Dry laboratories – Mapping the required instrumentation and infrastructure for online monitoring, analysis, and characterization in the mineral industry

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ABSTRACT

Dry laboratories (dry labs) are laboratories dedicated to using and creating data (they are data-centric). Several aspects of the minerals industry (e.g., exploration, extraction and beneficiation) generate multi-scale and multivariate data that are ultimately used to make decisions. Dry labs and digitalization are closely and intricately linked in the minerals industry. This paper focuses on the instrumentation and infrastructure that are required for accelerating digital transformation initiatives in the minerals sector. Specifically, we are interested in the ability of current and emerging instrumentation, sensors and infrastructure to capture relevant information, generate and transport high-quality data. We provide an essential examination of existing literature and an understanding of the 21st century minerals industry. Critical analysis of the literature and review of the current configuration of the minerals industry revealed similar data management and infrastructure needs for all segments of the minerals industry. There are, however, differences in the tools and equipment used at different stages of the mineral value chain. As demand for data-driven approaches grows, and as data resulting from each segment of the minerals industry continues to increase in abundance, diversity and dimensionality, the tools that manage and utilize such data should evolve in a way that is more transdisciplinary (e.g., data management, artificial intelligence, machine learning and data science). Ideally, data should be managed in a dry lab environment, but minerals industry data is currently and historically disaggregated. Consequently, digitalization in the minerals industry must be coupled with dry laboratories through a systematic transition. Sustained generation of high-quality data is critical to sustain the highly desirable uses of data, such as artificial intelligence-based insight generation.

1. Introduction

Digitalization is quickly transforming the labour landscape at large. Mechanization, automation, and information and communication technology have been key ingredients behind widespread changes in the minerals industry (e.g., Rogers et al., 2019; Zhang et al., 2022). The demand for raw materials, such as minerals and metals, is placing serious pressure on the exploration, extractive and processing industries to innovate, adapt and unfortunately in some cases, perish (Calzada Olvera, 2021). The industries are inseparable from the modern human

experience (and even continued traditional human experience), as many minerals and metals have been declared to be 'critical' in the sense of their essential roles in our society (Ghorbani et al., 2021b and references therein). In a free market economy, the survivability of individual businesses is contingent on their ability to compete in an evolving landscape. This digital reform of industries continues to occur rapidly and coincides with the exhaustion of high-grade, accessible, easily extracted and processed mineral deposits; although with efficiency improvements and favourable market conditions, complete exhaustion may be unlikely (Arndt et al., 2017). The requirement for improvement in exploration, extractive and processing efficiency is based on the trend that the industry is moving towards the discovery and use of more challenging types of ores, non-traditional resources (e.g., tailings), more complex mineralogical assemblages and increasing national and international environmental, labour and other ethical regulations (Arndt et al., 2017; Nwaila et al., 2021b). Digitalization and particularly the deployment of sensor networks, edge computing, online sampling and analysis, and material characterization is a promising area of infrastructural evolution towards higher levels of operational efficiency, safety and environmental friendliness. These sensors and sensor networks can generate vast amounts of mineral industry-related, asset conditions and operational data in real time (e.g., big data). Information technology improvements such as the deployment of widespread wireless networks (e.g., 5G cellular data technology and satellite-based global internet systems – Starlink, Federal Communications Commission, 2019) has enabled the timely transport of large amounts of data, even to and from remote locations. Combined, instruments (including sensors), data and their related infrastructure can sustainably feed modern data-centric laboratories that are focused on data-centric tasks (Ghorbani et al., 2022), which can inform the industries to make more cost effective, strategic and guided decisions, providing competitive advantages to those willing to participate in digitalization. Legacy data alone (without modern big data) is unable to sustain downstream data-centric and data-driven activities, which essentially makes sustained activities such as data analytics (including predictive analytics) isolated and periodic in occurrence. Analytical products or processes such as prospectivity potential maps, deposit characterization data and knowledge (e.g., for geometallurgy and resource assessment), environmental monitoring, business intelligence, supply chain tracking, control systems engineering and predictive maintenance enable their adopters to obtain competitive advantages in the market place and/or meet or exceed industry regulations. However, the upstream requirements of data, such as the engineering of data streams through the meticulously planned deployment, integration and retrofit of sensors and communications infrastructure is often overshadowed by the downstream activities of data usage (e.g., artificial intelligence-based insight generation). This is despite the fact that upstream and downstream portions of the data pipeline are intimately linked, and within the modern (data and digital) context, an explicit and formal feedback mechanism (data management and governance) exists to specifically promote data and infrastructure engineering thus ensuring that data generation is tailored for downstream consumption (e.g., Ghorbani et al., 2022).

The planning and implementation of a digital infrastructure plays a key role in the ability of any business to digitalize. The nature of the mineral industry is one that intimately interfaces with the natural world, and has historically been a great source of data (e.g., seismic, geological and geochemical surveys, environmental monitoring, macroscopic and microscopic material property analyses). Regardless of the type of data, such data have always been used to fulfil a purpose – one that generally produces a greater business outcome (which in the academies translates to furthering discipline goals) as gauged by some business metric. The ability to generate suitable data is an engineering exercise that incorporates an a-priori consideration of foreseeable downstream uses and repurposing, such as data analytics (e.g., using artificial intelligence, predictive modelling and data science). These considerations in the past and prior to data repurposing and *trans*-disciplinary uses of data (e.g.,

machine learning-based predictive modelling) were primarily within disciplines or gated stages in the mineral industry (e.g., geophysical and geochemical data, data for exploration, resource assessment, mineral processing and closure). Because dry labs are anticipated to host a variety of data from different disciplines and stages of the mineral industry, the employment of *trans*-disciplinary data analytical methods such as artificial intelligence and machine learning is thought to be a key component of modern dry labs (Ghorbani et al., 2022). However, this also adds *trans*-disciplinary requirements to the generation and specification of data, some of which may need to be harmonized (e.g., through a meaningful compromise) with discipline-specific requirements (e.g., the desire for abundant data versus the capability of current instrumentation for automated sampling). An obvious and probably critical *trans*-disciplinary requirement is the availability of an abundance of high-quality data, which in many cases, may be at the level of big data for artificial intelligence-based modelling purposes (Chen and Lin, 2014; Zhang and Lu, 2021). Certainly, it would be impractical and essentially pointless, if either predictive models are trained using only legacy data (e.g., manually sampled) or deployment of models cannot occur because online sampling is unavailable. From the data perspective, modern data (as opposed to legacy data; e.g., data that was gathered without explicit considerations for repurposing)has many properties that present specific challenges to its effective usage. For example, it can be voluminous and fast moving (e.g., big data), which can be produced from the deployment of sensor networks (e.g., in-situ monitoring of material streams or ambient ground conditions). This aspect is particularly challenging to data transport (e.g., from source to destination) and if the industrial infrastructure is not cognizant of the characteristics of such data, then digitalization may be difficult to realize. Legacy data also has the characteristic that it is difficult to merge or link, due to its compartmentalized nature, arising from the segmented nature of typical operations in the mineral industry and a strict adherence to mono-disciplinary practices.

Currently, data in the mineral industry is generated over a long timespan to guide decision-making, however in a discontinuous fashion from exploration to beneficiation. For instance, reconciliation exercises to adjust mineral resource and reserve models, as well as planning assumptions, are executed on the timescale of weeks, months or even years. Comparatively large amounts of data results from the need to understand production performance and efficiency. The generation of data throughout many processes serves to counteract the insufficiency in our knowledge regarding the nature of deposits, the intrinsic and induced variability in natural systems and the variability of production processes. The availability of real-time data leads to the availability of real-time monitoring, optimization and control, such as short-term sequencing and production control. Awareness of the necessity of this type of change in the industry appears to be increasing and more focused over the last few years. For example, the "Real Time Mining - International Raw Materials Extraction Innovation Conference" were conducted by the consortium of the EU H2020 in 2017, as a platform for inter-project communication and for communication with project stakeholders. It brought together several European research projects in the field of Industry 4.0 applied to mineral resource extraction. The projects in question are VAMOS (Sword and Bakker, 2017), SOLSA (Le Guen and Orberger, 2017) and UNEXMIN (Lopes et al., 2017). A comparison between discontinuous process and a real-time continuous closed-loop process are presented in Fig. 1.

Ghorbani et al. (2020a, 2022) coined the term "dry laboratory" or "dry lab" to describe a laboratory that primarily focuses on the use, generation and experimentation of data, such as data-centric activities. In their model, one of the primary functions of the dry lab is as a centre for data-driven innovation. However, such laboratories require external sources of data, ideally sourced from industrial and institutional operations. Legacy data (e.g., Ghorbani et al., 2021a; Nwaila et al., 2021b, 2022) and synthetic data (e.g., Nwaila et al., 2021a, b) would be insufficient to meet the needs of an operating dry lab that is expected to
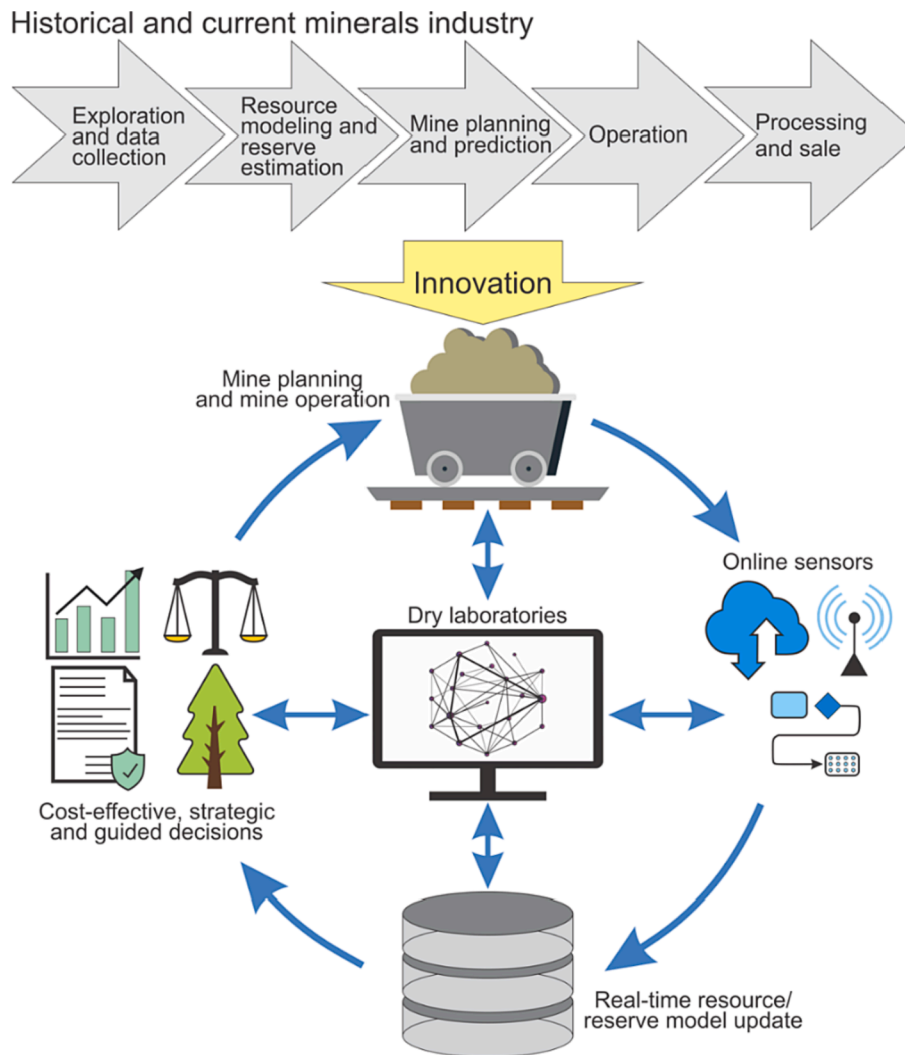
Fig. 1. Moving from a discontinuous process to a real-time continuous closed-loop process (adapted from Benndorf and Buxton, 2017).

provide timely insights to guide exploration and industrial operations. Even for dry labs that are entirely academically focused and would not serve the industry directly, it is impossible to sustain data-driven activities using solely legacy data, because its generation processes are impossible to automate, which integrates poorly with partially to fully automatable tasks in artificial intelligence (e.g., predictive modelling, anomaly detection and data mining).

This study aims to investigate the components, challenges and opportunities associated with mapping the necessary instrumentation and infrastructure for continuous data generation and usage through primarily online monitoring, analysis and characterization within three pillars of the minerals industry: mineral exploration, mining and mineral processing. We consider primarily key instrumentation and infrastructure external to dry labs, as general considerations were tended to in Ghorbani et al. (2022). However, because the dynamics of data generation, supply and consumption within a dry lab function essentially akin to a supply and demand system, instrumentation and infrastructure need to be considered both inside and outside of dry labs to enable an ideal coupling of dry labs to their clients. Hence, we highlight exceptional requirements that are anticipatable within the dry lab environment, which may not be obvious. We achieve this goal by assessing the important technologies and tools that will enable the digitalization, rapid generation and movement of data to feed dry labs, potentially in real-time. With recent advances in telecommunication and sensor systems, it is anticipated that the mineral industry will continue to move

away from segmented and manual data generation by implementing continuous observation, monitoring and control systems (e.g., for process monitoring and control).
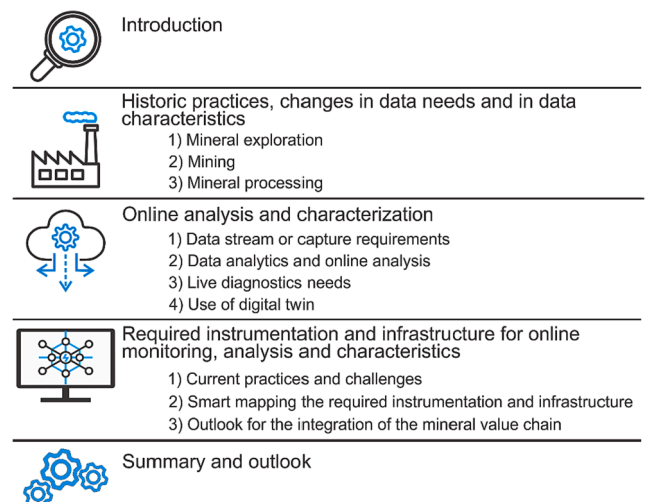

Fig. 2. Schematic overview or flow chart of this review.

2. Structure and methodology applied

This review is divided into three sections (Fig. 2) with the goal of providing a map for the required infrastructure and instrumentation for online monitoring, analysis and characterization in the mineral industry. The introduction provides background information and explains existing problems. In the historic practices section, we detail the developments witnessed by the mining industry over the past decades and highlight the need for additional infrastructure and instrumentation. We then explore online analysis requirements, as well as the required instrumentation and infrastructure necessary for the online transition within the mining industry. Finally, we provide a summary and outlook.

3. Historic practices, changes in data needs and data characteristics

As a primary industry, mining plays a crucial role in the sustainability of modern society, as mining impacts energy production (and therefore the economy), food supply, transportation, telecommunications and infrastructure development (Canart, 2018; Ivic et al., 2021). Globally, the mining industry has been successful in discovering new mineral deposits, developing new methods of mining and processing ore. This shows that despite slow adaptation in some mining process stages, the mining industry continues to embrace various types of transformation (Nasirov and Agostini, 2018). In the past, mineral exploration, mining, mineral processing and extracting valuable elements from minerals were conducted relying predominantly on implicit,[1] tacit[2] and explicit[3] human knowledge (Chiu and Chen, 2016). In fact, the mineral industry has been shaped by tacit knowledge for centuries. The difficulty of locating mineral targets, the expansion of mining operations and challenges in mineral beneficiation processes have all contributed to the complexity of mining (Sánchez and Hartlieb, 2020). The minerals industry must adapt to this natural evolution in both strategy and approach. Since the beginning of the 20th century, the mineral industry has witnessed developments such as the introduction of new exploration and mining techniques, the development of short- and long-range spatiotemporal sensors, automation and the application of artificial intelligence in both scientific and engineering contexts, and an increasing need for data-driven techniques related to spatial data visualization (Rodriguez-Galiano et al., 2015). In all cases, the abundance of high-quality data is a key factor to enable data-driven techniques, such as machine learning- and artificial intelligence-based inferential modelling (Chen and Lin, 2014; Zhang and Lu, 2021).

3.1. Mineral exploration

Technology has played a major role in the modern prospectivity and exploration of minerals. In the past, academia, industry and government developed geochemical and geophysical technologies that led to the term "Triple Helix" to describe *trans*-disciplinary and sectoral collaboration on how minerals are discovered (Leydesdorff, 2013; Samo and Huda, 2019; Fig. 3). There is evidence that mining company research and innovation activities have declined while university-related research and innovation geared toward industrial applications have increased over time (Filippou and King, 2011; Pietrobelli et al., 2018). Even with a decline in the industrial investment in exploration research

and development around the world, innovations such as remote sensing, tomographic imaging (i.e., developed in the medical community) and Global Positioning System (i.e., developed in the defence community) have enabled the creation of new technologies for mineral resource prospectivity, exploration and modelling (Chen and Wu, 2017). Numerous models of ore deposits have been developed by economic geologists as part of various stages of mineral deposit exploration (Cox and Singer, 1992). To understand how the mineral deposits form and their intrinsic characteristics, the conceptual and experimental models based on scientific hypotheses have been useful, particularly in greenfield exploration settings where data is often sparse or missing. Although as exploration gravitates towards deeper depths and less common deposit types and even unconventional resources, data-driven instead of knowledge-driven exploration (including data generation) may become more prominent and desirable, in general (Zhang et al., 2022; Nwaila et al., 2022). With new mineral discoveries and swings in commodity prices, research on geological ore deposits has begun to focus on critical minerals that are most in need to manufacture renewable energy technologies (Carranza and Laborte, 2015). Several mining districts have amassed a wealth of geologic data, but such data is not currently being utilized since it is largely not machine readable and would be difficult to convert to a digital format or are unavailable to the research community or industrial competitors (National Research Council, 2002).

Geological research on ore resources should be carried out by teams of economic and exploration geologists from industry, government and academia in the best-case scenario. Exploration geologists have been able to discover and map lower concentrations of the materials of interest using increasingly advanced analytical techniques and equipment developed over the last five decades (Cohen et al., 2010; Grunsky and de Caritat, 2019). The detection limits of these analytical techniques are now sufficient to meet industry needs for the vast majority of chemical elements. However, new technologies are being developed and/or employed for exploration and material stream profiling, such as laser fluorescence scanning, laser-induced breakdown spectroscopy (LIBS) and portable X-ray fluorescence (pXRF), which can directly detect element concentrations in rocks, and differential leaching procedures that provide additional information on sample mineralogy (Kauppinen et al., 2014; Liao et al., 2017).

Cross-borehole seismic tomography, for example, is a promising geophysical technique for determining geological formations and changes in physical attributes between boreholes (Nowack and Li, 2016). Since World War II, the mining industry has been performing research and development in geophysical methods for mineral prospecting (National Research Council, 2002). Seismic exploration is employed selectively in the exploration of ore deposits, even though it is already an important aspect of the oil and gas industry. The main reasons for this are technological and economic constraints. In the past, seismic technology was mainly used to collect data at rather significant depths (thousands of meters below the typical depth of mineral deposits that can be mined at profit). However, near-surface seismic imaging, on the other hand, is now commonly used to investigate mining resources (Allo et al., 2019; Sarkar et al., 2021). With increasing depths of anticipated mineral deposits due to exhaustion of near-surface ones, seismic imaging may become highly relevant for exploration purposes, aside from their in-mine use and monitoring aspects. In terms of data collection and processing, typical seismic surveys are costly. New computing capabilities have reduced expenses, but they are still out of reach for most mineral exploration budgets. Seismic firms have limited financial incentives and almost no government backing to engage in this form of research and development.

3.2. Mining

Since the 18th century, a never-ending search for new and innovative mining technology that can improve health, safety and productivity has been continuing (Corke et al., 2008). There has also been a growing

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[1] The implicit knowledge is acquired from exposure to various workplaces. It is the application of explicit knowledge. Skills that are transferable from one job to another are one example of implicit knowledge.

[2] Tacit knowledge is acquired through personal experience and on-the-job training. Knowledge gained from personal experience is more difficult to express.

[3] The explicit knowledge is obtained mainly through schooling and company manuals. The knowledge that is easy to articulate, write down and share.
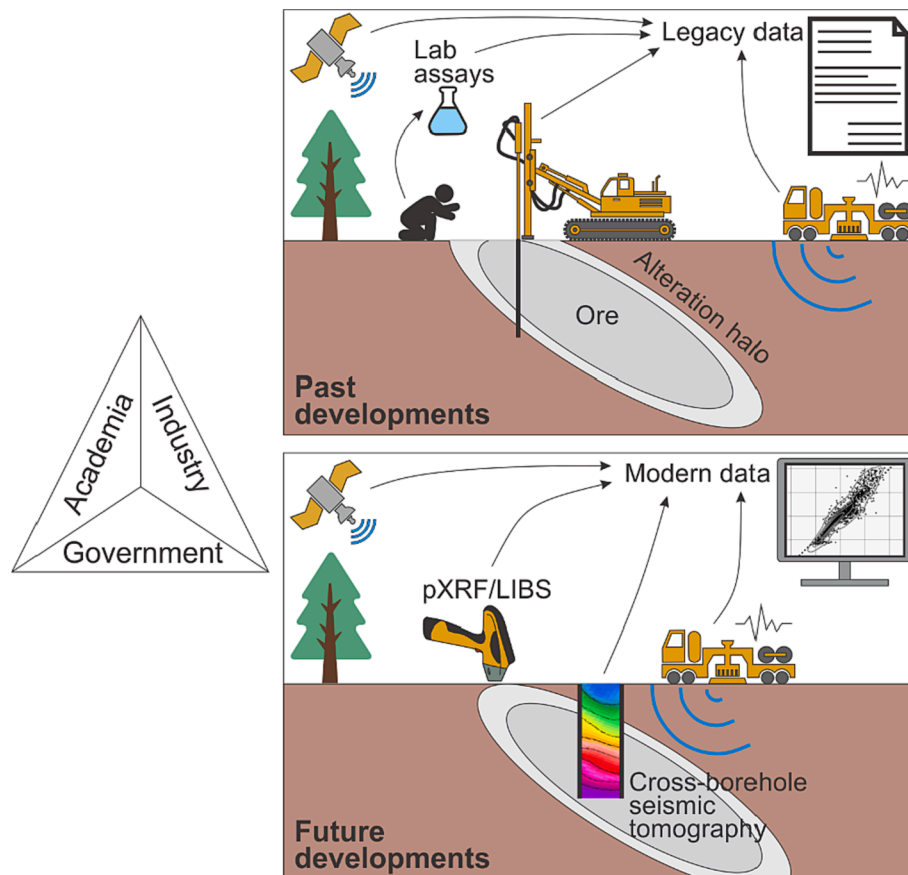
Fig. 3. Schematic diagram presenting several key technologies which have enabled and will continue to enable mineral exploration. pXRF = portable X-ray fluorescence instrument, LIBS = Laser-induced breakdown spectroscopy instrument.

awareness of mining's negative effects on the environment, human health and the ecosystem in recent decades. Among the significant milestones in mining extraction technology are continuous mining for cutting coal, rock bolts for ground support, open-pit mining for mining massive low-grade deposits, longwall coal mining, and in-situ and automated mining (Moosavi and Gholamnejad, 2016; Pekol, 2019; Ikeda et al., 2020).

Several geological issues can arise during the mining process, such as local thinning or thickening of the deposit, deposit loss, unanticipated dikes and faults (and other structures), and the intersection of gas and water reservoirs (Mkhabela and Manzi, 2017; Wagner, 2019; Sehoole et al., 2020). Even with detailed and advanced exploration at closely spaced intervals, mining operations have been compromised by a range of issues, which can result in personnel injuries, equipment and production losses (Zhi and Elsworth, 2016). New technologies based on advances in subsurface geophysics may be able to predict geological and geotechnical conditions in advance of mining ('glass rock technology'). Systems that can probe the rock mass ahead of a mining face rely on three main technical areas: sensors, data processing and analysis, and visualization (Arisona et al., 2020). All three areas of glass rock technology must be addressed simultaneously in order for progress to be made.

During mining, seismic methods have been used to create short- and long-range sensors (Havskov and Alguacil, 2004). Underground mining machines can be used as a source of sound (assuming mining is continuous), and receivers can be installed below the mining face (Glazer, 2016). During drilling and blasting operations, blasting-induced acoustic pulses become sources of energy that can be used to probe the orebody horizon at close range in both surface and underground mining environments. Despite its mechanistically simple nature,

this blast pulse method has been plagued with numerous complications. Current seismic systems do not support multiple signals or continuous-wave sources, such as those coming from mining machines (National Research Council, 2002). The electromagnetic spectrum and ground-penetrating radar are also potential sensing methods. The combination of several sensing methods should also be explored to maximize the potential for data fusion and integrated uses of data. The data processing method for interpreting seismic sensor data is an important area that requires further investigation (Gadallah and Fisher, 2009; Perumal et al., 2015). Technology that uses advanced parallel processing, as well as edge computing can be beneficial to in-situ monitoring and mining. Display and visualization of data are closely related to the processing and interpretation of data, since the insights extracted from data cannot be quickly acted upon by humans if they are not in a format that allows them to be reviewed quickly (Esbrí et al., 2021).

Currently, automation technology has provided a capable platform and a powerful foundation to vastly integrate all the elements of the mine operation. Automation generally builds up a comprehensive systematic connection in the mining process consisting of the advanced operational parameters, maintenance, environmental, safety, and energy and rock-type monitoring systems. In terms of data resulting from processes, it is important to capture as much data as possible to ensure that production would obtain the desired goals in the most sustainable, efficient and safe manner. High speed and wireless connectivity (e.g., 5G technology) simplifies the design and implementation of information technology infrastructure, and could prove to be a key enabling factor in full or supervised automation. The nature of the spatial compactness of mining operations and the present level of mechanization outside of artisanal mines provides many opportunities to integrate automation, data generation and transport and analytics (Fig. 4; Hoseinie et al.,
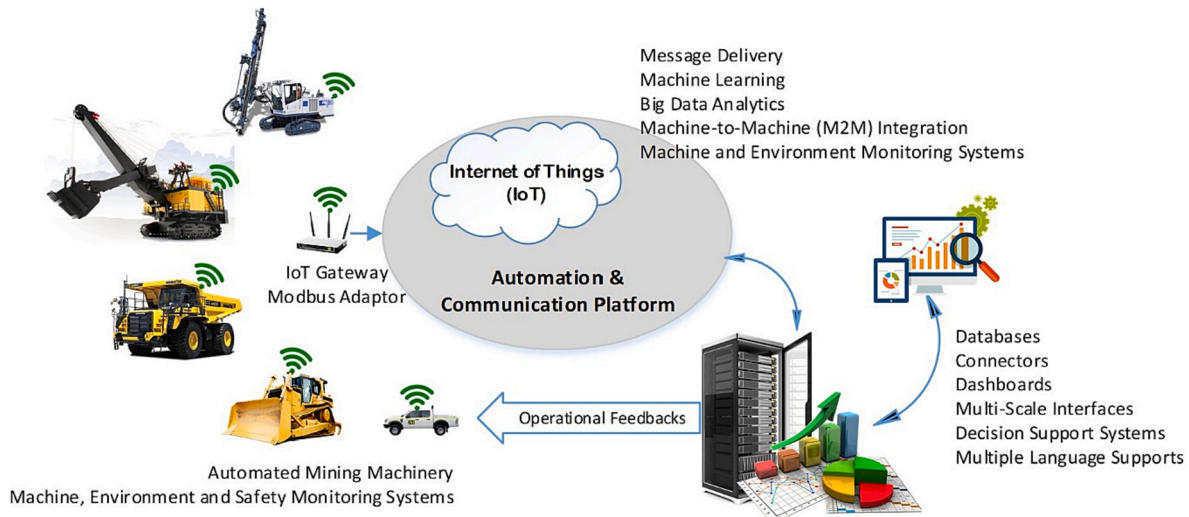
Fig. 4. Elements of automated production monitoring and control system engineering in digital mining operations.

2016).

3.3. Mineral processing

The very first online control systems were introduced in the mineral processing industry in the 1960s. By that time, control systems did not form an integrated system but were rather separated and aided in the control of physically delineable operational units. They usually delivered measurements of the pulp level and solid concentration and were principally used to normalize slurry flow. In the 1980s, basic regulation loops were already executed in many plants around the world, but integrated plant control actually started in the 1990s, when all data generated by sensors were gathered into a plant-wide control system. From there on, data was continuously recorded and stored, enabling the emergence of day-to-day plant management through data reconciliation (Sbarbaro and del Villar, 2010). With the development of process instrumentation, two different control strategies were implemented in parallel (Doebelin, 1983; Bentley, 1983; Considine, 1985; Hales, et al. 2009): expert systems[4] and model-based predictive control systems.[5] Hybrid systems have progressively emerged with the integration of simple models into expert systems. The adaptability of these control strategies is inherently limited by the accuracy of the predictive models. Hence, predictive models have been the focus of much attention since they are important both for process operation and for plant design.

The efficiency of any system is limited by the quality and relevance of data provided by the instruments. Online process analytical technology (PAT) is an important area of development in a wide range of industrial processes and a key element of Industry 4.0. Traditional instrumentation (such as pH and temperature probes) is being complimented with more advanced techniques such as spectroscopy (Michelson and Morely, 1887; Wold et al., 2001; Chew and Sharratt, 2010; Speed and Wood, 2020), which itself is increasingly being coupled with data analytics (O'Mahony et al., 2016; Srinivas et al., 2022). The majority of PAT implementations make use of vibrational spectroscopy – namely near-

infrared (NIR) spectroscopies (Bath, 2007; Cao, 2013), mid-infrared Fourier transform (FTIR) spectroscopy (Griffiths et al., 2007) and Raman spectroscopy (Rudolph and Hefter, 2009).

A key challenge within the minerals industry with respect to process monitoring and control is the difficulty of obtaining online measurements of key process variables and the effort required to keep such sensors operating reliably. Reusing sensor data and data fusion (e.g., soft sensors; Fortuna et al., 2006; Kadlec et al., 2009) implies that issues with the process itself, as well as those with the sensor or sensor networks could be preventatively diagnosed and corrective or preventative actions could be taken in a timely manner. In this case, it is clear that predictive maintenance is very useful to existing operations and can leverage the type of data that may already be available (see section 4.3, but also Fortuna et al., 2006; Kadlec et al., 2009). However, other sensors may also become feasible as analytics demonstrate that it is possible to extract useful process information from them, such as virtual sensors (Liu et al., 2009). For example, non-contact sensors and sensor networks, such as spectroscopy-based and microelectromechanical sensors may be installed in a manner that the environmental exposure of these sensors are minimized to maximize sensor life. These types of sensors (both direct and indirect types, without physical contact) may help to overcome the aggressive chemical and thermodynamic properties of process streams such as pulps and reagents, and the harsh environment in typical extraction plants. Retrofits for predictive maintenance is also trivial using existing sensors and soft sensors, because edge computing could be installed as part of a sensor system (a set of sensors and a low-powered computer with a deployed predictive model) in lieu of extensive data transport infrastructure.

4. Online analysis and characterization

4.1. Data stream or capture requirements

The systematic capturing of data in industrial settings began with control systems. In the minerals industry, control systems operate over industrial processes, such as extraction and processing of minerals. Control systems evolved from localized control panels that were patrolled by trained technicians to a centralized control room, where the enactment of control became isolated from the industrial processes. Modernization of control systems eventually used algorithms and software to replace dedicated hardware, in a manner that has vastly increased the flexibility and abundance of control loops and the number of process variables that can be controlled or monitored. In essence, with discrete control loops and systems, an engineering constraint in the

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[4] Expert systems tend to model the action of expert operators; they are based on algebraic decisions and can avert any deviation by monitoring a set of controlled points (Leiva et al., 2018). These simple systems have been extensively espoused by the mining industry since the 1970s. Currently, these systems are usually known as supervisory control and data acquisition (SCADA) systems.

[5] Model-based predictive control systems were at first based on the modelling of the unit processes, before later modelling the plant process as a whole.

generation of data is the recognition of key process variables that create the largest output variance in a production system (Chang and Brulo, 1983). Such variables are further refined using other criteria: economic feasibility, physical feasibility, control philosophy, and the reliability of a proposed control system. In particular, from the perspective of sampling, once a control loop is decided upon, all the components associated with its measurement system (e.g., sampling device or sensor, signal transmission cable, data presentation device, electrical/air/water supply systems and personnel) must be designed to purpose. An outcome of the historical constraints on control system engineering has been that data is gathered to a strict purpose, centring around key process variables.

The abundance of cheap sensors and sensor systems (e.g., based on microelectromechanical systems, such as microsensors) has been continuously removing constraints on control systems engineering, in a manner that is faster than widespread adaptation in industrial design heuristics or architecture. For instance, data dimensionality (e.g., spectral bands and elements measured) is negatively related to predictive modelling performance, due to the curse of dimensionality (Bellman, 1961). As such, with intermittent or manual sampling methods, a key bottleneck in the quality of data for predictive modelling is the abundance of data. In a different manner, accurate data, which used to be achieved through accurate sensors, can now be achieved through an abundance of comparatively less accurate data, when paired with artificial intelligence-based predictive modelling (e.g., noise suppression of noisy acoustic data using deep learning; Xu et al., 2015). Although some aspect of this was obvious even before artificial intelligence-based predictive modelling, for example, through data averaging over time or space to improve measurement reliability. A key challenge with a planned approach to data generation is that it is not obvious what the specific requirements are on the data stream, to achieve a given level of accuracy, due to the complex system nature of artificial intelligence algorithms (e.g., neural networks, which are universal function approximators; Pessa, 2009). This was not the case with previous control systems, for which the principles of metrology and modelling could be applied to adequately anticipate the data requirements because the control systems were not complex systems that exhibited emergent properties. Indeed, failure of autonomous systems is still a hotly discussed and researched area to understand the risks and impacts of automation (e.g., Macrae, 2021). However, the deployment of sensor networks and sensors is likely to shift most, but likely not all data that is generated at industrial settings from specific-purpose towards greater abundance and less accuracy, consistent with the need for pervasive monitoring that is in general, purposeless in the a-priori sense (e.g., the data stream is not created for a particular control loop, internet of things-type of general-purpose sensors). This is similar to the transition from targeted geological and geochemical surveys, to large areal geophysical surveys, to global remote sensing in the mineral exploration industry. To enable a similar transition in the industrial setting, a key requirement is the availability of low-cost, high reliability and data-rich sensors and sensor networks. For material characterization, spectroscopy-based systems such as portable and micro-XRF, LIBS, and hyperspectral imaging may be promising candidates, whereas for equipment and ambient environmental monitoring, microelectromechanical sensors may be suitable. Technologies such as pXRF, LIBS and hyperspectral imaging can provide a transitional bridge from classic laboratory instrumentation (e.g., chemical analysis via mass spectrometry) to fully non-contact remote sensing, in the sense that the physics and engineering of such technologies are fundamentally scalable to continuous, contactless and automated sensing. This is clearly not easy or possible for many analytical technologies, such as those that require substantial manual material preparation (e.g., electron backscatter imaging). In any case, the intention in modern data-driven sensor deployments may become less motivated by the philosophy of scientific reduction and the engineering need for direct process control toward system considerations (machine learning algorithms for example, treat

data at the system level and does not require data that is generated for solely scientific reduction), general monitoring (e.g., through the use of soft / virtual sensors) and innovation. The amount of data generated through process monitoring will be substantially greater than strictly necessary for typical process control (or scientific and engineering studies). This is a desirable effect to adequately feed dry labs with rich types and large amounts of data. However, the infrastructure to enable such data to reach dry labs in a timely manner necessitates additional and dedicated consideration.

There are two end-member approaches to the transport of data from its site of generation to the place of analytics. The first is on-site or local data transport, which implies that the flow of data is strictly between the site of data generation and the site of data usage (which may be the same), with no intermediary storage or requirements beyond infrastructure. The second is cloud-based data transport, which implies that the data flows from a source to a cloud destination, which also potentially provides for analytics and long-term storage capability. Similar to other fields, when the economy of scale begins to favour off-site, centralized and dedicated infrastructure for data and analytics, the argument for cloud-based solutions becomes more palatable. In smaller settings, particularly remote settings where extraction and processing may take place, a reliable connection to a cloud infrastructure may not even be available. The bandwidth needs of the data should also be taken into account, as well as the latency of the data over any possible transport mechanism. These factors affect the usability and value of the data.

In remote settings, where operations (e.g., a mine or exploration mission) are not located in the proximity of cities, the establishment of a new operation implies that some essential infrastructure must be created. However, in traditional mines in the sense of non-digitalized mining, the essential infrastructure does not cater to needs around data and analytics. The price for installing dedicated communications infrastructure may be prohibitive, and instead, wireless telecommunications infrastructure may be the best available option for communication (including data transport). However, with the rise of satellite-based global telecommunication, and particularly with the deployment of high-bandwidth, data-centric satellite networks (e.g., Starlink; Federal Communications Commission, 2019), remote access to high-bandwidth internet connectivity has become cheap, affordable and relatively reliable. Satellite-based internet provision may well become a key enabler of digitalization in remote communities, a reality that remote exploration and mining is most likely to benefit from. In any case, if the flow of data revolves at least partially around the transport of raw sensor data, considerations around the use of big data would apply. In these cases, it is pointless to capture the data stream in its entirety, but rather, just-in-time extraction of valuable snippets of data and insights should be the highest priority for the use of data. Considerations around the design of the analytics pipeline and the data transport infrastructure should take into consideration of the latency of data generation to insight extraction and feedback, in addition to the requirements of data bandwidth and the value of the data stream.

4.2. Data analytics and online analysis

Implementations of online sensors and central monitoring systems to perform data analytics, such as just-in-time process visualization and rapid management response exist (Massinaei and Doostmohammadi, 2010; Makokha and Moys, 2012; Nakhaei et al., 2012; Jahedsaravani et al., 2014, 2016; Jämsä-Jounela, 2019). Central to such approaches is the idea that modernized data analytics and online sensors can provide real-time or near real-time intelligence into industrial operations, in a manner that facilitates information comprehension and decision-making. However, there is a strong distinction between the addition of data analytics and visualization as a retrofit to existing operations and the design of new operations with a data-rich output that necessitates data analytics and visualizations. In the former case, the data that

enables central monitoring systems are likely legacy in type and its purpose orients around control systems. In the latter case, the data is at or could approach big data and therefore, without analytics, very little intelligence can be extracted from such streams. In the most pervasive manner in terms of considerations around the nature of data, in most cases a combination of legacy and new data streams will be required. In any case, with increasing data generation from increasing number of sources, a key task is to standardize data to allow data linking and merging for system-wide integration of data and therefore facilitating system-wide data analytics. However, progression towards data standardization and integration can lead to pervasive infrastructure and culture changes within existing organizations if they are not compartmentalized within a dedicated dry lab. As proposed in Ghorbani et al. (2022), interoperability as a business-operating layer and its predicate data management functions should ideally exist or be implemented prior to the use and collection of data. This is an explicit consideration in the operational model of dry labs. Retrofitting these layers into existing organizations such as private companies and institutions is possible, although such efforts are very time consuming because they involve vision establishment, stakeholder outreach, business requirement analysis, cultural change and management, and the actual effort may include other aspects such as infrastructure, governance and security. For larger organizations, the time that is required to accomplish such retrofits, along with an overall cultural awareness and change is likely to be far too long to reap short- and medium-term benefits of aggregated data and digital technologies. As such, dry labs, which are much more targeted and therefore much faster to establish, are a necessity in the development, generation and use of high-quality data. In general, we anticipate that dry labs would play a key role in the standardization and integration of data, from sensor-level engineering to data–quality engineering. The generation and use of data should serve to maximize some notion of return. For the minerals industry, this could be some metrics of the agility of operational control and efficiency. One key benefit of dry labs is their heavy use of data analytics to perform rapid insight extraction (Ghorbani et al., 2022). Consider a few hypothetical but technically feasible examples: (1) within the exploration setting, remote sensing, geochemical, geological, geophysical data and other environmental, social and governance data layers could be integrated to rapidly generate up-to-date prospectivity maps (e.g., Lawley et al., 2021); (2) within the extraction setting, dry labs can generate tomographic images of the environment and understand the dynamic stress–strain relationships of the mining environment within a mine (e.g., Wang et al., 2018; Zhu et al., 2021); and (3) within the mine waste management setting, dry labs can remotely monitor the state of tailing bodies using remote sensing and transmitted data (e.g., seismic and environmental sensors) to determine the integrity of the managed waste (e.g., Ma et al., 2018; Zwissler et al., 2017). In all of the above examples, a combination of legacy (e.g., geochemical and geological data) and modern (e.g., big data through online sensor data) underpin the downstream usage of such data. Where data had been fused or streams of data engineered, it is obvious that such efforts should not be duplicated on a per-project basis and therefore, centralizing data is a key enabler of cost-effective and rapid data analytics and online monitoring. This would help to advance the operational efficiency in all components of the minerals industry by providing high quality and timely insights.

Beyond the cultural aspect, in any deployment setting (where solutions from dry labs are being actively used), the infrastructure is key to enabling timely and reliable data that is supplied to dry labs. With either local, remote or cloud-based data transport, the transport infrastructure needs to address bandwidth concerns, which arise from the deployment of data-dense sensors. For example, hyperspectral imaging sensors (Chang, 2003) could be used to image mining surfaces and ore mixtures to fingerprint their chemistry (e.g., the Hyperspec instrument; Headwall, 2022), even in rapid moving streams of matter (Bodkin et al., 2012). The spectral data could then be relayed to a dry lab for analytics to guide further operations. The data stream from a single video-rate,

hyperspectral sensor that could be deployed in a mine or extraction plant may generate on the order of 100 megabytes of data per second, which even with hardware- or software-based compression (Dua et al., 2020) may be problematic if data infrastructure were not explicitly designed for the use of high-bandwidth sensors. In remote settings or for critical equipment, it might be impractical to transport these data streams over any type of infrastructure and some capability to properly use the data, such as the reduction of data streams to insights may be necessary in physical proximity to an operation.

The local and cloud-based approaches to data transport necessitate different considerations to the use of data. In a local setting, analytics may be performed close to the data source and in some situations; a dry lab could reside within a business operation. However, although this approach better handles the bandwidth requirements of data transport and analytics, it complicates the sourcing of talented staff. The nature of dry labs encourages remote working and collaboration, and from the perspective of talented geoscientific data scientists, working on-site is neither a requirement nor an attractive factor, since operational sites for mineral extraction and processing are usually remote. The opposite approach of transporting raw sensor data to a cloud, and leveraging remotely connected data users is far more conducive to talent acquisition and retention, but the requirements of bandwidth may be insurmountable, where operations require the deployment of large sensor networks. A meaningful combination of local and cloud-based data transport and usage would likely be key to a successful dry lab deployment. In any case, management and operational staff must be able to access, understand and act on data-driven insights. For this purpose, a non-technical user interface that displays business-level information (e. g., key performance indicators) must leverage the dry lab to generate high-level insights, some of which are likely to be based on operational data.

4.3. Live diagnostics needs (predictive maintenance, redundant sensors and processing pipelines)

Predictive analytics is highly useful for live diagnostics. One particular application is predictive maintenance (Botha et al., 2018), which uses non-destructive methods and often sensor repurposing to monitor the status of equipment, such that failures can be predicted ahead of actual failure events (e.g., using machine learning; Susto et al., 2015). Where the exact type of failure can be predicted (e.g., Amruthnath and Gupta, 2018), preventative action can be taken. The ability to schedule preventative maintenance ahead of failure can create more equipment uptime and lower operational costs associated with repairs, which may increase operational efficiency and personnel safety. For this task, sensor data repurposing seems to be an effective approach in existing operations. Isolated implementations outside of dry labs exist, for example, the smart maintenance platforms using predictive maintenance, which are generally called "eMaintenance" (Hoseinie et al., 2015). eMaintenance is very modern in the minerals industry and it has been used to facilitate fleet management and maintenance optimization in a cost-effective way. In a known implementation, it consists of an integration of the Information and Communications Technology (ICT) within the maintenance strategy and/or plan to face with new needs emerging from innovate ways for supporting production (Hoseinie et al., 2015). Operational data for this particular implementation is sourced from three main sources:

- Sensors (mounted on the machines);
- Entire enterprise system (including quality data, past history and trending); and
- External context (social, economic, geographical, etc.).

Using integrated current and historical data, eMaintenance can predict the future performance of machinery, instrumentation and the entire fleet. It also provides a powerful structure to get a very high level

of integration in automated systems. In essence, eMaintenance can be viewed as a specific product of a dry lab (Hoseinie et al., 2015). See Fig. 5 for the main structure and elements of eMaintenance in an automated mining operation.

For preventative maintenance, it is not essential that all data from sensors and sensor networks (e.g., vibration, temperature and acoustic sensors) be transported over an infrastructure. Instead, trained algorithms can be deployed on low-power computing hardware on each piece of equipment, such that data is locally captured and consumed within the proximity of the equipment. Pertinent information is only transmitted to a dry lab upon either periodic/manual polling or trigger conditions being met (e.g., failure predicted or probability of failure beyond a tolerance). The ability to compute at the edge of a sensor network is called 'edge computing' (Shi et al., 2016). Within the mineral extraction and processing industries, edge computing is potentially a powerful tool that could be applied in industrial settings, since it effectively tackles several infrastructure problems, through a reduction in data bandwidth requirements and correspondingly the amount of workload in dry labs. For many industrial settings that are pre-digitalization, edge computing could be an effective way to transition towards digitalization using a minimally invasive approach. Potential application examples of edge computing could include power and thermal monitors, seismic / vibration and ambient acoustic networks (including fibre optic-cable seismometers) and general equipment monitoring or control networks. In the extractive setting, the use of mechanical machinery should enable edge-computing deployment. In any case, the deployment of sensors and sensor networks is unavoidable as a source of data that feeds dry labs. Deployment of additional cheap sensors (and sensor networks or systems), such as those based on microelectromechanical systems (e.g., orientation sensors in smart phones) can bridge the gap between pure sensor repurposing and targeted retrofits in existing operations (e.g., Deng et al., 2014; Brazegar et al., 2022). The hardware associated with edge computing systems may be minimal in capability and cost, because they are not required to perform model training and development (instead serving only model deployment and communications functions typically). Therefore, edge computing hardware is usually not onerous, depending on the complexity of deployed models and the nature of the data used (e.g.,

Qasaimeh et al., 2021).

Physics-based modelling uses causal relationships to generate models of reality that are useful for analysis by simulating aspects of reality that are desirable for a particular phenomenon. Physics-based modelling has been used extensively in the extractive and processing industry, such as rock stress modelling (e.g., Hazzard et al., 2000; Zhou et al., 2019), mine planning (e.g., Newman et al., 2010; Savolainen et al., 2022), chemical kinetics (e.g., Leal et al., 2015; Lin et al., 2016) and partitioning and liberation/flotation (e.g., Ek, 1992; Aydın and Gül, 2021), particle and fluid dynamics (e.g., Narasimha et al., 2007; Cleary and Morrison, 2009), etc. Their use is unavoidable in advanced dry labs that are tasked with prediction of physical outcomes of industrial processes (e.g., liberation and grade reconciliation). Predictive models can be derived from physics-based modelling, e.g., the modelling of chemical kinetics for leaching. Predictive modelling using inferential modelling through artificial intelligence and machine learning is not physics-based but data-driven. However, hybrids do exist, for example, physics-informed neural networks (which can infer physically reliable estimates), which are in their infancy but are rapidly becoming useful (Raissi et al., 2019). For many tasks, decisions relying on physics-based models can be augmented by inferential models where physics-informed inferential models do not exist or are impractical. The manner in which physics-based models and inferential models can be integrated is unlimited and not strictly restricted to the manner in which physics-informed neural networks function. Physics-based models can naturally feed simulation data into inferential models, which can also source operational data from sensor networks. A predictive model can then discriminate for itself, when the predictions of the physics-based models are likely to be correct and generate hybrid insights through voting, assembling or stacking of models (Wolpert, 1992; Ting and Witten, 1997). This may be the most powerful approach, as artificial intelligence-based algorithms handle the difficult task of identifying the accuracy of various models. Other approaches are possible for example, artificial intelligence can be used to pre-process sensor data that feeds physics-based models and therefore ensure more realistic and powerful models.

To create both inferential models and physics-based models, powerful and sometimes onerous hardware is required (e.g., Khajeh-
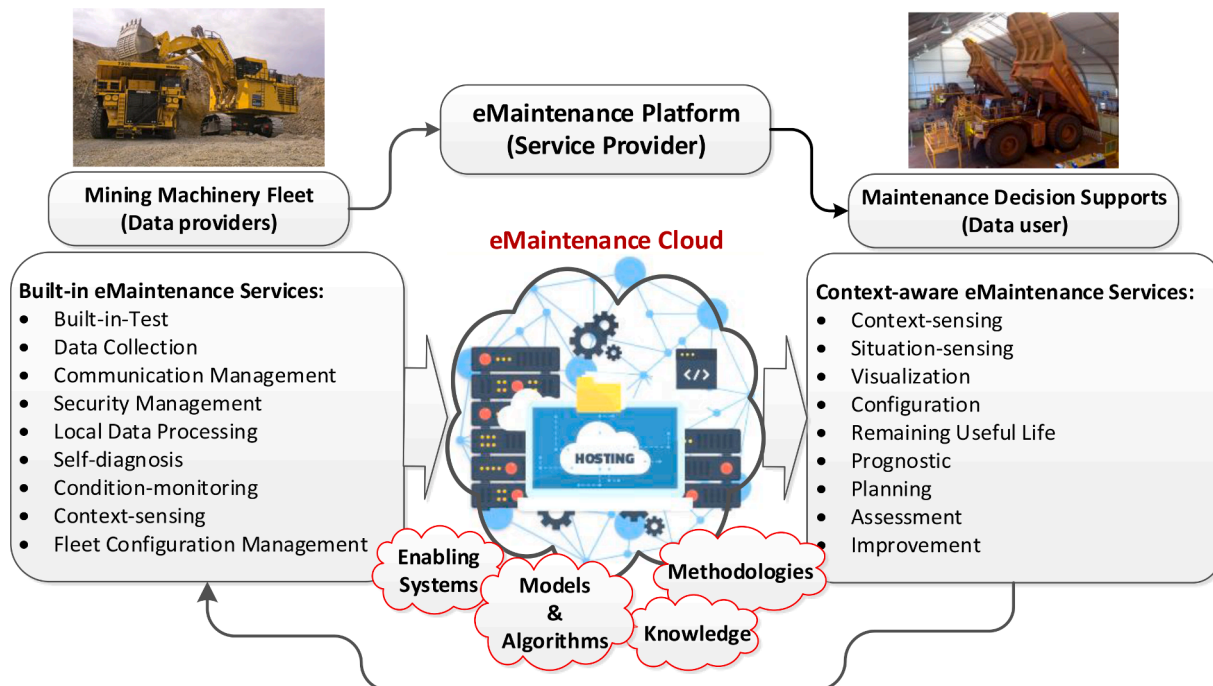

Fig. 5. Elements of eMaintenance and their interconnections in smart mining operations.

Saeed and Perot, 2013). The training and data processing that is associated with inferential models is typically compute-heavy in workload. Depending on the exact type of algorithm being employed, emphasis can either occur on general compute power, which is primarily served through central processing units (CPUs); or on graphics processing units (GPU) compute power. Sometimes the workload can be split evenly across both (e.g., Naveros et al., 2017). Critical infrastructure planning around the development of models in any dry lab should include powerful computers, GPUs and where relevant, the equivalent of these hardware within a cloud environment (although prototyping typically still occurs on local machines).

Dry labs that are catering to the creation of powerful models and the use of sensor data in this manner would require at least two connections to their client business operations. One of which is an ICT interface and the other physical access. The ICT interface is required to transport sensor data and perhaps to remotely access other resources. The requirement for physical access is an interesting one, because ultimately, all models created at the dry lab would require validation and re-calibration through time after their deployment. In deployment scenarios where dry labs are located in physical proximity to an operation, the operation gains the additional benefit of local verification of predictions, equipment status, etc. This intimate access to an operating facility constitutes an additional type of operational feedback outside of the data realm and can enable rapid improvements in the quality of data and models. For dry labs that are located distal to their client operations, the robustness of the infrastructure should be adequately planned for. A redundant linkage to enable data transport, in case of the failure of a primary infrastructure is key to operational resiliency. In this regard, having operational procedures that are optimised by the existence of dry labs and data-driven insights is an efficiency-enhancing necessity, but the core productivity of an operation (e.g., operational safety monitoring) must not be impacted by the failure of a single point in the infrastructure. This requires considerations of systems engineering and quality assurance and quality control in the design of the infrastructure.

4.4. Use of digital twin in the move towards real-time or new real-time monitoring

Mines and mineral processing plants can take decades to reach the end of their useful lives, and unlike other plants of similar age, only the most recent ones maintain digital records (Chen et al., 2017). In the past, much of the legacy data within mining and mineral processing enterprises were not machine readable. With the proliferation of modern data, the mining industry has seen major advancements in the use of

digital twins and soft sensors. By the nature of the existence of predictable control loops and known physical models (e.g., of reactions), it has gradually become possible to model in detail many extractive and processing processes, and hence the concept of digital twins. A digital twin is essentially a virtual simulation of mining and mineral processing activities; a digital carbon copy where a large number of factors can be changed to see how they affect upstream and downstream processes (Sierla et al., 2021; Fig. 6). Digital twins intend to reduce errors and unanticipatable outcomes by trialing desirable process changes in a compartmentalised manner, without jeopardizing the actual operation. In this sense, digital twins are thematically similar to dry labs in the sense that they both enable experimentation without spillover of risks into actual production environments. They are a powerful tool for system optimization. Several digital twin solutions for mineral processing have been developed in recent years (Schmidt and Lueder, 2018). Leonida (2018) gives the following examples:

- Petra Data Science MAXTA — MAXTA uses the mill as the best laboratory from the mine plan through the plant, allowing operators to track materials and gain insight into the plant's performance through block-by-block classification of behaviour characteristics.
- Metallurgical Systems - Met Systems has created a system that leverages tags inside the local historian to monitor processing in real-time and simulate the process reaction. This permits sensors to be developed and operators to obtain access to data.

The nature of digital twins, in that they are reliable simulations of actual systems means that they require a substantial amount of integrated and likely both legacy and big data (Fig. 6). As such, with non-modern practices around the generation and use of data, as well as accompanying infrastructure, they would require substantial manual labour to create. To realise the creation of digital twins within dry labs, because dry labs offer a centralising opportunity to leverage integrated data, the other necessary component would be a capable and secure ICT infrastructure to transport data. Infrastructure and data security are primary concerns for this type of data transport, because deleterious actions could result in industrial sabotage or other forms of compromise of key control systems and business information. In addition to ICT and data requirements, some digital twins may require large-format data visualization or process visualization capabilities, which could include physically large display panels to simulate control surfaces, visualise business and technical processes (e.g., dashboards), and provide operational and management oversight. These types of displays bridge the gap between the pace at which high-dimensional and sometimes rapidly
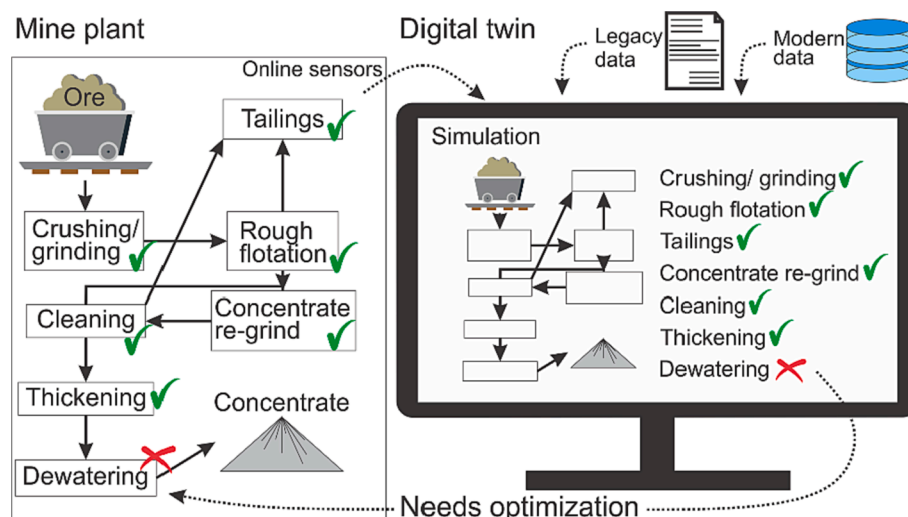

Fig. 6. Schematic representation of a digital twin which simulates mining and mining processing activities using mining, legacy and modern or big data.

changing insights are extracted with the human capacity for information absorption and therefore facilitates situational awareness.

5. Required instrumentation and infrastructure for online monitoring, analysis and characterization

5.1. Current practices and challenges

Sampling is the costliest and most difficult to replicate within any survey or project (Demetriades et al., 2018). Any deficiency at the sampling stage will have profound negative impacts on subsequent data usage and re-purpose. Currently, most samples are collected in a static or periodic manner using physical contact sampling, meaning that physical samples are selected at fixed, periodic or spatial intervals (e.g., systematic survey design in the case of exploration; Garrett, 1983). This type of sampling requires extensive training of personnel, as it is knowledge-based, to know what and how to adequately sample, and which analytical techniques (e.g., X-ray fluorescence versus inductively coupled plasma-mass spectroscopy) will yield the best results. Additionally, this type of sampling is both costly and time-intensive as it can only be achieved using manual labour. The combined impacts mean that static sampling is overall a slow and laborious process.

Automation is an ever-increasing presence, fulfilling a great diversity of roles (e.g., self-driving cars, moderating bandwidth connections, drones, etc.) as technology progresses. As of 2020, automation performs approximately 33 % of key job tasks and is projected to increase to 47 % by 2025 (Heller and Savargaonkar, 2021). Automation to aid sampling is still nascent but could serve to greatly increase the throughput and consistency of collecting and preparing samples. Depending on the task and sensors available, automated sampling could still be periodic or triggered by some pre-set conditions, or upon the detection of process anomalies (e.g., grade fluctuations). However, with the proliferation of non-contact sensors (e.g., photometry- or spectrometry-based sensors), it is possible to continuously sample a process without physical contact. For example, spectroscopic sensors could be installed to capture reflected or transmitted spectrums of material streams. This type of deployment, if successful, could decrease operational costs, reduce the need for manual labour, improve efficiency and safety, and potentially produces large amounts of data within shorter times as compared to static sampling. Opportunistic sampling using existing infrastructure but repurposing its intent for a purpose that could be conducted in parallel with their original duty is a particularly interesting way to maximise data generation. For example, optical fibres underground have been repurposed to serve as seismometers (e.g., Chang et al., 2020) and engine performance and monitoring data has been repurposed to perform predictive maintenance (e.g., Mathew et al., 2017). Where sampling could be automated, it may be possible to liberate human labour, such that humans may focus on the use and repurpose of data and other downstream activities, including the refinement of sampling equipment and methodology.

5.2. Smart mapping the required instrumentation and infrastructure

5.2.1. Mineral exploration

Mineral exploration has reached new frontiers in technology application (Malehmir et al., 2012, 2017). In recent years, four main techniques have gained popularity in mineral exploration, namely: (a) high-resolution remote sensing for large scale exploration surveys; (b) drone-based sensing; (c) portable and often handheld measurement devices; and (d) 3D near-surface seismics for subsurface exploration of metal deposits (Table 1). These technologies have the potential to improve mineral exploration targeting, which used to be based on field observations, knowledge of mineral deposits and systems and limited stream sediments sampling/drilling. Although the majority of known mineral deposits were discovered by either stream sediment sampling, geophysics and drilling, the depletion of near-surface mineral resources

Table 1
Modern geoscientific tools and technology for field data collection.

Online/on-stream analysers	Brief description	References
Satellite and hyperspectral sensing	In mineral exploration, remote sensing is used to provide data complementing field observations, since it allows mapping of geological characteristics of regions without having to physically interact with them. Hyperspectral imaging is an established method for remote mineral mapping and analysis based on the optical reflectance properties of minerals. Mineralogy and lithology on the walls of tunnels can be mapped with hyperspectral imaging at close range.	Transon et al., 2018; Peyghambari and Zhang, 2021
Drones	Remote sensing data are generally used to prepare mineral exploration maps. Drone imagery provides high-resolution images suitable for identifying mineralization anomalies and determining mineral exploration objectives.	Honarmand and Shahriari, 2021
Hand-held portable X-ray fluorescence (pXRF)	With the advent of pXRF in the last 30 years, it has developed into a valuable tool for field geochemical analyses, particularly for mineral exploration. This technology may be employed profitably to screen samples, select samples, plan dynamic sampling based on field observations, map a site and determine relative element abundance. More recently, exploration and mining geologists perform quantitative geochemical analyses of metal concentrations based on the data collected during grade control processes using pXRF.	Young et al., 2016
Laser-Induced Breakdown Spectroscopy (LIBS)	Lithium concentrations cannot be detected with conventional XRF and scanning electron microscope techniques. LIBS can be used to analyse light elements (Z *10), including lithium, in a qualitative and semiquantitative manner. Using this relatively inexpensive analytical tool, minimal sample preparation is required for very rapid analysis without sample damage.	Wood and Shattan, 2021
3D seismic surveys	In the same way that magnetic resonance imaging (MRI) produces a detailed map of the human body, 3D seismic surveying uses sound waves to find oil formations and mineral deposits deep below the surface. By eliminating drilling multiple exploratory holes and providing wide coverage of the target area, 3D seismic surveying significantly reduces the impact on the environment.	Siddiqui, et al., 2017; Malehmir et al., 2021; Rapetsoa et al., 2022

or regions that are not easily accessible for physical observations requires new mineral exploration techniques. In our opinion, the expectation that traditional forms of exploration techniques (and therefore also legacy data) would continue to be as effective for deeper, unconventional, as well as more complex and economically marginal deposits is naïve and probably unwarranted. A recent study by Rapetsoa et al., (2022) has demonstrated the value of in-tunnel 3D seismics, which are applicable to both greenfield and brownfield mineral exploration surveys. In particular, the use of data-driven methods may become unavoidable, although the bias of existing training data towards easily discoverable (e.g., near-surface and conventional) deposits is a notable drawback of supervised data-driven techniques.

5.2.2. Mining

Mining is primarily reliant on mechanical, motor-driven devices from initial extraction to transportation and metallurgical processing (Sganzerla et al., 2016). Productivity would surge if the machinery was improved (reducing downtime), operations were more efficient and maintenance expenses were reduced. To improve machine performance, better maintenance plans and automation methods must be developed and implemented (National Research Council, 2002). Improvements in mining efficiency would likely be made. Alternative systems may be wholly distinct from existing ones in certain cases, but they may also represent an inventive adaptation of existing systems' productive components in others (such as rapid mine-development techniques, continuous haulage systems, and more efficient ventilation procedures to improve health, safety, productivity, and resource recovery). Mineral firms have several aspects to consider in terms of technology and management. Each mineral deposit's geological properties (such as its location and physical, mineralogical, and chemical qualities) have a direct impact on technical and economic decisions. The environment is totally surrounded by rock within an underground mine, for example. Because mine development is a high-cash-outflow operation, new technologies must be used to shorten the current long lead times. To anticipate the infrastructure and requirements in the context of dry labs supporting mining operations, it is important to understand the anticipated technological changes in the mining sector.

It has long been a major focus of technology development to utilize automated mechanical cutting of rock for underground construction and mining (Bilgin et al., 2014; Sifferlinger et al., 2017). The availability and performance of high-production cutting tools and machines for coal and soft rock improved throughout the years, particularly in designs that minimize dust and optimize fragment size for downstream moving and processing (Wang et al., 2015). In contrast, hard rock presents a much more difficult challenge. Hard rock can be cut by tunnel-boring machines at reasonable rates, but the cutters are expensive, wear out rapidly and the machines require a high specific energy (the amount of energy necessary to excavate a unit of volume; Cigla et al., 2016). Additionally, tunnel-boring machines cannot follow orebodies that have variable strike and dip.

With improved blasting methods and better fragment control (and overall, more selective extraction), the cost of overbreak removal and downstream processing would be reduced (National Research Council, 2002). Both the mining and underground construction industries might benefit from research into the creation of more mobile, quick and reliable hard rock excavation (Poma et al., 2020). The first focus of this research should be on gaining a better knowledge of rock fracture mechanisms to create better cutters. Preconditioning the rock with water jets, thermal impulses, explosive impulses, or other procedures, for example, could weaken the rock and make subsequent mechanical cutting easier and more energy efficient (Dietze and Mischo, 2014). Novel preconditioning and cutting combinations should also be researched. Several proposals for rapid hard rock excavation were examined in the early 1970s, spurred forward by the defence community (Gertsch, 1992). These ideas should be revisited considering technical advancements over the last 30 years that may make some of them more

viable. The development of better and faster rock-cutting and fragmentation procedures, particularly for hard rock and in-situ mining, would result in significant productivity gains as well as some health and environmental hazards and benefits (Dietze and Mischo, 2014). Because it needs fewer unit operations, allows for speedier ground support installation, and exposes fewer employees to dangers, mechanized, continuous mining operations are viewed as intrinsically safer than traditional drill-and-blast mining (Ramezanzadeh and Hood, 2010). Continuous mining techniques for underground hard-rock mining would also significantly increase productivity.

Dry labs may host the research of hard rock cutting methodologies and tools, and improvements to blast design. This type of research in a dry lab would require some type of structural analytical instrument, such as micro-X-ray tomography instruments that are capable of imaging samples. However, if dry labs are not expected to generate their own analytical results, then computational modelling (e.g., microscopic and macroscopic simulations) and inferential modelling may suffice to utilise instrumental data to create models that describe rock responses to external forces. Improvements in blast design (e.g., computer-assisted simulations) would improve perimeter control, casting and fragment size management while also reducing the need for downstream crushing and grinding, resulting in significant energy savings (Katsabanis, 2020). New explosive tailoring and timing techniques would also be beneficial. The development of large-scale, in-situ processing methods would be aided by research into novel applications of blasting technology for the preparation of in-situ rubble beds for processing (Khademian and Bagherpour, 2017). New advancements in micro-explosives that can be poured into narrow fractures and detonated for in-situ fracturing and increased permeability for processing should be investigated. These techniques could be used for coal gasification and in-situ leaching (Sinclair and Thompson, 2015; Seredkin et al., 2016). In addition to method development-type of research, dry labs may also study the effects of environmental risks and health hazards associated with, for example, chemical permeability generation, the dangers of unexploded materials or dangerous by-products (De Silva et al., 2018).

The required instrumentation in a dry lab context would obviously be highly task dependent, as there is a range of improvements that could be technology-enabling and data-centric. However, in general, in addition to computing equipment, specific sensors that would be anticipated to be deployed (e.g., seismic sensors) may be required. Perhaps the most onerous infrastructure to enable dry labs to effectively support mining operations is the replication of a small section of an underground environment, such that analogue simulations and validation may take place. Examples of small-scaled analogues of underground mines in dedicated and dry lab-like environments include the DigiMine at the Wits Mining Institute (Ali et al., 2021; Atif et al., 2020a, 2020b). DigiMine is a replica of a mining environment that was funded by the stakeholder Sibanye-Stillwater, with the exact intent to facilitate research products into the development phase through enabling rapid simulations, prototyping and validation. This type of infrastructure may not be feasible in all cases, even where their presence is desirable, because of the cost associated with such an entity. However, where such infrastructure is required but not accessible, the development phase of many solutions offered by dry labs must be simulated, prototyped and validated in actual environments, which increases the latency to market of innovations, as well as potential hazards to dry lab personnel.

5.2.3. Mineral processing

Mineral processing disciplines have accumulated enormous amounts of data and technological advancements (Shikhov and Romashkina, 2018). For process simulation, current and legacy metallurgical plant data is being used to develop virtual reality environments (Duchesne, 2010). Virtual reality lets users immerse themselves in a user-created and often realistic environment. Virtual reality technology gives engineers a more realistic impression of working in a plant or a new environment without having to visit the facility in person (Lööw et al.,

2019). In addition to virtual reality, augmented reality overlays a digital visualization over a physical environment. In augmented reality, sound, video, applications and graphics are used to enhance the user's visual field (Hugues et al., 2012). In addition to reducing equipment maintenance costs, miners and mineral processing engineers use augmented reality to train using virtual simulators (similar to flight, surgical or military training, see Ghorbani et al., 2022). All these recent technologies are essential constituents for dry laboratories, where they participate in training or content development (e.g., capacity building). To enable effective use and development of these technologies, dry labs would also have to play a key role in the standardization and remediation of poor-quality legacy-type data related to mineral processing (e.g., Gaylard et al., 2009; Ghorbani et al., 2020b).

In the mineral processing plant, it is necessary to measure properties such as the flow rate of solids on conveyor belts, the flow rate and density of dirty liquids and pulps in pipes and launders, the particle size and size distribution of mill products in pulps, the flow rate and concentration of reagents in pulps and other chemical and physical properties of components that occur only in very small concentrations (see Table 2). Many of these properties can only be measured indirectly by employing appropriate primary and secondary sensing elements in series. Moreover, many standard industrial instruments developed for use in the chemical, petrochemical and similar industries are suitable only for relatively clean environments and cannot withstand chemically reactive pulps. In order to effectively improve plant performance, operators need accurate data on key elemental, mineralogical and physical information on ores at all stages of processing (See Fig. 7).

This information needs to be provided on a time scale suitable for process control to act on the data provided. New digitally-enabled measurement tools to aid decision-making will make processing lower-grade deposits more efficient and economically viable while ensuring valuable concentrations of metals are recovered and prevented from going to waste. Future instruments in processing industries including mineral processing plants will have to tackle the following challenges:

- A need for timely data though improvements to methods and tools. A move towards automated sampling without process interruption and towards approaches with minimal sample preparation.
- A need for instruments capable of imaging and analyzing individual particles. Such methods would be required to have:
  - Imaging capabilities for particle streams with extended particle size ranges
  - Imaging capabilities for variable material throughputs
  - Imaging capabilities for wet or dry particle streams
  - Imaging of dynamic streams of particles
- Totally Integrated Automation (TIA): TIA decreases the complexity of the automation solution and enables what really counts: the practical combination of optimally coordinated individual components – without interface problems. TIA integrates not only the production process but also all parts of the process plant management – from the field level to the management level. The result is a smoothly coordinated overall concept that empowers higher productivity.

5.2.4. Mining closure and tailing monitoring

In the mining value chain, mine closure is arguably-one of the most contested issues as the financial burden to manage delinquent mine sites and waste is generally not favourable to short- to medium-term business metrics. However, realizations around environmental factors, human health concerns and the perception of the public have gradually changed the nature of business metrics to focus on more long term and distal impacts of business activities. In a market system, timescales associated with sustainability of businesses is much shorter than that associated with environmental sustainability. As such, although the survival of businesses in a competitive system can be affected by effects of geo-engineering (e.g., acid mine drainage into deep water reservoirs), the

Table 2

List of some examples of instrumentation and infrastructure for online monitoring, analysis, and characterization in mineral processing plant.

Mineral beneficiation stages	Units/ Processing components or steps	Required instrumentation and infrastructure for online monitoring, analysis, and characterization	References
Comminution	Crushing and grinding	Monitoring milling efficiency Online condition monitoring (Sundström, 2013) Wear monitoring system Optimal mill load Grinding ball charge system Mill drive system	Gaulocher et al., 2011; Fuerst et al., 2012; Ashouri et al., 2016
Material transport	Conveyor belts and pipes	Weightometer Conveyor safety switches Tramp metal detectorsNon-contact material profiling sensors (e.g., spectrometry-based)	
Screening and classification	Screening after crushing and Hydrocyclones after grinding	Particle size analyser Flow meters Cyclone performance monitoring	WITec, 2022
Online/on-stream analysers	Particle size characterization in slurries Detailed characterization of the fine fraction in the particle size distribution	Ultrasonic attenuation measurements Systems based on laser diffraction	Wills, 2005; Coghill et al., 2002 Kongas et al., 2003; Remes et al., 2010
	Monitoring flocculation and on-line control of ore grades	Systems based on based XRF and focused beam reflectance	Koskinen et al., 1973; Kumar et al. 2013; Wills, 2005
	Unlike XRF, LIBS systems can partly determine light elements (lighter than Na). LIBS systems require high maintenance costs and are still under development. LIBS systems are only applied in few industrial cases.	LIBS	Barrette and Turmel, 2001
	Online monitoring of mineral phase transformation	Time gated Raman spectroscopy	Tanskanen et al., 2018
Separation processes	Physical separation	Density gauges	Thermo Fisher Scientific, 2022.
	Flotation	Slurry volumetric flow measurement Improved flotation cell performance Controlling air flow to flotation cells Level sensor, flow meters (flow rate of solids, liquids and pulps) The water content of	Thermo Fisher Scientific, 2022.

(*continued on next page*)

Table 2 (*continued*)

Mineral beneficiation stages	Units/ Processing components or steps	Required instrumentation and infrastructure for online monitoring, analysis, and characterization	References
	Chemical processing/ hydrometallurgy	a pulp Reagents measurement pH-Eh indicator Moisture analysers Mineral surface characterization to optimize flotation of valuable minerals Level sensor, flow meters (flow rate of solids, liquids and pulps) The water content sensors Reagents measurement pH-Eh sensors	Benndorf and Buxton, 2017.
Mineral characteristics	Chemical compositor Mineralogical compositor Mineral characteristics, particularly in flotation circuits	Elemental analysis X-ray based tomography E.g., the use of visible and near infrared light combined with on-stream XRF has proven successful to obtain a more robust and accurate prediction of grades in a copper – zinc flotation plant at Py-häjärvi, central Finland	Haavisto and Hyötyniemi, 2011; Hart et al., 2011
	Drill core scanning for geometallurgical approaches	Examples: Integration of visible/near-infrared (VNIR), short-wave infrared (SWIR) and long-wave infrared (LWIR) data for sensors with highly different spatial and spectral resolution Orexplore's digital laboratory system for drill cores - GeoCore X10 High-resolution hyperspectral imagery	Lorenz et al., 2019; Orexplore, 2022; Hyspex, 2022

most pertinent timely effects are instead driven by human desire for environmental stewardship. Hence, regulatory, civil society and financial issues, relating to the closure of a mine, are directly related to mining sustainability (Bentel, 2009). The ability to respond adequately to environmental protection and social responsibility requirements is shown by companies that operate and close mines in accordance with best practices, thus contributing to sustainability (Sánchez et al., 2014). Companies that consider such best practices and show tangible results will have an easier time obtaining operational clearances and licenses, securing financing, and acquiring social approval to operate (Esteves and Barclay, 2011). Although mine closure is evidently important, there is still uncertainty about how to proceed, because the effects occur on

multiple timescales up to and including the geoengineering timescale (Heikkinen et al., 2008). Indeed, as governmental policies (and energy and self-sufficiency concerns, including geopolitics and other civilizational priorities) change over decades or centuries, it is naïve to assume that closed mines and mine waste would continue to be managed in a consistent manner. There are often guidelines regarding mine closure in each country and jurisdiction, however, there are often contentious issues surrounding the process to be followed, financial and environmental liabilities, and post-closure rehabilitation strategies (du Plessis and Brent, 2006). Current practices involve:

- Contributions to mine closure liabilities from the commencement of mining operations (du Plessis and Brent, 2006);
- Decommissioning by putting the mining operation under care and maintenance in preparation for mine closure (Heikkinen et al., 2008);
- Mine closure—either temporary due to geotechnical concerns or unfavourable economic conditions, or permanent due to the depletion of economically valuable orebodies (Namba et al., 2010);
- Rehabilitation and ongoing monitoring following shutdown - there are two types of post-closure care situations considered: permanent and temporary care. The former requires the company's presence to carry out operations necessary to reach closure objectives, which could persist for several years. The required actions in the temporary care scenario are confined to tasks such as inspections, monitoring and other actions that are normally-one-time procedures (Spitz and Trudinger, 2009; Sánchez et al., 2014).

Changes to the mining plan, development of mineral reserves, development of new technological processes, the management or shareholder control changes, and mine accidents such as ground collapse should all be factored into the aforementioned stages (Sánchez et al., 2014; Western Australia, 2011). Despite the fact that various mine closure regulations require that mining corporations begin planning for closure as early as the design stage of a new mining operation, this rarely happens in practice and is frequently done merely for regulatory compliance purposes without proper actionable plans. In addition, resource extraction and processing have progressively moved to countries with comparatively relaxed environmental, labour and other types of legislation and policies (Burnett et al., 2022), eventually resulting in the action of many western countries to declare a need to secure their own "critical raw materials" (Rachidi et al., 2021 and references therein). Closure planning is included in a mine's feasibility assessment so that post-mining land use possibilities are examined alongside project development options (Sánchez et al., 2014). When it comes to mine closing difficulties, a proper transition is essential to ensure that mining corporations leave a positive legacy (ICMM, 2006, 2008, 2012, 2013). A mining firm should be able to contribute to sustainable development in addition to supporting economic growth so that the community can continue to thrive after the mining operation is completed. By pursuing efforts that promote the conversion of a local asset – the non-renewable natural resource – into another local asset of a different character, i.e., human and social capital, the mining business can play a critical role in community development (Sánchez et al., 2014). To that aim, the community's and region's current and future development plans should be connected with the strategic long-term company goals. Mine closure has often resulted in civic unrest, long-term environmental and social repercussions, and accidents due to the collapse of mine infrastructures such as dormant tailing dams and abandoned shaft headgears in nations such as South Africa, where ongoing mining has lasted over a century (Swart et al., 1998). South American regions have made significant headway on mine closure plans; despite the problems of dealing with spent heap leach piles that are frequently owned by no one (Castro et al., 2011; de Jesus and Sánchez, 2013). Mine closure challenges have been compounded by dynamic changes in surface and atmospheric processes such as heavy rainfalls, migrating wetlands, changes in landforms,
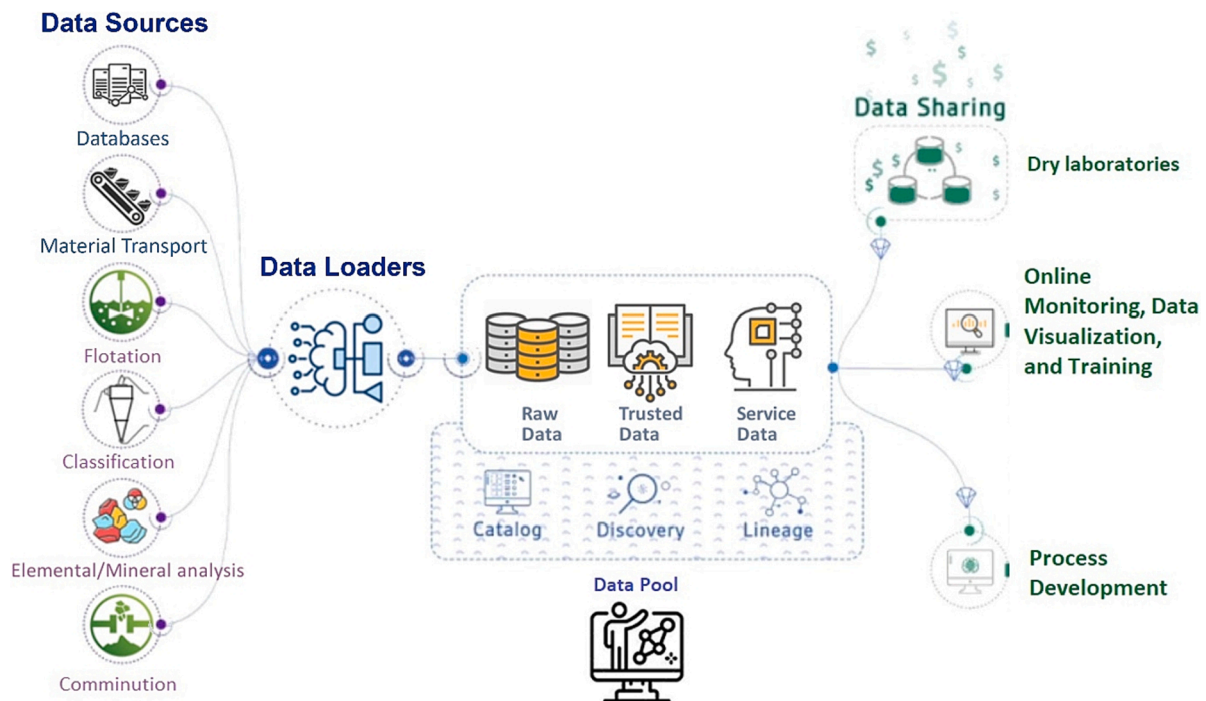
Fig. 7. Mapping the required instrumentation and infrastructure for online monitoring, analysis and characterization in the mineral processing plant.

biogeochemical processes, and mining-induced substances, demonstrating that there are no permanent solutions to mine closure, but that continuous monitoring and rehabilitation is required (United Nations Environment Program, 2001; World Bank, 2007, 2010, 2012). Perhaps the cheapest way to monitor surficial changes is through satellite-based multi- / hyper-spectral remote sensing (e.g., Li et al., 2015), which is a form of big data. Although in a similar manner, other instruments such as embedded geophones and strain/stress gauges (for failure and movement monitoring), ambient thermodynamic and chemical sensors and local and high-resolution photometry or spectroscopy sensors (e.g., lidar or drone-based sensing) are all suitable. An infrastructure to transport data would also be required, unless satellite-based remote sensing is the only type of data gathered, in which case, no direct ICT connections would be necessary to the monitored site. Environmental sensors around sites of management, such as those embedded downgrade of a mine waste, or above the local water table, but below the waste site facility, would serve well to detect environmentally damaging discharge events, such as unintended acid mine drainage, before they cause further downstream issues. For this purpose, edge computing-powered sensor networks also would work well, as they can lower the infrastructure requirements to enable big data-based monitoring, which would otherwise be impossible or very difficult in many countries without adequate (or any) modern infrastructure. In addition, the physical presence of such sensors can be minimized, such that tampering or environmental degradation would be less of a concern where human supervision is intermittent or unfavourable (e.g., conflict zones or environmentally harsh conditions).

5.3. Outlook for the integration of the mineral value chain

There remains a desire to integrate the mineral value chain, and both knowledge-based approaches (e.g., geometallurgy) and data-centric approaches (dry labs) exist, with the latter using data as a *trans*-disciplinary component which exhibits a unifying effect (e.g., Ghorbani et al., 2022). To facilitate the integration of the mineral value chain using data, there are foreseeable considerations around instrumentation and infrastructure. For example, from the geometallurgical perspective, the

earlier that metallurgically-relevant data could be generated within the mineral value chain and provided for downstream uses, the more effective the integration of the mineral value chain. For instance, the availability of geo-lithological data of ores, which can be easily characterized in the process of mineral exploration, is crucial to designing an effective pre-concentration process to reject gangue material at an earlier stage to reduce comminution energy usage. Other perspectives, such as environmental and economic optimization (e.g., optimization for beneficiation, market positioning, stockpiling and waste management) are also relevant. Essentially, a greater strategy towards any integration of the mineral value chain requires that the objectives and characteristics of all stages of the value chain be mutually considered. This may be difficult to achieve in the traditional siloed and gated approach to the mineral value chain, particularly around data. However, in a dry lab, it is comparatively easy to bi-directionally relay data requirements and capabilities (and by implication, instrumentation and infrastructure) between data generators and data users not just within a single stage (e.g., within exploration) but also across stages/disciplines (e.g., between exploration and mining). Considerations around the choice of instruments for example, could be based on their value in the context of the entire mineral value chain and not isolated to a single stage (e.g., exploration or mining). For instance, instruments that are capable of not only analyzing chemistry, but mineral composition and micro-structural relationships may be deployed during prospecting and exploration. For example, micro-X-ray tomography may be a valuable and cost-effective instrument for this purpose (e.g., Nwaila et al., 2022). In a similar manner, adoption of geometallurgical constraints that are derived from an appropriate choice of instrumentation early in prospectivity mapping would likely improve the usability of such products to latter stages of the mineral value chain. The differing characteristics of the various stages of the mineral value chain (e.g., the discontinuous process of mining versus the continuous process of mineral processing) may also play a role in the selection of sensors and instruments. For example, the spectroscopic profiling of bulk material at the extraction stage occurs at a different scale than the same technique used during mineral processing. This is a specific case of multi-scaled (multi-resolution) data. An effective implementation of integration may be to

provide standardization interfaces, such as through calibration conversions between various sensors used through the mineral value chain, such that data could be integrated for analysis. The discrepancies of material discretization through the mineral value chain are a challenge to integration but should be solvable either in a knowledge-driven (e.g., uniform conditioning to best match extraction capability with resource models) or data-driven (e.g., the generalized approach of data fusion) manner. Outlook in terms of infrastructure integration is somewhat more difficult to anticipate, as it is predicated on the choice and evolution of instruments and data requirements. In any case, it is possible to anticipate an increase in the need to transport timely data and its derived insights potentially over large distances across the mineral value chain. Supply chain tracking may be an example of a prototype chain-wide integration of information, sensor and data systems. Establishment of dry labs that uses data from all stages of the mineral value chain is a key strategic requirement to enable an effective, cross-industry perspective of the generation, management and use of data, its related instruments and infrastructure.

6. Summary and outlook

There are several initiatives in the 21st century minerals industry that will use digitalization strategies in conjunction with dry labs. Among them are rapid data-driven decisions to protect workers from hazards, which is closely related to achieving zero harm and minimizing fatalities. Along with this trend, digitalization enables further automation that should further increase operational efficiency and safety. Through real-time monitoring and analysis of production data, uncertainties associated with production forecasts would also be reduced. The global initiative to decarbonize future economies and climate change initiatives may be benefitted through reduced operational energy consumption (e.g., ventilation on demand for underground mines controlled autonomously) and continuous monitoring of emissions using satellite-based data when used in a dry lab setting. Since mechanization, the shift of labour onto machines has contributed to higher operational efficiency and safety in the prospecting, exploration, mineral extraction and processing industries. Dry labs will allow future workers in the minerals sector to develop new skills (e.g., Miner 4.0) that empower women in the minerals industry and enable hybrid working environments. With mechanization, the key to successful operations is multiple, including the ability to properly plan and support the mass deployment of machines, which necessitate their own infrastructure (e.g., energy, sensor and data systems). Similar to mechanization, to enable digitalization in the minerals industry, a necessary infrastructural and cultural transformation must take place. This includes the planning and mass deployment of data- and digital-centric infrastructure, such as high bandwidth communications systems, sensors and sensor networks, edge computing equipment and dry labs. Within our conception, the necessary infrastructure is the spokes of a wheel that connect various sensors and other data-generating devices on a network to a hub, which is the dry lab. In this model, characteristics of the communications infrastructure (e.g., bandwidth capability) are contingent on the characteristics of the sensors and the nature of the deployment scenario (e.g., remote geochemical profiling). Designing and engineering data streams that are fit for purpose for the dry lab environment is critical to the sustainability of all downstream data-centric activities, including data-driven activities, such as the use of artificial intelligence, machine learning and geodata science. Key infrastructure components that seem inevitable in any context include: a robust and highly capable communications network; a set of in-situ sensors and/or edge computing equipment; and a dry lab.

CRediT authorship contribution statement

Yousef Ghorbani: Conceptualization, Writing – original draft, Writing – review & editing. **Steven E. Zhang:** Conceptualization, Writing – original draft, Writing – review & editing. **Glen T. Nwaila:** Conceptualization, Writing – original draft, Writing – review & editing. **Julie E. Bourdeau:** Visualization, Writing – original draft, Writing – review & editing. **Mehdi Safari:** Visualization, Writing – review & editing. **Seyed Hadi Hoseinie:** Visualization, Writing – review & editing. **Phumzile Nwaila:** Writing – review & editing. **Jari Ruuska:** Writing – review & editing.

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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.

Data availability

No data was used for the research described in the article.

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