EVALUATION OF DATA-DRIVEN DECISION-MAKING IMPLEMENTATION IN THE MINING INDUSTRY

R.A.D.P. Bisschoff[1] & S. Grobbelaar[1*]

ARTICLE INFO

Article details
Presented at the 33rd annual conference of the Southern African Institute for Industrial Engineering, held from 3 to 5 October 2022 in Zimbali, South Africa

Available online 11 Nov 2022

Contact details
* Corresponding author
schalk.grobbelaar@up.ac.za

Author affiliations
1 Department of Engineering and Technology Management, University of Pretoria, South Africa

ORCID® identifiers
R.A.D.P. Bisschoff
0000-0002-5933-6786

S. Grobbelaar
0000-0001-7821-4373

DOI
http://dx.doi.org//10.7166/33-3-2799

ABSTRACT

The ability of organisations to collect and store vast amounts of data has become increasingly more accessible and affordable in recent decades thanks to the advancement of Industry 4.0. This ability is an enabler of data-driven decision-making (DDDM). However, converting data into knowledge that can inform decision-makers has proven challenging for many companies. The ability to perform DDDM effectively depends on a combination of capabilities that encompass the technological, analytical, and managerial aspects of a business. This research focuses on the mining industry, and used a scoping literature review to identify the different DDDM tools that are currently available, the potential benefits of DDDM, the key enablers of DDDM, and the lessons learnt from previous implementations. The objective of the paper is to assist mining industry organisations in developing a DDDM implementation framework.

OPSOMMING

Die vermoë van organisasies om groot hoeveelhede data in te samel en te berg het in die afgelope dekades toenemend meer toeganklik en bekostigbaar geword danksy die vooruitgang van Industrie 4.0. Hierdie vermoë is 'n bemiddelaar vir data-gedrewe besluitneming (DGB). Dit was egter uitdagend vir baie maatskappye om data in kennis om te skakel vir besluitnemers. Die vermoë om DGB effektief uit te voer hang af van 'n kombinasie van vermoëns wat die tegnologiese, analitiese en bestuursaspekte van 'n onderneming insluit. Hierdie navorsing het op die mynbedryf gefokus en het 'n literatuuroorsig gebruik om die verskillende DGB-instrumente wat tans beskikbaar is, die potensiële voordele van DGB, die sleutel-instaatstellers van DGB, en die lesse geleer uit vorige implementerings te identifiseer. Die doel van die artikel is om mynbedryforganisasies te help met die ontwikkeling van 'n DGB-implementeringsraamwerk.

1. INTRODUCTION

The South African (SA) mining industry plays a critical role in the SA economy, contributing to both socio-economic and human development [1], [2]. There are many challenges with which the mining industry needs to contend to ensure its continued success. Sishi and Telukdarie [2] mention some of these challenges, such as increased global demand, high production standards, and the drive to save environmental resources. Antin [1] points out that, although SA holds some of the largest resource deposits in the world, the production of raw materials is often lower than in countries with much smaller resource deposits. [1] describes the SA mining industry as having “severe productivity issues”.

According to [2], management decision-making in the mining industry could be improved by providing real-time data from all business areas to the decision-makers. [2] propose a combination of enterprise resource planning (ERP) systems and Industry 4.0 (I4.0) technologies to achieve this, essentially providing management with what could be called a data-driven decision-making (DDDM) tool. Brynjolfsson, Hitt & Kim [3] analyse a large sample of publicly listed firms, and conclude that DDDM is associated with higher productivity and market value [3]. They explain that many case studies and research studies indicate that investment in information technology (IT) is a driver of improved productivity, and that technologies such as big data and data science could dramatically transform the mining industry [4]. However, others suggest that the actual use of IT is an essential variable in addition to IT investment [3]. Therefore, it can be concluded that the capabilities to use and interpret information obtained from a DDDM tool are as important as the tool's implementation.

1.1. Technology implementation in the mining industry

The implementation of Industry 4.0 technologies in the mining industry is still lagging behind that of other industries such as manufacturing. [2] point out that the mining industry has had challenges with implementing data management systems such as ERPs because they have not been able to integrate these systems into the different levels of their business. In some instances, these systems cannot keep track of essential information, forcing users to intervene manually to capture the data [2].

1.2. Data-driven decision-making tools

Information technology (IT)-based tools can be used in different parts of the DDDM process. [3] mention the following technologies:

- Enterprise information technologies such as ERP, supply chain management (SCM), and customer relationship management (CRM) systems are used to capture, store, and manage large quantities of data. As a result, these technologies typically fit into the data-gathering and data-integration steps in the DDDM process.
- Data analytics technologies and business intelligence (BI) systems are used to analyse data and visualise information. These technologies typically fit into the information and insight steps of the DDDM process.
- Data-generating technologies such as IoT-based sensors, smartphones, and radio frequency identification (RFID) sensors are used to generate real-time information. These technologies can fit into both the data-gathering and the evaluation steps of the DDDM process.

Davenport, Harris, De Long & Jacobson [5] describe the technology that enables a DDDM process as the hardware and software used for data capturing, cleaning, extraction, and analysis. In addition to these, network infrastructure and capabilities to transfer data and provide access to end-users are also vital [5]. These technologies are grouped as either transaction systems (similar to the enterprise information technologies mentioned by [3]) or analytical technologies [5].

According to [5], transaction systems tend to be relatively generic, and can be implemented by IT professionals without in-depth knowledge. Many of the functions in these systems can also be automated on the basis of predefined sets of rules [5]. On the other hand, analytical technologies and the infrastructure they require are more complicated, and require a better understanding of the organisation; these technologies also require more human involvement [5].

One of the many analytical technologies that provide capabilities for decision support systems is digital twin technology. Van der Horn and Mahadevan [6] provide a generic definition for a digital twin: it is "a virtual representation of a physical system (and its associated environment and processes) that is updated through the exchange of information between the physical and the virtual system". Coelho, Relvas, & Barbosa-Póvoa [7] also propose that the definition of a digital twin should be updated to include the dimension of a decision support system.

Simulation modelling is another technology that can provide insight to guide decision-making. Simulation modelling is often confused with digital twins because they are often used together, and can even use the same computational model. [6] explain that the main difference between a digital twin and a simulation model is that a digital twin is used to track the current and past state of a system, while a simulation model is used to predict future states of the same system.

In their case study, [7] discuss the development of a simulation-based digital twin for an in-house logistics system. One of the key dimensions of this digital twin was to serve as a decision support system. [7] state that, for effective planning and control of these types of operation, decision-makers need to know the system's current state and to be able to analyse different scenarios to assess these scenarios in comparison with the current state. The digital twin provides decision-makers with this functionality.

1.3. Data-driven decision-making capabilities

Jia *et al*. [8] find that the literature has focused mainly on promoting the concept of DDDM by discussing its benefits, while the issue of building DDDM capabilities has been given little attention. Therefore, their study focuses on identifying the components of DDDM capabilities and how organisations could build these capabilities.

[8] define DDDM capabilities as an organisation's capabilities to use data, information, and insights within a series of coordinated decision-making processes to support, inform, or make decisions. They also propose a DDDM capabilities framework with the following five capabilities:

- Data governance
- Data analytics
- Insight exploitation
- Performance management
- Integration

However, not all of these capabilities can be obtained or enhanced by simply applying the DDDM tools. Data governance and integration can be improved by using transaction systems. Data analytics can be improved by using analytical technologies. Insight exploitation and performance management depend more on the organisation's culture and internal processes than on any specific technology.

1.4. Research objectives

This study aimed to evaluate the opportunities and challenges related to the implementation of DDDM in the mining industry by answering the following questions:

1. Which DDDM tools are currently being used in the mining sector?
2. What are the potential benefits of DDDM in the mining sector?
3. What are the key enablers of DDDM in the mining sector?
4. What are the main lessons learnt from implementors of DDDM in the mining sector?

2. SEARCH PROTOCOL

2.1. Introduction

This section describes the methodology used for the scoping review. The protocol aimed to identify concepts related to DDDM. The results were sorted by their relevance using Google Scholar, and only the most relevant results were reviewed. Then the documents were screened by reading the abstracts to identify those that met the inclusion criteria.

2.2. Exclusion criteria

Documents were excluded based on the following criteria:

- The document is not available in English.
- The document is not available through the University's online library.
- The document does not mention a relevant concept related to DDDM.
- The document does not mention the mining industry.

2.3. Search strategy

2.3.1. Keywords and concepts

The main concepts included in the research were:

- Data-driven decision-making
- Industry 4.0

These concepts were combined with “mining” or “mining industry” to form search phrases. From the initial search results, it was apparent that specific terms should be excluded from the search phrase to reduce the number of non-relevant results. The specifically excluded phrases were “data mining” and “process mining”. Google Scholar enables users to exclude specific phrases by using the “-” symbol as part of the search phrase. The search phrases and the number of results returned by each phrase are listed in Table 1.

Table 1: Results returned per search on Google Scholar

Search phrase	Number of results
“Data driven decision making” AND mining -“data mining”	5 290
“Industry 4.0” AND “mining industry” -“data mining” -“process mining”	1 750
Implementation AND “mining industry” AND “data driven decision making” -“data mining” -“process mining”	89

Three additional documents were included from the literature that was found during the initial idea formulation and proposal writing phases. These documents did not focus strictly on the mining industry, but contained meaningful information that was relevant to the research.

2.3.2. Study selection

The papers were read and evaluated against the inclusion/exclusion criteria in order of relevance, as Google Scholar sorted them. This screening process reduced the number of documents to 43 eligible documents for further analysis. During that further analysis, an additional three documents were found to be irrelevant to the research topic and were excluded. As shown in Figure 1, the final number of documents included in the study was 40.

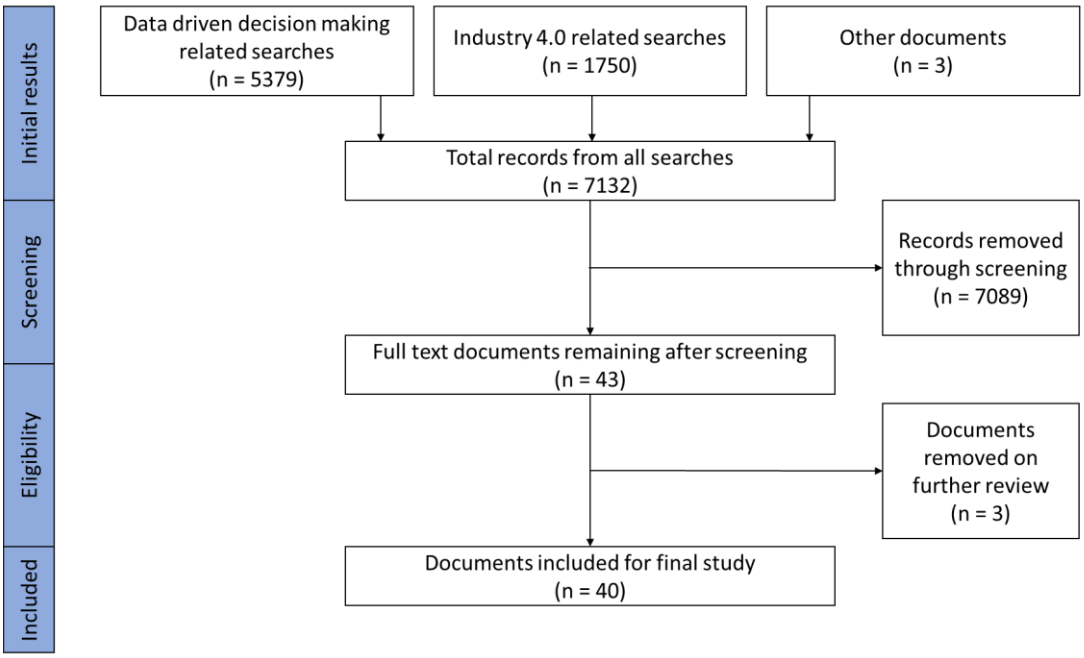

Figure 1: Document selection process

2.3.3. Data collection process

Document management and analysis were performed using Atlas.ti, a qualitative data analysis tool and virtual 'workbench' designed to assist with record-keeping and organisation during academic research. The following tasks were performed using Atlas.ti:

1. Storing all eligible documents selected for further analysis.
2. Assigning documents to document groups in line with predefined metrics.
3. Reviewing the documents and assigning relevant codes to specific phrases at the researcher's discretion. The codes used are listed in Table 2.

Table 2: Codes assigned using Atlas.ti

Category	Codes	Times coded
DDDM	DDDM – Benefits	18
	DDDM – Challenges	22
	DDDM – Enabler	32
	DDDM – Framework	3
	DDDM – Implementation	18
	DDDM - Lessons learnt	11
	DDDM – Prerequisite	3
	DDDM - Tools	30
Industry 4.0	Digitisation	6
	I4.0 Benefits	20
	I4.0 Challenges	20
	I4.0 Enablers	2
	I4.0 Implementation	16
	I4.0 Lessons Learnt	1
	I4.0 Prerequisite	4
	I4.0 technologies	15
	Mining 4.0 / Smart mining	5
	Technology resistance	3
	Use of I4.0	26
Decision-making	Decision-makers	1
	Decision-making time	1
	Decision-making	33
	Decision types	18
Data	Big data	2
	Cognitive computing	2
	Data analysis	3
	Data analytics outcomes	3
	Data collection	22
	Data driven	8
	Data integrity	6
	Poor utilisation	2

Category	Codes	Times coded
Skills/Capabilities	Analytic capability	1
	Capability building framework	1
	Capability	11
	DDDM – capability	1
	Human resources	2
	Knowledge	2
	Training and skills	2
Mining industry	Maintenance	5
	Mine planning	1
	Mining challenges	9
	Mining industry need	12
	Mining safety	1
	South African mining	4
	Technology in mining	3

The document groupings and codes were used to extract and collect data from the documents.

3. LITERATURE STUDY RESULTS

3.1. Literature selection

As shown in Figure 2, journal articles made up 62.5% of the documents, while conference papers made up 27.5%. The remaining 10% combined industry periodicals, thesis papers, and economic or industry reports.

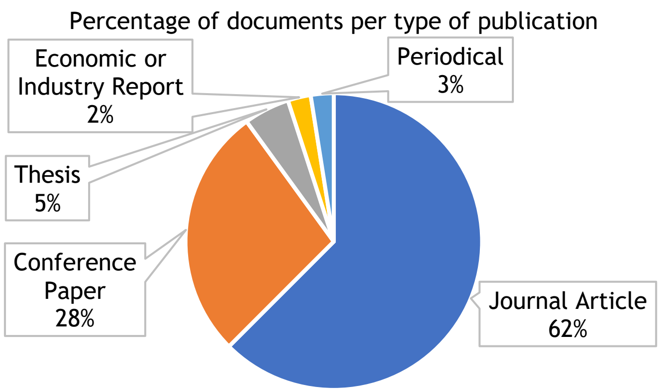

Figure 2: Documents per type of publication

Figure 3 shows how the number of publications per year dramatically increased from 2015 to 2021. Figure 4 shows the number of publications per region of focus. Russia was counted as a region on its own because of the high number of publications focused specifically on Russia, and the fact that Russia spans both Europe and Asia. All 19 documents that focus on Russia and Europe were published from 2015 to 2021. The increase in documents published in Europe and specifically in Russia during this period could be related to the Russian National Technology Initiative, which was developed in 2014 and has incorporated positive aspects from European technology platforms developed since 2001 [9].

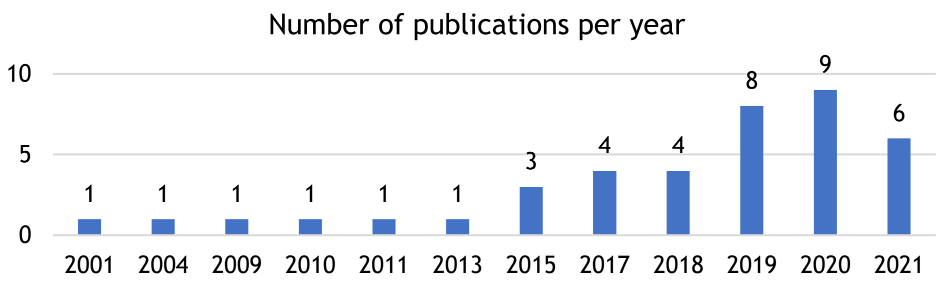

Figure 3: Document publications per year

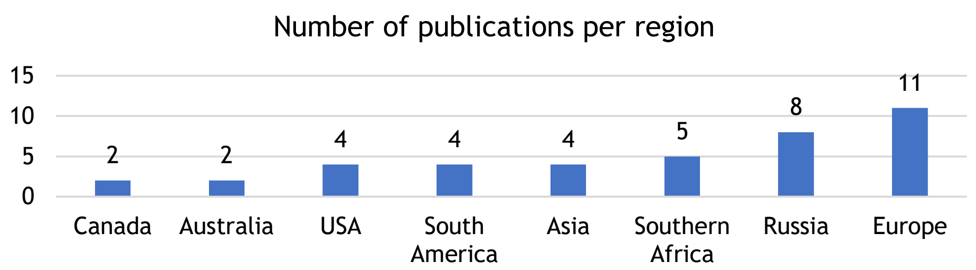

Figure 4: Document publications per region

3.2. Relevant information and concepts found in the literature

Some common concepts were identified and linked to documents using the document group functionality in Atlas.ti. Figure 5 shows the identified concepts and how many documents referred to each concept. A single document could refer to more than one concept. The top three reoccurring concepts were I4.0 and concepts related to I4.0, such as automation and Mining 4.0. Concepts related to decision-making were number four on the list of reoccurring concepts.

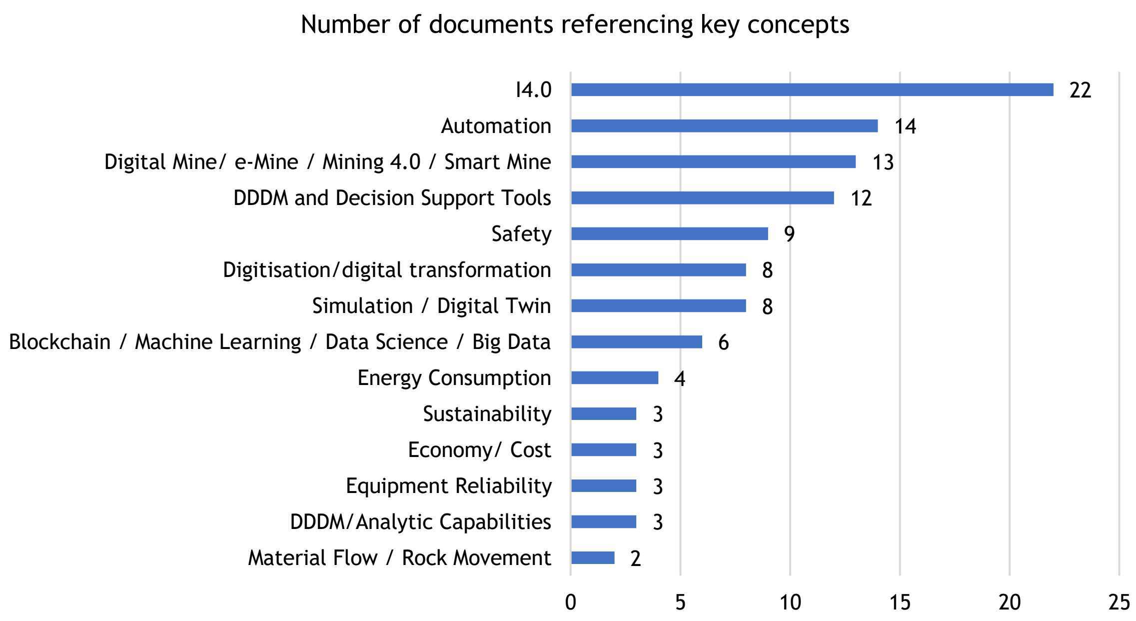

Figure 5: Number of documents referencing key concepts

3.3. Relevant definitions found in the literature

Several definitions for important concepts related to I4.0 and DDDM were identified during the literature review.

Table 3 provides a list of definitions found in the literature.

Table 3: Definitions of key concepts

Term	Definition	Source
Big data	"Big data can be defined as a disruptive and integrated set of technologies that reframes business intelligence in companies' information systems and that involves cyclic activities of research, collection, organisation, processing and storage of large collections of data."	[10]
DDDM	"Data-driven decision making is a real ideology that conceives data as a strategic resource, rather than on intuition and experience and requires the active role of leadership in fostering an innovation-oriented culture and the careful attention to data management in each step of decision making."	[10]
	"Data-driven decision making refers to the practice of basing decisions on the analysis of data rather than purely on intuition."	[11]
Digital transformation	"A process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies."	[12]
Industry 4.0	"Industry 4.0 is not only and not so many new technologies; rather, it is a new approach to production and consumption. It is based on the principles of sustainable development, implementation of 'green' technologies, collection of big data, its processing and use for coordinated actions and operation timing performed without human intervention. The base trend of Industry 4.0 development is the attribution of such functions as optimisation and setting of autonomous operation to machines and mechanisms."	[13]
	"The concept of Industry 4.0 is about blurring the barriers between the real world of production machines and the virtual world of the Internet and information technology. The idea is to create factories that will form a closed circuit of information flow. People, machines, IT systems are to be integrated and automatically exchange information during production."	[14]
	"This concept is based on an advanced digitisation of production processes and the combination of internet-oriented technologies, allowing the connection between smart sensors, machines, and IT systems across the value chain."	[12]
Internet of Things	"The convergence of information technology (IT) and operations technology (OT)."	[15]
	"An interconnection of sensing and actuating devices providing the ability to share information across platforms through a unified framework, developing a common operating picture for enabling innovative applications. This is achieved by seamless ubiquitous sensing, data analytics and information representation with cloud computing as the unifying framework."	Gubbi, Buyya, Marusic & Palaniswami, as quoted by [16]
Mining 4.0	"For the raw material sector, Mining 4.0 does not mean a one-to-one transfer of the Industry 4.0 objectives to industrial raw material production. Rather, Mining 4.0 means the advance of automation during extraction, transportation and processing."	[17]

3.4. General discussions of information found in the literature

3.4.1. DDDM and analytic capability

[8] present a framework for DDDM capability that describes the relationships between the various capabilities and between each capability and the overarching DDDM capability [8]. In addition, the module illustrates that the relationship between any two capability dimensions could be causal, correlated, or bi-directional [8].

[8] state that, for an organisation to be in a position where it can benefit from DDDM, it must first understand the five dimensions of DDDM capability (governance, analytics, insight exploitation, performance management, and integration) and spend the required time and resources to build these capabilities to support DDDM.

[5] discuss the importance of building analytical capability to turn data into knowledge and knowledge into results. [5] find that many companies have invested in the technologies required to perform DDDM, but have neglected the capabilities to turn data into knowledge and results. They provide a three-tier framework for building analytic capability based on context, transformation, and outcome [5]. Context represents the framework's base, which is a prerequisite for analytical capability [5]. Transformation represents the actual process of data analysis, where data is transformed into knowledge that can support decision-making [5]. The final tier, outcomes, represents things expected to change within an organisation because of DDDM [5].

Bertayeva *et al*. [18] state that constant training, both in a formal capacity and in the workplace, is required to ensure that technology will be effective in the mining environment. Sukiennik [19] finds that the lack of staff who are qualified in DDDM is a big obstacle for the mining industry, where there is already an observed shortage of basic working staff. This shortage will become even more pronounced when mines require staff who are well-versed in new technologies [19].

3.4.2. Data collection and data analytics in the mining industry

The lack of reliable quantitative data is one of the main reasons that the mining industry often relies on experience and intuition when making decisions [20]. With the advancement of I4.0 in the mining sector, mining organisations can collect and store more data than was previously possible. Paduraru and Dimitrakopoulos [21] state that the decreased cost of sensor and data storage technologies and better standardisation in using these technologies have allowed more information to be collected from mining operations. Gackowiec and Podobińska-Staniec [16] explain that Internet of Things (IoT) platforms can improve the organisational capability to collect and process information.

Increased data collection can improve the understanding of mining's complexity and its internal processes, and enable the mine to improve through better decision-making [16], [21]. However, [21] warn that the increased amount of available data could make it challenging to make the best decisions based on new information. Troisi *et al*. [10] add that merely collecting large data sets does not provide a competitive advantage. The value added by the data depends on data accessibility, quality, heterogeneity, analysis, synthesis of solutions, management's attitude towards data, and their ability to analyse and interpret data [10].

The impact of I4.0 technology on the ability to collect and analyse data is mentioned in several documents:

- [2] mention that IoT allows for the collection of vast amounts of data and the use of modular mining systems (MMS), which allows historical data to be captured on a shift-by-shift basis.
- Pałaka *et al*. [14] mention how mining machines can be fitted with sensors that allow them to collect data on the work that they are doing. Machine learning can then be used to improve machine effectiveness [14].
- [19] state that the mining industry will reach a point where every machine and device will be collecting data, and all processes will have to be monitored and recorded. This will require mining organisations to perform regular data analysis on vast amounts of data [19].

- Gackowiec and Podobińska-Staniec [16] list some of the most common functionalities of IoT platforms, including real-time data capturing and cloud-based analytics.
- Sánchez and Hartlieb [12] compare the mining industry with high-tech industries, based on their early adoption of advanced monitoring systems to collect and analyse large amounts of data.
- Gackowiec *et al*. [22] state that data collection is the starting point for implementing improvements at all levels of management in an organisation.
- Duarte *et al*. [23] discuss how photographic data can be collected and used as part of open-pit mine planning by extracting information from the pictures.
- Brodny and Tutak [24] discuss the importance of data reliability and how machine availability analysis is more accurate when performed on data automatically collected by machines or sensors rather than collected by personnel who could be subjective in their data capturing.
- Adjiski *et al*. [25] discuss the potential to improve mining safety by using devices to collect and share all personnel's real-time location and health information in a mine.

The literature indicates a clear recognition within the mining industry of the benefits and possibilities that data collection can bring; however, there is more mention of data collection than of data analysis. In some cases, data analysis is mentioned in the context of machines or systems performing the data analysis, and not as something in which humans are involved [12], [14], [16]. There is a risk that mining organisations might invest large amounts of capital in technology that collects vast volumes of data without investing in the capabilities required to use the data. [5] state that technology investments would not reach their full potential if organisations did not build the technical and human capabilities to turn data into knowledge and results.

The concepts of data quality and data integrity are not often mentioned in the literature, even though it is an essential aspect of DDDM. [8] state that decisions should be made using high-quality and well-organised data to avoid bad decisions resulting from poor data. In the mining industry, decisions made on the basis of low-integrity data can prove very costly. [26] recommends that the same data be obtained from more than one source to allow for comparisons between data sources to identify discrepancies in the data.

3.4.3. Data-driven organisation

Gökalp *et al*. [27] consider building DDDM and analytical capabilities further by introducing the concept of transitioning into a data-driven organisation – that is, one that bases all business decisions on insights derived from data rather than from managers' intuition. [27] state that organisations do not generate value from data science investments because of a lack of organisational management alignment and culture, rather than because of ineffective data or technologies. [27] propose that, to become data-driven, an organisation needs to improve its capabilities in five management processes:

1. Change management
2. Skill and talent management
3. Organisational learning
4. Strategic alignment
5. Sponsorship and portfolio management

[27] provide a model to assess an organisation's capability level for each management process mentioned above. The model consists of six levels numbered zero to five, representing increasing levels of capability [27]. An organisation that achieves a level four rating for all five management processes has fully transitioned from an organisation that is intuition-driven to one that is data-driven [27].

The capability levels provided by [27] are:

- **Level 0: Incomplete** – The organisation does not perform base practices for the specific management process, and has no initiative to transition from intuition-driven to data-driven [27].
- **Level 1: Performed** – The organisation largely performs base practices for the specific management process, but these are done on an ad-hoc basis [27]. Processes are primarily reactive, unpredictable, and poorly controlled [27].

- **Level 2: Managed** - The organisation thoroughly performs base practices for the specific management process [27]. Processes start becoming better defined with specific performance objectives [27].
- **Level 3: Established** - Management processes are standardised and are well-defined and controlled [27].
- **Level 4: Predictable** - Processes are managed through quantitative data that describes the performance and variations in best practices [27]. Processes are planned, performed, and monitored to ensure consistent performance [27].
- **Level 5: Innovating** - The organisation thoroughly performs all process attributes, and learns continuously from and innovates processes to improve its data-driven effectiveness [27].

4. ANSWERS TO RESEARCH QUESTIONS

4.1. What DDDM tools are used in the mining industry

Various tools contribute to the process of DDDM, and are described in Table 4.

Table 4: DDDM tools in the mining industry

Type	Tool/Technology	Source
Enterprise information technologies/transaction systems	ERP systems	[2]
	IoT platforms	[28], [29]
Data analytics technologies/tools	DISPATCH™	[30]
	Reinforcement learning methods	[21]
	Analytic hierarchy process	[20]
	3D geological modelling	[31]
	Life cycle cost analysis	[32]
	Artificial intelligence and smart algorithms	[29]
	Cloud computing	[28]
	Big data	[28]
Data-gathering technologies	Near-infrared reflectance spectroscopy	[21]
	Geographical positioning systems (GPS)	[21]
	Radiofrequency identification (RFID)	[21]
	Sensors	[21]
Simulation/digital twin technology	Simulation models	[30], [33]
	Digital twin	[12], [29]

4.2. What are the benefits of DDDM tools?

Companies that use data to make decisions are more productive than companies that do not use DDDM [11]. In addition to productivity, DDDM has also been correlated with a more favourable return on assets, asset utilisation, and market value [11]. Table 5 provides a list of DDDM benefits that have been observed in the mining industry.

Table 5: Benefits obtained from DDDM in the mining industry

Benefit	Explanation	Source
Increased production	DDDM concept was applied in a long-wall coal mine to implement a predictive maintenance schedule, resulting in increased productivity.	[34]
	Advanced process control systems that were implemented using IoT technology provided information that could be analysed and used to improve the mining process, increasing production.	[15]
What-if analysis	Simulation modelling was used to provide a decision-making tool for the materials-handling operation in a coal mine. The simulation model allowed decision-makers to test multiple combinations of the amount of equipment active in the system, and provided key outputs to indicate the expected outcome of each scenario. This enabled decision-makers to make faster decisions with less uncertainty.	[30]
Improved safety	DDDM was used in the form of a deep-mining safety-control decision-making system. This system used geological information to identify potential safety risks in underground mining.	[31]
Decreased energy usage	Advanced process control systems implemented using IoT technology provided information that could be analysed and used to improve the mining process, decreasing energy usage.	[15]
Prolonged equipment life	Advanced process control systems implemented using IoT technology provided information that could be analysed and used to improve the mining process, extending equipment life.	[15]
Faster decision-making	Having more information about complex mining processes and the interaction between mining equipment made it possible to automate many decisions that engineers previously made in a time-consuming way. This freed up the engineer’s time to focus on more important work.	[15]
Improved maintenance	The implementation of IoT and its capability for DDDM made it possible to implement predictive maintenance, taking the pressure on maintenance staff and reducing the cost of maintenance.	[15]

4.3. What are the key enablers of DDDM tools?

In recent years, the advancement of I4.0 and IoT has revolutionised many industries, enabling computer-based tools to support and improve processes. [16] state that there is a specific application of IoT technology to extract valuable information from complex processes. According to [8], DDDM becomes particularly useful when businesses have access to large interconnected data sets from past and current operations. Extrapolating from this, the ability to collect large data sets can be a DDDM enabler, assuming that the required analytical capabilities are also present. Table 6 lists the DDDM enablers that have been identified in the mining industry.

Table 6: Enablers of DDDM in the mining industry

Enabler	Explanation	Source
Availability of real-time data	Integrating different parts of a value chain through digitisation or implementation of IoT technologies enables all stakeholders to share and access data easily across the value chain, enabling them to make data-driven decisions.	[2]
	Mining machines can now monitor mining activities and environmental conditions, providing this information to operators in real time.	[35]
	Smart sensors can be used throughout mining operations to collect information from machines and equipment, supporting decision-making.	[12]
Availability of sensor data	Sensor data can provide an improved understanding of the complex mining process, which assists decision-making.	[21]
Availability of integrated data	The availability of integrated qualitative data assists with decision-making that considers the holistic nature of mining activities and their social impact.	[20]
Data visualisation	IoT platforms include functionality such as visualising large data sets to make it understandable to the observer, allowing them to perform visual exploration and analysis.	[16]
Data processing/analytics	In the Australian mining industry, advanced data processing technology is used to process large amounts of data collected from sensors, allowing the data from different sections to be reconciled. This has allowed the establishment of data-driven decision support systems.	[36]
	The use of big data and data analytics enables the comprehensive assessment of data obtained from various sources, and enables real-time decision-making.	[36]

4.4. What lessons can be learnt from previous DDDM implementations?

The literature reviewed for this study contained several references to instances where DDDM or tools related to DDDM were implemented. In some cases, specific lessons can be learnt from these case studies.

- The implementation and integration of advanced technologies at different levels of the mining business are not as simple as often promised [2]. For example, many ERP systems cannot provide transparency for lower-level processes because they were not explicitly designed for the mining industry [2].
- The mining industry often does not make the best use of the available technology that would allow it to integrate information and report from different systems [2]. Usually these systems are operated in silos, requiring manual data transfer and reporting between systems [2].
- Quality data is required for DDDM; decisions made from data with high uncertainty are often unreliable, and can even be costly to a mining organisation [20], [26].
- Even though large amounts of data are often available, the implementation of complex models can often be limited because the correct data is not available or the appropriate people do not have access to the required data [32].
- Implementation of DDDM is not only technology-dependent, but also depends on organisational effort [15]. An organisation that has not received the required training or that does not see the advantage of DDDM will likely be unsuccessful in implementing it [15].

- Data that is not integrated between systems is often not available to decision-makers, causing decisions to be made without considering information that would have influenced them [28].
- Information related to equipment maintenance and operations that could be used to implement predictive maintenance is only usable if the maintenance organisation or department is prepared to take advantage of the information [15].

5. CONCLUSIONS

DDDM requires the technology to collect data and the ability to analyse the collected data. Having one without the other would make it very difficult to get value out of DDDM. Therefore, mining companies must be aware of the capabilities needed for DDDM and of the need to build an organisational culture that strives to be data-driven.

Many mining companies are aware of DDDM, and have invested in the technology that would enable it. Still, it is not yet clear that they have become data-driven organisations. [19] find that many mining companies struggle to retain staff with the required expertise in new technologies and to modify their business models to allow the better use of technologies that enable DDDM.

The literature suggests that the mining industries in some countries or regions have made more progress in adopting DDDM than in others. Russia and Australia specifically stand out as countries that have made good progress or that are currently focusing on DDDM and I4.0 in their mining industries [9], [36].

6. RECOMMENDATIONS

This scoping review has considered only four articles published by South African researchers. Thus, it lacks local context. Nevertheless, researchers [1], [2] have argued that there is substantial potential to improve the productivity and societal contribution of the local mining industry. Therefore, a qualitative study based on primary data and focused on evaluating the available tools, the potential benefits, the key enablers, and the lessons learned from local projects related to DDDM could assist with developing an implementation framework for the South African mining industry. Apart from this, a further thematic review could strengthen the arguments of this paper.

REFERENCES

[1] **D. Antin**, "The South African mining sector: An industry at a crossroads," *Economy Report South Africa*, 2013. [Accessed Online 26 October 2022]. Available: https://southafrica.hss.de/fileadmin/user_upload/Projects_HSS/South_Africa/170911_Migration/Mining_Report_Final_Dec_2013.pdf

[2] **M. Sishi, & A. Telukdarie**, "Implementation of Industry 4.0 technologies in the mining industry: A case study," *Int. J. Min. Miner. Eng.*, vol. 11, no. 1, pp. 1–22, 2020.

[3] **E. Brynjolfsson, L.M. Hitt, & H.H. Kim**, "Strength in numbers: How does data-driven decision making affect firm performance? 2011 [Accessed Online 26 October 2022]. Available: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1819486.

[4] **C. Qi**, "Big data management in the mining industry," *Int. J. Miner. Metall. Mater.*, vol. 27, no. 2, pp. 131–139, 2020.

[5] **T.H. Davenport, J.G. Harris, D.W. de Long, & A.L. Jacobson**, "Data to knowledge to results: Building an analytic capability," *Calif. Manage. Rev.*, vol. 43, no. 2, pp. 117–138, 2001.

[6] **E. van der Horn, & S. Mahadevan**, "Digital twin: Generalization, characterization and implementation," *Decis. Support Syst.*, vol. 145, no. 1, pp. 1–11, 2021. doi: 10.1016/j.dss.2021.113524.

[7] **F. Coelho, S. Relvas, & A.P. Barbosa-Póvoa**, "Simulation-based decision support tool for in-house logistics: The basis for a digital twin," *Comput. Ind. Eng.*, vol. 153, no. 1, pp. 1–15, 2021.

[8] **L. Jia, D. Hall, & J. Song**, "The conceptualization of data-driven decision making capability," Presented at Twenty-first Americas Conference on Information Systems, Puerto Rico, 2015.

[9] E. **Dotsenko, N. Ezdina, N. Breider, & S. Khouri**, "Digital modernization of the Russian mining sector in accordance with the National Technology Initiative and Mining 4.0," in E3S Web of Conferences, vol. 278, 2021, p. 3003.

[10] **O. Troisi, G. Maione, M. Grimaldi, & F. Loia**, "Growth hacking: Insights on data-driven decision-making from three firms," *Ind. Mark. Manag.*, vol. 90, 1, pp. 538–557, 2020.

[11] **F. Provost, & T. Fawcett**, “Data science and its relationship to big data and data-driven decision making,” *Big Data*, vol. 1, no. 1, pp. 51–59, 2013.
[12] **F. Sánchez, & P. Hartlieb**, “Innovation in the mining industry: Technological trends and a case study of the challenges of disruptive innovation,” *Mining, Metall. Explor.*, vol. 37, no. 1, pp. 1385–1399, 2020.
[13] **D. Radchenko, & A. Bondarenko**, “Mining engineering system as an energy asset in Industry 4.0,” in E3S Web of Conferences, vol. 58, 2018, p. 1009.
[14] D. **Pałaka, B. Paczesny, M. Gurdziel, & W. Wieloch**, “Industry 4.0 in development of new technologies for underground mining,” in E3S Web of Conferences, vol. 174, 2020, p. 1002.
[15] **S. Fiscor**, “Putting Information to work,” *Eng. Min. J.*, vol. 218, no. 2, pp. 40, 2017.
[16] **P. Gackowiec, & M. Podobińska-Staniec**, “IoT platforms for the mining industry: An overview,” *Inżynieria Miner.*, vol. 21, no. 1, pp. 267–272, 2019.
[17] **T. Bartnitzki**, “Mining 4.0: Importance of Industry 4.0 for the raw materials sector,” *Artif. Intell.*, vol. 2, no. 1, pp. 25–31, 2017.
[18] **K. Bertayeva, G. Panaedova, N. Natocheeva, & T. Belyanchikova**, “Industry 4.0 in the mining industry: Global trends and innovative development,” in E3S Web of Conferences, vol. 135, 2019, p. 4026.
[19] **M. Sukiennik**, “Challenges faced by businesses in the mining industry in the context of the industry 4.0 philosophy,” *Multidiscip. Asp. Prod. Eng.*, vol. 1, no. 1, pp. 621–626, 2018.
[20] **V.N. Kazakidis, Z. Mayer, & M.J. Scoble**, “Decision making using the analytic hierarchy process in mining engineering,” *Min. Technol.*, vol. 113, no. 1, pp. 30–42, 2004.
[21] **C. Paduraru, & R. Dimitrakopoulos**, “Responding to new information in a mining complex: Fast mechanisms using machine learning,” *Min. Technol.*, vol. 128, no. 3, pp. 129–142, 2019.
[22] **P. Gackowiec, M. Podobińska-Staniec, E. Brzychczy, C. Kühlbach, & T. Özver**, “Review of key performance indicators for process monitoring in the mining industry,” *Energies*, vol. 13, no. 19, pp. 1-20, 2020.
[23] **J. Duarte, F. Sousa, & B. Valente**, “Use of geotechnologies in mining planning in quarries carbonated rocks: Contribution to the digital transition (Industry 4.0),” In *IOP Conference Series: Earth and Environmental Science*, vol. 906, no. 1, 2021, p. 12015.
[24] **J. Brodny, & M. Tutak**, “Analysing the utilisation effectiveness of mining machines using independent data acquisition systems: A case study,” *Energies*, vol. 12, no. 13, pp. 1-15, 2019.
[25] **V. Adjiski, Z. Despodov, D. Mirakovski, & D. Serafimovski**, “System architecture to bring smart personal protective equipment wearables and sensors to transform safety at work in the underground mining industry,” *Rud. Zb.*, vol. 34, no. 1, pp. 37–44, 2019.
[26] **J.N. de Meyer**, “Validating the integrity of single source condition monitoring data,” M. thesis, North-West University (South Africa), 2020.
[27] **M.O. Gökalp, K. Kayabay, E. Gökalp, A. Koçyiğit, & P.E. Eren**, “Assessment of process capabilities in transition to a data-driven organisation: A multidisciplinary approach,” *IET Softw.*, vol. 15, no. 6, pp. 376–390, 2021.
[28] **G. Wang, Y. Xu, & H. Ren**, “Intelligent and ecological coal mining as well as clean utilization technology in China: Review and prospects,” *Int. J. Min. Sci. Technol.*, vol. 29, no. 2, pp. 161–169, 2019.
[29] **D. Kulkarni**, “Internet of Things in Finnish metal industry,” Master of Science thesis, Tampere University of Technology, Finland, 2018.
[30] **C. Meng, S.S. Nageshwaraniyer, A. Maghsoudi, Y.-J. Son, & S. Dessureault**, “Data-driven modeling and simulation framework for material handling systems in coal mines,” *Comput. Ind. Eng.*, vol. 64, no. 3, pp. 766–779, 2013.
[31] M. **Li, X. Zhang, S. Mao, & Q. Liu**, “Study of deep mining safety control decision making system,” *Procedia Earth Planet. Sci.*, vol. 1, no. 1, pp. 377–383, 2009.
[32] **H. Al-Chalabi, J. Lundberg, A. Ahmadi, & A. Jonsson**, “Case study: Model for economic lifetime of drilling machines in the Swedish mining industry,” *Eng. Econ.*, vol. 60, no. 2, pp. 138–154, 2015.
[33] **M. Hodkiewicz, S. Richardson, & R. Durham**, “Challenges and opportunities for simulation modelling integrating mine haulage and truck shop operations”, Proceedings of 2010 Australian Mining Technology Conference, pp. 163-172, Perth, 2010.
[34] **A. Morshedlou, H. Dehghani, & S.H. Hoseinie**, “A data driven decision making approach for long-wall mining production enhancement,” *Min. Sci.*, vol. 26, no. 1, pp. 7–20, 2019.
[35] M. **Rylnikova, D. Radchenko, & D. Klebanov**, “Intelligent mining engineering systems in the structure of Industry 4.0,” in E3S Web of Conferences, vol. 21, 2017, p. 1032.
[36] **H. Jang, & E. Topal**, “Transformation of the Australian mining industry and future prospects,” *Min. Technol.*, vol. 129, no. 3, pp. 120–134, 2020.