unquestionably can be preferred over a conventional solid model that has no extensibility. Yet, considering the unforeseen of the mine workings' framework, different from the standardised building parameters, the implementation of BIM and parametric modelling may need more practice in standardisation, validation, and verification. This also poses a further challenge in 3D model development for mining visualisation. Hence, more studies are demanded to achieve a data-driven visual model development solution, which could digitalise the solid model into datasets and could be real-time reconstructed with user interaction.

C. DATA MANAGEMENT AND DATA ANALYTICS

Big data refers to large growing datasets that include heterogeneous formats: structured, unstructured, and semi-structured data [91]. Despite the ubiquity of big data in research entities, there is currently no consensus on what amount of data can be called big data [92], [93], [94]. To date, due to the development and adaption of advanced technologies, industries are facing challenges when handling the increasing data, such as collecting, integrating, storing, and information sharing.

According to recent research, the application of big data is mainly summarised as three parts: data collection, data structuring, and knowledge extraction, as shown in Figure 2. To fine the procedure, data management emerges as a critical role, which aims to facilitate data analytics and complex multidimensional data visualisation [19], [94], [95], [96]. For example, lots of geological surveys have more than two dimensions which poses challenge on data analytics and visualisation [97], [98], [99], [100].

However, the information isolation, also known as data silos, is emerging with the development of data management and information system construction. This normally presents as difficult data exchange and information sharing across different applications, systems, and procedures, which also hinders the process of data fusion. Given that, the research on data can help handle these issues, including data management, data standardisation, data exchange, etc. [19], [49], [74], [92], [98], [101] Yet, regarding recent studies, the development of data management and the utilisation of multi-resource data in the mining industry are far behind our ability to collect and store data [102], [103], [104].

On the other hand, the goal of data analytics is to analyse the cleaned data to detect hidden patterns, which is achieved by performing data management procedures on raw data prior to the analysis. The discovered data patterns are expected to facilitate the applications in identifying hazard and predicting future events. As an example, the analytics of rock mass response data is utilised to discriminate rock burst and correlated geological activities. In terms of various types of data in mining operation, machine learning models receives attention on mining data analytics. In this regard, mining data can be numerical, text-oriented surveys/reports, image/video, drawings. Yet, different from other modern industries, data quality and quantity can be challenging due to continuous increase and its broadly spatial variation.

D. DATA FUSION, VISUAL ANALYTICS, AND DIGITAL TWIN

In the field of information technology, timely concern topics are including: managing and processing multi-source datasets, data fusion, visual analytics, and digital twin, which covers the topic across data analytics, visualisation, and real-time data processing. While the definition of these entities varies across different fields, there is a consensus that these approaches can help manage the constantly growing amount of data and improve decision-making and analysis capabilities [11], [105]. The ultimate goal is to make data analytics more precise and compatible with evolving technological needs [16], [84], [106], [107].

TABLE 2. Some examples of various digital twin constructions across different industries.

Industries	Status	Target
Manufacturing [116]–[118], [126], [134]–[137]	Verification and validation of proposed framework and function modules. Broad sense and narrow sense definitions are applied while constructing a digital twin.	A comprehensive digital twin system to fuse physical models and virtual models. Realise real-time data sharing and decision-making.
Production lifecycle management (PLM) [14], [138], [139]	Based on manufacturing digital twin designs, it focuses more on physical and virtual connection and real-time information exchange.	Synchronised data origins from physical products and virtual space operations. Reflecting the effectiveness of digital twin towards handling the products as it moves through typical lifespan stages. Focusing on the connection between the physical and virtual product, enabling designers to conceptualise, compare, and collaborate.
Oil and Gas industry [83], [127], [128], [140]	Providing the top alternative technologies for digital twin construction. Develop a five-component digital twin framework based on typical applications.	Integrating digital technologies to address skill gaps and maximise production and revenue while reducing HSE risks and operational costs.
Construction, built, and environment [33], [54], [141]	BIM technology is well-applied in the digital twin construction (Automatically and semi-automatic geometric digital twinning)	Fulfilled the requirements of geometric digital twinning for existing buildings based on existed digital twin framework.
Mining engineering [5], [70], [142]–[144]	Concept discussion. Micro conception on permeability prediction of porous sandstone. The development of a digital twin-based hydraulic supports in coal mine shield support system. A digital twin system for mining shaft and hoisting.	Discussion on the availability of digital twin system in rock mechanics analytics and the integration of ML and related AI models. It's a micro perspective simulation and prediction. A VR digital information visualisation platform. To develop a comprehensive monitoring system of mine shaft infrastructure and tools for supporting diagnostics management.
Safety training [145]	Combined with Virtual reality to finalise safety training in emergency situations	Providing intuitive stress-free and safe method for the safety training.

Yet, conventional data fusion and analytics have limitation in understanding data correlations. For example, the spatial-temporal connections are not as simple as distance-oriented in underground mining. Visualisation and recognition can be a critical part in understanding data distribution. Hence, visual analytics emerges as an efficient tool in enhancing the recognition of data and complex data correlations. Visual analytics is aiming to generate knowledge and discover hidden opportunities from massive and complex data, which integrates the human effort to make the analytics more reliable [46], [102], [108], [109]. It highlights the visualisation and interactive operation in analytics, aiming to facilitate data analytics and knowledge discovery through customise visualisation and interaction. As underground mining is much more like a black-box issue [110], [111], visualisation and custom interaction is an important tool in operation, which can help extract more underlying information to analytics as well.

To extend visual analytics in a real-time mode, the digital twin concept has been prevailing in various industries, which is expected to be an integration platform for all available advanced technologies [14], [112], [113], such as data visualisation, data analytics, data fusion, and even visual analytics. The basic idea of the digital twin is to link physical and digital objects in an accurate and real-time manner [114]. In a narrow sense, the digital twin is about information that fully describes a potential or actual physical production from the micro atomic level to the macro geometrical level [115], [116]. Some industry examples are listed in Table 2.

The development of digital twin has got more applications in manufacturing. Some studies [117], [118], [119] have focused on framework design and the integration of state-of-the-art techniques, for instance, the blockchain for data security. Some scholars [116] proposed a digital twin framework for production life-cycle management, which consists of three parts, physical space, virtual space, and information-processing layer. In the context of digital twins, some typical frameworks are concluded, all adapted frameworks in recent research are developed from them.

- Digital Twin Reference Architecture: This framework was developed by the Industrial Internet Consortium (IIC) to provide a common language and understanding for digital twins. It consists of four layers: the physical layer, the virtual layer, the data and analytics layer, and the application layer [120], [121].
- Cyber-Physical System (CPS) Reference Architecture: This framework was developed by the National Institute of Standards and Technology (NIST) to provide a common language and understanding for cyber-physical systems, which include digital twins. It consists of five layers: the physical layer, the communication layer, the computation layer, the control layer, and the application layer [122], [123], [124].
- Smart Manufacturing Systems (SMS) Reference Architecture: This framework was developed by the National Institute of Standards and Technology (NIST) to support the development of smart manufacturing systems, which can include digital twins. It consists of five layers:

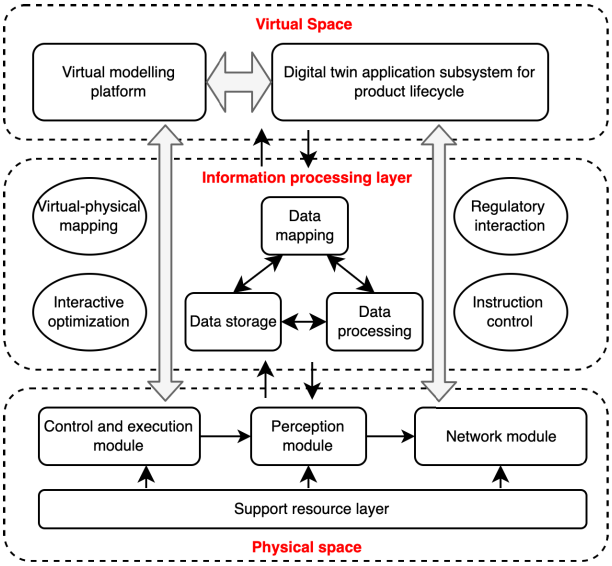


FIGURE 3. A typical five-component framework of digital twin system [116].

the physical layer, the connectivity layer, the information layer, the functional layer, and the enterprise layer [125], [126].

Figure 3 shows one of the well-accepted digital twin frameworks, also known as the five components framework (physical space, virtual space, connection between them, data and service) [40], [116], [117], [122], [127], [128], [129], [130]. Besides the five components framework, some researchers [54] proposed a closed-loop digital twin framework under the integration of BIM, IoT, and data mining (DM) techniques. The proposed framework takes advantage of BIM and IoT techniques to realise the 4D visualisation and task-centred or worker-centred process model, which is the visual model to simulate both the tasks execution and worker cooperation [128], [131], [132], [133].

III. DATA VISUALIZATION

This section provides an overview of mining visualisation application by generic classifications, including scientific visualisation, information visualisation, and visual analytics. Visual analytics is a combination of conventional visualisations. Driven by the development of visual analytics, the automatic generation of the visual environment is emerging as a vital branch of the development of data visualisation, for instance, parametric modelling and BIM. In addition, as the digital twin is a platform integrating visualisation and analytics, this section will also cover applications of mining digital twin system.

A. CONVENTIONAL VISUALIZATION

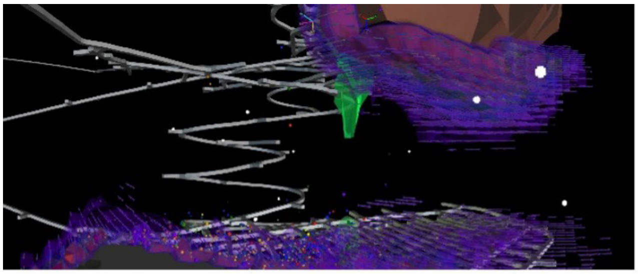
Scientific and information visualisation are two conventional visualisations. Scientific visualisation is used to explore and understand complex scientific data. In mining, it is used to visualise geological data such as seismic data, geological models, and mineralogy. This helps geologists and mining engineers to better understand the subsurface environment and make informed decisions about resource extraction. Information visualisation is used to represent data in a graphical or pictorial format. In mining, this can be used to visualise production data, equipment performance data, and other operational data. Information visualisation helps mining engineers and operators to quickly identify trends and anomalies in the data, and make more informed decisions.

In the development of visualisation, visual model is the virtual replica of the physical world. The visualisation is working with all the visual model and conveying information to users. According to current visualisation solutions, there are some generic methods in visual replica generation.

- Generating 3D model from 2D drawings (CAD) by model development software, such as 3Ds Max, blender, and SolidWorks. The generated 3D model is normally recognised as 3D solid model. This method is often used to create detailed representations of mining equipment and infrastructure, allowing engineers and operators to visualise the components and their relationships in a 3D environment. For example, Figure 4 (a) is a VR-based interactive undeground mining scenario.
- Directly visualising the 2D structures according to the datasets generated from 2D drawings. This method involves visualising the 2D drawings and datasets on a computer screen, without converting them to a 3D model. This can be useful for quickly reviewing and analysing the data, without the need for a complex 3D model.
- Interpreting numerical data and generating visual representation by default 3D models, such as sphere, box, and cylinder. For example, Figure 4 (b) is a scenario to dynamic present mining production data. This method involves using default 3D models to represent numerical data, such as the volume or concentration of minerals in a mining area. These models can help engineers and operators to quickly visualise and analyse the data, without the need for complex 3D modelling software.

As the complexity of underground mining operation, engineers and operators prefers to visualise 3D models and interact with the visual model. Yet, the 3D solid model is an object-oriented geometry model, which is hard to update over time. This can impede the application in long-term operation of the mining industry. To address this challenge, some studies are exploring parametric modelling and information modelling solutions in the development of an information system construction [90]. It aims to digitalise all general components into standard parameters, which can be reconstructed into 3D model following the program commands. However, while these solutions can help to create more adaptable models, they still face limitations in terms of interactivity and real-time updates.

(a) VR-based interactive underground model presenting



(b) Dynamic mining working presenting

FIGURE 4. Examples of the use of an immersive VR theatre for mining data visualisation [146].

B. PARAMETRIC MODELING AND INFORMATION SHARING

The objectives of parametric modelling and information sharing include digitalising 3D visual models into datasets and binding more data information into visual model. The bound information can help realising various visualisation and analysis purposes, such as multi-source visualisation comparison and integrating visualisation data with analytics procedures. To achieve these objectives, CAD systems have been improved by recognising the connectivity of shapes through sharing parameters and building links. Currently, the parametric modelling system is typically classified into three branches [76], [87], [89], [90], [147].

- Solid modelling, which defines the complex shapes or assemblies using key parameters, such as roadway section, transport composition, etc.;
- Assembly modelling, it allows the creation of assemblies of individual objects; and
- Topology-based modelling. It uses mathematical topology to define shapes and structures, often allowing for more complex and flexible modelling than traditional solid modelling techniques.

However, the interaction with visualisation models is challenging the parametric modelling, which drives the development of BIM. BIM integrated two forms of 3D solid modelling techniques, namely the boundary representation (Brep) and the Constructive Solid Geometry (CSG), to realise functions of editing, visualising, measuring, clash detection as well as other non-editing use [86], [87]. This development has strengthen the interaction across visualisation objectives, complex datasets, and users. But, it is still challenging BIM applications in handling complex non-standarded structures in underground mining scenarios.

According to recent study, some scholar proposed a parametric entity and mesh fused modelling solution. The solution emphasised the spatial parameters in 3D solid model development. The proposed multi-factor spatial-temporal data structure has several advantages, one of which is the potential to create a parametric underground environment and realise auto-extension [148]. As for the BIM in mining engineering, someone [31] proposed a BIM-oriented tunnel design integrated with geological-geotechnical information and ground conditions. The proposed implementation of the geological and geotechnical model allowed:

- To manage and update soil data during the entire site investigation process;
- To share the results of site and laboratory tests in a common data environment in order to properly calibrate the geotechnical model for the specific problem, that in turn re-enters in the BIM flow; and
- To possibly generate 2D stratigraphic profiles, calculate volumes and finally export results into other interoperable BIM platforms.

In addition, Huang et al. [147] integrated machine learning and computer vision techniques, consolidating the tunnelling BIM into a powerful tool for data analysis. They also introduced an interactive platform by case study, which considered the comprehensive and collaborative integration of GIS, 3D geological modelling, construction methods, and sensing technologies into the BIM in order to form a reliable basis for decisions and management in the lifetime of the underground project. Li [90] proposed a 3D information modelling technique for linear mine workings. Localised Industry Foundation Class (IFC) standard was designed for sinking and driving engineering. The proposed information model includes 3D mine geological modelling and mine data information construction. However, this prototype of mining BIM needs more concern on the balance of construction and information. Compared to the application in tunnelling, computer science techniques are required in order to integrate and ensure the prototype could fuse with data analytics and decision making, rather than another information island.

The BIM applications show the insights into near real-time modelling, data-driven modelling, and analytics fusion. Based on this, 3D Simultaneous Localisation and Mapping (SLAM) and related point cloud data model development are emerging and attracting mining managers [149]. Ren et al. [55], [56] studied utilising high precise SLAM and UAV devices to model underground workings. Its application could improve underground production safety and contribute to risk management and evaluation. However, given the tremendous data and high requirements in computation, the applications are relatively isolated from others, and general issues, such as data management and structure integration, are broadly existing.

C. MINING DIGITAL TWIN DEVELOPMENT

The development of mining digital twin has been focusing on fields below:

- Eliminate data silos, such as incorporating real-time data from various information systems, including underground mobile equipment, ventilation, and electrical systems, to provide a comprehensive view of the mine's operation.
- Integrate multi-source data. This focus will incorporate data from various sources, including geological surveys, drilling data, and equipment telemetry, to create a detailed model of the target mine [5].
- Optimise specific procedure. For example, optimising time-based maintenance policy in the mining industry [150], [151], [152], the simulation and decision making for raise boring method.
- Specific experiment field. This is a research-oriented field. It can be a real-time virtual synchronisation of an experiment sample, for example, a rock sample in rock mass properties test [142].

A digital twin-based decision analysis framework for the operation and maintenance of tunnels has been developed to integrate the life cycle spatio-temporal data of tunnels [153]. The framework includes a four-layer decision analysis process, which consists of the twin data acquisition layer, twin data fusion layer, model building layer, and service layer. To facilitate the application of BIM in tunnels, the COBie (Construction Operations Building Information Exchange) standard has been extended to tunnel objectives. This extension enables effective fusion of spatio-temporal data of the digital twin tunnel. The application of this framework highlights the importance of data standardisation and compatibility in the development of a digital twin system.

In terms of risk estimation, one digital twin system for oil and gas industry has been proposed using prognostic and ML techniques [152]. It focuses on the integration of sensor data to analyse hazard likelihood pace of oil pipelines and propose a virtual intelligent integrated automated control system to predict the risk rate. This case provides reasonable reference in data fusion and ML applications in risk estimation. To optimise and improve the accuracy of decision-making in the process of raise boring method for underground infrastructure, some study focuses on the development of a digital twin-based decision making paradigm [151]. It proposed a five-dimension framework that contained physical entity, digital representation, service entity, cross-systems entity and connection entity. Incorporating the five-dimension framework, four models were developed, including the hybrid modelling of data-based model, visual geometric models, domain knowledge-based model and physics-based model.

To facilitate the underground space planning and management, some study has developed a underground space visualisation-oriented digital twin system to guarantee the planning of underground development and planning. It also referred a five-component digital twin framework, including service system, physical entity, virtual model, information connection, and twin data. The research, to some extent, realises digital collaboration through attribute information and associated information. Additionally, some Scholars have integrated 3R applications into the digital twin construction as well. For example, a VR-based emergency scenario has been developed by [145]. It focused on the education and training fields that contributed to the development of an efficient fusion of 3R and digital twin in the potential operations in the mining industry.

As a result, there is a growing focus on the development of digital systems in the mining industry. These systems aim to optimise mining production, facilitate planning and management, and enhance the collaboration of advanced technologies. One popular framework that has been adapted is the five-component framework, which is inherited and evaluated to suit specific mining operations. However, given the objectives and involved technologies, the final framework can be varied based on discussion of the framework classification in Section II-D.

IV. DATA MANAGEMENT AND ANALYTICS

Efficient data management can provide a reasonable data structure for data analytics, which can reduce the pre-process work and improve efficiency. This symbiotic relationship becomes even more important as industries increasingly seek to utilise data effectively. This section will review the data related fields, such as data management and correlated analytics applications. Finally, incorporating data fusion and visual analytics, the development of data integration will also be reviewed in this section.

A. DATA MANAGEMENT AND INFORMATION SYSTEMS

Data management is an essential aspect of developing and maintaining information systems, particularly in the mining industry [154].The challenges related to data management in comprehensive mining information systems arise due to several factors, such as the absence of standardisation and a robust data structure, the intricate nature of the data generated, and the high volume of data [19], [154], [155]. These challenges can cause system isolation, which can hinder the development of fusion analytics in most scenarios.

In particular, mining operations use different systems and processes to collect, store, and analyse data, which makes it difficult to integrate data from different sources and ensure data quality and consistency. Moreover, the structure of the data generated can be complex and varied, making it challenging to manage and analyse the data, especially when different data types need to be integrated [156]. Additionally, the massive volume of data generated in the mining industry can lead to data redundancy and inconsistencies, which can affect data quality and accuracy.

To address these challenges, it is crucial to develop efficient data management systems, standardise data collection and management, and implement data quality control measures.

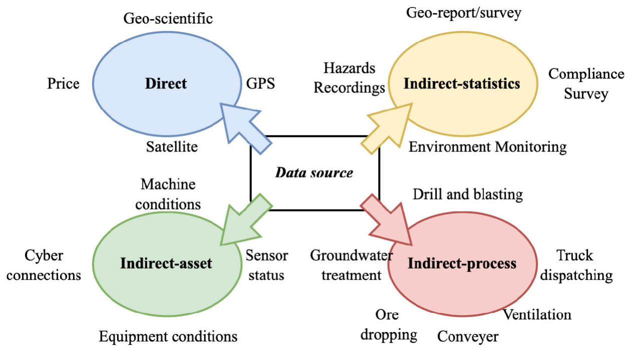


FIGURE 5. Data sources in the mining industry.

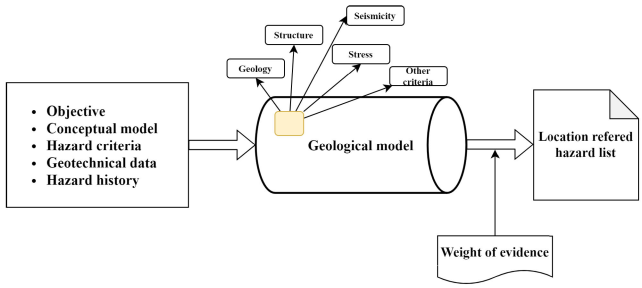


FIGURE 6. The workflow and an earth model data structure [16].

These measures can help ensure that the data is accurate, reliable, and consistent and support effective decision-making in the mining industry. The mining data management objectives have been summarised through a literature review and presented in Figure 5.

To handle the ever-increasing data volumes and complexity, some study focuses on the Hadoop Distributed Files System (HDFS) and Not only SQL (NoSQL) database. Regarding the advantages of HDFS, it can be concluded as:

- Scalability: HDFS is designed to scale out horizontally across commodity hardware, allowing for the storage and processing of massive amounts of data.
- Fault-tolerance: HDFS is built to be fault-tolerant, with data replication and automatic failover to ensure that data remains available even in the event of hardware failures.
- Cost-effective: HDFS can be run on inexpensive commodity hardware, making it a cost-effective solution for storing large amounts of data.
- High throughput: HDFS is optimised for high-throughput access to large files, making it well-suited for batch processing of big data.

Additionally, the NoSQL database has arisen as a solid alternative [73], [157]. In contrast to a relational database, a NoSQL database is one that is less structured/confined in format, and thus, allows for more flexibility and adaptability. Nonetheless, due to the non-relational structure of NoSQL database, the application requires uniform data diagram to realise data sharing.

In this regard, Li [158] and Qi [156] studied and constructed Hadoop-based mining data analytics platforms. They concentrated on the production safety of coal mines and challenges from increased monitoring data. In this regard, they proposed an optimised Hadoop strategy for efficient data management. Different from traditional information systems, the proposed cloud platform merits tremendous data processing from cloud computing, which provides more potential possibilities for further data analytics and resource scheduling.

On the other hand, the development of automation increases the number of mechanical devices. These bulky mining equipment fleet are vital in mining production, and its maintenance becomes a key issue simultaneously. Teng et al. [150], [159], [160] have proposed device repair and maintenance systems merit a highly efficient cloud database and collaborative data sharing framework. In addition, Agioutantis [160] also considered the compatibility of the designed system, providing access to a different platform/system. To some extent, it releases the isolation of information systems in mining digitalisation, and it is the trend of developing all data management and related information systems.

In order to utilise the time series data in visualisation and analytics, which is so-called 4D data, some scholar proposed mining 4D data structure (Figure 6), incorporating with 4D data management and data analytics [16]. The proposed 4D data is based on a dynamic-static classification of underground mining data, in which the dynamic data can have time attribute and vary over the mining operation. From the data management perspective, the data classification can improve the processing efficiency in handling the ever-increasing data.

In order to realise data storage, preliminary analysis, data cleaning, and even initial data visualisation, information systems are developed through the integration of correlated data procedures [156], [158], [161]. Considering various requirements of the system, different platforms are developed, such as gas monitoring and dynamic alarming system, air quality pollution monitoring, deformation and risk monitoring, etc. [70], [162], [163], [164] To achieve more flexible and security data storage, cloud databases and web services provide more possibilities and emerge as an important role in information system construction [89], [154]. The most popular and well-accepted framework in information system construction is summarised as five layers [34], [156], [158]: data layer, collection layer, storage layer, analytics layer, and application layer (Figure 7). As a result, Table 3 shows some examples of mining information systems incorporating cloud database and web service platform. Currently, cloud service mainly contributes to real-time data exchange and statistical routine data demonstration. Most Cloud computing-based risk analytics and decision-making are limited to data fusion strategy and data processing outcomes [165], [166], [167], [168], [169], [170].

TABLE 3. Some examples of mining information systems.

Information system classification	Data visualisation	Data management	Data analytics
Air quality pollution and environment monitoring [163], [171], [172]	✔Scientific visualisation	✔Relational database	✗
Deformation and risk monitoring [173]–[177]	✔Scientific visualisation	✔Relational database	✔Risk analysis and early warning
Maintenance [5], [88], [106], [148]	✔Scientific visualisation	–	✗
Support monitoring [56], [70]	✔Information visualisation	✔Relational database	✔Stress-strain curve for further analysis
Intelligent control information platform [169], [178], [179]	✔Statistics and property distribution visualisation	–	Cloud database supported decision making
Seismic monitoring platform [180]–[184]	✔Heatmap and time series visualisation	✔Relational database	✔Back-end ML support for risk discrimination and forecasting
Education and training [18], [67], [148], [185], [186]	✔3R applications	–	✗
Risk management [146], [186]–[190]	✔Scientific visualisation	✔Relational database	✔ML and AI model-based analytics
Geological and geotechnical information system [146], [167], [191]–[194]	✔Information visualisation and 4D visualisation	–	✗

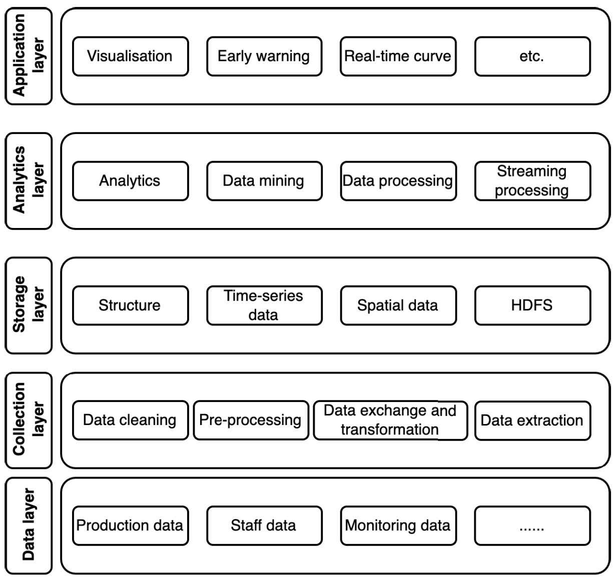


FIGURE 7. Well-accepted information system framework [34], [156], [158].

B. DATA ANALYTICS

Conventional data analytics in mining engineering can be classified into two types: single-factor analytics and multi-factor analytics. Single-factor analytics are typically performed in isolation, from data collection to analysis. This often involves the development of a separate information system to process the data and facilitate further analysis. However, as mining operations become more complex, single-factor analytics may not be sufficient to interpret and present geological and geotechnical activities accurately. As a result, multi-factor analytics, which takes into account multiple variables simultaneously, are becoming more popular. In addition, considering traditional data sources, such as surveys and reports, unstructured data sources such as text, speech, and images are increasingly being used to gain insights into geological and geotechnical activities. To extract meaning and insights from these unstructured data sources, techniques such as semantic analytics and correlated machine learning models are being developed, often with the support of Natural Language Processing (NLP) [80], [195], [196], [197], [198].

With the development of data management, data analytics is getting more opportunities to extract potential connections among various datasets, which drives the emergence of data fusion as well. Emerging AI algorithms are developed in multiple situations, such as rockburst prediction, seismic data processing, fall of ground hazard discrimination and prediction, etc. [194], [199], [200], [201], [202], [203], [204], [205]

This section has also reviewed some general algorithms in mining data analytics. Various machine learning (ML) models, such as SVM, k-NN, RF, and XGBoost, have widely applied in mining event discrimination and prediction. Some study shows that it has contributed to the mining hazards discrimination and classification through a good quality production data [206]. In summary, machine learning (ML) can provide the following advantages in engineering applications [198], [207], [208], [209], [210], [211]:

- ML can deal with high-dimensional data. As varied sensors and integration of information systems generate a huge amount of data of high dimensions, it is difficult to understand or find a relationship by traditional data-mining methods.
- ML has the ability to learn and adapt. As an information system faces external unpredictable events and internal complexity, the predefined modelset by humans becomes powerless in dealing with uncertain events. So ML, which can learn from the data by itself, provides a feasible way to dynamically respond to such challenges.

- ML is able to derive knowledge. While data available explodes in information systems, knowledge for decision-making does not grow synchronously. By learning from big data, knowledge can be derived from manufacturing systems that were data-rich but knowledge-sparse.

In addition to the aforementioned cases, data analytics in mining can be summarised into three aspects: hazard prediction and evaluation, production management, and time-series (4D) data analytics. Compared to the typical 3D concept, 4D data and its analytics play an essential role in the development of information systems as it incorporates the time dimension, which improves the accuracy of analytics and predictions.

For hazard prediction and forecasting, time-based prediction is crucial to understanding, assessing, and acting upon mining geomechanical risks [78]. Researchers have studied 4D data analytics for hazard prediction in the mining industry and proposed a system that covers the 4D data management module and the Weight of Evidence (WoE) algorithm-based data analytics module [16], [79], [212].

C. DATA FUSION

One of the most accepted definitions of data fusion was provided by the Joint Directors of Laboratories (JDL), which stands for ''multi-level, multifaceted process handling the automatic detection, association, correlation, estimation, and combination of data and information from several sources'' [213]. Leading in data fusion in mining engineering is an emerging research area that focuses on integrating and analysing multiple sources of data to improve the understanding of mining processes and optimise mining operations. According to recent research in the mining industry, data fusion applications are focusing more on safety concerns and risk assessment.

In terms of the safety concerns in underground coal mines, some scholars have focused on underground fire detection based on a multi-dimensional data fusion solution [214]. They involved various entertainment datasets, such as temperature, gas and radon concentration. Incorporating the borehole temperature measurement and gas measurement methods, they proposed the index of fire zone delineation based on multidimensional data fusion, resulting in a high accuracy model for the detection of underground shallow cola seam fire ares. As for risk assessments, some study focuses on utilising data fusion to evaluate the risk of water inrush from the coal seam floor [187]. The data covers grouting quantity, the loss of drilling fluid, gamma value, water temperature, average water absorption, distance between grouting loss points, water pressure on coal seam floor, etc. The outcome of this fusion showed that the analysis and risk prediction can be consistent with the area of higher risk scores. Rockburst risk assessment research has also integrated various experiment data for prediction, such as UCS, geological parameters, tunnel shape, etc. [215], [216] McGaughey [16], [80] proposed data fusion analytics with geological data and static rock mass data for hazard prediction. Wang et al. [217] concluded the workflow of data fusion technology for multisource collaborative monitoring in underground engineering. Data fusion proposed to be processed in data level and feature level by algorithms such as principal component analysis (PCA), Wavelet transform, independent component analysis, etc. After fusion, standardisation and normalisation of data would contribute to standardising the data for further model trning. Thirdly, data analytics model, for example prediction model, will be trained by KNN, ANN or DL algorithms. Finally, a safety state identification and prediction model could be finalised after mode analysis.

While data fusion can result in a higher accuracy and reliable outcome, it is challenging the data quality and quantity in practice. To facilitate data fusion application, AI-oriented algorithms and ML models are receiving attention in raw data processing and further analysis. Based on the traditional random fusion methods such as the weighted average method, Kalman filter method, and multi-Bayesian estimation method, multivariate data fusion is the trend combined with AI algorithms such as fuzzy logic theory, neural network, rough set theory, and learning technology [11], [105], [218].

V. DISCUSSION

A. DATA VISUALIZATION

Visualisation is an essential tool to facilitate the understanding and recognition of complex underground procedures. Yet, according to recent research, the limitations to the development of underground mining visualisation can be summarised below:

- The flexibility and adaptability to long-term operation
  Conventional visualisation is currently relying on the solid model, which lacks the capability of expansion with long-term operation. When a solid model is used to represent a complex system, such as a mining operation, changes or updates to the system may require significant modifications to the solid model. This can be time-consuming and costly, especially if the model was not designed with future changes in mind. Furthermore, as a mining operation progresses and evolves over time, the solid model may become outdated and no longer accurately represent the current state of the system. This can lead to errors and inefficiencies in decision-making and planning based on the model.
  To address these limitations, researchers and practitioners in visual modelling are exploring alternative approaches that allow for more flexibility and adaptability, such as using parametric models or generative design techniques. These approaches enable the visual model to be updated or modified more easily as the system changes over time, which can lead to more accurate and efficient decision-making and planning.
- The interaction with visual model

With the development of 3R applications, the interaction with the visual environment has received more attention in the underground mining industry. These 3R technologies provide a more immersive and intuitive way for users to interact with the mining environment, which can greatly enhance understanding of mining operations and facilitate the design of long-term mining plans. However, the current interaction design is limited by the adaption of solid models, which are often static and lack the flexibility to adapt to changes in the mining environment. As a result, the current state of interaction design is not sufficient to fully realise the potential of 3R technologies. Future research should focus on developing more dynamic and adaptable interaction design solutions that can keep pace with the evolving needs of the mining industry.

- The association of visual model and routine data
The visual environment plays a crucial role in data representation and interpretation. To facilitate routine data presentation, information visualisation systems have been developed to present various monitoring data by spatial distribution. However, these systems are limited in terms of compatibility with specific datasets, which limits their applicability in different contexts. Additionally, due to the lack of up-to-date visual models, the accuracy of routine data visualisation cannot be guaranteed. As a result, there is a need to develop visualisation systems that can accommodate a variety of datasets and incorporate updated visual models to ensure accurate and efficient data representation. This would allow for better decision-making, improved safety, and increased productivity in mining operations.
- The transformation between drawings and visual environment
One possible solution for automatic visual model generation is to transform CAD drawings into a visual environment. However, this requires efficient data diagrams and reasonable data exchange workflows to support the conversion process. Currently, there is limited research and case study support for data management that can meet the demands of data-driven visual model generation and update procedures.
- The digitalisation of visual model
With the rise of digital twin and data fusion applications, there is a growing need for targeted interaction with specific components of visual models. This requirement can be met through the digitalisation of visual models, which involves a more detailed decomposition of the model into datasets that can be used for analytics and interaction purposes.Unlike the transformation of drawings, which primarily involves converting a visual representation into a digital format, digitalisation goes further by breaking down the visual model into discrete components that can be analysed and manipulated. This approach enables more targeted and efficient interaction with the model, allowing users to focus on specific aspects of the model that are relevant to their needs.
Despite its potential benefits, digitalisation of visual models is still an area of limited focus. More research and development is needed to fully realise the potential of this approach and to develop effective workflows for digital twin and data fusion applications.
- The fusion with conventional analytics
Multi-modality analytics has gained attention in data fusion, given its ability to combine data from multiple sources. In underground mining, visualisation data can provide critical information about geological and geotechnical structures, as well as complex rock mass features. Incorporating visualisation data into analytics procedures can enhance the accuracy of ML models. However, this requires effective transformation and digitalisation procedures, which can decompose visual models into datasets for analysis and interaction. Furthermore, robust data management and workflow design are essential for the success of multi-modality analytics in mining engineering.
- The limitation of visualisation applications
According to limited visualisation applications, visualisation is still playing an information demonstration tool in mining engineering. While the concept of digital twin and visual analytics have boosted the development of visualisation platform construction, the objectives are still limited to demonstration. There are some potential scopes in visualisation application.
  - Dynamic path finding-oriented underground space navigation. Due to the complexity of underground space, workers and automation equipment are hard to make quick decision in an emergency scenarios. In this regard, a real-time data visualisation platform, which is adapted with data-driven model generation solution, can facilitate dynamic path finding visualisation and provide dynamic safety routine plan in real-time.
  - Interaction-oriented underground mining design. Incorporating with the data-driven model generation, visualisation platform can play role in design validation. In this scenario, users can plan regular operation in a visualisation system, then the embedded analytics model can facilitate the validation and proceed feasibility verification, so that to enhance efficiency and safety in long-term operation.

B. DATA MANAGEMENTN AND ANALYTICS

In the big data context, data management can facilitate the utilisation across different applications, such as decision-making, data-driven visualisation, multi-modality data analytics. Yet, according to current mining applications and academic research, the development of mining data management is hindered by lacking uniform data diagram. This causes the low efficiency in raw data processing and cleaning, as well as the data exchange and data interpretation. Considering the data fusion and the development of information systems, such as digital twin system, the multi-modality data becomes the key role in data management [34], [35], [114], [126], [210], [211]. In this regard, the following issues should get more efforts in the development of data management and analytics:

1) DATA VARIETY AND DATA QUANTITY

This situation poses significant challenges for data management in the mining industry. The diverse classification of data types and properties leads to difficulties in integrating and storing data, resulting in data silos and data fragmentation. This hinders the ability to effectively analyse and make informed decisions from the available data. Additionally, the increasing volume of data generated by new technologies can exceed the capacity of traditional data storage and management systems, leading to issues with data processing and retrieval. Therefore, efficient and effective data management solutions are crucial for successful and sustainable mining operations.

2) DATA EXCHANGE AND INFORMATION-SHARING

Data exchange and information-sharing are crucial aspects of data management, as they allow different managers within a mining operation to access and use data for various purposes. However, data exchange and information-sharing can also be challenging due to issues such as data format incompatibility, data security concerns, and differing data access rights among managers. To address these challenges, standardisation of data formats and protocols can be helpful to ensure interoperability between different systems and stakeholders. In addition, clear guidelines for data access rights and sharing agreements can help ensure that sensitive data is protected while still enabling information-sharing among relevant parties. The utilisation of cloud database can also facilitate data exchange and information-sharing by providing a central location for storing and accessing data from different sources. Finally, the use of advanced data analytics techniques such as machine learning and data fusion can enable more effective use of shared data by providing insights and predictions that can inform decision-making across the mining operation.

3) TIME SERIES DATA AND ITS EVER-INCREASING FEATURES

Time-series data refers to a sequence of data points that are measured at regular intervals over time. In mining engineering, examples of time-series data include sensor readings from equipment, temperature and humidity measurements in underground tunnels, and geological monitoring data. The ever-increasing features of time-series data refer to the increasing number of variables or parameters that are measured and recorded over time. With the advancements in technology and the rise of IoT, more and more sensors are being deployed across mining operations to capture a wide range of data points, resulting in complex and high-dimensional time-series data. The management of such data requires efficient storage, retrieval, processing, and analysis techniques to extract valuable insights and support decision-making.

4) MULTI-MODALITY DATA

Multi-modality data refers to the integration of data from different sources and types, such as text, images, audio, and numerical data. In the context of mining engineering, multi-modality data can include geological and geotechnical data, sensor data, visual data from cameras and drones, and digitalised visualisation data. The challenge with multi-modality data is to effectively integrate and process the data in a meaningful way that can provide valuable insights for decision-making. This requires advanced data management and analysis techniques, such as data fusion, machine learning, and NLP.

5) DATA UNIFICATION

The challenges of data unification arise due to the various classifications and types of data generated in mining operations. These different data types may require different storage and processing methods, which can lead to fragmentation and difficulty in integrating the data. Additionally, data may be generated from different sources or systems, which can also lead to inconsistencies and difficulties in unifying the data. The lack of standardisation in data formats and structures further exacerbates the challenge of data unification. Furthermore, data quality and completeness can also be an issue, as the data may be incomplete, inconsistent, or inaccurate. The sheer volume of data generated also poses a challenge for data unification, as the process of collecting, cleaning, and integrating large amounts of data can be resource-intensive and time-consuming.

6) DATA SECURITY

Data security have received more attention due to the data applications in various sections. In recent research, blockchain offers a robust and resilient mechanism for distributing and storing record history over the internet. The chain structure links data blocks sequentially in chronological order and thereby ensures that this distributed ledger cannot be tampered with or forged cryptographically [219], [220], [221], [222], [223]. With the high requirements of data security and fidelity, blockchain has become one of the most prevalent technologies to ensure transparency, trust, and security. There are at least nine potential use cases for blockchain in mining, which include (1) digital identity for assets and people, (2) data integrity, (3) provenance, (4) cradle to grave blockchain for assets, (5) workflow automation in combination with IoT, (6) supply chain optimisation, (7) tokenised mines, (8) workforce health recording, and (9) human resources management.

C. DATA FUSION

1) DATA FUSION SCENARIOS

The objectives of data fusion is integrating reasonable data sources and reasoning potential insights and hidden mechanism of target event, such as geological activities, rock mass response, etc. Yet, regarding complex scenarios and corresponding datasets, data fusion schemes may be different. Through the review, this study concludes typical scenarios of data fusion in mining engineering:

- Geological Exploration and Characterisation: Data fusion can integrate geological data from various sources, such as drilling, sampling, geophysical surveys, and geological maps to create a comprehensive geological model. This model can then be used for various applications, including resource estimation, mine planning, and risk assessment.
- Mineral Processing: Data fusion can combine data from different stages of mineral processing, including ore characterisation, comminution, flotation, and dewatering. The integrated data can provide a more detailed understanding of the processing plant's performance and improve the overall recovery rate.
- Mine Safety and Risk Management: Data fusion can integrate various types of data related to mine safety, including geotechnical data, ventilation data, and environmental monitoring data. This integrated data can help in risk assessment and decision-making related to mine safety.
- Asset Management: Data fusion can integrate data related to equipment condition, maintenance history, and operational data. This integrated data can provide insights into equipment performance, predict equipment failures, and optimise maintenance schedules.
- Environmental Management: Data fusion can integrate various types of environmental data, including air quality, water quality, and noise pollution data. This integrated data can help in environmental impact assessment, compliance monitoring, and remediation planning.

In terms of data types in data fusion applications, this study summarised potential fields of data fusion applications:

- Numerical data analytics. It can be single factor analytics and multi-factor integrated analytics. This is the initial stage of data fusion in mining. For example, the discrimination of seismic activities.
- Multiple data sources analytics. This can be a high dimension data analysis scenario. It can help improve accuracy in decision-making, risk assessment, and resource optimisation.
- Semantics analytics. As geological surveys and reports are broadly adapted in mining engineering, the integration of semantics analytics can help to identify patterns and relationships between different types of data, such as geological and geotechnical data, equipment performance data, and operational data. By applying semantics analytics to these diverse data sources, it is possible to gain a more comprehensive understanding of the mining operation as a whole, and to identify opportunities for process optimisation and cost reduction.
- Graphy Neural Networks (GNNs). Graph Neural Networks (GNNs) are a type of neural network that is well-suited for non-Euclidean data because they operate directly on graphs or other non-Euclidean structures. By leveraging GNNs, mining engineers can analyse and model the relationships between different elements of a mining system, such as the geological structures, mining equipment, and production processes. This can help to optimise mining operations, improve safety, and reduce costs. For example, GNNs can be used to predict equipment failures, optimise ore processing, and model the flow of materials through the mining system.

2) FUSION CHALLENGES

Considering all the potential scenarios and applications in mining engineering, some typical challenges are discussed:

- Data quality and heterogeneity: One of the main challenges in data fusion is dealing with the heterogeneity of the data sources, including different data formats, structures, and quality. It is important to ensure that the data is of good quality and that any biases or errors in the data are identified and corrected.
- Data unification: With the various classifications of data, unifying different data sources into a single format can be difficult, especially when dealing with multi-modal data. This requires a consistent and systematic approach to data management, including data pre-processing and feature extraction.
- System compatibility: When integrating different data sources, it is crucial to ensure that the different systems and technologies are compatible with each other. This includes issues related to data storage, data transfer, and data processing.
- Semantic interoperability: Ensuring that the data from different sources are semantically compatible can be a major challenge in data fusion. This requires the use of common vocabularies, ontologies, and other semantic models to ensure that the data can be understood and used in a consistent manner.
- Uncertainty and variability: Dealing with uncertainty and variability in the data can be difficult, especially when integrating data from different sources with different levels of uncertainty. This requires the use of appropriate statistical methods and modeling techniques to account for uncertainty and variability in the data.
- Computational complexity: As the volume of data and the complexity of models increase, the computational complexity of data fusion algorithms can become a significant challenge. This requires the development of efficient algorithms and computational methods to handle the large-scale data and complex models.

- Human factors: The adoption and integration of data fusion technologies in the mining industry depend on various human factors such as the skills and expertise of the workforce, cultural and organisational barriers, and resistance to change.

D. FUTURE POTENTIALS

In spite of all challenges, data fusion technologies will be rapidly adapted in the mining industry, numerous opportunities will be led in many fields as well. Several future potentials are discussed in this section.

To facilitate the development of high efficiency data management, a uniform data diagram can be proposed. The data diagram can fuse the routine data and visual model data so that to realise data-driven visualisation and analytics in one integrated platform. Incorporating the uniform data diagram, complex data exchange workflows will be designed as well. This will provide a more efficient and accurate way to manage and process the complex and ever-increasing data in long-terms operation.

With the support of the standardised data diagram, a more standardised and comprehensive approach of visualisation can be realised. It can be a data-driven mode for all geological and geotechincal structures, mining development, and interoperation data visualisation. Benefiting from the data exchange workflow design, the interaction can be realised across user-visual space and visual-physical design. It can provide a more accurate and real-time demonstration of the mining operation, which will improve the efficiency and accuracy of decision-making and visualisation.

Due to the low quality and quantity of collected data in the very beginning, data fusion can be difficult to apply and present a reasonable outcome. In this regard, the interpolation-based data fusion can facilitate the decision-making and ML model training. It can help to address some of the challenges associated with data integration and compatibility. By using advanced interpolation techniques, such as kriging, data sets can be effectively integrated and analysed to provide more accurate insights into mining operations.

Finally, a visual analytics pipeline system can be designed and developed aiming to realise interoperation and real-time visual-physical communication, which can also be a digital twin prototype of mining digital twin system. It can provide a powerful tool for mining engineers to better understand and manage complex mining operations. By integrating real-time data and analytics into a digital twin prototype, engineers can simulate and analyse different scenarios to optimise mining operations and improve safety. Additionally, these systems can provide a platform for ongoing monitoring and predictive maintenance of mining equipment and processes.

VI. CONCLUSION

The fusion of advanced technologies is a fast-growing topic in modern industries. It is expected to extract more potentials to provide informed decisions in operation. This paper has reviewed the timely concern topics in the process of mining digitalisation, including data visualisation, data management, data analytics, data fusion applications, and digital twin construction as well. In order to fuse more data into visual environment and facilitate the interaction with visual model, conventional data visualisation is limited to the flexibility and scalability. Hence, the parametric modelling and BIM become one solid alternative. However, considering the unforeseen of the complexity of mining workings and geological and geotechnical structures, an effective data-driven visual model development solution can be the trend in the fusion of visualisation and analytics. While it could pose challenges to the data management domain. On the other hand, the lack of uniform data diagram/structure emerges as the most essential issue of the development of digitalisation. The data management is facing various challenges, including data variety and quality, the efficiency of data exchange, the solution to handle data variety over time, visualisation-oriented multi-modality fusion, and also data security. Therefore, one main domain of future trend of mining digitalisation is data unification-oriented data management. Nonetheless, as the data fusion emerging as the trend of data analytics and ML model development, the fusion scenarios are discussed in the mining industry. It can be adapted in various fields, such as geological exploration and characterisation, mineral processing, mine safety and risk management, asset management, and environmental management. In this regards, this paper concluded the challenges as well. Incorporating with the data and visualisation domains, the challenges are including data unification, the solution of data-driven visual development, interoperation-based data fusion design, and the pipeline system development. Finally, the overview and future potentials in the mining industry are proposed according to the fusion of visualisation and analytics.

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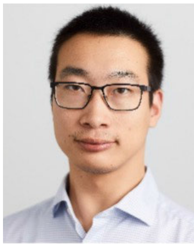

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