A value-add driven report development framework for mining industries

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Thesis accepted in fulfilment of the requirements for the degree *Doctor of Philosophy Development and Management Engineering* at the North-West University

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Graduation: August 2021

Student number: 23527986

ABSTRACT

Title: A value-add driven report development framework for mining industries

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The South African mining industry is vital to the country's economy, but it is under pressure to remain profitable and sustainable. Although many studies have focussed on how to optimise mining operations, they have used a single underutilised optimisation strategy as their data. Several industries use business intelligence (BI) to create value by gathering, analysing and presenting data. The South African mining industry is, however, still in the early stages of adopting BI.

Practical outcomes from BI start by developing reports. These reports are used for making data-driven decisions that add value to businesses. Since no BI implementation guideline has been developed specifically for the mining industry, this study analysed the available guidelines critically to compare with the mining industry's BI requirements.

Three shortcomings were identified from the existing BI implementation guidelines. Firstly, none of the available guidelines evaluate the impact of developed reports on real-world operations. Secondly, these guidelines are too high level and lack the structure that will allow incremental improvements to be identified in reporting. Thirdly, there is a lack of practical guidance for report developers within the available guidelines.

A comprehensive literature review was completed in three different research fields with the aim of addressing each shortcoming. The knowledge gained from the literature review was used to create a new report development framework for mining industries that addresses these shortcomings. The framework consists of three phases. In the first phase, planning is completed in a structured manner by using structured reporting qualities identified in the literature review. These reporting qualities are focus area, data availability, analytics, and visualisation. The structured reporting qualities allows report developers to assess each reporting quality and identify specific objectives for incremental improvement.

Practical guidance is provided by using project management concepts such as identifying specific role players, prioritising objectives and completing them in an iterative manner to deliver practical results. The iterative execution of objectives takes place in the second phase of the framework to deliver a report that can be used for valuable data-driven decision-making. In the third phase of the framework, both the qualitative and quantitative impact of the developed report are evaluated through end-user surveys.

The framework was verified by successfully applying it to three diverse case studies in the gold mining industry. In Case Study A, a report was developed to assist with mine operational water management by using available data that has not been used previously. Case Study B focussed on equipment condition monitoring and presented a data-rich problem for which a report was developed to rank equipment condition. Case Study C converted ad hoc calculations to interactive reports to evaluate future carbon tax liabilities.

The case studies show that clear reporting objectives can be identified using structured reporting qualities. These objectives can be executed incrementally to achieve practical results. The qualitative and quantitative impact evaluation by end-user surveys indicate a total value add from R80 000 to R15.4 million for all three case studies. The information collected from the end-user surveys were validated by comparing the results with associated literature. This impact evaluation validated that increased data utilisation in the developed reports adds value to the respective mining operations.

This study was found to be applicable to multiple possible use cases in addition to the case studies presented in this document. It is, therefore, expected that the application of the developed framework can add value to the mining industry in general.

Keywords: Data-driven decision-making, business intelligence, reporting, mining industry, structured reporting, practical guidance, impact evaluation.

RELATED PUBLICATIONS

Two peer-reviewed journal articles have been published to support this document. These articles were submitted to be presented at the annual South African Institute for Industrial Engineering conferences. Firstly, the papers were peer-reviewed before presentation. Secondly, both papers were selected as part of the best papers and were reviewed for publication as full journal papers in a special edition of the ISI-listed (International Scientific Indexing) *South African Journal of Industrial Engineering*.

The first article is titled "Finding the four qualities of intelligent industrial reporting" [1]. It was presented at the 30th annual conference of the South African Institute of Industrial Engineering, held from 1–3 October 2019 in Port Elizabeth, South Africa. The theme of the conference was *neXXXt: Alternative realities, real alternatives*. This conference was selected as the platform to present the paper since reports may present an alternative to understand the intricate nature of real-world operations better. The full article is given in Appendix C.

The second article is titled "Evaluating the impact of operational reports" [2]. It was presented at the 31st annual conference of the South African Institute of Industrial Engineering, held virtually from 5–7 October 2020. The theme of the conference was *Green: Being the change*. This conference was chosen to present the paper as it focussed on evaluating the impact of reports of environmental importance in the South African mining industry. The full article is given in Appendix B.

ACKNOWLEDGEMENTS

I would like to thank Prof. Edward Mathews, Prof. Marius Kleingeld and Dr Hendrik Brand for the opportunity and resources to continue with my post-graduate studies. Thank you to Enermanage (Pty) Ltd and its sister companies that provided the financial support to make this study possible.

I would also like to thank my fellow students and colleagues at the Centre for Research and Continued Engineering Development Pretoria for their assistance throughout this study. A special thanks for the valuable inputs from Johan Bredenkamp.

To Dr Waldt Hamer and Dr Walter Booysen, thank you for your guidance, time and support. You are the Jedi masters of my professional and academic career. Your leadership and mentoring are greatly appreciated.

To my father, Andre Botes, a very special thanks for your continued support throughout my years of study. Finally, I would also like to thank Grant Watters for your love and support.

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GLOSSARY

This section defines terms used throughout this document in context with the scope of this study.

Business intelligence	A combination of technological systems used to gather, analyse and present business-related data to end users by means of reporting. Business intelligence (BI) intends to use business-related data to improve operations by means of data-driven decision-making.
BI implementation guideline	A set of guidelines to follow when gathering, analysing and presenting business-related data.
Data-driven decision-making	The notion to rely on data sources (rather than intuition or experience) to trigger and support business-related decisions. Data sources are typically traceable to measurement points captured via a data pipeline.
Data pipeline	A data pipeline refers to the flow of data through the various technologies, infrastructure and processes used to gather, analyse and present business-related data. Data pipelines are used to gather data from measurement points and supply it in usable formats for reporting purposes.
Report	Used to convey specific information regarding operations to aid data-driven decision-making. A report may be based on different reporting mechanisms such as batch, automated or interactive reporting outcomes depending on the data pipeline's capabilities. A report may refer to a single report (such as a document or dashboard) or a set of similar reports forming a group report (such as a set of documents or a reporting platform).
Reporting application	The process of developing a report by means of gathering, analysing and presenting business-related data. Reporting applications extract data from a data pipeline, analyses it, and presents it via a report to end users.
Report developer	Term used to collectively refer to all role players involved with the reporting application.
Operation	The term collectively refers to the business activities, systems, sites or organisations where a BI reporting application takes place. Since this study focusses on the mining industry as opposed to financial institutions, reports mainly refer to operational reports that contain information with respect to measured parameters on practical operations.
Value add	The value obtainable in real-world operations resulting from the use of reports for data-driven decision-making, which may lead to action. This value may be qualitative or quantitative in nature.

ABBREVIATIONS

Abbreviation	Description
BI	Business Intelligence
CRISP-DM	Cross-Industry Standard Process for Data Mining
DIKW	Data-Information-Knowledge-Wisdom
DSR	Design Science Research
GDP	Gross Domestic Product
GHG	Greenhouse Gas
ISI	International Scientific Indexing
IT	Information Technology
IWWMP	Integrated Water and Waste Management Plan
KDD	Knowledge Discovery in Databases
KDDA	Knowledge Discovery via Data Analytics
KDDM	Knowledge Discovery and Data Mining
KPI	Key Performance Indicator
OPC	Open Platform Communication
SEMMA	Sample, Explore, Modify, Model, Assess
SCADA	Supervisory Control and Data Acquisition
SLR	Systematic Literature Review
TDSP	Team Data Science Process

CHAPTER 1

BACKGROUND AND RELEVANCE

1. BACKGROUND AND RELEVANCE

1.1 MINING INDUSTRY

The South African mining industry plays a vital role in the country's economy. The sector contributes to the gross domestic product (GDP), employment, generating tax revenues, and export sales. In 2019, the mining industry contributed 8.3% of the total GDP while contributing 460 015 jobs [3]. The mining industry's contribution to the GDP and employment has, however, been decreasing over the past few years in comparison with other industries in the country [4].* The mining industry faces challenges that threaten its survival and competitiveness [5]. As an example, despite holding the third-highest ranking in gold ore reserves, South Africa's gold production has decreased significantly from their once leading position while the global gold production has been on an upward trend [6], [7].

The industry faces ever-increasing production costs such as electricity, labour and infrastructure [5]. To remain profitable, the mining industry should use all available tools to assist business. The South African mining industry requires practical solutions owing to unique challenges [5], [8], such as being home to some of the deepest mines in the world and using conventional labour-intensive mining techniques [5]. Multiple studies specifically on South African mines have, therefore, focussed on optimising mining operations, energy efficiency and water usage [7], [9]–[12].

Business intelligence (BI) is a tool used by various industries to add value. Data is increasingly being viewed as an important resource with significant potential value in business [13]. The increasing use of BI is further supported by the need to comprehend information from data, which is generated continuously and increasingly, for business benefits that are nearly impossible by manual means [14].

It has been shown that developing countries [15] and South African industries [16] in general are lagging behind in digital transformation. More specifically, the South African mining industry is still facing challenges with adopting BI [17]. It has further been reported that although the South African mining industry generates a vast amount of operational data, it does not use it for value creation [18]. Durrant-Whyte [19] reports that some mining companies use less than 1% of their available data due to a lack of capturing, analyses and visualisation of data. This is presented in Figure 1-1. Thus, it can be deduced that the South African mining industry is still in the early stages of BI adoption.

*The Editor. The impact of mining on the South African economy and living standards. *The Federation for Sustainable Environment*, 2018. [Online]. Available: http://fse.org.za/index.php/item/593-the-impact-of-mining-on-the-south-african-economy-and-living-standards [Accessed: 14-Feb-2021].

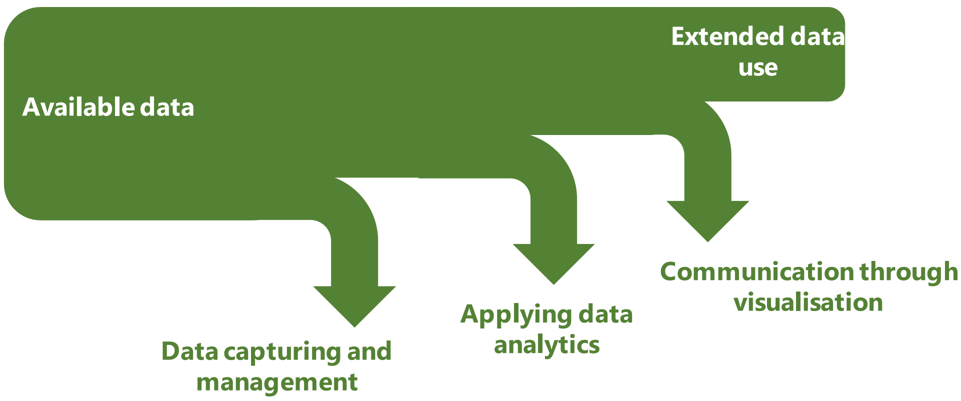


FIGURE 1-1: CHALLENGES ASSOCIATED WITH THE EXTENDED USE OF DATA [19]

The underutilisation of data creates scope for additional research in the field of BI and the South African mining industry to create practical value. To explore this further, the next section elaborates on BI requirements.

1.2 BUSINESS INTELLIGENCE REQUIREMENTS

What is business intelligence?

Data generation is increasing at a rapid speed. As early as 2015, it was projected that data quantities would increase annually with 4 300% by 2020 [20]. The increase is attributed to the availability of various technologies that cause data to expand in volume, be generated at higher velocities, and becoming available from a variety of sources [21]. This is referred to as big data. With the aim of creating a competitive advantage, industries want to use this data for knowledge discovery [21].

Industry refers to the process of transforming data into information and knowledge as BI [22], [23]. This knowledge contributes to valuable data-driven decision-making. BI uses various technologies to gather, analyse and present data for managerial purposes [24]. Figure 1-2 shows how BI concepts aid in the decision-making process.

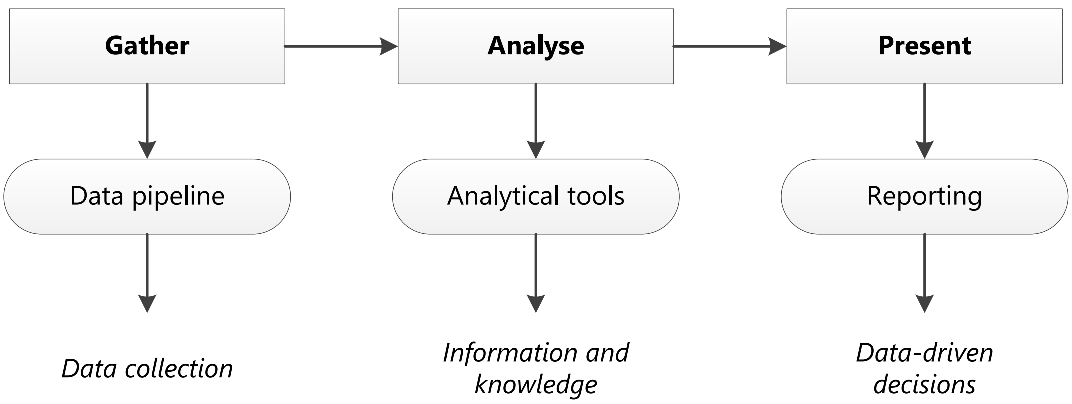


FIGURE 1-2: THE ROLE OF BI IN DATA-DRIVEN DECISION-MAKING (ADAPTED FROM [24]–[26])

Data pipelines are used to collect, store and manage the various forms of generated data, which is used as an input to the BI process. Analytical tools are used to extract information and knowledge from the data. Thereafter, analyses are presented to relevant decision makers in various forms such as reports and dashboards. Users view reports to understand their systems and identify decisions that need to be made, which lead to valuable outcomes.

The value of business intelligence

Figure 1-3 depicts the Data-Information-Knowledge-Wisdom (DIKW) hierarchy [27], [28]. It starts with raw data in its unprocessed state, which is generally available at a high level of detail, but a low level of value. With data analytics in BI systems, wisdom can be extracted and the pinnacle point of the DIKW hierarchy can be reached. Wisdom generally contains a low level of detail and high value insights.

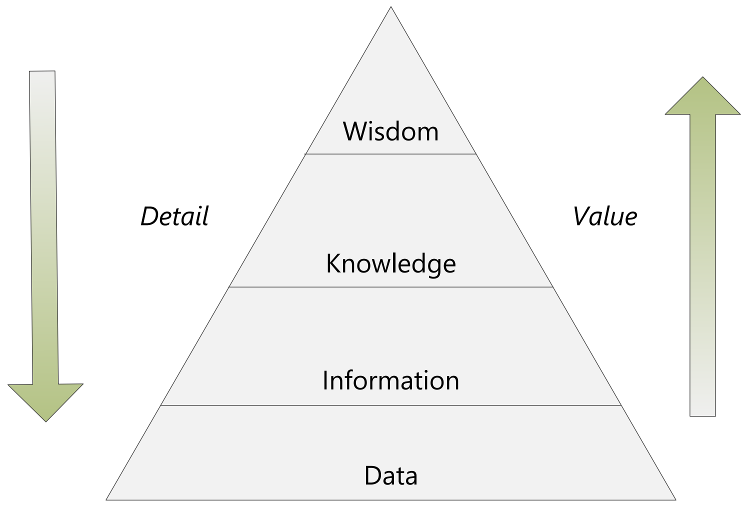


FIGURE 1-3: THE DIKW HIERARCHY [27], [28]

Analytical techniques are applied in various cases, such as analysis, monitoring, observation, knowledge generation, diagnosis, decision-making, feedback, and optimisation [29]. Many studies have reported the benefits of implementing BI as [30], [31]:

- Data and information access
- Threat and opportunity identification
- Knowledge discovery
- Information sharing
- Efficiency assessment
- Increase in business performance and management thereof
- Decision-making
- Time and cost saving

However, the core driver for applying BI in industry is objective data-driven decision-making [1], [11] in order to obtain timely and accessible information about an organisation, from which insights can be acquired to assist with decision-making [33], [34]. It has been shown that the use of data-driven decision-making as an alternative to intuitive-based decision-making increases an organisation's productivity and profitability [35].

However, Olszak and Ziemba [25] explain that BI implementation and report development are time, financially and resource intensive. Thus, when applying BI to the mining industry, it is critical to evaluate the impact of reports. This will not only prove and identify the exact value that is obtained and enable transparent communication to all stakeholders involved, but also justify the inputs required for report development.

Operational reporting as a first step towards business intelligence adoption

Various BI maturity models exist [36]–[38], which represent a BI adoption life cycle [36]. As the adoption of BI changes over time, the BI maturity models detail the level of BI adoption and the evolutionary path of transformation from an initial level to a target level [37]. BI maturity models include the following:

- Business Information Maturity Model [39], [40]
- Wayne Eckerson's TDWI's Business Intelligence Maturity Model that mainly focusses on technical maturity assessment [41]
- Gartner's Maturity Model for Business Intelligence and Performance Management [36]
- AMR Research's Business Intelligence/Performance Management Maturity Model [42]
- Business Intelligence Maturity Hierarchy based on the DIKW hierarchy [43]

Rajteric [36] compared many of these BI maturity models. This section summarises the comparison and evaluates the BI outcomes from the different models. Figure 1-4 presents the different maturity models while their BI outcomes are shown in green at the bottom of the figure. Each model evaluates BI maturity according to different aspects, such as technologies, data reliance and management methods. However, as the main focus of this study is to add value from data utilisation, the BI outcomes identified from the different models are evaluated in this section.

The BI maturity models identify that the BI outcomes during the initial levels of BI adoption evolve from spreadsheets and ad hoc reporting to automated and interactive reports [36], [39]–[43]. Thereafter, more advanced prediction and modelling tools are incorporated. The mining industry thus need to adopt the culture of using their available data in the first levels of BI before adopting advanced technologies such as prediction and modelling tools. Therefore, report development is the focus of this study, which excludes advanced levels of BI such as artificial intelligence (AI).

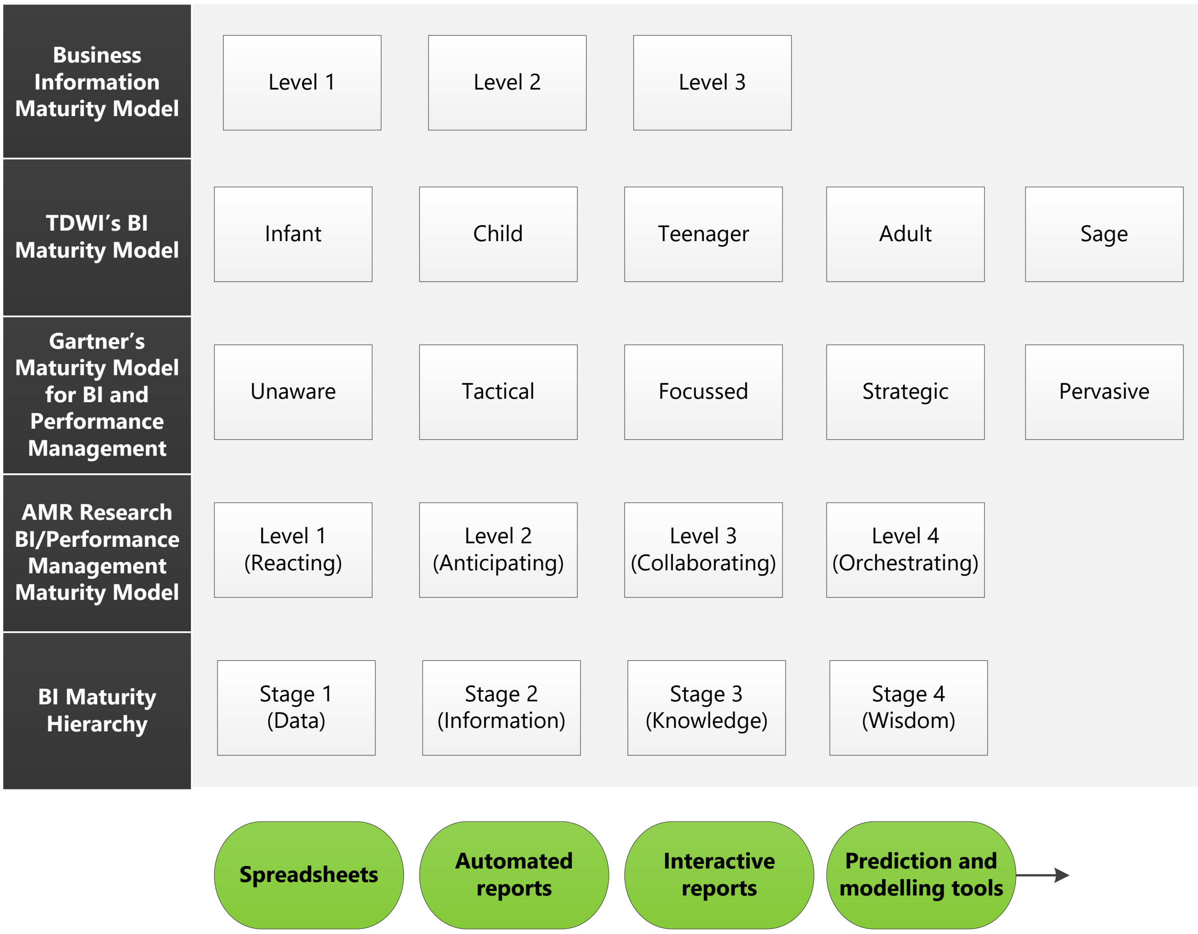


FIGURE 1-4: BI MATURITY MODELS WITH THEIR OUTCOMES (ADAPTED FROM [36], [39]–[43])

Considering that the South African mining industry has been identified as being in the early stages of BI adoption (Section 1.1) and that BI has different phases of adoption that change over time (BI maturity models), it is critical to implement BI improvements incrementally. It is further required to identify where reporting is in this incremental process in order to identify which incremental step to take next for advancing with reporting.

Practical implementation of business intelligence

Multiple studies have evaluated the critical success factors for BI implementation. A study by El-Adaileh [44] identified the following success factors:

- Management support
- Data sources systems
- Organisational resources
- Information technology (IT) infrastructure

- Vision
- Project champion
- Team skills
- Project management
- User participation
- Change management

A study conducted by Yeoh [45] identified similar success factors:

- Committed management support and sponsorship
- Business user-orientated change management
- Clear business vision and well-established case
- Business-driven methodology and project management
- Business-centric championship and balanced project team composition
- Strategic and extensible technical framework
- Sustainable data quality and governance framework

In this study, the above-mentioned success factors are grouped into three main groups, namely: managerial support; technical skills; and project management and practical guidance. Before adopting BI, success factors such as vision and managerial support are important (managerial support group). During the implementation of BI, practical guidance is critical to know how to use available technical skills, manage change, and ensure practical results. It is, therefore, critical that guidelines for BI implementation provide sufficient practical guidance. The requirement for comprehensive practical guidance is supported by the fact that the mining industry is in the early stages of adopting digital concepts.

Summary of key requirements for business intelligence implementation guidelines

This section evaluated BI and identified requirements of BI implementation guidelines in the South African mining industry. It was identified that BI implementation guidelines must:

- Evaluate impact [25], [30], [31], [35]
- Be structured [36]–[43]
- Provide practical guidance [44], [45]

It was highlighted that the main driver for BI implementation is data-driven decision-making. However, because BI implementation is time, resource and financially intensive, it is necessary to evaluate the reports comprehensively to fully gauge the impact that reports have on real-world operations.

It was identified from the BI maturity models that BI evolves through various phases as time goes by. Taking this and the fact that the South African mining industry is in the early stages of BI adoption into consideration, BI implementation guidelines should be structured to allow for incremental improvements. This structure should allow report developers to evaluate their reporting applications and identify specific areas for improvement.

By evaluating the BI success factors it was identified that BI implementation guidelines have to provide sufficient practical guidance. This guidance is necessary to ensure that practical results are obtained that provide value. The South African mining industry requires this guidance since they are in the beginning phases of utilising data fully.

1.3 CRITICAL ANALYSIS OF AVAILABLE GUIDELINES

This section describes how research was conducted to identify the guidelines for report development, whereafter a critical analysis of available guidelines was completed. Table 1–1 shows the criteria for study selection during the search.

TABLE 1-1: CRITERIA FOR CRITICAL ANALYSIS STUDIES SELECTION

Criteria	Justification
Journal articles or conference proceedings.	High academic relevance.
Between 2000 and 2020.	Up-to-date guidelines (a quick search in relevant databases revealed that BI started being relevant from the early 2000s).
Business/organisation guidelines.	The aim of this study is to achieve practical outcomes and, therefore, guidelines published by businesses and organisations with practical experience are included.
Keywords (BI framework, big data analytics framework, industrial analytics, practical).	Although the focus of this section is on identifying guidelines for report development, an initial search showed that published guidelines refer to a broader pool of terms and not specifically to report development frameworks.

The search resulted in 14 relevant guidelines. It was found that no guidelines were available for report development specifically. Available guidelines commonly refer to data exploration or high-level BI adoption. Furthermore, no guidelines were specific to mining industries. The 14 guidelines are summarised in Table 1–2 while a detailed critical analysis and description of each guideline are presented in Appendix A.

Each guideline was analysed critically to evaluate its usefulness to the mining industry for report development by using the three requirements for BI implementation as identified in Section 1.2. Firstly, it was evaluated whether the guidelines allow for impact evaluation of the outcomes. Secondly, it was evaluated whether the guidelines were structured to allow for incremental improvements. Thirdly, it was evaluated whether the guidelines provide sufficient practical guidance, such as describing project management steps and ensuring that practical results can be obtained.

Table 1-2: Summary of critical analysis of existing BI implementation guidelines

No.	Ref	Guideline	Impact evaluation	Structure	Practical guidance
1	[34]	Life Cycle of BI System	✘	✘	✘
2	[25]	Methodology of Implementing BI Systems	✘	✘	✘
3	[21]	Snail Shell KDDA Process Model	✘	✘	✘
4	[46]	Big Data Analytics Process	✘	✘	✘
5	[47]	Cross-Industry Standard Process for Data Mining (CRISP-DM)	✘	✘	✘
6	[48]	Big Data Analytical Framework for Energy-Intensive Industries	✘	✘	✘
7	[49]	Data Science Process	✘	✘	✘
8	[50]	Industrial Analytics Process	✘	✘	✓
9	[51]	Data Value Chain for Predictive Maintenance	✘	✘	✘
10	[52]	Process of Knowledge Discovery in Databases (KDD)	✘	✘	✘
11	[53]	Framework for Implementation of Big Data Projects In Firms	✘	✘	✓
12	[54]	Process Model for Big Data Driven Smart Energy Management	✘	✘	✘
13	[55]	Team Data Science Process (TDSP)	✘	✘	✓
14	[56]	Sample, Explore, Modify, Model, Assess (SEMMA)	✘	✘	✘

Impact evaluation

All the guidelines end with operational decision-making or indicate that the knowledge gained from data relates back to real-world operations. However, none of the guidelines elaborate the decisions made or how to evaluate the impact of those decisions. This is a shortcoming in existing literature. The impact of the end result of BI systems (such as operational reports) should be evaluated and included in development guidelines. Guidelines should further be given on how this impact should be evaluated.

Structured

None of the available guidelines provide structure. The guidelines are too high level with generic steps. They were not developed specifically for the mining industry in the early stages of BI adoption. Guidelines need to be more structured to provide the mining industry with sufficient and comprehensive guidelines.

Industries in the early stages of BI adoption will most likely not achieve advanced results immediately and will have to move towards an end goal incrementally. Thus, they have to evaluate where they are in the process and have guidelines for improvement. The available guidelines are oversimplified or one-dimensional, which restricts this identification for incremental improvement.

Practical guidance

Eleven of the 14 available guidelines lack practical guidance. These guidelines contain high-level steps and do not consider practical guidance for implementation. This is supported by Saltz, Shamshurin and Crowston [57] who also explain that many of these well-known guidelines do not have sufficient practical guidelines.

Only the industrial analytics process [50], framework for implementation of big data projects in firms [53], and the TDSP [57] contain practical guidance for identifying specific role players involved with various steps of the process. It is required to identify what practical guidance is required and whether the guidance provided by these two guidelines is sufficient. This is done in the literature review in Section 2.4.

1.4 NEED FOR THE STUDY

Section 1.1 explained that the South African mining industry is vital to the country's economy. However, the industry is under pressure and needs to use all the available tools to add value to operations and to remain profitable and sustainable. Although BI uses data for valuable data-driven decision-making, the South African mining industry is still in the early stages of BI adoption.

Section 1.2 conducted a review of BI. It was found that the first levels of BI adoption include the development of various reporting mechanisms. Key requirements for BI implementation were also identified. Section 1.3 evaluated available BI implementation guidelines against the key requirements. It was determined that the available guidelines are oversimplified and lack impact evaluation, structure and practical guidance for industries that are in the early stages of BI adoption, such as the mining industry.

Impact evaluation is required to fully gauge the impact of data-driven decision-making and evaluate whether reporting has an impact on real-world operations. Structure is required to ensure incremental improvements in reporting and to allow users to identify areas of improvement. Practical guidance is critical to ensure that practical results are obtained. Thus, there is a need for a new value-add driven framework for report development for the South African mining industry that:

- Evaluates impact
- Is structured
- Provides practical guidance

1.5 RESEARCH METHODOLOGY

This chapter highlighted the need for a new value-add driven framework for report development for mining industries that evaluates impact, is structured, and provides practical guidance. To develop the new framework, this study uses a research methodology. Various applicable research methodologies exist, such as action design research [58], design science research (DSR) [59]–[61], and quality research management [62]. Since DSR bridges the gap between 'research' and 'action', it was chosen as the research methodology for this study.

DSR consists of three cycles, namely rigour, relevance, and design. According to Hevner [60], the relevance cycle bridges the relevant environment of research with the design process. The rigour cycle links the design process with knowledge from literature. The design cycle involves building and evaluating design artefacts. Overall, this research is based on the DSR cycles. The document structure is shown in Figure 1-5.

Literature is presented as part of the rigour cycle for each of the three needs highlighted for this study (Chapter 2). The new framework is developed by combining the separate research fields as part of the design cycle (Chapter 3). In Chapter 1, the mining industry was highlighted as the relevant environment of this study. Chapter 4 verifies and validates the developed framework by applying it to case studies in the relevant mining industry. The document ends with a summary of work done and recommendations for future work (Chapter 5).

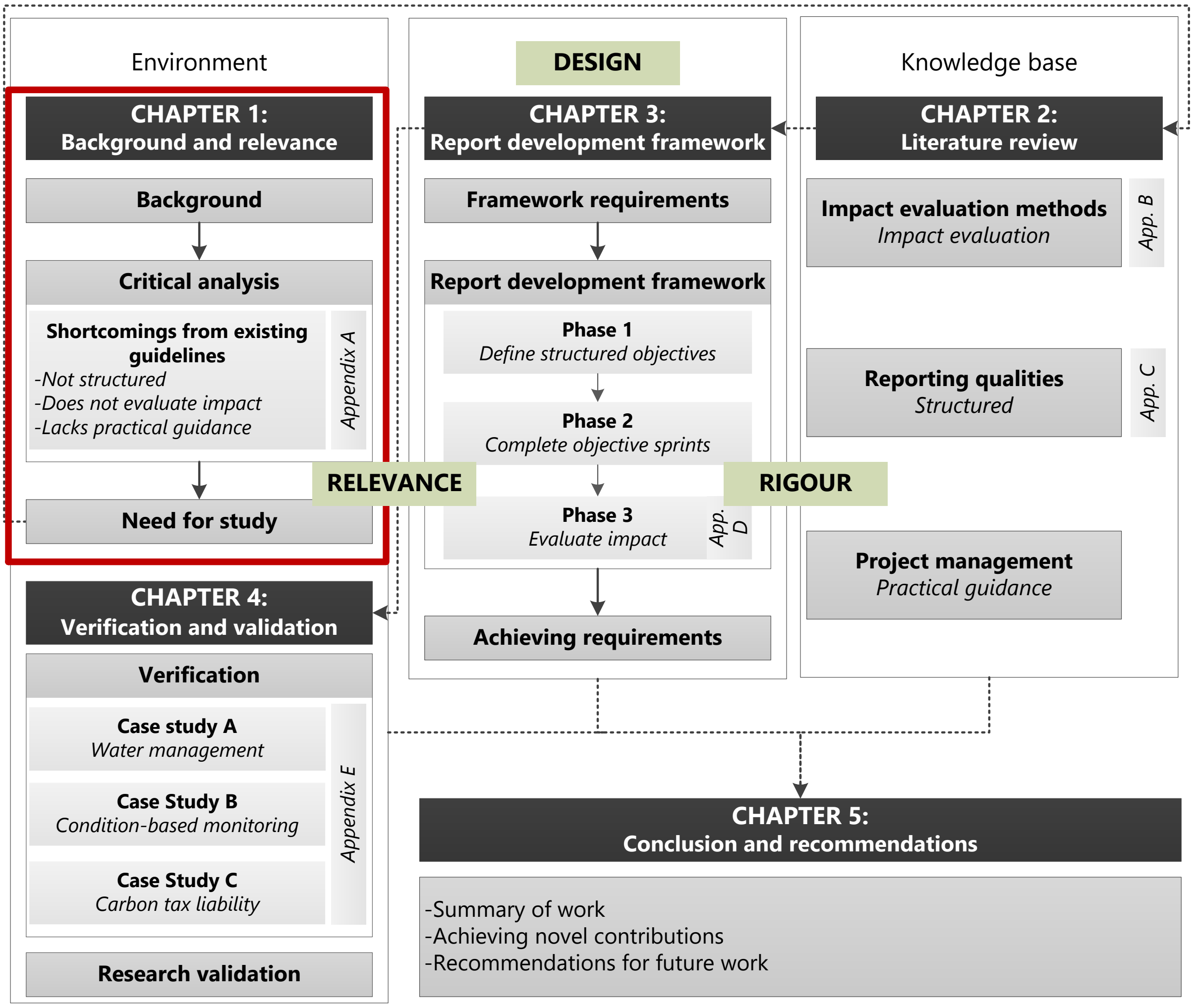


FIGURE 1-5: RESEARCH METHODOLOGY AND DOCUMENT STRUCTURE

1.6 CONTRIBUTIONS OF STUDY

This study highlights the need for a new framework to develop reports that will add value to the mining industry. This framework is developed throughout this document and applied to relevant case studies. The four contributions of this study are listed below and are reviewed again in the concluding chapter (Chapter 5). Contributions 1 and 2 are supported by publications in a peer-reviewed journal [1], [2].

Contribution 1: Evaluation of the impact of operational reports

Chapter 1 highlighted that none of the existing BI implementation guidelines allow for the evaluation of the impact of reports on real-world operations. This is critical since the time and resources put into report development need to be justified while developed reports must add value in practical environments. This value needs to be evaluated.

A systematic literature review (SLR) is completed, which shows that although qualitative factors of reports are generally evaluated via end-user surveys, very little is done to quantify the impact of reports. Knowledge gained from literature is combined to create a new end-user survey to evaluate both the qualitative and quantitative impact of operational reports.

The research is presented in Chapter 2 (Section 2.2). This contribution was published in a peer-reviewed journal [2] (the manuscript of this article is provided in Appendix B). It was also presented at the annual conference of the South African Institute of Industrial Engineering (held virtually from 5–7 October 2020).

Contribution 2: Identification of structured reporting qualities

Chapter 1 demonstrated that existing BI implementation guidelines lack structure for incremental improvement in reporting applications. This is critical since the mining industry is in the early stages of BI adoption and requires structured guidance to identify areas of improvement.

A comprehensive literature review is done by formulating research questions relating to the incremental implementation of BI guidelines. Thereafter, individual research fields are evaluated to address each research question. The four structured qualities of reporting are derived from the literature review, namely: focus area, data availability, analytics, and visualisation. Each quality is verified with practical application to data-driven studies.

The research fields are presented in Chapter 2 (Section 2.3.). This contribution was also published in a peer-reviewed journal [1] (the manuscript of this article is provided in Appendix C). It was also presented at the annual conference of the South African Institute of Industrial Engineering (held during 1–3 October 2019 in Port Elizabeth, South Africa).

Contribution 3: Creation of a new value-add driven report development framework

The critical analysis in Chapter 1 identified shortcomings in existing literature regarding BI implementation guidelines for report development, including the lack of impact evaluation, structured implementation guidelines, and practical guidance. A new framework is developed to address these shortcomings by combining separate fields of research into a new report development framework (Chapter 3). The framework allows for the qualitative and quantitative impact evaluation of developed reports by using end-user surveys as suggested from literature. The framework allows for a structured evaluation of existing reporting applications to identify areas of improvement and to achieve results incrementally. Lastly, the framework provides sufficient practical guidance by using project management concepts such as identifying specific role players, prioritising objectives, and completing them in an iterative manner to deliver practical results.

Contribution 4: Practical implementation of BI concepts on mining case studies

Chapter 1 explained that the South African mining industry is in the early stages of BI adoption [17] and that they do not use their available data to the full extent for value creation [18], [19]. This industry is relevant since it is under pressure to remain cost competitive and profitable [5], [8]. The industry further needs to be innovative with their existing systems to remain sustainable [8], [63]. The chapter clarified that the South African mining industry requires unique solutions for unique problems [5], [8].

The newly developed framework is tested on real-world case studies in the South African mining industry (Chapter 4) to address relevant problems faced in the industry. A diverse range of applications is selected to test the generic applicability of the developed framework. Specifically, reports are developed for three different applications, namely operational water management, condition-based equipment monitoring, and carbon tax liability.

The chapter describes how the impact evaluation end-user surveys prove the quantitative and qualitative value obtained after applying the framework. Independent verification of the value add is completed to validate that data utilisation in the mining industry adds value to real-word operations.

1.7 OUTLINE OF DOCUMENT

Chapter 1

Chapter 1 served as an introduction to this study and provided relevant background. This chapter critically analysed the existing BI implementation guidelines and identified three shortcomings. These shortcomings highlighted the need for a new value-add driven report development framework for mining industries.

Chapter 2

Chapter 2 presents a comprehensive literature review to address each of the three shortcomings identified in Chapter 1. Firstly, existing impact evaluation methods are reviewed to identify how report impact needs to be evaluated. Secondly, the steps involved with existing BI implementation guidelines are studied, which are supported by additional literature to provide structure to the existing steps. Thirdly, project management methodologies are reviewed to identify the key concepts required for practical guidance during report development.

Chapter 3

In Chapter 3, the new value-add driven report development framework is developed by combining all the knowledge gained from the literature review in Chapter 2. The new framework consists of three phases. Firstly, structured planning takes place to identify precise objectives. Thereafter, the objectives are executed in an iterative manner. Lastly, the completed report is evaluated to gauge its impact on real-world operations.

Chapter 4

Chapter 4 verifies the new framework by applying it to three actual case studies. Each case study focusses on a relevant challenge faced by the mining industry, including operational water management, condition-based equipment monitoring, and carbon tax liability. Precise objectives are identified through structured planning. These objectives are executed practically in an iterative manner and the impact of the developed reports are evaluated. Lastly, the impact of the reports on real-world operations are validated by comparing them with associated literature.

Chapter 5

Chapter 5 provides a summary of the work completed in this study. This chapter refers back to the contributions listed in Chapter 1 to prove that all novel contributions have been achieved. Recommendations are made for future studies.

CHAPTER 2

LITERATURE REVIEW

2. LITERATURE REVIEW

2.1 INTRODUCTION

Chapter 1 explained the shortcomings of existing BI implementation guidelines, including the lack of report impact evaluation, structure for incremental improvement and sufficient practical guidance. This chapter provides a comprehensive literature review to address each of these shortcomings. Figure 2-1 shows how the literature fits into the overall research methodology of this document.

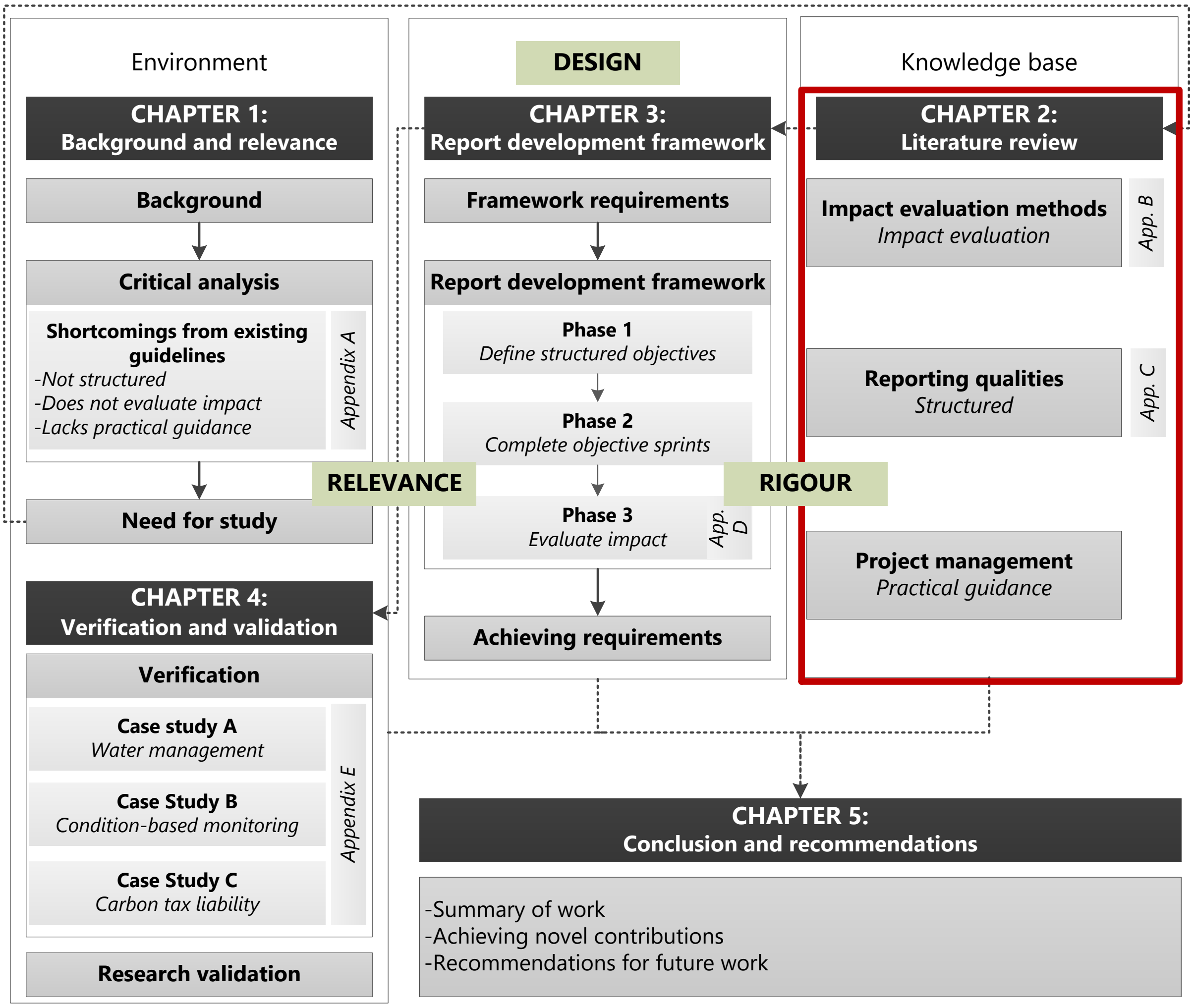


FIGURE 2-1: STUDY RESEARCH METHODOLOGY – CHAPTER 2

Chapter 1 (Section 1.2) described how data from real-world operations is gathered, analysed and presented to end users for data-driven decision-making within BI. Figure 2-2 shows the scope of the literature in this chapter within a basic reporting structure. Firstly, an SLR is conducted to identify how reports are evaluated in existing literature in order to identify how the impact of reports should be evaluated (Section 2.2). Secondly, the steps of BI implementation guidelines are investigated to identify how a structure can be provided that will allow incremental improvement (Section 2.3). Lastly, project management is reviewed to identify how practical guidance can be added to report development frameworks (Section 2.4).

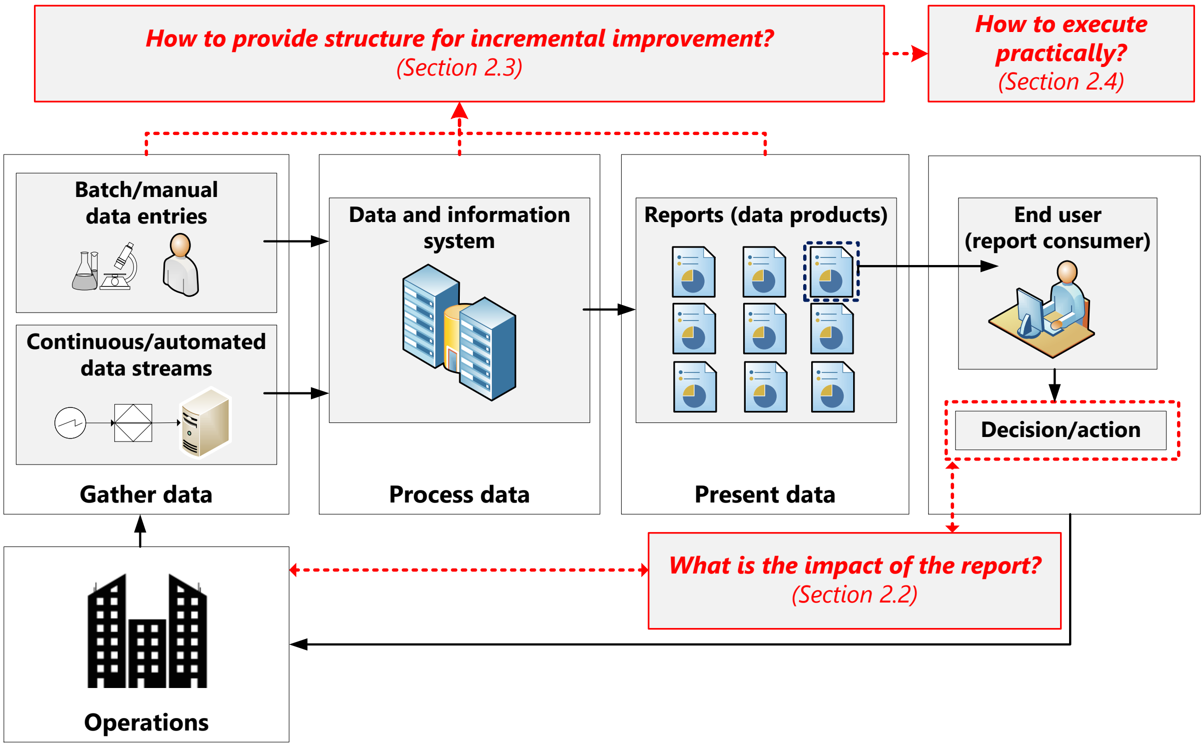


FIGURE 2-2: SCOPE OF LITERATURE REVIEW WITHIN A BASIC REPORTING STRUCTURE

2.2 EXISTING IMPACT EVALUATION METHODS

Chapter 1 explained that none of the available BI implementation guidelines evaluate the impact of developed reports. This is important since report development is time, resource and financially intensive [25]. Report developers thus need to know if the inputs are justifiable. Many reports are developed to address certain objectives or to aid with specific decision-making. However, current guidelines do not evaluate the impact of reports to identify the extent to which these objectives are being reached. Evaluating the impact has the potential of not only increasing communication to stakeholders, but also identifying areas of improvement if objectives are not met. The scope of this section of the literature review is shown in Figure 2-3.

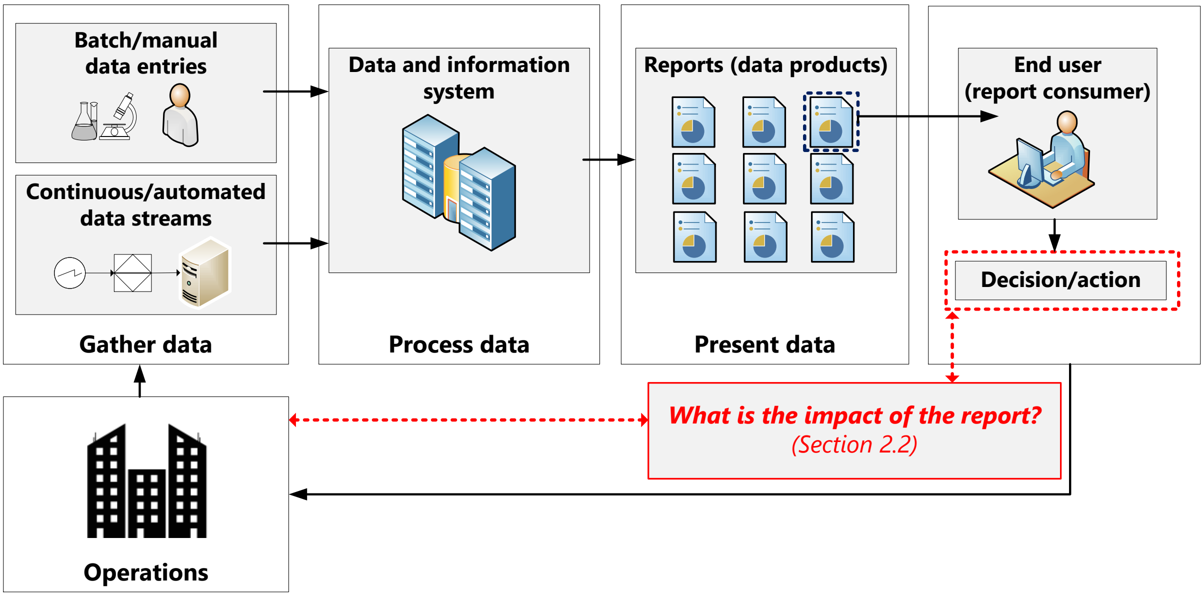


FIGURE 2-3: REPORT IMPACT EVALUATION – SCOPE OF LITERATURE WITHIN A BASIC REPORTING STRUCTURE

Therefore, this section evaluates existing report impact evaluation methods by completing an SLR. Thereafter, the results are reviewed to identify how reports are currently evaluated and suggestions made.

The work in this section is supported by an article published in a peer-reviewed journal [2]. It was also presented at the annual conference of the South Africa Institute of Industrial Engineering held virtually from 5–7 October 2020. The full article can be seen in Appendix B.

2.2.1 SYSTEMATIC LITERATURE REVIEW

An SLR is a step-by-step process used to identify and evaluate available research on a specific topic [64]. This section describes how an SLR was completed to identify and review different methods of evaluating the impact of reports.

An SLR has three main steps [64], [65]. Firstly, databases are searched using relevant keywords. Secondly, the results are filtered to ensure their relevance. Thirdly, the final results are summarised and evaluated critically. The method followed in this study is shown in Figure 2-4 and described thereafter.

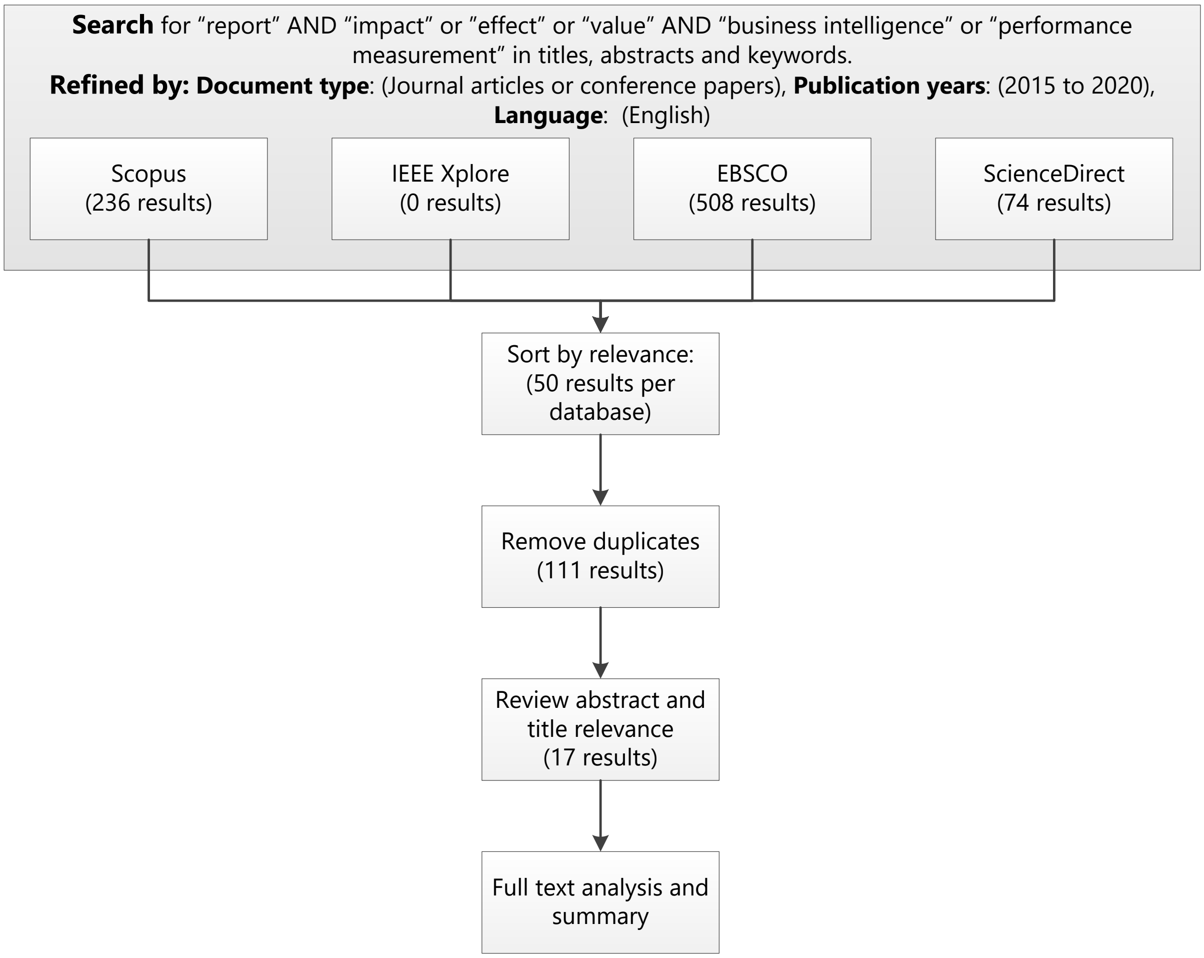


FIGURE 2-4: SLR METHOD AND RESULTS

Keywords were chosen to obtain studies that evaluate the impact of reports in the BI field. Synonyms were included for a holistic search, for example, "impact" or "effect" or "value", and "business intelligence" or "performance measurement". The final keywords used in the database search were "report" and "impact" or "effect" or "value" and "business intelligence" or "performance measurement". The search was completed in four credible databases, namely Scopus, IEEE Xplore, EBSCO and ScienceDirect.

High quality results were ensured by refining the search results to only include journal articles and conference papers. Results were further refined to only consider results from 2015 to 2020 to ensure that the latest studies were included. Only English studies were considered. The initial search results were sorted by relevance and only the top 50 results per database were considered. This ensured that the most relevant studies were included in the evaluation. Thereafter, duplicates were removed, which resulted in a total of 111 unique results. For each of the 111 results, the titles and abstracts were reviewed to establish the relevance to this study. A study was considered relevant if a report was developed or if the impact of either a report or BI system was evaluated. This yielded a total of 17 unique and relevant results.

The full text of the final 17 results was screened to identify four aspects. Firstly, it was identified whether a report was evaluated since some studies developed a report, evaluated an existing report, or evaluated an existing BI system. Secondly, it was identified what method, if any, was used to evaluate the impact of the report or BI system. Thirdly, the factors that were considered in the evaluation were identified. Lastly, the text was screened to identify any listed benefits or achievable value resulting from the associated report or BI system. This was included to gauge the extent of the identified value add from a reporting or BI system. A visual representation of the SLR results of the 17 studies is shown in Figure 2-5.

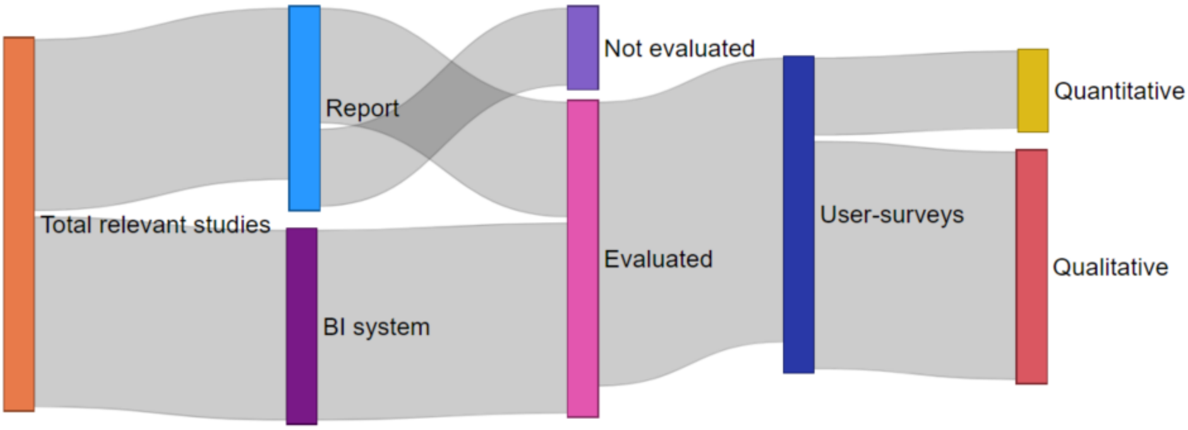


FIGURE 2-5: VISUAL REPRESENTATION OF SLR FULL TEXT RESULTS

Only 17 relevant results were obtained from four large and credible databases [13], [30], [66]–[80]. This low number of studies further emphasises the need for research to evaluate the impact of reports. It was found that mostly BI systems were evaluated and that specific reports were not always evaluated. User surveys were exclusively used to evaluate both reports and BI systems. These surveys prevalently evaluated qualitative factors. Although some studies [73], [74], [79] considered quantitative factors such as time savings, profitability and costs, these factors were still evaluated in a qualitative manner (for example, determined whether profitability increased or decreased without indicating by how much). Other studies highlighted the importance that impact reports should have on quantitative factors, but this impact was not quantified.

Many studies revealed that reports are important to aid with operational and managerial decision-making. A variety of possible benefits resulting from BI systems or reports were obtained from the 17 studies. However, none of the studies attempted to quantify the impact of these possible decision-making values. The listed benefits as a result of decision-making varied from direct impacts (such as making beneficial operational changes and monitoring savings) to indirect impacts (such as complying with guidelines and ensuring sustainable operations).

The next section uses the literature found in this section to identify how reports can be evaluated to fully gauge their impact on real-world operations.

2.2.2 QUALITATIVE AND QUANTITATIVE IMPACT EVALUATION FACTORS

The literature review (Section 2.2.1) revealed that qualitative evaluations are mostly being done; however, little is done to quantify the impact of reports. It is important to consider both qualitative and quantitative factors to fully the impact of reports gauge. Additionally, it could be useful to identify any mismatches between the two factors, which will assist report developers to improve on existing reporting. Therefore, there is a need for a new report evaluation method that considers both qualitative and quantitative factors.

It is suggested that the new report evaluation method makes use of user surveys since surveys are used exclusively in available literature as identified in the SLR. User surveys further provide an indication of the qualitative and quantitative factors from the end user's perspective. This is important since the end user forms a critical part in utilising the reports to make data-driven decisions and ultimately achieve practical impacts on operations.

The following sections describe the qualitative and quantitative factors that were considered in available literature (studies in SLR) and that need to be considered during a new report impact evaluation survey.

Qualitative factors

Table 2-1 summarises the qualitative factors evaluated in the studies obtained from the SLR.

TABLE 2-1: QUALITATIVE FACTORS EVALUATED IN SLR STUDIES

SLR reference	Qualitative factor evaluated
[73]	Productivity, time savings, standardised key performance indicators (KPIs), reliable data sources, effective visualisation, managerial control.
[74]	Performance measurement capabilities: profit-planning information and non-financial KPIs. Competitive advantage: sales growth, market share, profitability (qualitative assessment).
[75]	Strategic and operational capabilities.
[76]	Sophisticated formats and presentation features, interactive reporting, easy to use, rapid refresh times.

SLR reference	Qualitative factor evaluated
[13]	Data quality (accurate, comprehensive, correct, consistent), representational fidelity (understandable, easy to interpret, not overwhelming), actionability (applicable, usable), and transparent interactions (easy to access, available when needed, easy to extract).
[77]	Effectiveness, user involvement and usability.
[78]	Dashboard system quality (accessibility and viewpoint integration) and information quality (completeness and currency – how current the information is).
[79]	Reliability, responsiveness, costs, asset management, agility.
[80]	Visibility, flexibility, learnability, operability, error control and help, effectiveness, efficiency.
[66]	Availability of data, completeness of information, information management strategy, integration in reporting systems, analytical capability, actionability, information suitability for decision-making, information presentation, accessibility and availability, predetermined formats.
[67]	–
[68]	–
[69]	–
[30]	Overall performance, return on investment, cost savings, increase sales, customer service quality, data quality, time savings, access to data, decision-making, user interface, business process efficiency, number of active solvers, satisfaction of employees.
[70]	Specific use of reports.
[71]	Emotional factors influencing the intention to use BI systems.
[72]	System quality, information quality, task compatibility, task significance, task interdependence, task specificity, tsk significance, use, user satisfaction.

Jetter, Eimecke and Rese [81] propose that the qualitative factors be evaluated in a survey format by means of a semantic differential scale. This scale consists of a five-point rating that has direct opposites of each qualitative factor on each end. For example, 1 indicates that the report is not used while 5 indicates that the report is used. This provides easy and clear communication of each evaluated factor.

Quantitative factors

Quantitative factors in this study refer to measurable benefits arising due to reporting. This study proposes that quantitative impacts be derived from benefits obtained or value achieved from report utilisation. Table 2-2 therefore summarises the benefits or achievable value from the SLR studies. These benefits are used in Chapter 3 to develop a new report impact evaluation survey.

TABLE 2-2: BENEFITS OR ACHIEVABLE VALUE FROM STUDIES IN SLR

SLR reference	Benefits/value achievable
[73]	Increased productivity of review meetings, less time analysing data, and more time making action plans.
[74]	Competitive advantage (increase in business effectiveness and efficiency).
[75]	Strategic and operational business value.
[76]	Management control activities.
[13]	Decision-making or actionability, which leads performance benefits.
[77]	Communicates strategic goals, guides development decisions, identifies improvement opportunities.
[78]	Facilitates decisions, strategy surrogation.
[79]	–
[80]	Makes integrated information available, improves organisational performance, improves support for managing strategic goals, enhances decision-making, provides more and better information.
[66]	Strategic planning.
[67]	Improves educational quality, avoids student dropouts.
[68]	Decision-making, identifies problematic areas and decides whether improvement measures should be taken.
[69]	Assists auditor work.
[30]	Increases overall performance and competitiveness of business, and time savings.
[70]	Health system decision-making, assists with selecting healthcare providers, community advocacy, creates users trust in good healthcare provision.
[71]	–
[72]	Improves patient progress and financial reporting and enhances learning in hospitals.

2.3 STRUCTURED REPORTING QUALITIES

Chapter 1 identified that existing BI implementation guidelines lack the structure that is necessary to assist report developers in identifying specific areas of improvement and achieve outcomes incrementally. In this section, research is done to address this shortcoming. The aim is to identify critical reporting qualities from the high-level BI implementation steps and break each of them up into smaller incremental levels. The scope of this section of the literature review is depicted in Figure 2-6.

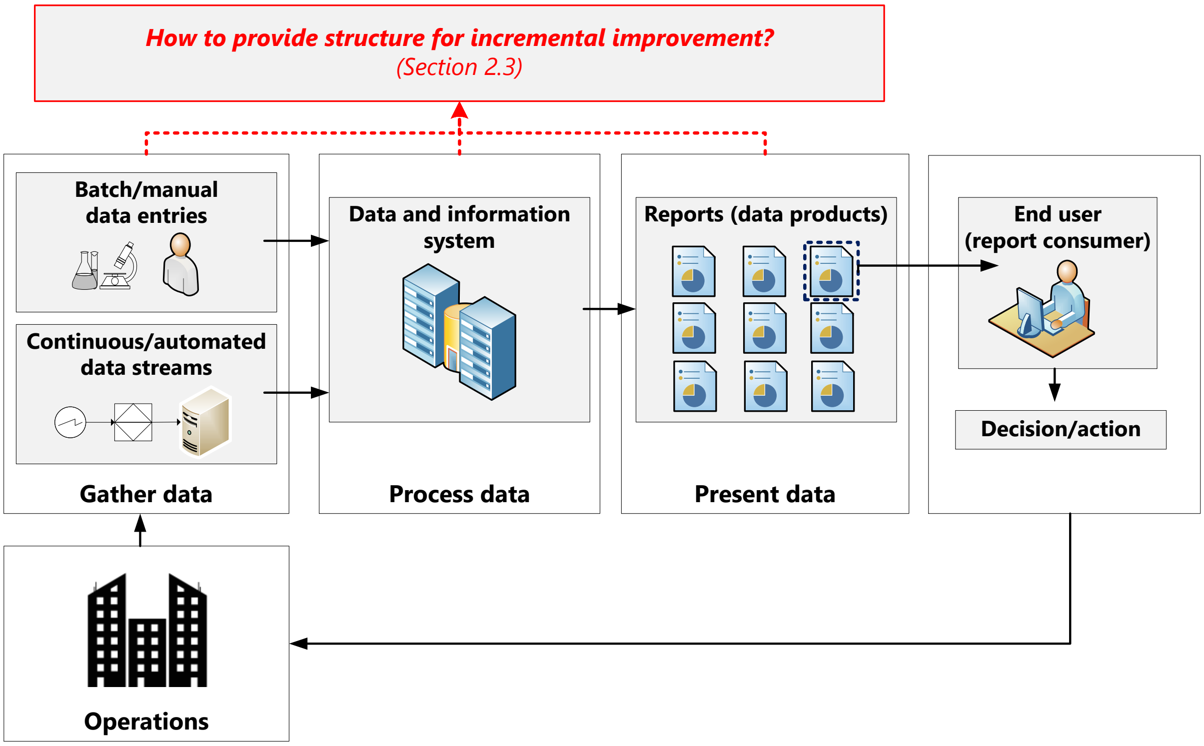


FIGURE 2-6: STRUCTURED REPORTING QUALITIES – SCOPE OF LITERATURE WITHIN A BASIC REPORTING STRUCTURE

Critical reporting qualities are identified by first formulating research questions based on existing BI implementation guidelines (Section 2.3.1). Thereafter, individual research fields are reviewed with respect to each research question (Section 2.3.2). From the individual research fields, incremental levels are identified with respect to each reporting quality. These incremental levels provide structure to the high-level steps identified in literature. Lastly, 40 additional studies related to the practical application of reporting application are obtained and used to verify that the incremental levels are used in practice (Section 2.3.3).

The work in this section is supported by an article published in a peer-reviewed journal [1]. The manuscript of this article is provided in Appendix C. It was also presented at the annual conference of the South Africa Institute of Industrial Engineering held during 1–3 October 2019 in Port Elizabeth, South Africa.

2.3.1 FORMULATING RESEARCH QUESTIONS

In this section, research questions are formulated by questioning the structure provided by each of the steps of the existing BI implementation guidelines presented in Chapter 1 (Section 1.3). Only certain guidelines presented in Chapter 1 are included in this section.

The KDD [52], CRISP-DM [47] and SEMMA [56] guidelines were selected since they are the most commonly used methods in existing literature [55], [57], [82]. General BI steps were included since BI forms a crucial part of this study. TDSP was included since it is a newer guideline that was launched by Microsoft in 2016 [57].[†]

From the guidelines examined in Chapter 1 and shown in Table 2-3 it is evident that different BI implementation guidelines exist, which all involve different steps. However, overall, they all aim to achieve the same outcome with generic steps that can be summarised as: understand business, collect data, model, and present and deploy. The aim of this section is to analyse these generic steps to identify where structure is necessary to complete each step incrementally. This was highlighted as a shortcoming in the available guidelines in Chapter 1.

TABLE 2-3: GENERIC BI IMPLEMENTATION STEPS

BI [24]	**KDD** [52]	**CRISP-DM** [47]	**SEMMA** [56]	**TDSP** [55]	**Generic steps**
Gather data	Domain understanding and KDD goals	Business/ research understanding	–	Business understanding	Business understanding
	Selection	Data understanding	Sample	Data acquisition and understanding	Data collection and understanding
	Pre-processing	Data preparation	Explore		
Analyse data	Transformation		Modify		
	Data mining	Modelling	Model	Modelling	Modelling
	Interpretation/ evaluation	Evaluation	Assess		
Present data	Visualisation and integration	Deployment	–	Deployment	Present and deployment
	–	–	–	Customer acceptance	

Generic step 1: Business understanding

During this step, the project objectives should be understood from a business perspective. The problem must be understood and a clear problem statement made that can be used to identify objectives or

[†] Smith, D. Recent updates to the Team Data Science Process. 2017. [Online]. Available: https://blog.revolutionanalytics.com/2017/10/recent-updates-to-the-team-data-science-process.html [Accessed: 23-Feb-2021].

targets that should be met during the project. Relevant data to address the objectives is also identified during this generic step [47], [52], [56].‡

This first step sets the stage for the completion of the remaining steps and is, therefore, crucial. The aim of the step is to create direction; however, guideline users may find this step daunting and struggle to know where to focus when starting.

Research question 1: Where should the focus be placed?

Generic step 2: Data collection and understanding

In this step, data is usually collected and preliminarily investigated and cleaned before final use in modelling. In real-world operations, data is available from multiple data sources and collected using various methods. The different availabilities of data limit the extended and continuous use thereof in further steps. Additionally, the different availabilities of data enhance or restrict certain methods of preliminary data analysis and cleaning.

Research question 2: How can available data be used to the maximum?

Generic step 3: Modelling

In this step, the collected data is used to model the desired outcomes. The various guidelines in Table 2-3 use some of the following terms to refer to this step: developing models, exploring data patterns and correlating data. Results are evaluated to ensure that the modelling methods achieve the original objectives.

When referring to the word ‘modelling’, different views may exist on the actual outcome thereof. This is evident in the available guidelines that discuss the modelling step. As an example, the newer TDSP refers mostly to predictive models while the older models refer to correlations and patterns in data. Modelling capabilities have changed and advanced in recent times and most users immediately view modelling as these advanced methods. Advanced modelling may seem daunting for guideline users when the goal is only to calculate and explore KPIs in a reporting application. Therefore, modelling needs to be identified that is fit for purpose, and more structure is needed regarding how these modelling results are actually calculated.

‡ Microsoft. What is the Team Data Science Process? 2020. [Online]. Available: https://docs.microsoft.com/en-us/azure/machine-learning/team-data-science-process/overview [Accessed: 19-Feb-2021].

Research question 3: How are results calculated?

Generic step 4: Presentation and deployment

In the presentation and deployment step, the modelling results are implemented in the actual environment where it will be used, which includes incorporating the modelling into the data pipeline and presenting the results to end users. Artefacts for the presentation and deployment of results include websites, spreadsheets, dashboards, and batch or automated reports [36].§

Many tools exist to present modelling results, including information systems [83], business-specific reporting systems, and data visualisation software such as Microsoft Power BI and QlikView. To use these tools, businesses with internal systems have internal guidelines on how their systems work, while online forums and courses are available for using software such as Microsoft Power BI and QlikView. An uncertainty that can remain when presenting results is how to communicate results effectively to extract information from the data and, in turn, to assist users with decision-making.

Research question 4: How must results be communicated?

2.3.2 ADDRESSING RESEARCH QUESTIONS

Four research questions were formulated in the previous section regarding the structure provided by BI implementation guidelines. In this section, each of the research questions are addressed by reviewing relevant research fields.

Quality 1: Focus area through business objectives

The first research question is: Where should the focus be placed? Research was done regarding KPIs and business objectives to understand where focus should be placed in a reporting application. KPIs were chosen since they are widely used in performance measurement. KPIs can be financial, quantitative or qualitative measurements of performance for organisations [74], [76], [77], [84].

Kritzinger [84] states that a pitfall of KPI generation is not linking measures to strategies from high level management or driving these measures from lower levels of an organisation. The level of business where focus is placed is therefore important. Sondalini [85] further highlights that different KPIs are available that are important on different levels of a business to achieve specific objectives per level, which is

§ Microsoft. What is the Team Data Science Process? 2020. [Online]. Available: https://docs.microsoft.com/en-us/azure/machine-learning/team-data-science-process/overview [Accessed: 19-Feb-2021].

necessary to achieve the overall business goal and strategies. Therefore, the focus should be placed on the levels of business objectives when developing reports.

Levels of business objectives in literature

Sondalini [85] conducted a study that focussed on KPI selection for informative and actionable maintenance. This study highlights that successful KPI selection starts with a pathway of goals from the top of an organisation to the bottom. Sondalini [85] further explains that even though the goals are set from the top of an organisation, the actions taken to achieve these goals are achieved from the bottom up.

Three levels of business objectives are identified, namely: corporate goals, (site goals, and departmental and individual goals). In terms of maintenance, the purpose of the KPIs is defined at the corporate level. The organisation needs a good return on investment or regulatory compliance. The effect of the KPIs are seen on the site level, for example, plant availability or lost time. The causes of failure take place and individual behaviours are altered on the departmental and individual level [85].

Stubbs [86] wrote a book focussing on the value of business analytics. The chapter "The importance of business analytics" explains that business analytics supports strategic planning, creates competitive advantage, and delivers tactical value. It is further shown that strategic planning takes place on three levels of an organisation, namely: organisational, business, and functional. The organisational level refers to the highest level of organisational planning where the company vision and key markets are identified. On the business level, individual strategies are identified that lead to the organisational strategies. In turn, organisational strategies lead to competitive differentiation. The functional level refers to the operational activities required to achieve the business strategies and where the execution thereof takes place.

Watts [87] focussed on performance management systems that support control. A performance wheel was developed to be used by large or small businesses. The performance wheel is divided into three sub-groups of an organisation, namely: top management, middle management, and operational employees. These three levels align with strategic objectives, critical success factors, and KPIs.

A master's dissertation by Kritzinger [84] focussed on determining the effectiveness of KPIs in a steel manufacturing company. The literature review of the master's dissertation evaluated the balanced scorecard, which is a performance measurement model. It was highlighted that different levels of an organisation should be integrated to achieve organisational success, namely: the organisational, business unit, and individual level.

A conference paper published by Stan *et al.* [88] focussed on KPIs for evaluating employees on industrial production lines. The paper showed that KPIs can be regarded from multiple perspectives, such as strategic, operational, and team.

Levels of focus area

The previous section identified various levels where business objectives are set in literature. It further showed that KPIs can be set at a variety of different levels. Table 2-4 summarises these studies and gives a generic description of the levels of focus area used in this study.

Table 2-4: Levels of focus area identified from literature

Description used in this study	Levels of business objectives in the literature
Enterprise	Corporate goals [85], organisation [86], top management [87], organisational [84], strategic [88].
Site	Site goals [85], business [86], middle management [87], business unit [84], operational [88].
System	Department and individual [85], functional [86],operational employees [87], individual [84], team [88].
Equipment	

It is important to identify these levels of focus areas so that appropriate KPIs are chosen per level to address specific needs and that relate to executable tasks on the associated levels. Additionally, these levels identify what data is available for each level of focus area, which influences any further implementation. Lastly, these levels of focus area assist with aligning reporting with strategic goals.

Each of these levels can be staggered according to their respective level of management and detail. Figure 2-7 illustrates how the various levels of focus area are staggered. The enterprise level is the highest management level of an organisation, while the equipment level is the lowest management level. The highest amount of detail is contained on the equipment level where execution takes place. Similarly, the level of detail decreases as the level of management increases (e.g. from equipment to enterprise).

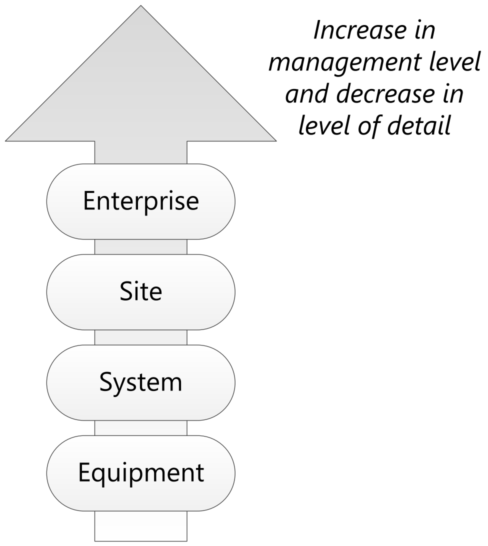


FIGURE 2-7: STAGGERED LEVELS OF FOCUS AREA

Quality 2: Data availability through big data enablement

The second research question is: How can available data be used to the maximum? To know how to use the available data to the maximum, one needs to know what kind of data is available within the available data pipeline. Depending on the technological investment of operations, there will be various levels of big data pipeline implementation. Therefore, research was done in the field of big data enablement to understand the flow of data within big data platforms. This helped to understand what data is possibly available, which affects the extent to which it can be used.

Data pipelines in big data enablement from literature

Zhang *et al.* [48] conducted a study to develop a big data driven analytical framework for energy-intensive manufacturing industries. In this framework, data flows from equipment and measurement devices such as meters and sensors to real-time data acquisition. Data is generally stored in data warehouses, whereafter it is used for various processing functions and analyses.

Van Jaarsveld [63] developed an integrated information system for condition-based equipment monitoring in the mining industry. The data used for condition monitoring is obtained from equipment measurements via an open platform communication (OPC) server that transfers the data from a local supervisory control and data acquisition (SCADA). Thereafter, the data is transferred and stored on a centralised and local server.

Du Plessis [83] developed a supervisory system for energy management systems in the mining industry. The study describes that a basic energy management system's data is generated by measurement equipment that connects to a programmable logical controller, which then communicates with a SCADA system via an ethernet communication. Thereafter, an OPC server is used to transfer the data to energy management system servers.

Motegi *et al.* [89] reviewed case studies of energy information systems and related technology in the building industry. The study explains the typical architecture of energy information systems to collect data on-site via various measurement equipment, whereafter a communication device dispatches the data to a database server via the internet. Lastly, the database stores and archives the data, which can be accessed remotely via a web browser.

Liu *et al.* [90] focussed on a big data framework to assess electric power data quality. In the proposed framework, data is obtained from various measurement equipment, whereafter a connection to the measuring equipment allows the acquisition and transmission thereof. This can be done in real time. Lastly, the data is stored to allow a history of data to be available.

Elhussein *et al.* [91] focussed on a big data framework for health informatics. The study illustrates that in an analytical framework for big data, data is first generated by doctors and patients, whereafter it is acquired and stored. Thereafter, the data can be used for various analytics.

Levels of data availability

Table 2-5 summarises the different data pipelines available in literature (discussed above) and correlates them to the level of data that is available.

TABLE 2-5: LEVELS OF DATA AVAILABILITY IDENTIFIED FROM LITERATURE

Description used in this study	Data pipeline of big data platforms
Sample data	Equipment and measurement devices [48], equipment measurement [63], equipment measurements [83], data collection on-site [89], measurement [90], data generation [91].
Continuous real-time	Real-time [48], acquire data [63], OPC communication [83], database server via internet [89], real-time data submission [90], data acquisition [91].
Long-term	Data warehousing [48], transfer and storage [63], store and archive data in database [89], data storage [90], data storing [91].

It is important to identify these levels of data availability since they will restrict or enhance the extent of reporting. For example, it is possible that some organisations may generate data, but not collect or store it. This data is only available as sample data, which restricts the reporting application by only allowing batch reports to be made and by making report compilation a manual process.

More established organisations monitor data in real-time, which can be used in automated and continuous reporting. Some organisations may store long-term data, which makes it possible to compare the current operation with the historical performance. These levels provide structure to the extent to which available data can be used in reporting applications.

Figure 2-8 illustrates the staggered levels of data availability, with sample data being the lowest level and long-term data the highest level. The levels of data availability were staggered based on the increase in data variety and volume. The higher levels of data availability not only increase the accessibility to a variety of data variables, but also have a longer period of data (volume).

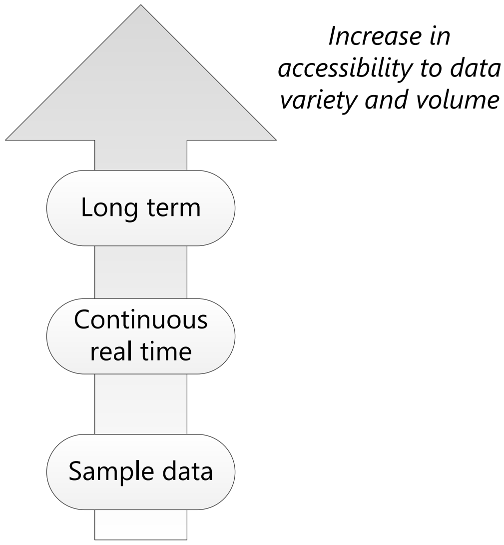


FIGURE 2-8: STAGGERED LEVELS OF DATA AVAILABILITY

Quality 3: Data analytics

The third research question is: How are results calculated? To address this question, research was done in the analytics field. Analytics are done to increase the value of data and reduce the level of detail by converting raw data to knowledge and wisdom [27], [28]. This is done since raw data is not enough to assist with decision-making. Available literature divided analytics into different levels. These levels are described in the next section.

Data analytics in literature

It was found that various analytical methods exist, which are covered extensively in available literature. These methods include but are not limited to regression, statistical methods, and AI [29], [46], [84], [86]. All the methods vary in the complexity of the questions they address as well as in computational complexity. Due to the variance in complexity, the analytical methods are classified into four different levels. These levels were obtained by a review of relevant literature [92]–[96] and generically consist of descriptive, diagnostic, predictive, and prescriptive analytics.

Descriptive analytics does not address any complex questions, but rather simply describes occurrences by using past and present data. However, diagnostic analytics highlights the cause and effect of occurrences, and can therefore address what has happened in scenarios. This is particularly useful for providing actionable information by transferring knowledge regarding influencing factors to industrial operations.

Predictive analytics uses historical data to predict future outcomes. This is done to address the question "What will happen in the future?". Prescriptive analytics prescribes actions to the decision maker regarding multiple predictive analyses. This level of analytics aims to assist in actions that should be taken by decision makers.

Levels of data analytics

The different levels of data analytics identified from literature as well as the generic description used in this study are summarised in Table 2-6.

TABLE 2-6: LEVELS OF DATA ANALYTICS IDENTIFIED FROM LITERATURE

Description used in this study	Types of data analytics used in the literature
Descriptive	Descriptive [92]–[94], historical view [95], reporting and trending [86], simple data analysis and statistical methods [29], statistical methods [46], samples and comparisons [96], characterisation [84].
Diagnostic	Inquisitive [92], descriptive [95], segmentation [86], graph analysis [29], diagnostic [94], data mining [46], relationships [96], evaluation [84].
Predictive	Predictive [92]–[96], predictive modelling [86], AI [29], machine learning [46], prediction and preparation [84].
Prescriptive	Prescriptive and pre-emptive [92], prescriptive [94], improvement [84].

The structure provided by the identification of these analytics levels is important for multiple reasons. Firstly, it provides clarity on what is meant by modelling, which is the step involved with existing BI implementation guidelines. Secondly, different types of analytics are broken up into different levels, which allows an organisation to identify a level of analytics that fits their needs and aligns with their objectives. This removes the pressure since organisations will perform a level of analytics that fits their needs instead of aiming to complete advanced analytics, which might not be necessary.

Figure 2-9 illustrates the levels of data analytics that are staggered according to the number of data variables considered and the complexity of questions addressed.

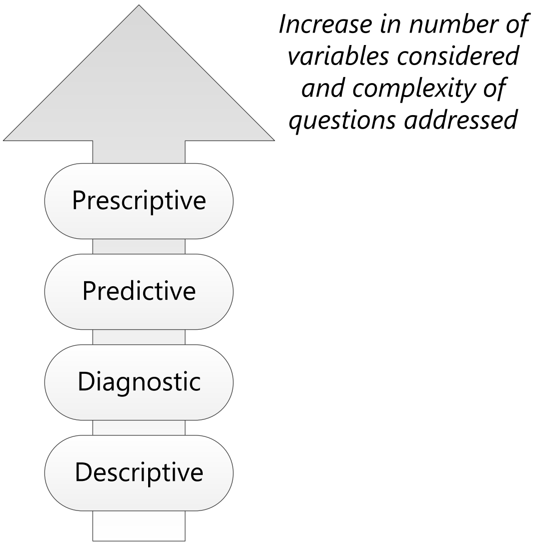


FIGURE 2-9: STAGGERED LEVELS OF DATA ANALYTICS

Quality 4: Data visualisation

The fourth research question is: How must results be communicated? To address this question, research was done in the visualisation field. It was found that various visualisation methods exist and, similar to analytics, these methods vary in the complexity of questions they address and increase in the number of data variables considered. The following sections describe the researched visualisation methods.

Data visualisation in literature

A study by Chen and Golan [97] identified four levels of visualisation. These levels include disseminative, observational, analytical, and model developmental visualisation. Disseminative visualisation purely provides information regarding the data, but does not address any complex questions. An example of disseminative visualisation is single variable line graphs. Observational visualisation allows the speedy and/or intuitive observation of the displayed data. This level of visualisation aims to answer "what has happened?" by using statistics and limits. Analytical visualisation aims to answer why scenarios happened by showing the relationship between different variables. A scatter plot is the simplest example of this level of visualisation. Lastly, model developmental visualisation aids in the development of new and/or existing methods or models by displaying different variables in order to see how one scenario leads to the next.

Other studies regarding data visualisation were also evaluated [96], [98]–[100]. These studies mostly described different visualisation methods such as the bubble plot, bar chart, and scatter plot. Furthermore, these studies discussed what the different visualisation methods are used for; for example, which visualisation methods can be used to show comparison, relationships, or increases and decreases. It was found that these methods of visualisation can be grouped into the levels identified by Chen and Golan [97].

Levels of data visualisation

The levels of visualisation identified by Chen and Golan [97] were used in this study. Table 2-7 summarises the different types of visualisation identified in literature according to the levels of visualisation.

TABLE 2-7: LEVELS OF DATA VISUALISATION IDENTIFIED FROM LITERATURE

Description used in this study	Types of data visualisation in the literature
Disseminative	Bar chart, line chart, histogram and pie chart [98], samples [96], dials, iconic representation, Chernoff face and test [99].
Observational	Funnel plot, maps and tree maps [98], comparison, distribution and composition [100], comparisons [96], point representation, star plots, magnification and mosaic plots [99].
Analytical	Bubble plot and dynamic plot [98], relationship [96], [100], scatter plots and parallel coordinate plots [99].
Model developmental	Multidimensional scaling plot, maps and dynamic plots [98], patterns and theme river [99].

The structure provided by identifying the levels of visualisation allows for the appropriate visualisation to be chosen to communicate the objective of a reporting application effectively. The appropriate type of visualisation further aids in the usability of a report. For example, the extensive use of disseminative visuals may lead to cognitive overload when used in the incorrect context. On the other hand, the extensive use of analytical visualisation in reports for users who do not fully understand the methods decreases the usability of a report.

Figure 2-10 illustrates that these levels are staggered according to the number of data variables considered and the complexity of questions they address.

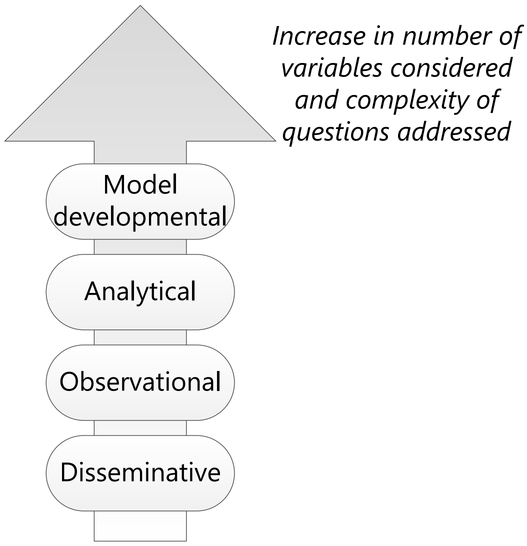


FIGURE 2-10: STAGGERED LEVELS OF DATA VISUALISATION METHODS

2.3.3 PRACTICAL APPLICATION OF IDENTIFIED QUALITIES

This section aims to verify that the qualities and respective levels identified in the previous sections are used practically. Therefore, studies related to the practical application of data-related studies were obtained by using keywords such as analytics, practical application, industrial, data-driven, and performance measurement/metric. The results were filtered according to their titles and abstracts to ensure relevance. This resulted in 40 practical application studies, which were mostly journal articles. The timeline and type of references are depicted in Figure 2-11.

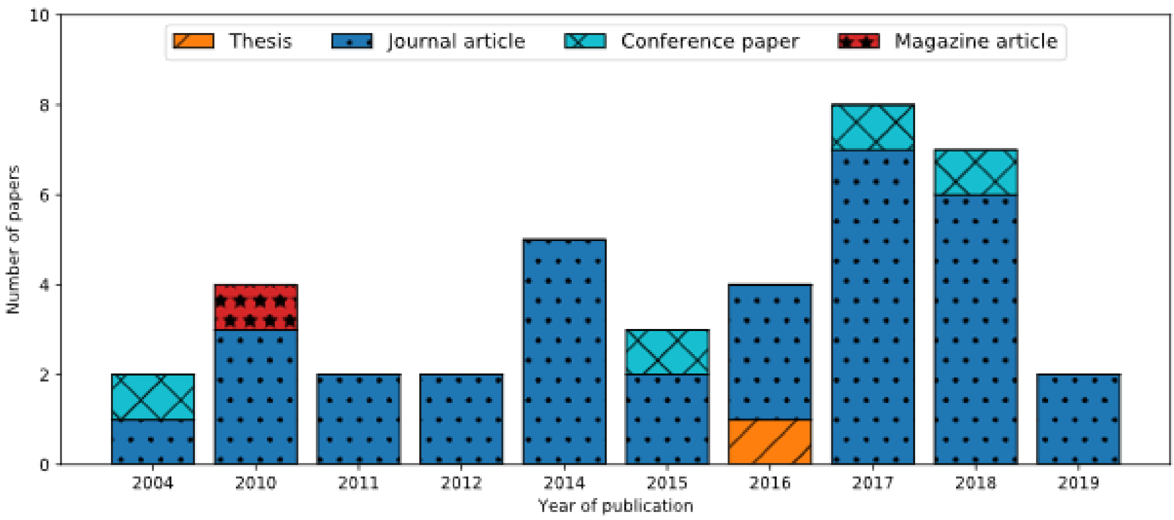


FIGURE 2-11: TIMELINE AND TYPE OF REFERENCES FOR PRACTICAL APPLICATION OF IDENTIFIED QUALITIES

Each of the 40 studies were reviewed to identify whether the qualities and respective levels identified in the previous sections were utilised. Figure 2-12 summarises the use of the identified qualities in the 40 practical application studies.

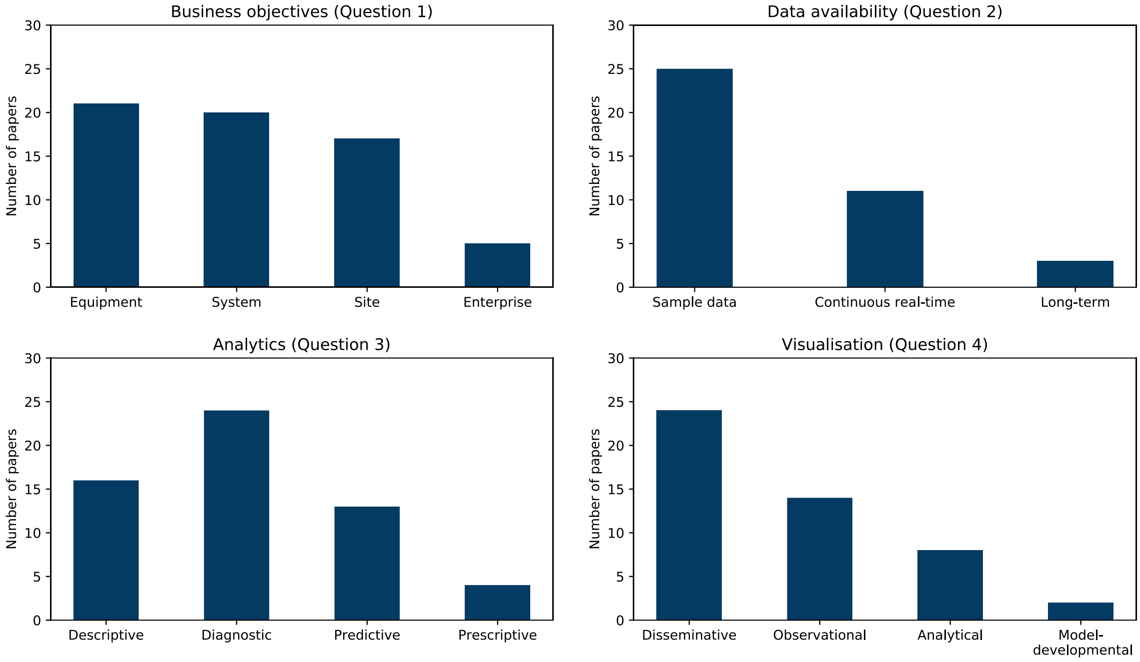


FIGURE 2-12: SUMMARY OF PRACTICAL APPLICATION OF REPORTING QUALITIES

The results show that data-related studies are applied across the four qualities and their respective levels as identified in the previous section. It can also be seen that mostly the lower levels of each quality are used across all four reporting qualities. This verifies that the identified qualities from literature are used in practical environments.

2.4 PROJECT MANAGEMENT

Chapter 1 identified that existing BI implementation guidelines need to incorporate practical concepts into frameworks to achieve practical results. This section investigates project management methodologies to obtain key practical concepts to be included in a new report development framework. The scope of this section of the literature review is depicted in Figure 2-13.

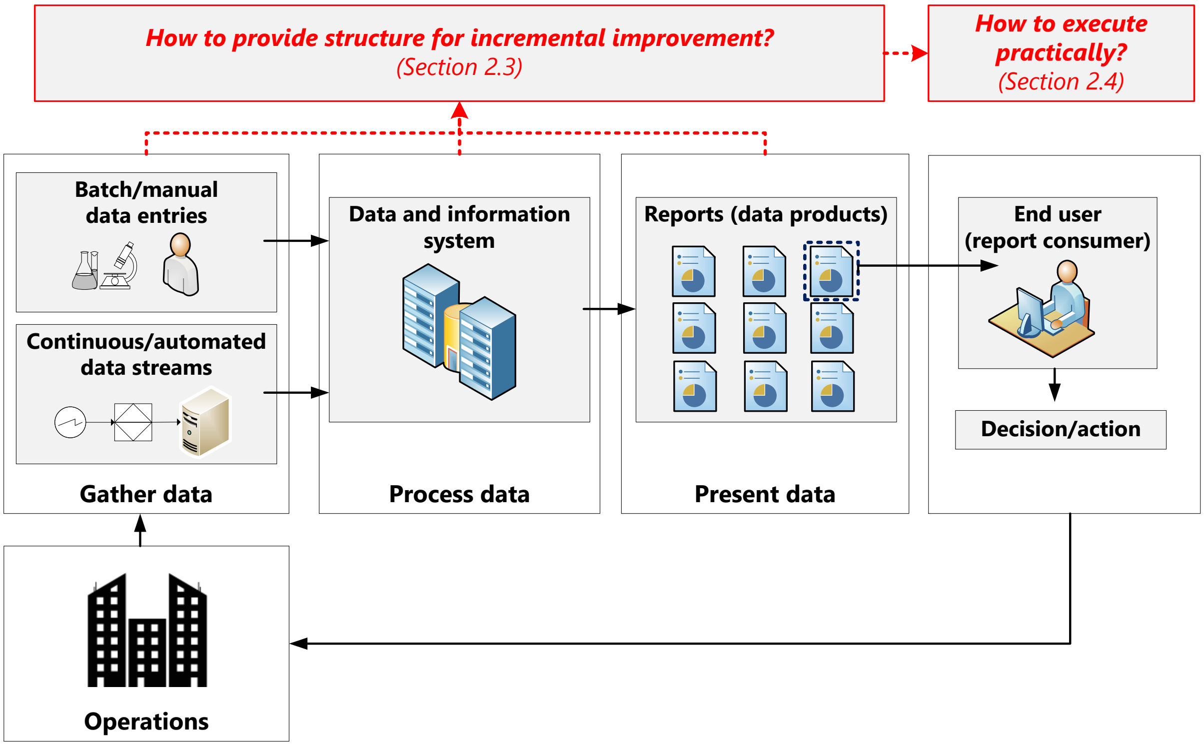


FIGURE 2-13: PROJECT MANAGEMENT – SCOPE OF LITERATURE WITHIN A BASIC REPORTING STRUCTURE

Project management is most commonly defined as principles that a project team relies on to achieve project results successfully [101]. Project management is prevalently either traditional or agile [102]. The chosen approach depends on the specific project characteristics [101], [102].

This section of the literature review assesses both traditional (Section 2.4.1) and agile project management methodologies (Section 2.4.2). Thereafter, project management for report development is discussed to identify the practical concepts required for report development in the mining industry (Section 2.4.3).

2.4.1 TRADITIONAL PROJECT MANAGEMENT METHODOLOGIES

Definition

In traditional project management, project phases are implemented in sequence. These phases generally include analysis, design, development, testing, and deployment [103]. The implementation of these phases takes place linearly or sequentially [103], [104]. Thus, the next phase is only started once the previous phase is completed and this method is followed from the start to the end of the project life cycle.

When to use

Traditional methods are best for smaller projects that have a clear picture of the final product. Time is usually not a constraint and changes are not expected. Traditional methods are ideal for projects with non-physical deliverables, but that are service orientated such as coding, copywriting and design projects [105].

Advantages

The main advantages of traditional methods are the following [105], [106]:

- Provide structure for organising and controlling a project
- Proper design phase saves time during implementation
- Proper technical documentation
- Accurate cost and time estimations if the procedure is followed properly
- Completion of one phase before moving on to the next
- Easy-to-replicate project plan on similar projects

Disadvantages

Disadvantages of traditional methods include the following [101], [105]:

- Not easy to replicate on projects that are different
- Clear statement of project requirements required at the beginning of project
- Do not accommodate changes in scope
- Only deliver workable product after the project life cycle

Most common method

The most common traditional method is the Waterfall model [103]–[105]. The Waterfall model is depicted in Figure 2-14 and shows five phases that are implemented sequentially, namely: requirements, design, implementation, testing, and release. Each phase is signed off before the next phase commences [107].

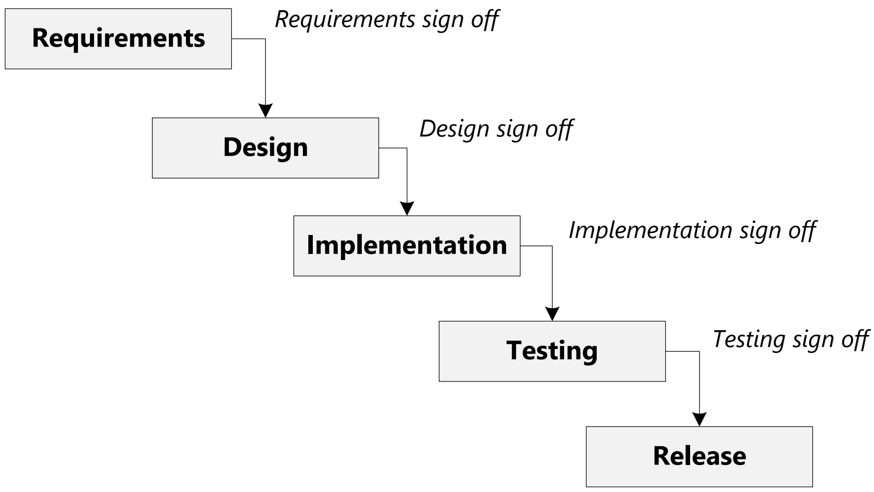


FIGURE 2-14: WATERFALL MODEL (ADAPTED FROM [107])

First, the requirements of the project are set and signed off with sufficient documentation, whereafter a design is made to meet the requirements set out in the first phase. The design is reviewed and approved by respective technical and management teams before implementation can commence. Thereafter, testing is done. If it is realised in this phase that some requirements are outstanding from the initial scoping of the project, it can be costly and ineffective to make any changes to the project. Once testing is signed off, the project is released and maintained.

2.4.2 AGILE PROJECT MANAGEMENT METHODOLOGIES

Definition

During agile project management, results are delivered as short iterations [103] that are responsive to change, are flexible, and promote team integration [102]. Common characteristics of agile methods include iterative development, focus on interaction, communication, and reduction of resource-intensive intermediate artefacts [106].

Agile methods generally consist of five stages, namely: envision, speculate, explore, adapt, and close [101], [106], [108]. During the envision phase, the project scope is defined. During the speculate phase, the product characteristics and time constraints are evaluated to plan for iterations. In the explore phase, tested parts are delivered in short iterations (referred to as sprints). During the adapt phase, the deliverables of the project, current situation, and team behaviour are evaluated and adapted, if necessary. Lastly, in the close phase, the project is closed and lessons learned are noted.

When to use

The iterative and adaptive nature of agile methods makes them ideal for projects without well-defined requirements and that are expected to change [104], [105].

Advantages

Advantages of the agile methods include the following [105]:

- Work well on projects of different sizes
- Adapt well to change
- Enhance teamwork
- Make a working product available in the early stages
- Require minimum documentation
- Enhance communication between all parties involved, which ensures focus on the final product instead of the processes and tools used

Disadvantages

Despite its many advantages, agile methods also have disadvantages, including [109], [110]:

- Communication must constantly be ensured since this is where requirements for the project are given
- Require clear organisational structure to manage project team and phases
- Lack of documentation creates a challenge to familiarise new employees with necessary information of the processes followed
- Constantly changing requirements may lead to a waste in resource time
- Difficulty for resources to regularly change their scope of work

Most common method

One of the most commonly used agile methods is Scrum [111]. Scrum can be seen as an alternative to the traditional Waterfall method by completing the steps of a Waterfall method in short iterations. Each iteration, called a sprint, is completed in a fixed, given time, which is project dependent. James and Walter [112] state that a sprint should be no longer than 30 days while Shaydulin and Sybrandt [111] suggest a week. After each sprint, a potentially tested and releasable version of the envisioned end product is delivered [112]. The iteration process is depicted in Figure 2-15.

FIGURE 2-15: ITERATIONS PROCESS OF THE SCRUM METHODOLOGY [112]

Scrum has three main role players, namely: a development team, product owner, and scrum master [111], [112]. The product owner is responsible for defining the product vision and outlining business requirements by being a core contact point between the development team and the product end user. The scrum master leads the development team through the Scrum process to ensure an efficient working environment and that Scrum principles are followed. The development team executes tasks during a sprint by working closely together.

Constant communication is key to ensure successful project implementation. Each sprint involves four main meetings of role players to ensure communication [111], [112]. The first meeting is sprint planning during which the team plans which items will be completed during the sprint. The second type of meeting is daily scrums of up to 15 minutes that are held by team members to align tasks completed the previous day, plan for the day ahead, and discuss challenges. The third meeting is a sprint review that is held at the end of a sprint to discuss any adaptions required to the product as it emerges. During the sprint review, a demo of the product is presented to all interested parties (such as team members and end users). Lastly, a sprint retrospective meeting is held for the team to reflect on the processes that worked or did not work during the sprint.

James and Walter [112] describe a fifth meeting, which they refer to as backlog refinement. Although this does not have to be an exclusive meeting, the action of refining the backlog is necessary. During backlog refinement, the items initially set out for achieving the desired product are reviewed and planning is adjusted according to sprint timelines.

Three artefacts are defined in a Scrum process, namely: product backlog, sprint backlog, and increment [112]. A product backlog is a prioritised list of items that are required to achieve the desired end product.

This list should be reprioritised constantly by the product owner. Each item on the backlog should describe what is required of the item. The sprint backlog consists of a list of items selected from the product backlog that will be completed in a given sprint. These items are discussed during the daily scrum meetings. An increment refers to the workable product released after each sprint.

2.4.3 PROJECT MANAGEMENT FOR REPORT DEVELOPMENT

This section identifies project management concepts with the aim of developing practical reports in the mining industry. Kisielnicki and Misiak [104] completed a study that compared agile and traditional BI implementations. It was shown that due to their progressively adaptive nature, agile methods deliver more valuable BI to organisations. Kisielnicki and Misiak [104] thus recommend agile methods for BI implementation so that results still satisfy user needs as opposed to lengthy traditional methods where the needs have changed by the time of completion. This study also recommends an agile report development framework.

Well-known agile BI implementation guidelines include CRISP-DM and TDSP [55]. CRISP-DM was introduced in the 1990s and contains six iterative steps, namely: business understanding, data understanding, data preparation, modelling, evaluation, and deployment. Although CRISP-DM provides insight to which steps should be completed, the challenge is that it does not provide guidance on how to execute these steps practically since it does not consider factors such as team coordination [55].

TDSP was launched by Microsoft in 2016 and aims to provide an agile and iterative method to deliver predictive analytics applications [55]. Microsoft provides resources on GitHub to assist with practical implementation, such as a project charter template, process flow diagrams, documentation resources, and model reports. TDSP is based on the life cycles of CRISP-DM, but includes additional agile principles such as doing iterative sprints, planning sprints and defining specific role players.

Figure 2-16 illustrates the TDSP tasks and role players. Since TDSP leverages on Scrum sprint concepts, this method experiences the same challenges that exist with Scrum, such as difficulty to estimate how long a specific exploratory task will take while a fixed sprint length does not accommodate smaller or larger tasks.

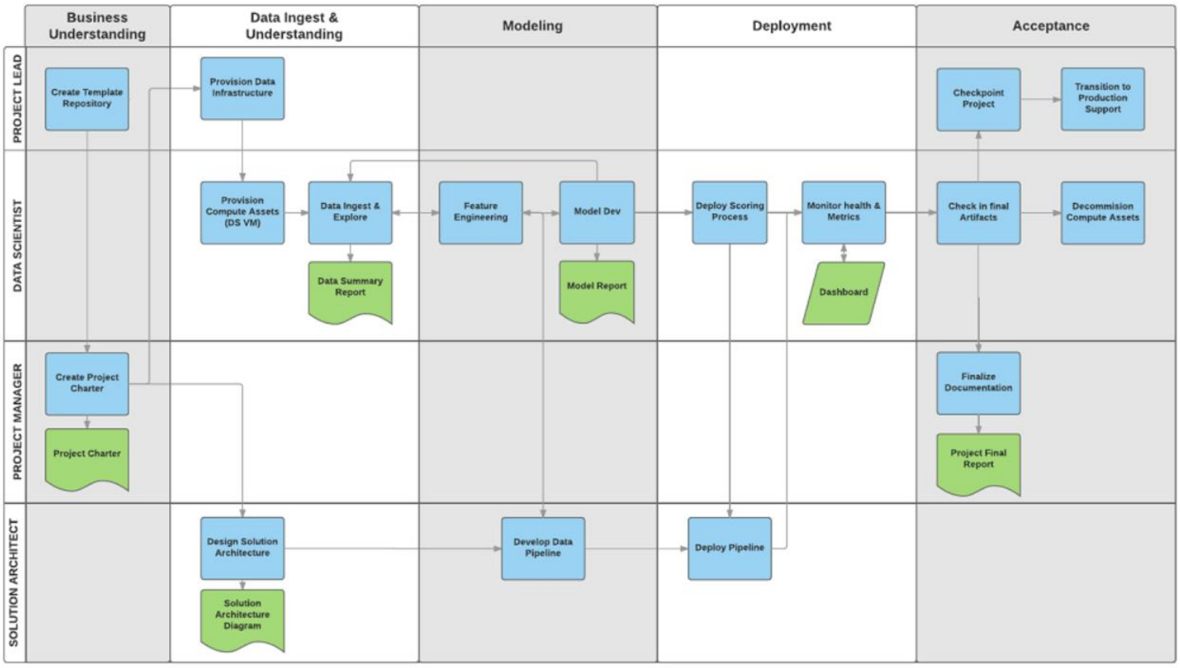


FIGURE 2-16: TDSP ROLES AND TASKS**

By evaluating the literature discussed in this section (Section 2.4), critical concepts of agile methods that are relevant for report development in the mining industry are identified. Firstly, it is highlighted that report development must be agile to adjust for changes and deliver practical results. Secondly, role players need to be identified since a clear organisational structure is required for agile methods to be successful. These role players further need to be allocated specific responsibilities within each step in the report development process. Third and lastly, both a product and sprint backlog are required, which contribute to the clear organisational structure that is required to complete the report and iterative sprints successfully to deliver a working product after each sprint. For this to happen, goals need to be defined clearly at the beginning of each sprint and the product backlog must be reviewed frequently.

The industrial analytics process [50], framework for implementation of big data projects in firms [53], and TDSP are the only existing guidelines that incorporate some of this practical guidance (Chapter 1). Table 2-8 compares the critical concepts of agile methods with associated concepts in the industrial analytics process and TDSP. Table 2-8 it shows that TDSP incorporates all of the agile concepts required for practical report development. However, a shortcoming is that the end user does not form part of the role players in TDSP.

** Microsoft. What is the Team Data Science Process? 2020. [Online]. Available: https://docs.microsoft.com/en-us/azure/machine-learning/team-data-science-process/overview [Accessed: 19-Feb-2021].

TABLE 2-8: CRITICAL AGILE CONCEPTS IN THE BI IMPLEMENTATION GUIDELINES THAT CONTAIN PRACTICAL GUIDANCE

Agile concepts	Industrial analytics process	Framework for implementation of big data projects in firms	TDSP
Iterative	Not iterative.	Not iterative.	Iterative life cycle.
Identify role players	Operation technology team, IT team, data analytics team, embedded analytics team.	A cross-functional team consisting of various stakeholders, business units, IT experts, data modellers, and relevant decision makers.	Project lead, data scientist, project manager, solution architect (aligns each step and artefact with a specific role player).
Product backlog	No product backlog.	No product backlog.	Project charter (scope of project).
Sprint backlog	No sprint backlog.	No sprint backlog.	Sprint planning (stipulate tasks).

Kisielnicki and Misiak [104] state that a report by Gartner in 2017 listed problems associated with BI implementation, one of which is that end users are not involved in the development cycle. This is also seen in the TDSP method. To adapt reports according to an end user's needs, it is recommended that the end user forms an integral part of the role players in a report development framework. Other agile concepts used in TDSP can also be used in the report development framework for mining industries that is developed in this study.

2.5 CONCLUSION

This chapter reviewed literature to address the shortcomings of the available BI implementation guidelines identified in Chapter 1. Firstly, report impact evaluation methods were reviewed. It was identified that both qualitative and quantitative evaluations are required, while limited quantitative evaluations are done in available literature. Report impact evaluation can be achieved by the use of end-user surveys. Secondly, structured reporting qualities were identified to provide incremental structure to the high-level steps in available BI implementation guidelines. These qualities were identified as focus, data availability, analytics, and visualisation. Incremental levels for each of these qualities were also identified. Third and lastly, project management methodologies were reviewed to identify critical concepts that will provide practical guidance to report development. It was identified that report development should be agile, identify specific role players, and produce a product backlog and sprint backlog.

This chapter is supported by supplementary descriptions provided in Appendices B, C, and D, which include manuscripts of the sections of this study that have been published in a peer-reviewed journal

[1], [2]. The next chapter uses the literature in this chapter to develop a new value-add driven report development framework for the mining industry.

CHAPTER 3

REPORT DEVELOPMENT FRAMEWORK

3. REPORT DEVELOPMENT FRAMEWORK

3.1 INTRODUCTION

Chapter 1 identified that existing BI implementation guidelines do not evaluate the impact of reports, are not structured for incremental progress, and do not provide practical guidance. Chapter 2 presented a comprehensive literature review to address each of the identified shortcomings.

This chapter describes how the literature in Chapter 2 was combined to create a new report development framework. The aim was to address each of the identified shortcomings to deliver practical value from data utilisation. The outline of this chapter is shown in Figure 3-1. First, the new framework requirements are identified (Section 3.2), thereafter the framework is developed (Section 3.3), and lastly it is shown how the new framework achieved the requirements (Section 3.4).

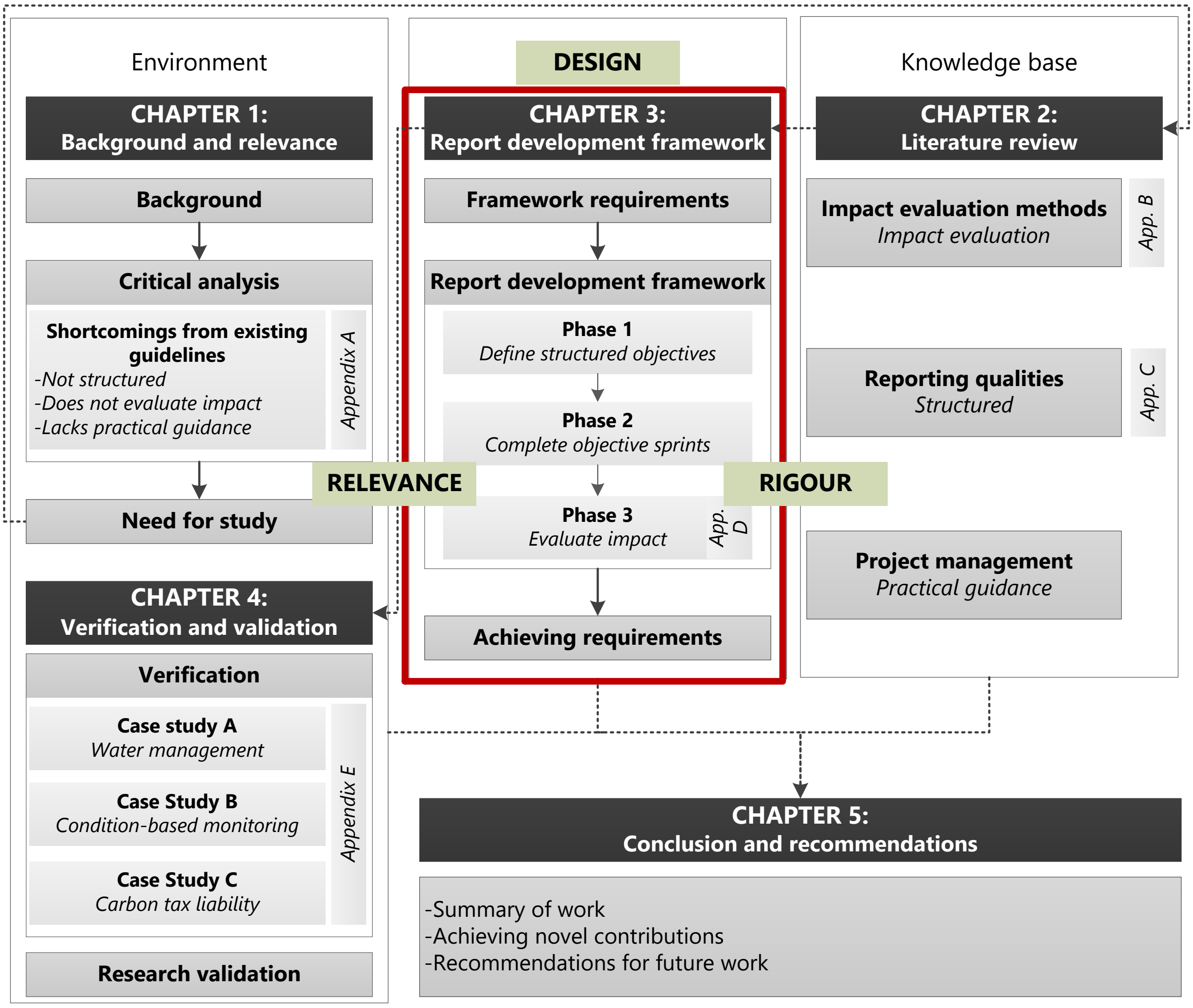


FIGURE 3-1: STUDY RESEARCH METHODOLOGY – CHAPTER 3

3.2 FRAMEWORK REQUIREMENTS

Chapter 1 highlighted that a report development framework is required that evaluates the impact of developed reports, is structured to achieve and improve outcomes incrementally, and provides practical guidance during report development. This section elaborates on the requirements of the new framework by taking the knowledge gained from the literature review (Chapter 2) into consideration.

Evaluate report impact

Chapter 1 identified that available BI implementation guidelines do not evaluate the impact of reports on real-world operations. Chapter 2 reviewed relevant literature and highlighted that user surveys are mostly used for evaluation. It was further explained that both qualitative and quantitative factors should be evaluated in these surveys. Therefore, an end-user survey should be developed in the new report development framework and used before and after report development to evaluate the qualitative and quantitative factors of reports. The before-report development evaluation will give an indication of the potential of the report development. This can be completed as interviews to obtain a preliminary impact evaluation. It is important that the report impact is also evaluated after report development to gauge the impact thereof on real-world operations. Experienced and qualified personnel should be used to obtain an objective indication.

The exact qualitative and quantitative factors to be evaluated were deduced from available literature and described in Section 2.2.2. The qualitative factors included data quality, information and representation, while the quantitative factors included time savings, direct impacts and indirect impacts.

Define structured objectives

Chapter 1 highlighted that there is a need for structure by breaking high-level report development qualities into smaller incremental levels. This structure is necessary to assist report developers to identify areas of improvement and achieve outcomes incrementally.

Chapter 2 reviewed the generic high-level report development steps in existing BI implementation guidelines to identify reporting qualities with associated levels, which provide structure to each quality. The reporting qualities include focus area, data availability, analytics, and visualisation.

To use the structure provided by the reporting qualities and their associated levels during report development, reports need to be assessed according to the qualities prior to report development. This allows report developers to identify the existing state of reporting, and what can be done to improve reporting and achieve the report needs. The assessment is used to define objectives for report development. The focus area quality forms a crucial part of determining the objectives and scope.

The levels associated with the data availability, analytics, and visualisation are also necessary during execution of report development to provide a clear indication of what the report development team should focus on.

Provide practical guidance

Chapter 1 highlighted that practical guidance is required to ensure that practical results are obtained during report development. Chapter 2 reviewed project management methodologies and identified that guidance is available that can be used in this study.

Reports need to be developed that meet the end users' needs. Chapter 2 explained that since these needs are not always well defined from the start, an agile approach is necessary to achieve relevant results. The required concepts of an agile method for report development as identified in the literature review include the following:

- Iterative
- Identification of role players
- Product backlog
- Sprint planning and backlog

Execution of report development must take place in an iterative manner. Thus, the steps involved with the reporting qualities must be repeated over short periods of time to deliver a working report continuously. These periods are referred to as sprints. At the beginning of each sprint, a sprint planning meeting needs to be held with all role players involved to plan which objectives will be completed during the sprint. These objectives must come from a product backlog. The product backlog should be created at the beginning of report development and prioritised. The backlog should be created by assessing an existing report or new report requirements. As report development is continuous, the product backlog must be reviewed during sprint planning sessions to adapt to any changes in report requirements and evaluate that completed objectives have been met.

Role players are necessary to provide organisational structure while completing agile projects. In this study, three generic role players are proposed. Each role player may represent a single or multiple persons. The generic role players are a project lead, contributor and end user.

The project lead should consult with the end user to establish the initial scope of the report and preliminary impact evaluation. The project lead should understand the end user's needs to be a bridge between the contributors who develop the report and the real-world requirements. The project lead must play a vital role in evaluating existing or new reports according to the structured reporting qualities to identify and prioritise report objectives.

The contributor may be one person or multiple persons depending on their skill sets (data, analytics, visualisation). If there are multiple contributors, they should still work in close proximity to ensure execution within the organisational structure. A contributor executes sprint objectives by collecting relevant data, performing analytics and visualising data.

An end user may be one person as a lead, or it can be a team of people who will be using the report in real-world applications. The end user is involved with the preliminary impact evaluation of the report to ensure that the ends justify the needs. The end user is also involved in feedback meetings to evaluate practical relevance of report and remaining objectives. Lastly, the end user should complete an end user survey to the evaluate report impact.

3.3 REPORT DEVELOPMENT FRAMEWORK

This section combines the framework requirements discussed in the previous section into a new report development framework, which is presented in Figure 3.2. The method of visualising the framework and identifying which role players are involved with which steps is based on TDSP as discussed in Chapter 2.

The role players are presented in the first column in Figure 3.2 and are generic to TDSP with the addition of the end user who was not initially included in TDSP. The high-level steps are presented in the first row and are based on the four structured reporting qualities as identified in Chapter 2. Evaluation was added as an additional step to accommodate for report impact evaluation.

The report development framework consists of three main phases for execution. Each phase is represented by the red dotted lines. These phases include structured planning, iterative execution and evaluation.

The outcome of each phase is indicated in green. For structured planning, the outcome is a report backlog, and for iterative execution, it is a working report. Lastly, the outcome of the evaluation phase is the end-user survey results. Each phase is discussed in detail in the following sections.

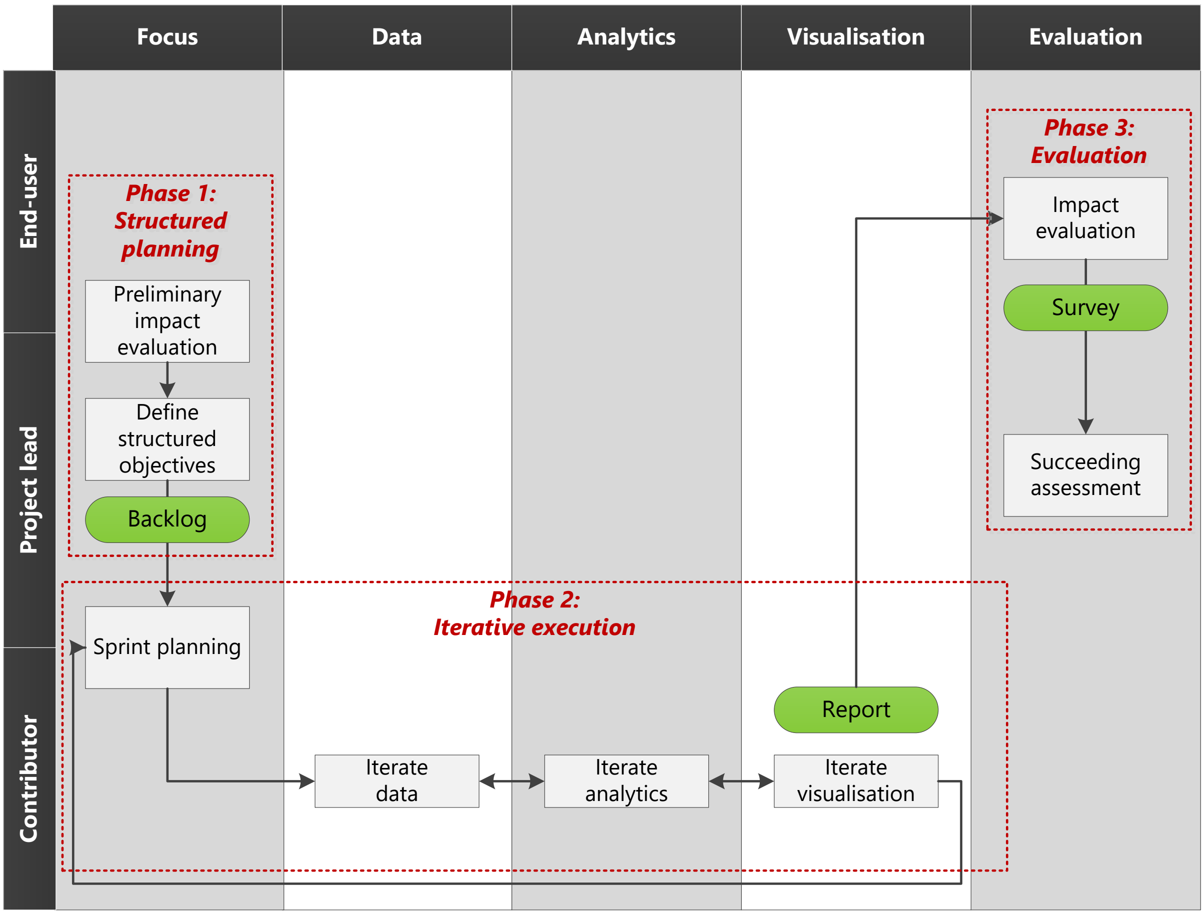


FIGURE 3-2: VALUE-ADD DRIVEN REPORT DEVELOPMENT FRAMEWORK

3.3.1 STRUCTURED PLANNING

Evaluate the preliminary impact

During the preliminary impact evaluation step, the project lead and end user evaluate the preliminary impact of the report. This may be in the form of informal interviews. The goal of this step is to highlight the possible value of reports before the development process starts. This may assist with assigning resources and time to the project. Both qualitative and quantitative factors should be evaluated as highlighted in the end-user surveys (Appendix D).

Define structured objectives

In order to define the report development objectives, the reporting application needs to be assessed according to the structured reporting qualities. The assessment needs to take place according to the reporting qualities as identified in Chapter 2 to identify on which level the existing reporting application is. This includes assessing the reporting application's focus area, data availability, analytics, and visualisation according to each of the associated levels. The reporting qualities and their associated levels for the initial report assessment are shown in Figure 3-3.

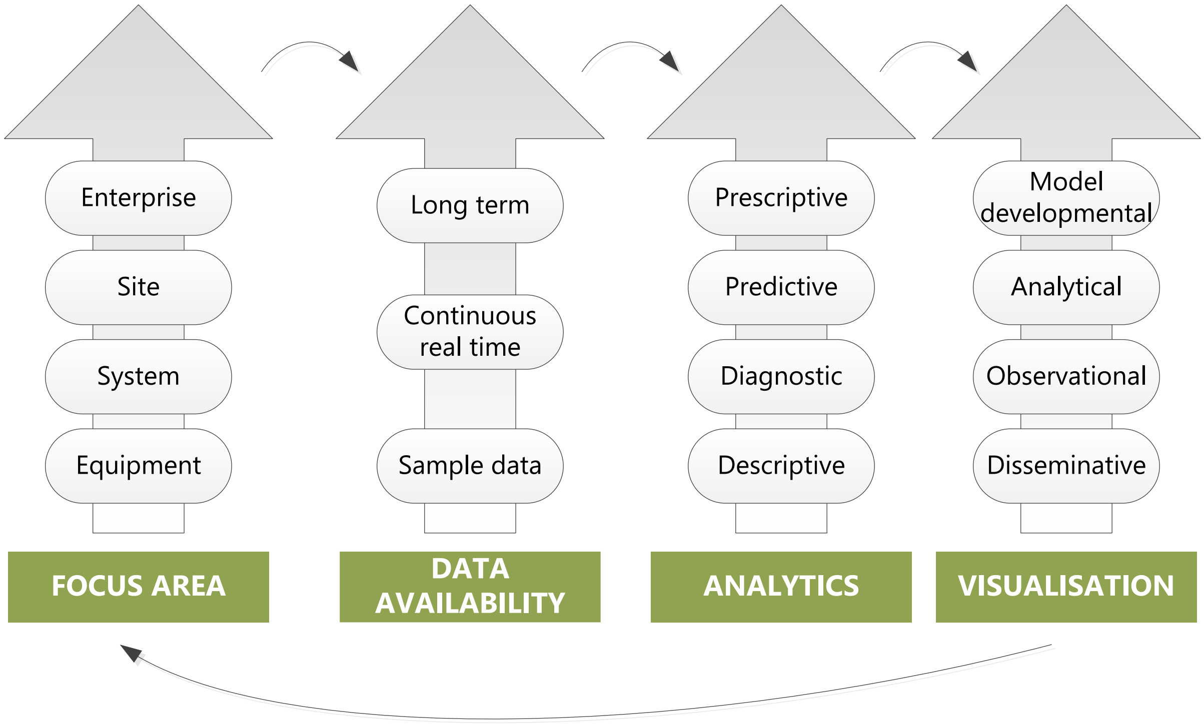


FIGURE 3-3: INITIAL REPORT ASSESSMENT

The assessment of the existing reporting application shows what features lack for each reporting quality, which in turn can be used to identify what needs to be done for improvement.

The levels are especially important for highlighting where one currently is and where to go next. However, it is important to note that the end goal is not always to reach the pinnacle points of each reporting quality. The level of progression depends on the needs of the report and how it will be used in practice, the acceptance of report users to change, and what infrastructure is available (e.g. incremental change is required because availability of long-term data is required before predictive analytics can be performed).

As discussed in literature (Section 2.3), KPIs can be set on the various levels of focus. Therefore, it is important to evaluate the effectiveness and relevance of existing KPIs on the respective levels of focus area during this step. Alternatively, any required KPIs that need to be reported on should be considered.

It is suggested that the initial assessment be summarised according to each reporting quality in a table format, which should include the lacking features to achieve the reporting needs. From this, required features can be identified for improvement. Table 3-1 shows an example of the initial assessment summary table.

TABLE 3-1: EXAMPLE OF INITIAL ASSESSMENT SUMMARY TABLE

Initial assessment	Lacking features	Required feature for improvement
Focus area *(description of initial assessment)*	Description of lacking features to obtain the goal of the reporting application.	Description of features necessary to improve the existing application.
Data availability *(description of initial assessment)*	…	…
Analytics *(description of initial assessment)*	…	…
Visualisation *(description of initial assessment)*	…	…

Prioritise the objectives

The required features identified from the initial report assessment need to be prioritised to aid with the practical execution thereof. This can be done by prioritising the features in a product backlog based on the scope of the feature, cost for completion, and time it will take to complete. Figure 3-4 shows an example of an objectives backlog.

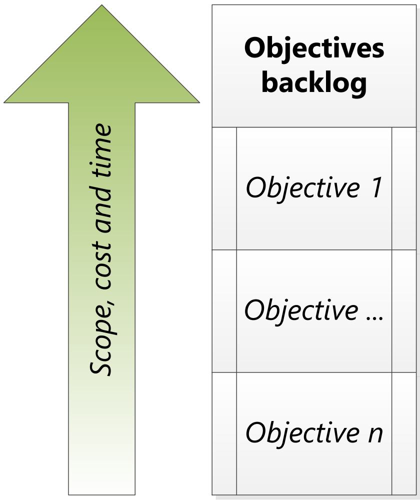


FIGURE 3-4: EXAMPLE OF PRIORITISED LIST OF OBJECTIVES

3.3.2 ITERATIVE EXECUTION

The goal of the iterative phase is to complete each objective in short sprints to obtain rapid and practical results in the form of a report. The report needs to be evaluated after each objective sprint to determine whether it still meets the original reporting needs. Short sprints allow the report to be changed as the needs of the end user change. This phase is based on the project management guidelines evaluated in Chapter 2 to ensure that practical guidance is provided and practical results are obtained.

Sprint planning

Before the completion of each objective, sprint planning must be completed between the project lead and contributor(s). This is important to allow clear communication between role players, discuss any changes to be incorporated in the report, identify clear goals for the sprint ahead, and to re-evaluate the objectives backlog constantly.

Objective sprints

From the structure provided by the reporting qualities, different types of sprints may exist. These sprints are depicted in Figure 3-5. Three types of sprints can exist in the given framework, which are defined as an explorative sprint, all-inclusive reporting qualities sprint, and reporting quality specific sprint.

An explorative sprint is required when an objective has an explorative nature. During this sprint, the report's focus, data, analytics and visualisation may be explored and outcomes may be achieved that may influence the remaining scope of objectives. This type of sprint takes place at the beginning of objective completions as it sets the scope for the report development. Each objective was derived by evaluating the reporting qualities and using their associated levels. Therefore, the completion of the objectives is still in the realm of the reporting qualities.

Objectives are completed by quick sprints of data collection, analysis, and visualisation. This correlates with the reporting qualities: data availability, analytics and visualisation. Some objectives focus on improving a specific reporting quality. For an all-inclusive reporting quality sprint, the objective is to improve multiple reporting qualities. During this sprint, iteration between the focus area, data availability, analytics, and visualisation takes place.

When the objective is to improve a specific reporting quality from one level to the next, the sprint is referred to as a reporting quality specific sprint. In this case, data must be collected, analysed, and visualised in iterations until the reporting quality has improved from one level of the reporting quality to another. This is depicted in Figure 3-5 as an example of the visualisation reporting quality.

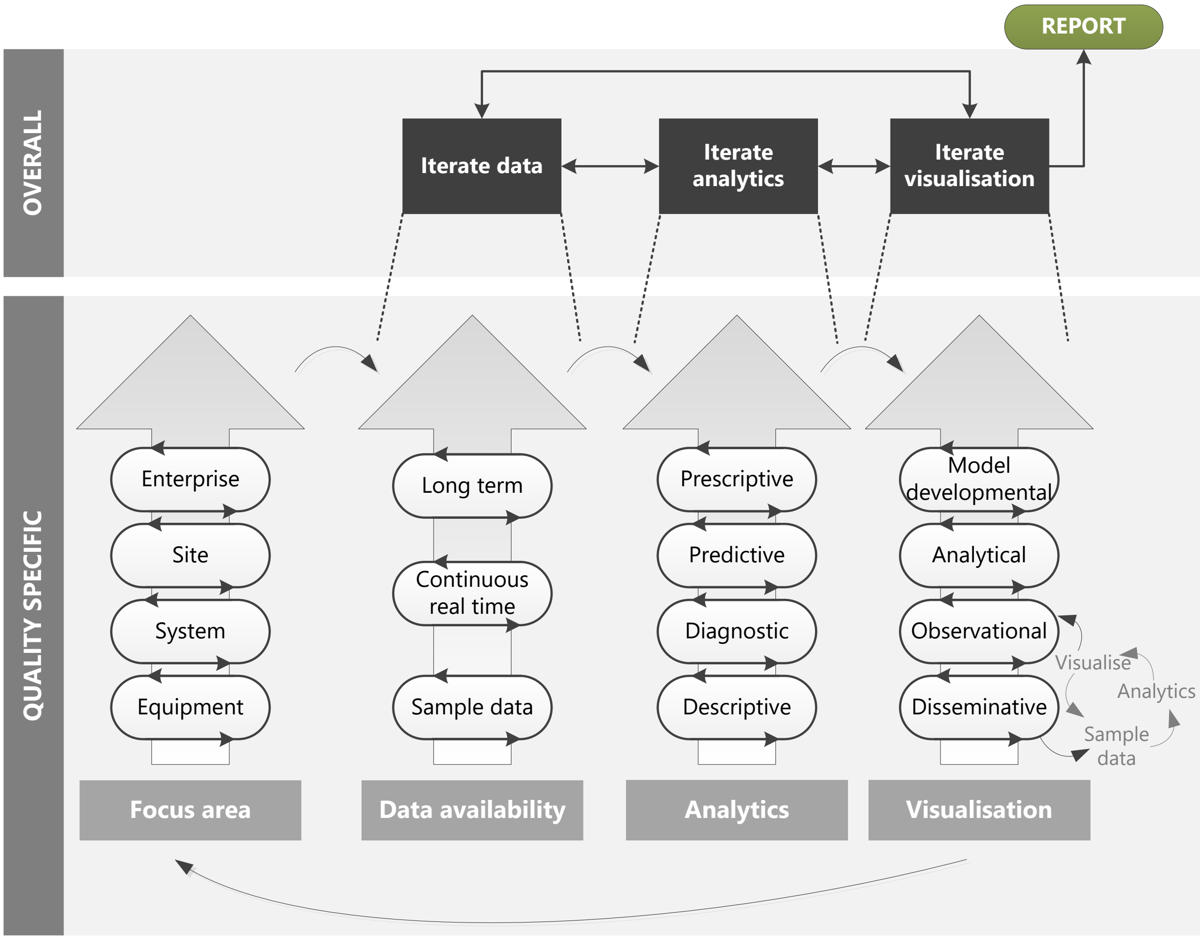


FIGURE 3-5: COMPLETION OF OBJECTIVE SPRINTS

3.3.3 EVALUATION

Impact evaluation

Chapter 1 emphasised the importance of evaluating the impact of reports on real-world operations. The literature review (Chapter 2.2) evaluated existing impact evaluation methods, which identified that an end-user survey is the most suitable method for evaluating the impact of reports. This section develops the end-user survey and describes how to evaluate the survey results (survey shown in Appendix D).

After completion of the report, end users need to complete a survey to evaluate both the qualitative and quantitative factors of the report. The selected end users who complete the survey should have sufficient experience in the real-world application field to deliver objective and trustworthy survey results.

Qualitative factors were identified in Section 2.2.2. Groupings were made from the available literature, which are summarised in Table 3-2.

TABLE 3-2: QUALITATIVE IMPACT EVALUATION FACTORS

Evaluating factor	Description
Data quality	Data source reliability, data accuracy, data refresh time.
Information	Information relevance, assistance in process assessment, information actionability, usability.
Representation	Report understandability, report accessibility, effectiveness of visualisations.

Data quality evaluates the quality of data used in the report. This includes the reliability of the data sources used in the report, the accuracy of the data used in the report, and if the data has an acceptable refresh time (i.e. is it up to date enough for the intended report purpose). Together these factors evaluate the quality of data used in reports.

Information evaluates the level of information/knowledge that can be obtained from the data in the report. This includes evaluating whether: the information is relevant, it assists end users to assess their operations, it is actionable in real-world operations and, lastly, the report is used by the end users.

Representation evaluates the end product of the report. This includes evaluating whether: end users can understand the representations used in the report, end users can access the report easily, and the visualisations used in the report are effective in communicating relevant information.

Literature suggested to evaluate the qualitative factors with a five-point rating scale that has direct opposites of each qualitative factor on each end. Survey results can be represented as shown in Figure 3-6. The dots represent the average rating obtain for a qualitative factor, while the diamonds show the maximum and average rating obtained.

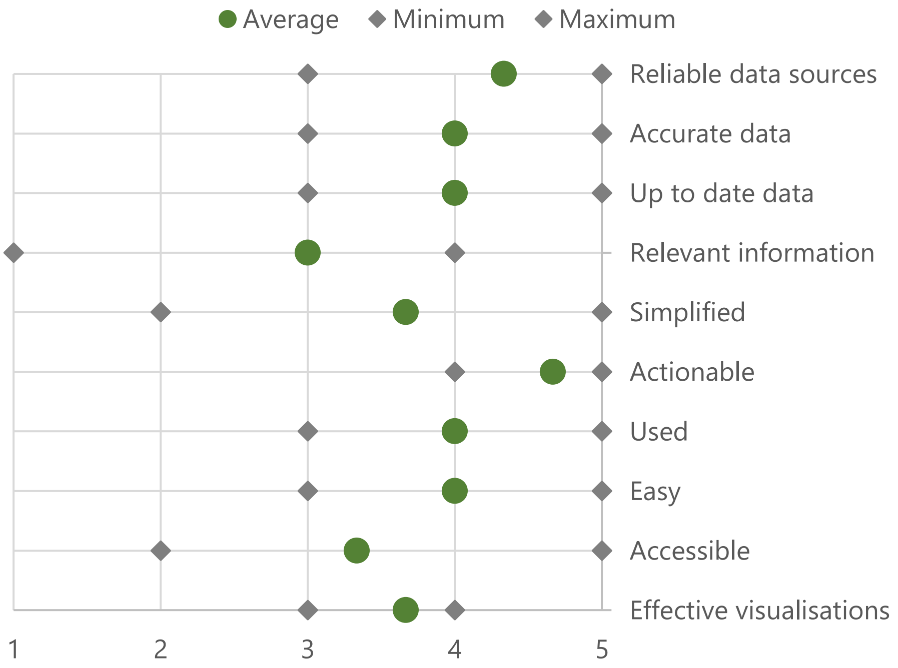


FIGURE 3-6: EXAMPLE OF QUALITATIVE IMPACT EVALUATION RESULTS

Quantitative factors in this study refer to measurable benefits arising due to reporting. This study proposes that quantitative impacts be derived from benefits obtained or value achieved from report utilisation. The literature presented in Section 2.2.2 summarised the benefits or achievable value. From an analysis of the literature, the quantitative factors summarised in Table 3-3 were identified.

TABLE 3-3: QUANTITATIVE IMPACT EVALUATION FACTORS

Evaluating factor	Description
Time savings	Increase in productivity or data analysis time savings.
Direct impacts	Direct impacts associated with specific report, e.g. operational changes and incentives.
Indirect impacts	Indirect impacts associated with specific report, e.g. compliance to guidelines and avoided costs.

The first quantitative factor includes any time savings due to the increased productivity of end users or decrease in time to complete data analyses. This quantitative factor was highlighted by multiple studies in the SLR. In this study, the estimated time savings are converted to monetary savings by correlating the time saved to the average wages of the end users. This method was also proposed by literature [113].

The SLR highlighted that reports can result in accurate decision-making. The impacts thereof were further grouped into direct and indirect impacts. This study suggests that the specific direct and indirect impacts should be identified and quantified. Distinguishing between direct and indirect impacts allows for clear communication on the type of benefits achievable from a report.

The survey should thus allow end users to list direct and indirect impacts associated with the reports with an estimated monetary value thereof. This will show the perceived benefit of the report. Although this monetary value is potentially subjective, it will be considered reliable since the end users should be chosen to be relevant, qualified and experienced personnel.

Quantitative impact estimations include time savings that are converted to monetary savings considering wages estimations, direct impact, and indirect impacts. These survey results can be presented as shown in Figure 3-7.

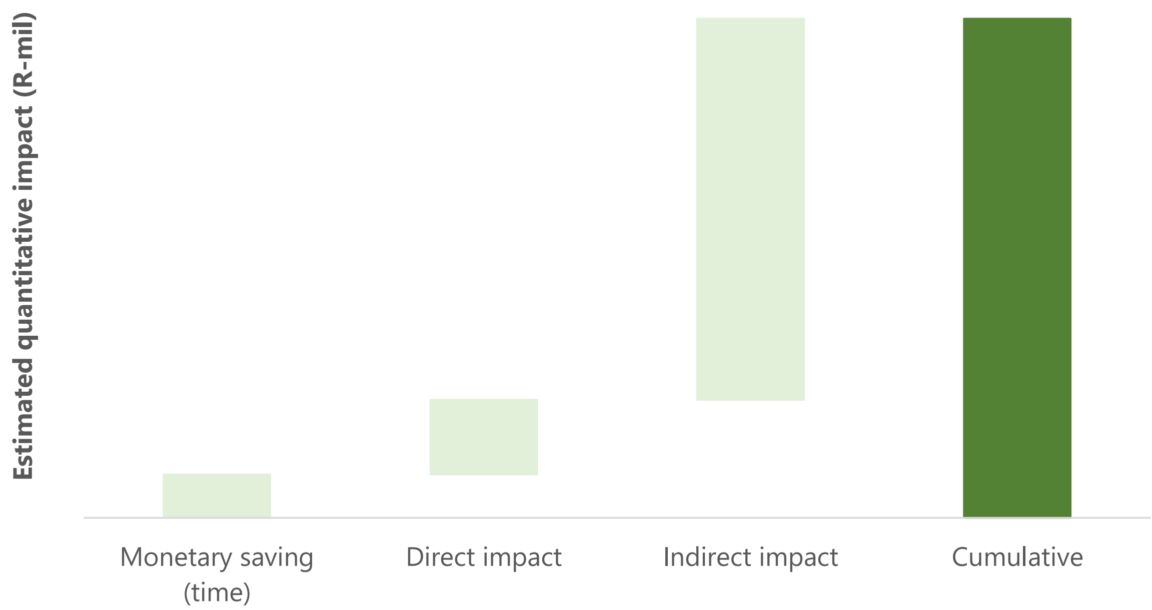


FIGURE 3-7: EXAMPLE OF QUANTITATIVE IMPACT EVALUATIONS

Both the qualitative and quantitative results should be considered to motivate changes, expansions, or curtailment of reports. The survey results further provide clear communication regarding the report impact to all role players and stakeholders involved.

Succeeding assessment

Each of the reporting qualities should be assessed to determine the improvement in reporting and identify future areas of improvements. This can be done by assessing each of the reporting qualities as done in the structured planning phase (Phase 1). An example of the succeeding assessment is shown in Figure 3-8.

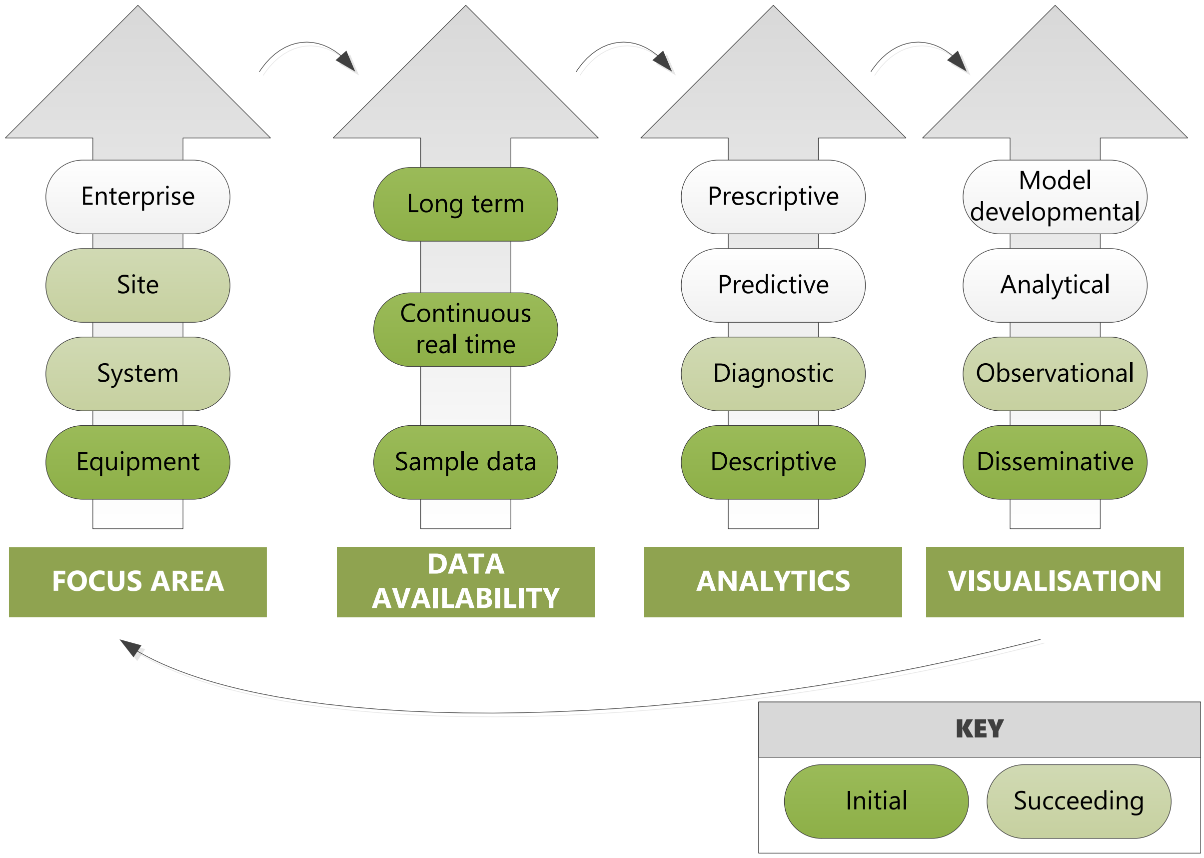


FIGURE 3-8: EXAMPLE OF SUCCEEDING EVALUATION

3.4 ACHIEVING FRAMEWORK REQUIREMENTS

Chapter 1 identified shortcomings from existing implementation guidelines. This, in turn, led to the identification of requirements for a new report development framework. These requirements include evaluating the impacts of reports, providing structure to report development frameworks for incremental improvement, and providing practical guidance throughout the framework. This section investigates whether the requirements of the framework developed in this chapter have been achieved.

Evaluate impact

In Chapter 2, research was conducted to identify existing impact evaluation methods. It was shown that few impact evaluation methods exist. When the impact of reports was evaluated, end-user surveys were mostly used that focussed on the qualitative factors of reports.

This study compiled an end-user survey that evaluates both the qualitative and quantitative impact of reports. This survey was developed in Phase 3 (Evaluation) of the report development framework presented in this chapter (survey shown in Appendix D). This allows report end users to evaluate the impact of developed reports on real-world operations.

Define structured objectives

Chapter 2 evaluated each step of existing BI implementation guidelines to identify whether enough structure is provided to complete the steps incrementally in order to achieve advanced results. This identified four reporting qualities while further research in individual research fields identified the levels associated with each reporting quality. The reporting qualities include focus area, data availability, analytics, and visualisation. The levels associated with each reporting quality provide structure to the original high-level steps in existing BI implementation guidelines. The levels allow report developers to view the original high-level steps involved with BI implementation as an incremental process.

This structure is incorporated in all three phases of the new report development framework. In Phase 1, (structured planning) the reporting qualities and their associated levels are used to assess existing reporting application which, in turn, enables the identification of precise objectives.

During Phase 2 (iterative execution), the completion of objectives can take place by focussing on the improvement of a specific reporting quality or multiple. This gives focus and structure to the execution of reporting development. In Phase 3 (evaluation), the reporting qualities and their associated levels are used to assess the completed reporting application to enable continuous improvement.

Provide practical guidance

In Chapter 2, research was conducted regarding project management, which identified that report development needs to be agile. Agile project management for report development is required to ensure that practical results are obtained. This means that developed reports must be adjusted continuously to ensure that it satisfies the end user's needs.

It was further identified that the agile principles required were a backlog, iterative nature, and identification of role players. A backlog is created in Phase 1 and continuously reviewed during sprint planning in Phase 2 of the new framework. Iterative execution of the objectives in the backlog takes place in Phase 2. In this study, generic role players are identified, which include a project lead, contributor(s), and end user(s). These role players are involved with various tasks throughout all three phases of the framework.

Table 3-4 shows that the newly developed framework aligns with the five phases of agile projects (discussed in Chapter 2). This shows that the new developed framework follows an agile approach.

TABLE 3-4: AGILE PROJECT PHASES VS PHASES OF NEW DEVELOPED FRAMEWORK

Five phases of agile projects [101], [108]	**Phases within framework in this study**
Envision	Phase 1: Structured planning
Speculate	Phase 2: Iterative execution
Explore	
Adapt	Phase 3: Evaluation
Close	

3.5 CONCLUSION

In this chapter, the knowledge gained from the literature review in Chapter 2 was used to develop a new reporting framework aimed to add value. This framework consists of three phases. Structured planning take place in the first phase. The reporting qualities and their associated levels are used to assess the initial state of a reporting application. This assessment allows for objectives to be identified that will meet the end user's needs.

These objectives are executed in an iterative nature in the second phase whereafter they are reviewed continuously to ensure that the developed report will satisfy the end user's needs. In the third phase, the qualitative and quantitative impact of the report is evaluated by means of end-user surveys. Once again, the reporting qualities are used to assess the reporting application to enable continuous improvement.

It was further shown that the new framework achieves the requirements based on the shortcomings identified from existing BI implementation guidelines in Chapter 1. This includes showing that the newly developed framework evaluates report impact, provides structure, and provides practical guidance. The next chapter describes how to implement the framework on real-world case studies.

CHAPTER 4

VERIFICATION AND VALIDATION

4. VERIFICATION AND VALIDATION

4.1 INTRODUCTION

In Chapter 3, a new value-add driven report development framework was developed. The focus of this chapter is to verify the framework and validate the research of this study. The outline of this chapter is shown in Figure 4-1. The framework is verified by applying it to three diverse case studies in the mining industry. The case studies were selected since they included relevant issues faced by the South African mining industry. These case studies include water management (Section 4.2), condition-based equipment monitoring (Section 4.3), and carbon tax liability (Section 4.3). The research is validated by independently quantifying the value add of each case study (Section 4.4).

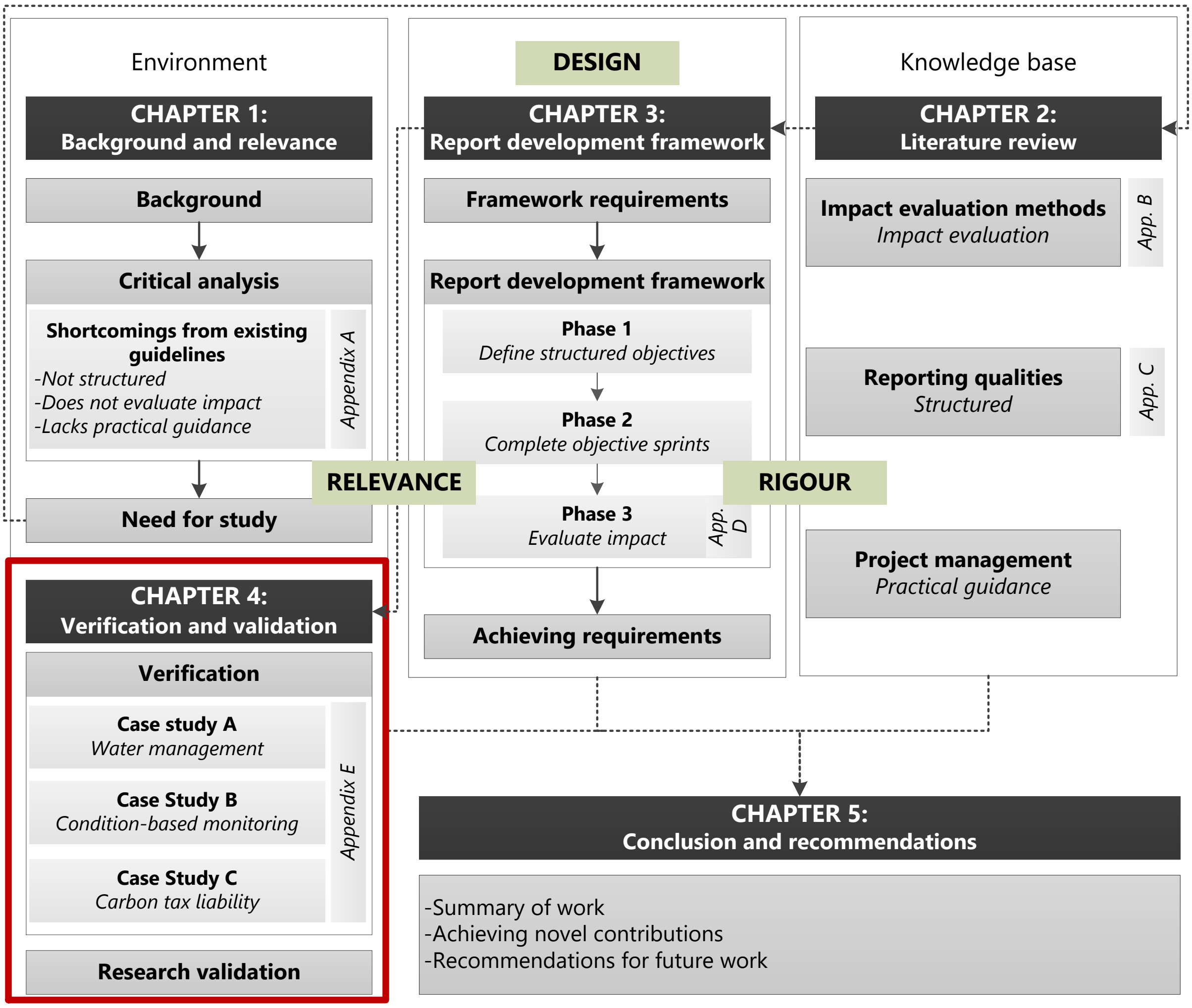


FIGURE 4-1: STUDY RESEARCH METHODOLOGY – CHAPTER 4

4.2 CASE STUDY A: OPERATIONAL WATER MANAGEMENT

4.2.1 CASE STUDY SELECTION AND BACKGROUND

The importance of water management in mining

Water is a valuable resource and the sustainable utilisation thereof is critical. This is clear since water management has been highlighted as an important consideration in the top ten trends in mining during 2018 and 2019 [114], [115]. Furthermore, it has been predicted that by the year 2030, approximately 25% of mining production will be subjected to water shortages [114]. Industries thus need to manage their water consumption to remain sustainable.

In general, water is cooled and used for various underground activities in deep-level mines [116]. These activities include providing ventilation through bulk air coolers, cooling drilling machines, lubricating drilling equipment, and cleaning stope faces [116]. Effective water storage and dewatering of the underground areas are further important to maintain accessible and safe working conditions.

In South Africa, the use of water in underground mining industries is subject to various legal frameworks [117]–[119]. These frameworks require, amongst others, the disclosure of water conservation plans and integrated water and waste management plans (IWWMP) [119]. The compilation of an IWWMP is essential to assist mines when applying for a water use licence in terms of section 40(1) of the National Water Act, 1998 (Act No. 36 of 1998) [119].

In 2008, the Department of Water and Sanitation (at that stage known as the Department of Water Affairs and Forestry) published a best practice guideline for water management for underground mines [118]. The document allows Department of Water and Sanitation officials to understand the integrated water management problems and risks when reviewing IWWMPs. It is necessary to monitor underground water reticulation to track and update the water management strategies accurately. Therefore, the use of data-driven reports can play a significant role in supporting, monitoring and executing water management strategies.

Case study background

This case study focussed on the underground water reticulation system of a deep-level gold mine. The mine produces about 9 394 kg of gold annually, which is mined at depths ranging from 1 600 m to 2 600 m. On surface, the water reticulation system consists of a two-stage pre-cooling dam, four chillers (refrigeration system) and three bulk air coolers. Figure 4-2 illustrates the basic layout of this system.

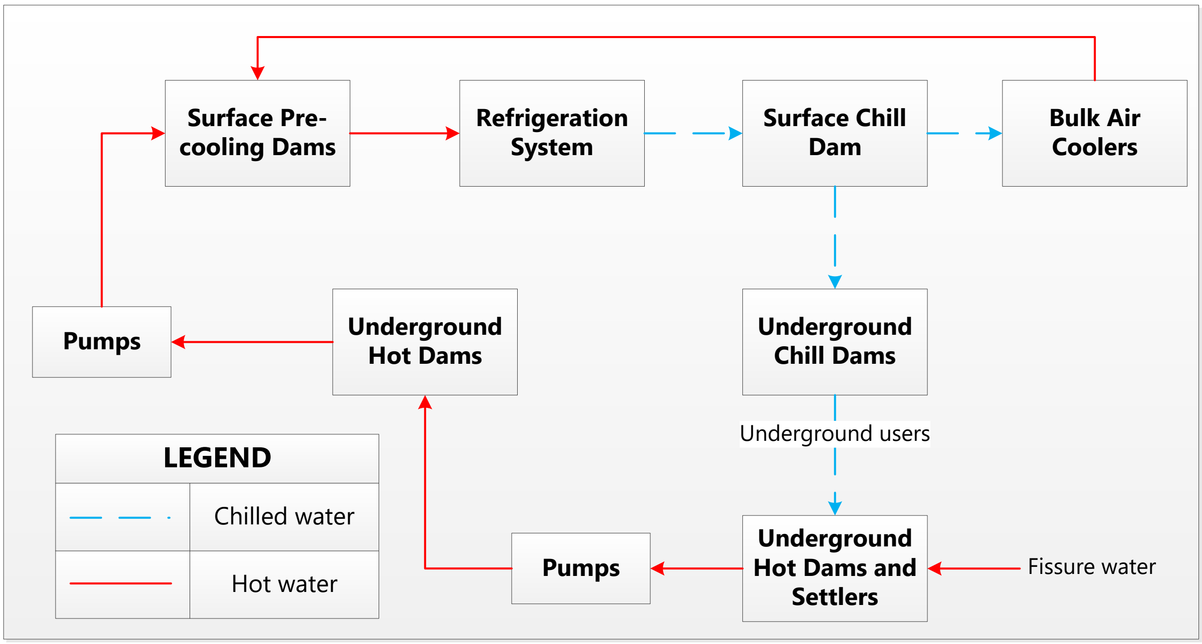


Figure 4-2: Basic water reticulation system (Case Study A) (Adapted from [120])

As shown in Figure 4-2, the pre-cooling dams are used to cool down the hot water from underground before entering the refrigeration system, which cools the water to an even lower temperature. In turn, the chilled water is used to cool hot air in the bulk air coolers, which is necessary to provide the required temperatures underground for mining personnel. The chilled water is sent underground, where it is used during drilling shifts and cleaning of stope faces. There is another bulk air cooler underground, which uses water to provide sufficient cool air in the mining areas. After being used, the hot water is captured along with fissure water by various underground hot water dams. The water undergoes a settling process underground before being recirculated back to surface and reused throughout the water network. Various pump stations are used to recirculate the water.

Multiple engineers are involved with projects to ensure optimal and efficient operation of critical equipment. Many of this equipment and projects form part of or have an effect on the mine's water reticulation system. Thus, these engineers are included as the main end users of the reporting application. For this case study, the end users included three engineers. Furthermore, a single project lead and contributor were identified, respectively.

Owing to the complexity of these systems, it is important to use data derived from measurements in order to monitor, control and manage water effectively. Before the framework was applied, a study had not yet been conducted on how the available data sets could be used to improve water management as a whole. Therefore, the case study was well-suited for this research because it represented a scenario for which data was available, but was not utilised to its full extent.

4.2.2 Phase 1: Structured planning

Evaluate preliminary impact

The project lead and end user held a meeting before commencing with the reporting application in this case study. During the meeting it was highlighted that a significant amount of important information regarding water management is required to analyse daily operation. However, to obtain this data is not easy and requires extensive manual data processing. It was, therefore, expected that a report would increase the accessibility to information.

Define structured objectives

At this mining case study specifically, various water-flow and dam-level measurements are taken throughout the water reticulation system. This data is captured by the mine's SCADA system. From there, an OPC connection ensures that the data is captured and stored in a database. This enables the real-time and long-term availability of the water reticulation data. This data is mostly used for day-to-day monitoring to ensure safe and continued operations.

During the initial evaluation of the existing reporting application, it was found that there was no report designated for the mine's underground water reticulation. However, isolated data trends relating to the water reticulation network featured in different reports. These trends were included in the reports with custom requirements from specific mine personnel within the mine. Thus, any reporting relating to the mine's water reticulation was overly customised with a disconnect from high-level requirements. The existing data system is illustrated in Figure 4-3.

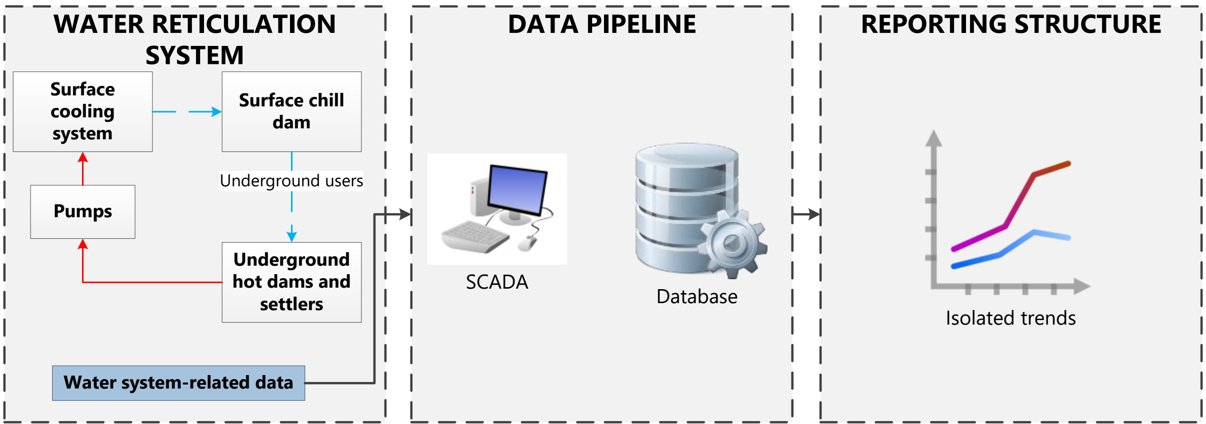


Figure 4-3: Existing mining system, data pipeline and reporting structure (Case Study A)

Due to the isolated evaluations, the application was ranked on an equipment level with respect to the focus area quality. The initial evaluation is depicted in Figure 4-4. The data used in the isolated evaluations regarding the mine's water network was not only available real time, but also included up to 30 days of data. The application was, therefore, ranked on the long-term level regarding data availability.

The isolated evaluations simply displayed information and did not use any analytics. The analytics could thus be identified as being descriptive. Lastly, disseminative visualisation methods were used to convey the information. These methods included single variable trends and tables with information.

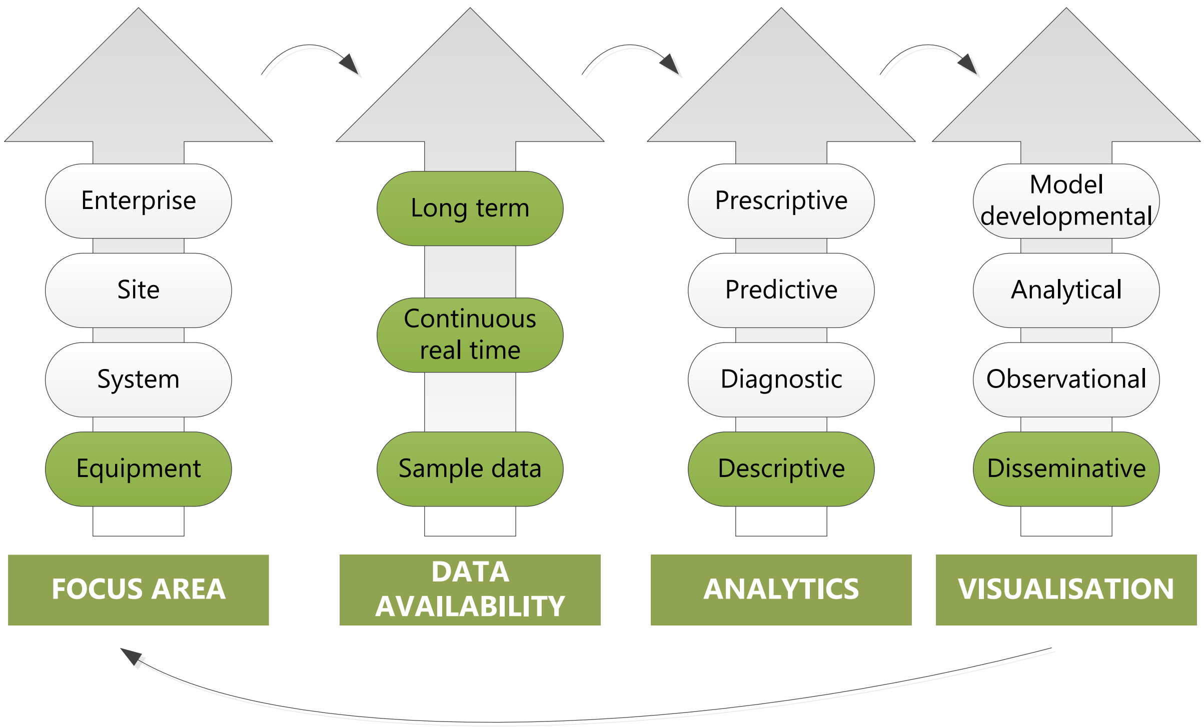


FIGURE 4-4: INITIAL REPORTING ASSESSMENT (CASE STUDY A)

From the focus area quality of the initial assessment, it was deduced that the mine required a standardised report that considers the mine's underground operational water system. This report had to provide an overview of water management. An evaluation was necessary to identify each of the critical parameters that formed part of the KPIs required in such a report. These parameters had to enable the monitoring and assessment of the underground water use.

The initial assessment highlighted the use of a 30-day period of data, which was available continuously. This data availability was deemed acceptable and no additional features were suggested for improvement. During the initial assessment it was noted that no analytics was used and visualisation simply displayed raw data trends.

In order to take the level of analytics and visualisation to the next level, each of the critical reporting parameters necessary for a standardised report had to be reviewed individually to improve the analytics and visualisation used to convey information. A summary of the initial assessment is shown in Table 4-1.

TABLE 4-1: SUMMARY OF INITIAL ASSESSMENT (CASE STUDY A)

Initial assessment	Lacking features	Required feature for improvement
Focus area: *Only isolated evaluations on equipment level*	No overview of water management	Identification of critical parameters to enable reporting on site level
Data availability: *Long-term and continuous data used*	None	None required
Analytics: *Only raw data on a descriptive level provided*	No evaluations that allow for the speedy observation of water use	Evaluation of the necessary analytics per critical reporting parameter
Visualisation: *Only single variable trends used to display information*	No observational visualisation used for easy interpretation of water use	Evaluation of necessary visualisation of each critical reporting parameter

During the first phase of implementation, it was observed that the identified reporting qualities were useful in identifying and describing objectives. The role players were able to understand the need to improve the reporting of water management monitoring. This provided the platform to move ahead with Phase 2 of implementation.

Prioritise objectives

The first objective was to identify the critical reporting parameters to develop a standardised water reticulation report. These parameters had to enable the effective monitoring and analysis of the water reticulation system. This objective was crucial to the scope of the entire application and was therefore the first objective. Defining these critical reporting parameters was done in two sub-tasks. The first task was to evaluate the need of the report from the report users. Secondly, the isolated evaluations identified in the initial evaluation were investigated. These two sub-tasks were combined to identify the critical reporting parameters.

The remaining objectives consisted of evaluating the analytics and visualising each of these critical parameters to display the respective information. The remaining objectives therefore depended on the completion of the first objective. The prioritised list of objectives is presented in Figure 4-5.

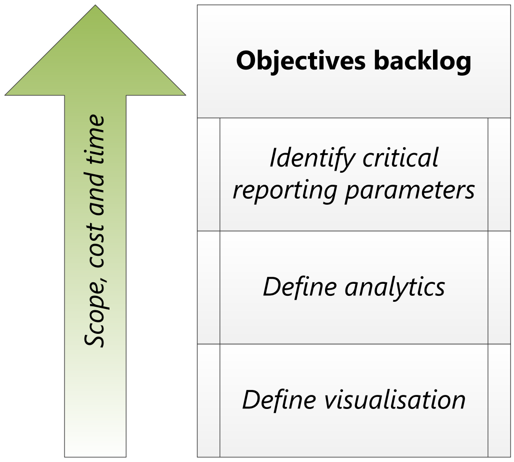


FIGURE 4-5: PRIORITISED LIST OF OBJECTIVES (CASE STUDY A)

4.2.3 PHASE 2: ITERATIVE EXECUTION

Objective 1: Identify critical reporting parameters

The first objective was to identify the critical reporting parameters needed to manage the water reticulation system and was explorative in nature. These parameters were identified by obtaining each of the report end users' respective needs from a water reticulation report. The end users use the report to realise impacts on real-world applications and, therefore, they were considered in the selection of critical parameters. End users want to see whether critical equipment is used correctly, that the mine is not flooding, and that there is enough water in the system for the required processes. It is further critical to be aware of where measurement devices are located and whether they are faulty. Lastly, end users need to know how much water is used for underground operations and how much fissure water is pumped to surface.

A second method used for selecting the critical parameters was to assess the existing isolated evaluations concerning the water reticulation system. These evaluations were assessed to identify which questions they aimed to address. An attempt was made to address these questions through the critical reporting parameters. The end users' needs, as well as the isolated evaluations, were used to select the following critical report parameters:

- Water reticulation layout (necessary to understand system for all users)
- Water consumption (speedy observation of water consumption)
- Water balances (estimation of fissure water)
- Breakdown of water consumption (to know where the most or least water is used)
- Evaluation of dam limits (ensure that pumps are used accordingly to prevent mine flooding)

The chosen critical report parameters were approved by the project lead and report end users and were deemed acceptable to move on to the next objective. Since the methodology is iterative in nature, this objective could always be repeated if results from the next objectives deemed it necessary.

Objective 2: Define analytics for each reporting parameter

The second objective focussed on improving the analytics of the reporting parameters. Thus, this objective was reporting quality specific and aimed to deliver analytics that would allow for the speedy observation of water use. This moved the level of analytics from descriptive to diagnostic.

Relevant data was gathered and used to iterate through the analytics reporting quality for each reporting parameter. This included collecting data and exploring different analytics for each reporting parameter. Table 4-2 summarises the selected analytics per critical reporting parameter.

TABLE 4-2: SUMMARY OF SELECTED ANALYTICS (CASE STUDY A)

Critical reporting parameter	Selected analytics
Water reticulation layout	No analytics required
Water consumption	Water usage intensity calculated as the water sent to working areas divided by the tonnes of ore hoisted per day
Water balances	Water balance between the water volumes sent underground and pumped back up provided an indication of fissure water
Breakdown of water consumption	Water balance of water sent to various working levels indicated use
Evaluation of dam limits	Calculating the daily hours each dam was over or under its desired level limits was deemed as a speedy observation of exception of dam limits

Completion of Objective 2 delivered a report that showed the results of the analytics in table format. No visualisation was explored since a separate objective was specified for that purpose. Completing the objectives in this way allowed a version of a report to be available to end users to use the information straightaway, which provided feedback of the usefulness thereof before an extensive amount of time was spent on report development that did not meet end-user requirements.

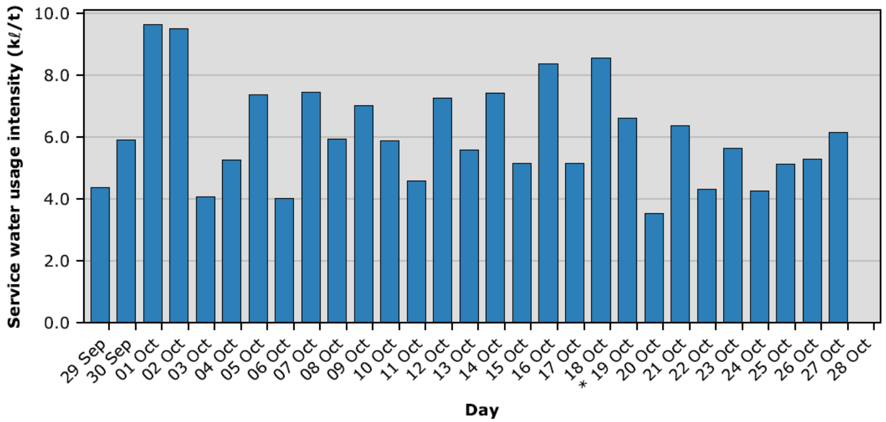
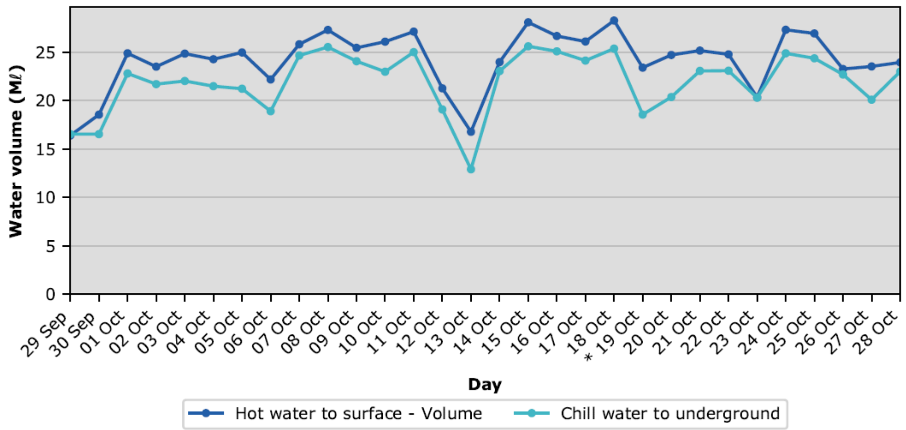
Objective 3: Define visualisation for each reporting parameter

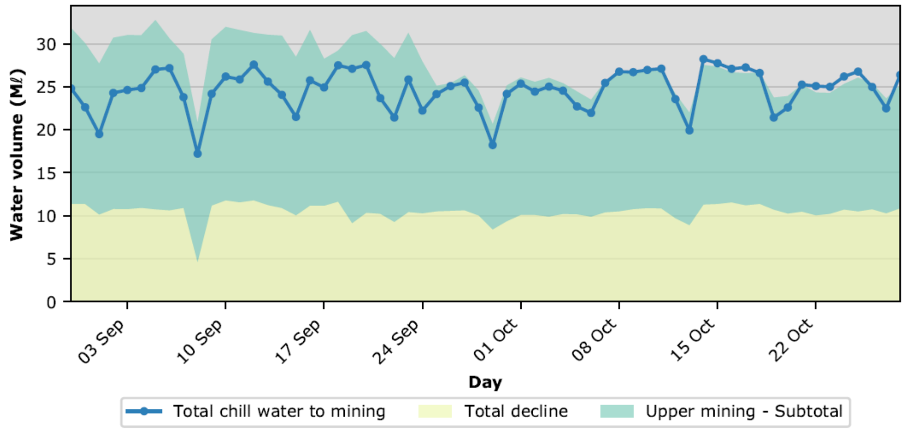
The aim of the third objective was to improve the visualisation of the reporting application, which is a reporting quality specific objective that focussed on delivering visualisations from which speedy observations could be made regarding the captured data.

The data required and included in report to quantify analytics results was used to explore visualisation methods for each of the critical reporting parameters. This process was iterated and the visualisation methods adapted until acceptable results were obtained. A summary of the selected visualisation for the critical reporting parameters is shown in Table 4-3. The aim of each visualisation method was to develop visuals on a diagnostic level with easy interpretation of water use.

After completion of Objective 3, a report was delivered with acceptable reporting parameters, analytics, and visualisations as identified from the structured planning phase (Phase 1). An example of a developed report is given in Appendix E.

TABLE 4-3: SUMMARY OF SELECTED VISUALISATION (CASE STUDY A)

Critical reporting parameter	Selected visualisation	Example from report
Water consumption	Bar graph over 30 days of water usage intensity to evaluate any trends or extreme cases.	
Water balances	Line graph showing the water sent underground and pumped up. This indicates whether there is a large deficit between the two values.	

<table>
<tr><th>Critical reporting parameter</th><th>Selected visualisation</th><th>Example from report</th></tr>
<tr><td>Breakdown of water consumption</td><td>Stacked graph of service water consumption and total service water sent to the working areas. This indicates any misbalances or waste of water.</td><td>
</td></tr>
<tr><td>Evaluation of dam limits</td><td>Tables with each dam in the first column and dates (seven days) in the first row. The hours that each dam exceeded its upper or lower level limit are colour-coded to show extreme cases.</td><td>Table 2.4: Hours exceeding upper limit
<table>
<tr><th>Description</th><th>10 Oct</th><th>11 Oct</th><th>12 Oct</th><th>13 Oct</th><th>14 Oct</th><th>15 Oct</th><th>16 Oct</th></tr>
<tr><td>Surface pre-cooling dam 1</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td></tr>
<tr><td>Surface pre-cooling dam 2</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td></tr>
<tr><td>Surface chill dam</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td></tr>
<tr><td>45L Chill dam 1</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td></tr>
<tr><td>45L Chill dam 2</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td></tr>
<tr><td>45L Hot dam 1</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td></tr>
<tr><td>45L Hot dam 2</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td></tr>
<tr><td>66L Hot dam 1</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td></tr>
<tr><td>66L Hot dam 2</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td></tr>
<tr><td>66L Hot dam 3</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td></tr>
<tr><td>66L Hotdam 6</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td><td>0.0</td></tr>
<tr><td>66L Dirty dam</td><td>4.0</td><td>6.5</td><td>5.0</td><td>19.0</td><td>0.0</td><td>1.0</td><td>1.5</td></tr>
<tr><td>69L Dirty dam</td><td>0.0</td><td>0.0</td><td>0.0</td><td>17.5</td><td>0.0</td><td>0.0</td><td>0.0</td></tr>
</table></td></tr>
</table>

4.2.4 Phase 3: Evaluation

Impact evaluation

After completing all objectives, a survey was sent to the report end users. This survey considered both the qualitative and quantitative impact of the developed report on real-world operations. This section provides the survey results. Details of the end users who completed the survey are shown in Table 4-4. The survey results were deemed trustworthy due to the end users' qualifications and experience.

Table 4-4: Details of end users who completed the impact evaluation surveys (Case Study A)

End user	Qualifications	Experience in mining industry	Experience in water reticulation system
1	B. Eng, M. Eng, PhD	6	6
2	B. Eng, M. Eng, PhD, Pr. Eng	9	9
3	B. Eng	3	3

Figure 4-6 shows the qualitative survey results and indicates the minimum and maximum ratings. It can be seen that all qualitative factors obtained a relatively high rating from end users. The largest difference between the minimum and maximum rating from end users was obtained for the usability of the report. The accessibility and relevant information factor received high ratings from end users, which addressed the end users' needs as discussed in the preliminary impact evaluation step in Phase 1.

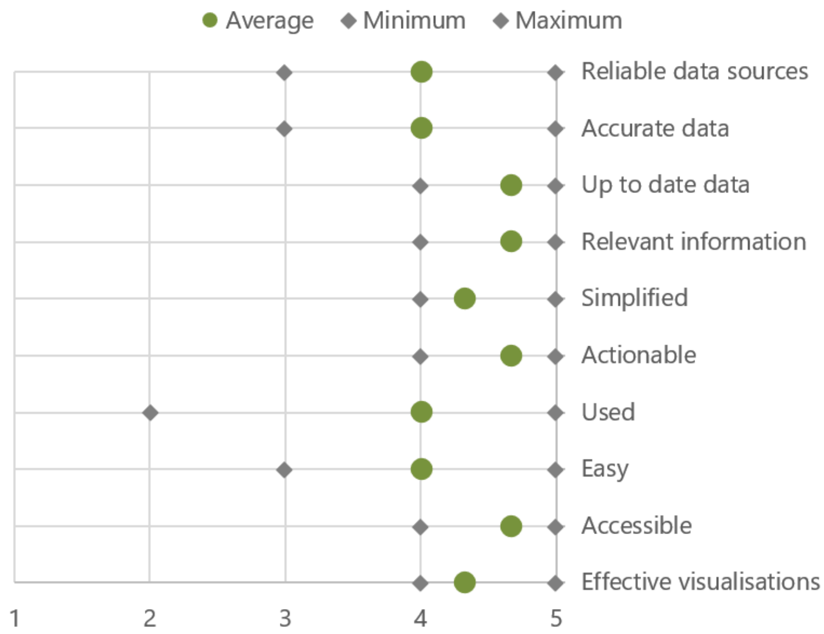


Figure 4-6: Qualitative impact evaluation results (Case Study A)

The quantitative survey results are shown in Figure 4-7. All end users agreed that using the report saved them time doing manual data collection and analyses. By using the average salary of a mining engineer in South Africa, the average time savings were converted to an annual monetary saving. This amounted to R500 000 annually. The report was further used to do fault-finding, which had a direct and significant impact on energy savings for pumping and cooling. This amounted to a saving of up to R300 000 for the incident. In extreme cases, faulty operations regarding the water reticulation system could lead to a loss of a production shift. End users stated that the report could be used to rectify such problems in a timely manner and an avoided cost of R6.6 million per day could potentially be obtained. The cumulative quantitative impact amounted to R7.3 million.

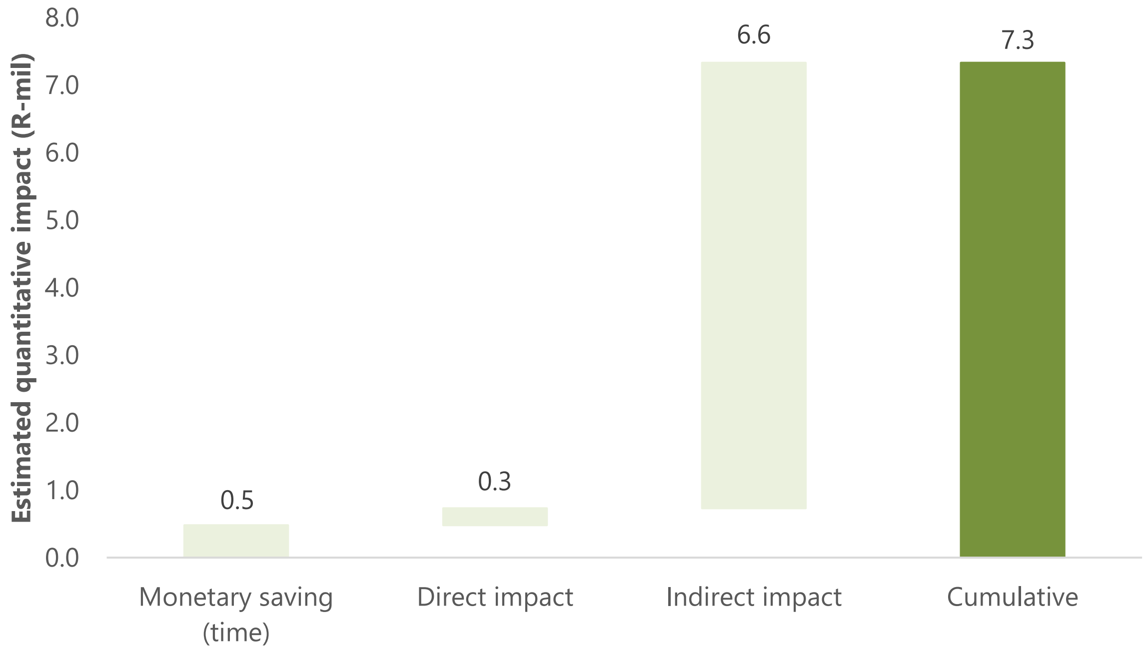


FIGURE 4-7: QUANTITATIVE IMPACT EVALUATION RESULTS (CASE STUDY A)

The high indirect impact motivated the continued use of the report, while the lower direct impact indicated that report usability had to be improved to increase this value. This was supported by the qualitative evaluation that indicated that the usability of the report had a distributed rating between end users.

It is recommended to meet with end users regularly to understand value-add incidents and adjust reporting to increase the usability thereof. This is expected to increase the direct quantitative impact of the report. It is further recommended to investigate whether more end users could use the report and obtain impact evaluation surveys from them to increase the sample size of results.

Succeeding assessment

During the initial assessment, the framework enabled objectives to be identified for the development of a water reticulation report. This section describes how a succeeding assessment was done to evaluate the improvement in reporting by applying the framework and identifying future areas of improvement. The succeeding assessment is shown in Figure 4-8 and discussed thereafter.

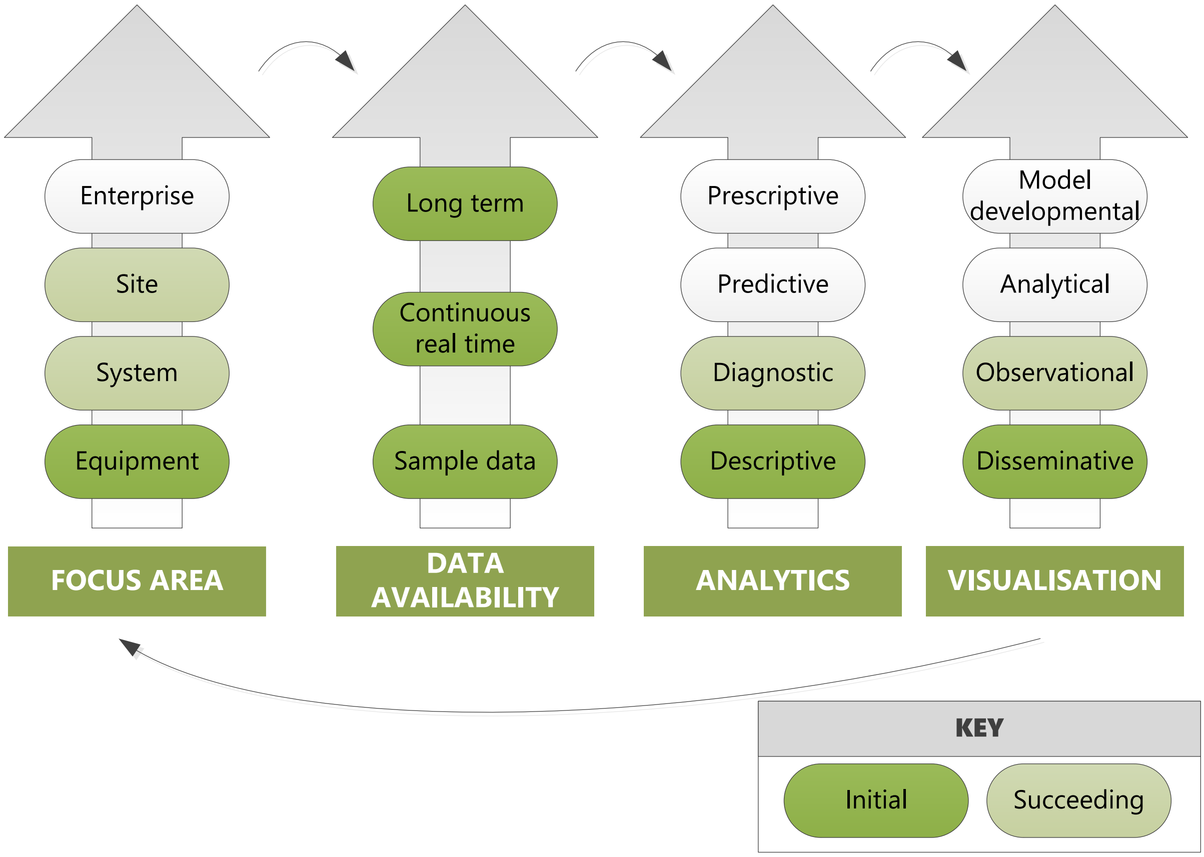


FIGURE 4-8: SUCCEEDING REPORT ASSESSMENT (CASE STUDY A)

During the initial assessment, the focus area quality was ranked on the equipment level due to the availability of isolated water management related graphs in unrelated reports. The objective was thus set to identify critical reporting parameters associated with water reticulation reporting. This enabled a standardised report to be developed for a specific site. In turn, this ranked the focus area on a site level after applying the framework.

The isolated graphs that featured in unrelated reports used data over a 30-day period. Therefore, during the initial assessment, the data availability quality was ranked on a long-term level. After applying the framework, long-term data was still used throughout the report and the data availability quality remained on the long-term level.

The initial assessment ranked the analytics and visualisation qualities on the descriptive and disseminative levels due to the large amount of information displayed through single variable trends and tables. However, after applying the framework, the analytics and visualisation qualities improved to the diagnostic and observational levels, respectively. A summary of the succeeding assessment is given in Table 4-5.

TABLE 4-5: SUMMARY OF SUCCEEDING ASSESSMENT (CASE STUDY A)

Initial assessment	Succeeding assessment	Changes implemented
Focus area: *Only isolated evaluations on equipment level*	Report developed for entire water reticulation system on a site	Critical reporting parameters identified for a standardised water reticulation report
Data availability: *Long-term and continuous data utilised*	Long-term and continuous data used	Long-term data still used, and performance compared with historical data
Analytics: *Only raw data on a descriptive level provided*	Observation of water consumption relative to demand	Calculation of water usage intensity
Visualisation: *Only single variable trends used to display information*	Captured data was observed speedily	Used stacked area graphs, colour-coding, limits and descriptive site layout

The succeeding assessment showed that the next step will be to roll out the report to all business units. The standardised method of reporting will assist with the development of objective data-driven water strategies. Quantifying the water usage intensity of various business units on the same principle will further allow water-intensive mines to be identified, which will assist in deciding where water-reducing initiatives should focus.

4.3 CASE STUDY B: CONDITION-BASED EQUIPMENT MONITORING

4.3.1 CASE STUDY SELECTION AND BACKGROUND

The importance of equipment condition-based monitoring

The South African gold mining industry is experiencing a decline in production, while global gold production figures are increasing [6], [7]. One of the main challenges that contribute to this decline is increasing production costs [6]. The gold mining industry thus needs to be innovative with their existing infrastructure to remain profitable [6], [63], [121]. Several new technologies exist to aid in improving operations and sustainability [19], [115], [122]. One such technology is condition-based equipment maintenance [63], [122].

Deep-level mines use various systems to provide underground areas with cold water, compressed air and ventilation [63]. Monitoring of this equipment is vital to ensure reliable operation thereof. This, in turn, influences mine production and the safety of underground workers [63].

Condition monitoring contributes to maintenance planning by indicating where maintenance is needed [63]. This is done by evaluating the data that relates to the condition of equipment to identify possible risks of failure [123]. The information is used to make valuable decisions regarding maintenance of equipment [124], [125].

Case study background

The selected case study focussed on the various equipment used in deep-level gold mines. The specific gold mining company measures the condition-monitoring parameters of the various pieces of critical equipment of five gold-processing plants and 11 gold mining shafts. Thus, 16 business units were considered. The company and equipment hierarchy is shown in Figure 4-9.

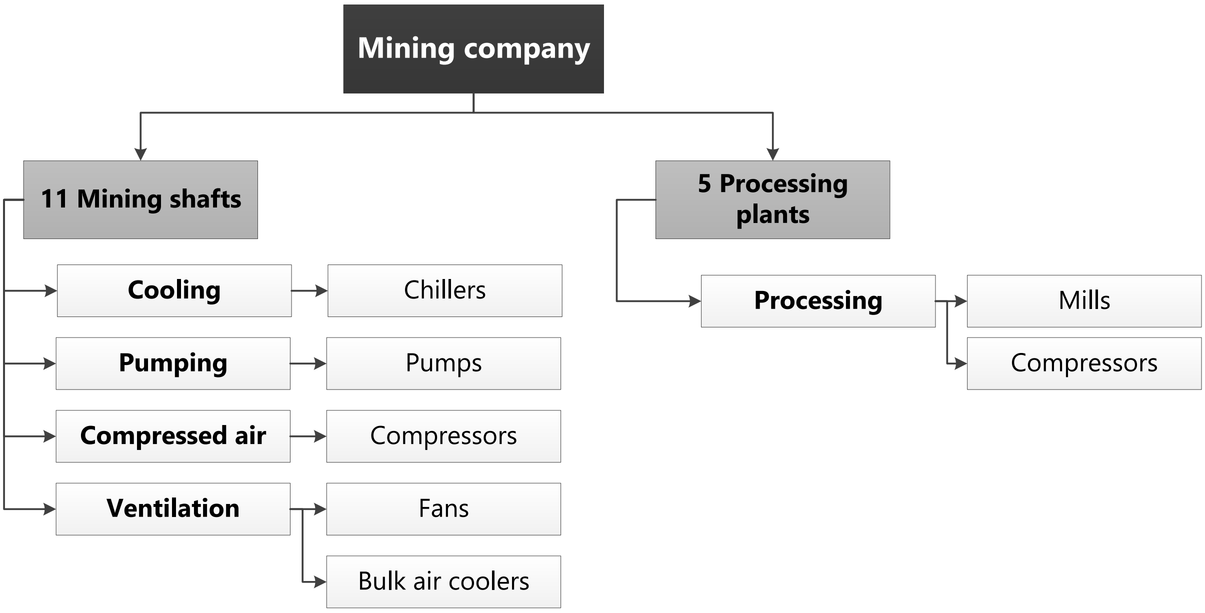


FIGURE 4-9: COMPANY AND EQUIPMENT HIERARCHY (CASE STUDY B)

The plant mills and compressors are used during gold processing. On the shafts, complex systems, consisting of various equipment, are necessary to provide underground areas with cold water, compressed air, and ventilation. Hot water is cooled by chillers and sent underground. The cold water is used during drilling shifts to clean stope faces and to cool hot air through bulk air coolers. After using the water, pumps circulate the hot water back to the surface. In order to comply with legal and safety regulations, fans are used to provide sufficient ventilation throughout the mine. Lastly, compressors provide compressed air, which is used during drilling shifts for gold ore production.

Each of these systems, i.e. mills, chillers, pumps, fans and compressors, are vital to the gold production process. Therefore, the parameters associated with the condition of each of these systems are measured, including the running status, critical temperatures, and vibrations. As a whole, hundreds of parameters need to be considered. This creates a data-rich problem where data analysis is important.

The maintenance on all shafts and plants in this case study is managed and inspected by a central asset and maintenance team. This team consists of a team lead with a member per critical system on the business units (such as chillers, pumps, and fans). For the purpose of this study, the asset and maintenance team leader was considered as the main end user. A project lead and contributor were also identified.

Several studies were conducted on the implementation and maintenance of condition monitoring on this specific case study, which were published [63], [122]. This scenario is unlike Case Study A, for which no previous studies were conducted. However, the case study is still relevant for this research because it represents a scenario for which a concise effort was already made to improve reporting. Thus, this case study would show whether a well-established report could also be assessed and improved with the developed framework.

4.3.2 PHASE 1: STRUCTURED PLANNING

Evaluate preliminary impact

Before commencing with the reporting application in this case study, a meeting was held between the project lead and end users. This meeting highlighted that the end users had a need to prioritise all the incoming information related to condition monitoring. The expected outcome was that the most critical equipment would be prioritised for maintenance.

Define structured objectives

In this case study, the measured condition-monitoring data was available locally via the on-site SCADA system. The data acquisition process was facilitated by an OPC connection, which provided continuous real-time access to the data. Lastly, as data was acquired, it was stored continuously in a cloud database. The existing mining equipment, data pipeline, and reporting structure are shown in Figure 4-10 and discussed further thereafter.

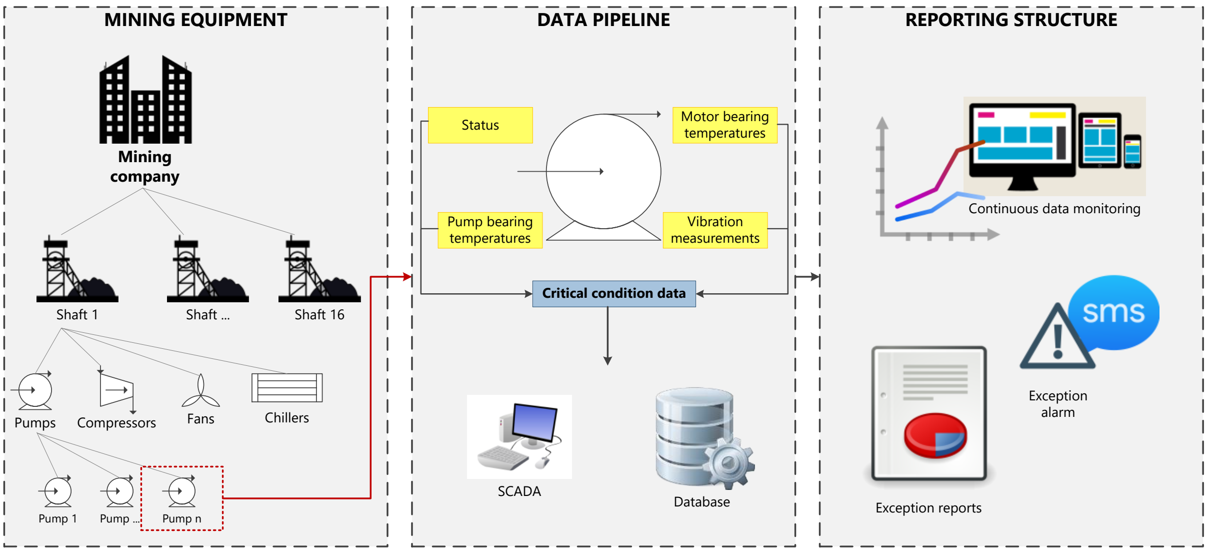


FIGURE 4-10: EXISTING MINING EQUIPMENT, DATA PIPELINE AND REPORTING STRUCTURE (CASE STUDY B)

Continuous real-time graphs were generated on each of the condition-monitoring parameters for all of the equipment. The data points in the graphs were updated every 30 minutes and could be viewed remotely by users via an online website. A total of 2 100 graphs was generated on a daily basis for the 16 business units.

Upper limits for each parameter were set to prevent equipment from running in unsafe regions. Whenever a parameter exceeded the given limit, an SMS was sent to notify the relevant mining personnel. On average, 4 400 messages were sent out per month for all 16 business units. All the exceptions that occurred the previous day were summarised in daily reports. Daily exception reports were compiled for each shaft and plant.

The existing reporting structure was considered during the initial assessment. The reporting structure was assessed according to its level of focus area, data availability, analytics, and visualisation. The initial assessment is depicted in Figure 4-11.

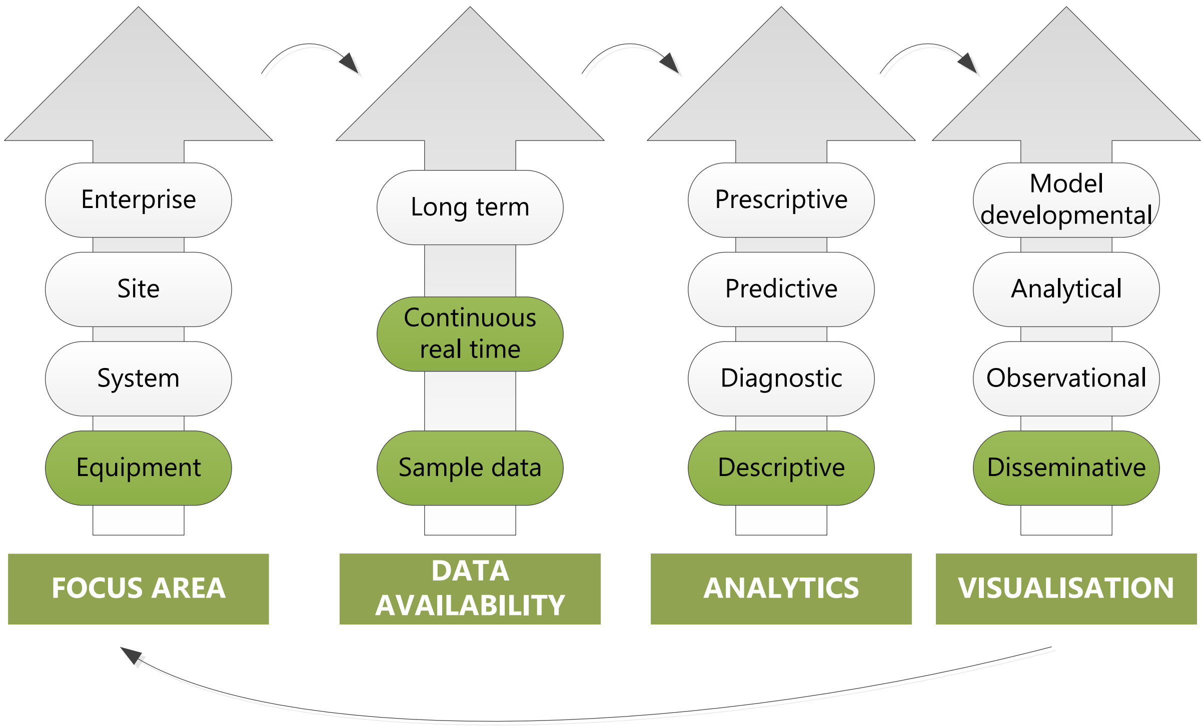


FIGURE 4-11: INITIAL REPORTING ASSESSMENT (CASE STUDY B)

All existing reports, i.e. real-time graphs, alarm SMSs, and daily exception reports, were equipment focussed. The focus area was thus ranked on an equipment level.

It is noted that the existing reporting structure already provided a basis for data-driven decision-making. However, all reporting was done in a real-time or daily manner. Although reporting in real time was valuable, there was no indication of long-term deterioration of equipment. This was, however, possible since all data was stored in a cloud database. Therefore, the data availability for the existing reporting application was ranked on a continuous real-time level.

Numerous graphs were available on a daily basis. These graphs consisted of single variable trends that described what happened to each condition-monitoring parameter throughout the day. Due to the large amount of information conveyed by these graphs, the analytics and visualisation were ranked on a descriptive and disseminative level, respectively.

Based on the initial assessment, objectives were defined to improve the existing application. The initial assessment was used to identify the required features to improve each of the reporting qualities. The required features, in turn, were deduced from identifying features lacking in the initial assessment.

When considering the focus area, the initial assessment ranked the reporting and monitoring on an equipment level. However, most decisions regarding the expenditure of capital, time and resources on maintenance were made on an enterprise level. Therefore, the use of equipment-level evaluations restricted the existing condition monitoring to be used in high-level decisions. The equipment-level evaluations thus needed to be rolled up to an enterprise level. The higher level of focus area enabled the identification of equipment operating the closest to failure. This, in turn, would ensure that the use of resources on maintenance was based on informed decisions. The newly developed reports should not replace the existing system, but should rather be an extension thereof to higher level personnel for valuable decisions.

However, rolling the evaluations up to an enterprise level required an adjustment to the level of analytics. The initial assessment revealed that the analytics was on a descriptive level due to the large amount of information that was conveyed per condition-monitoring parameter. All this information could become overwhelming for end users to analyse. It was clear that the available evaluations did not only had to be rolled up to a higher level of focus area, but also had to be prioritised according to their risk of failure per piece of equipment. This risk of failure per piece of equipment had to incorporate all of its associated condition-monitoring parameters (e.g. temperatures and vibrations). Using the prioritised equipment as a KPI moved the level of focus area from equipment to enterprise while also moving the level of analytics from descriptive to diagnostic.

From the initial assessment it was identified that although continuous real-time data was used, there was no long-term indication of the deterioration of equipment condition. In order to achieve this, the equipment risk of failure had to be evaluated over a longer period of time.

Lastly, the initial assessment ranked the visualisation methods used as disseminative due to the use of numerous daily single variable trends per condition-monitoring parameter, which obstructed the speedy observation of equipment condition. Therefore, the visuals used to display the equipment risk of failure had to incorporate all the parameters associated with a piece of equipment and give an indication of the responsible parameter for the deteriorating condition.

The required features identified from the initial assessment with respect to each reporting quality are summarised in Table 4-6. These features are required to improve the existing condition-monitoring application.

TABLE 4-6: SUMMARY OF INITIAL ASSESSMENT (CASE STUDY B)

Initial assessment	Lacking features	Required feature for improvement
Focus area: *Reporting and monitoring focussed on equipment level*	Difficulty making high-level decisions based on equipment-level evaluations	Prioritise the condition of equipment to roll up to enterprise level
Data availability: *Continuous real-time reporting*	No long-term indication of equipment deterioration	Evaluate equipment risk of failure over a longer period of time
Analytics: *Vast amount of descriptive information conveyed*	Large amount of information may become overwhelming	Determine the risk of failure for all equipment based on all of its condition-monitoring parameters
Visualisation: *Utilisation of numerous daily single variable trends*	Obstruction of speedy observation of the condition of equipment and the trend of its deterioration	Show equipment deterioration and responsible condition-monitoring parameter

Prioritise objectives

None of the required features shown in Table 4-6 required capital expenditure. The scope and time intensiveness of each objective were therefore considered to develop a prioritised list of objectives. The most important objective to enhance the quality of the report was to determine the risk of failure for each piece of equipment based on all its condition-monitoring parameters. The remaining features depended on the completion of this objective. Therefore, the first objective was to develop a prioritisation concept.

The first objective consisted of two sub-tasks, namely, the quantification of a risk of failure and thereafter the prioritisation thereof to identify the most critical equipment among multiple pieces of equipment. The risk of failure and prioritisation had to be done over a longer period of time to incorporate the need to have a long-term indication of equipment failure.

After developing the prioritisation concept, the visualisation method was established. As identified in Table 4-6, the visualisation had to indicate the trend of equipment deterioration and the responsible condition-monitoring parameter thereof. This objective had two sub-tasks, namely, to establish how the trend of deterioration and cause thereof would be illustrated, respectively. The objectives described in this section are shown in Figure 4-12 and addressed in the following sections.

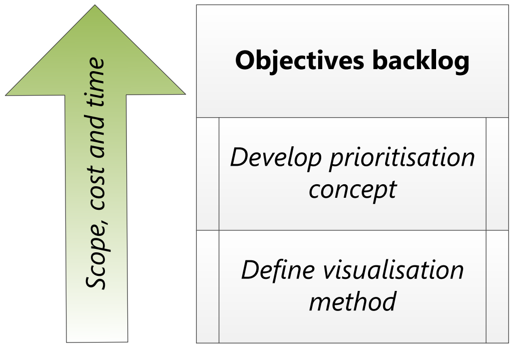


FIGURE 4-12: PRIORITISED LIST OF OBJECTIVES (CASE STUDY B)

4.3.3 PHASE 2: ITERATIVE EXECUTION

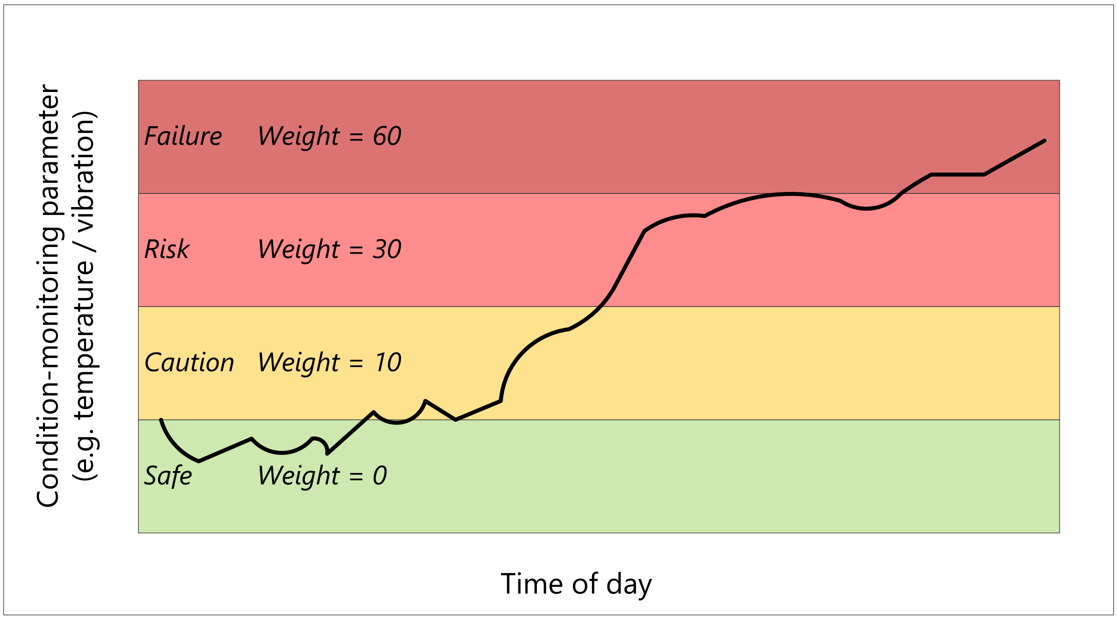
Objective 1: Develop prioritisation concept

Establishing a method of equipment risk quantification and prioritisation is specifically focussed on extracting more valuable information from the descriptive data shown in the initial reporting application. This objective was thus reporting quality specific data with the aim of moving from descriptive to diagnostic analytics.

Sample data was obtained by the contributor and a method of quantifying risks was explored. Progress and feedback were discussed with the project lead on a weekly basis. This process was iterated until satisfactory results were obtained. Thereafter, the next sub-task of this objective, namely prioritising the risks scores, was completed by following the same process.

Van Jaarsveld [63] suggests that risk scores be used to identify the risk of gold mining equipment failing. The method proposed by Van Jaarsveld [63] was used in this study. Risk scores were quantified by characterising four different operating regions per condition-monitoring parameter throughout the day, which included safe, caution, risk, and failure regions. Thereafter, weights were attributed to each of the regions to quantify a risk score. These weights were arbitrary numbers, which were zero in the safe region while the failure region had the largest weight. The weights used in this study were 0, 10, 30 and 60 for the safe, caution, risk and failure regions, respectively.

For a specific parameter, a daily risk score was quantified by multiplying the percentage of time operated in each region by the respective region weight. A risk score was quantified per piece of equipment by adding all of the risk scores of the associated parameters together. An example of the region weights and risk score quantification of a single parameter is shown in Figure 4-13.



Daily risk score = percentage operation in region × region weight

FIGURE 4-13: ILLUSTRATION OF RISK SCORE CALCULATION (CASE STUDY B)

The method resulted in a daily risk score per equipment. During Phase 1 (Section 4.3.2), it was explained that a longer period of data had to be evaluated to determine the deterioration of the equipment's condition. Therefore, the risk scores per piece of equipment were calculated on a daily basis and accumulated over a 30-day period. This allowed the risk scores to not only be representative of a day's condition, but also of a 30-day period.

After establishing the risk of failure quantification, the second sub-task required the equipment condition to be prioritised by ranking the pieces of equipment according to their accumulated risk scores. The equipment with the highest accumulated risk score was ranked as the most critical condition, while the equipment with the lowest risk score was ranked as the least critical. This ranking was done per critical system since the end user indicated that the asset and maintenance team had a representative who would investigate each system.

The iterative nature of completing this objective and continuous communication with the end user identified three refinements that had to be made to the risk score calculation. Firstly, in the case of a piece of equipment running in the safe region and thus having no risk for a specific day, the accumulated risk score would remain constant. However, in such a case, it might be more beneficial to place focus on equipment whose risks are still increasing. Therefore, the accumulated risk scores were adapted to decrease when no risk was achieved. In order to further focus on pieces of equipment that were deteriorating more rapidly, this risk score decreased exponentially the longer no risk was observed.

Secondly, a further adjustment to the accumulated risk scores was made to consider the rate at which the equipment's condition was deteriorating. This was done by scaling each daily risk value of the different pieces of equipment according to the piece of equipment with the highest risk score. This way, pieces of equipment that were deteriorating rapidly could be highlighted even further.

Thirdly, a specific case study identified that refinement was required in the risk calculation method. In the specific case, maintenance was completed on Mill B on 16 July. After the maintenance was completed, the risk value still increased marginally due to the parameter running slightly in the caution region. It was further found that the end user was only interested in equipment running in the risk or failure regions. The original operating regions were thus too stringent. The risk calculation method was reviewed and the caution region discarded.

Before the risk calculation was refined, the risk of Mill B marginally increased after maintenance occurred on 16 July. After the risk calculation was refined, the risk decreased to 0 after the maintenance was completed. This decrease further led to determining that another mill's risk overtook Mill B's risk, and the mill was thus prioritised for maintenance.

The completion of this objective delivered a report that summarised the top five pieces of equipment with the highest risk of failure per system. An example of the table given in this one-page report is illustrated in Table 4-7.

TABLE 4-7: EXAMPLE OF PRIORITISATION OF RISK SCORES (CASE STUDY B)

Ranking	Compressor	Fan	Fridge plant	Pump
1	Mine A Comp 3	Mine C Fan 1	Mine B Ammonia Plant 5	Mine B Pump 1
2	-	Mine A Booster Fan	Mine C Fridge Plant 4	Mine D Pump 4
3	-	Mine C Fan 2	Mine B Ammonia Plant 6	Mine A Pump 4
4	-	Mine B Main Fan 3	Mine B Ammonia Plant 1	Mine A Pump 3
5	-	Mine A Main Fan 2	Mine B Ammonia Plant 2	Mine A Pump 2

Objective 2: Define visualisation method

The analytics defined in Objective 1 was seen as a reporting quality specific objective. Sample data of the risk scores was taken and methods of visualisation explored in order to move from disseminative to observational visuals. Feedback meetings between the contributor and project lead were held twice a week until the desired result was obtained. Two graphs were chosen to show the trend of deterioration and the cause thereof. The first graph showed the trend of the accumulated risk score over a 30-day period. In order to decrease the large amount of information displayed, only the top five most critical pieces of equipment were displayed on this graph. This focussed the attention of maintenance planners on the most critical equipment. Figure 4-14 shows an example of the accumulated risk scores of various pieces of equipment.

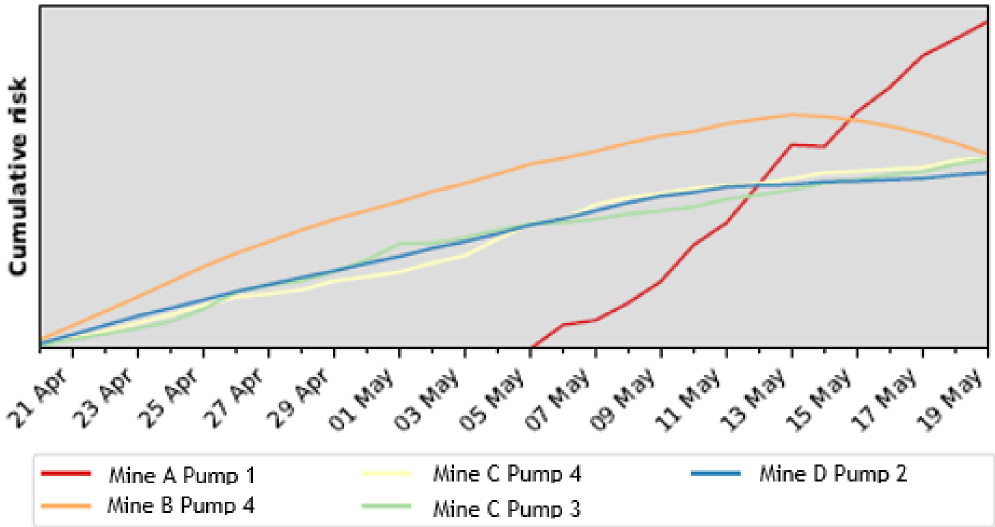


FIGURE 4-14: EXAMPLE OF CUMULATIVE RISK SCORE VISUALISATION

From the example in Figure 4-14 it can be seen how the risk of different pieces of equipment increased and/or decreased over time. The most critical pieces of equipment were identified by their highest risk scores. The rate of deterioration was determined by inspecting the gradient of the different lines. For example, the condition of Mine A Pump 1 increased rapidly from the 5 May until its condition was worse than the remaining equipment.

The second graph was a bar chart that illustrated the distribution of the various condition-monitoring parameters to the final accumulated risk score of the top five critical pieces of equipment. This graph enabled mine personnel to establish which parameter contributed the most to the deteriorating condition of equipment. Thus, mine personnel could determine which type of maintenance was required. An example of the distribution of the risk scores is shown in Figure 4-15.

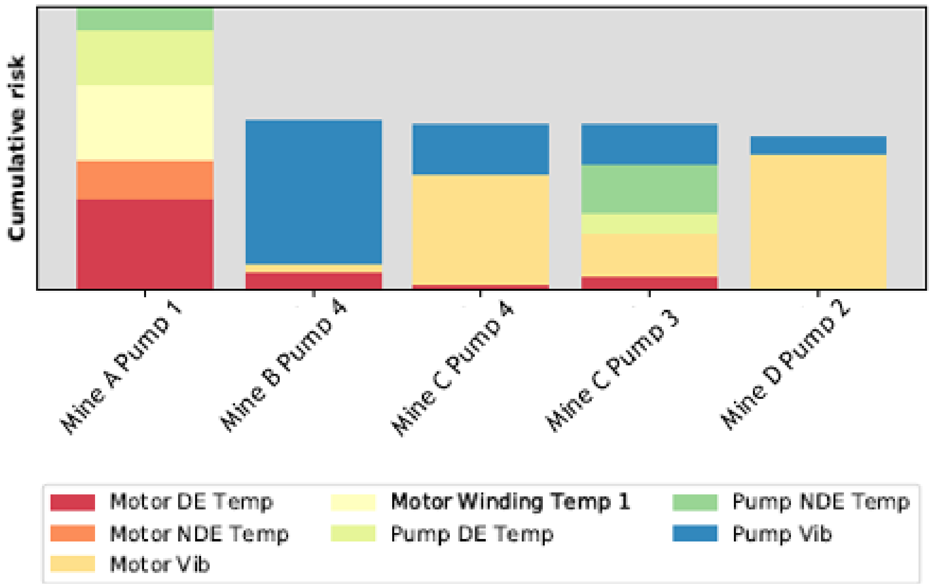


FIGURE 4-15: EXAMPLE OF DISTRIBUTION OF CUMULATIVE RISK SCORE

By inspecting Figure 4-15, the cause of the rapid deterioration of Mine A Pump 1 was attributed to temperature issues. Furthermore, the graph shows the cause of deteriorating condition of the remaining equipment.

The completion of this objective yielded a report per shaft/plant (site level) and a report that contained data for all shafts and plants (enterprise level). An example of a developed report on an enterprise level is given in Appendix E. The specific shaft/plant names have, however, been removed from the example report for anonymity. This report contained both the summarised and prioritised table as an outcome of Objective 1 as well as the two visuals discussed in Objective 2. These reports were sent out automatically on a weekly basis to assist the end user with the prioritisation of equipment maintenance.

4.3.4 PHASE 3: EVALUATION

Impact evaluation

After completing all objectives, the end-user survey was sent out. The end-user information is shown in Table 4-8 while the qualitative results are shown in Figure 4-16. All selected end users had ample experience in the mining industry and in the field of condition monitoring specifically and were highly qualified. Due to the end users' experience and qualifications, they were deemed relevant to complete the end-user surveys.

TABLE 4-8: DETAILS OF END USERS WHO COMPLETED THE IMPACT EVALUATION SURVEYS (CASE STUDY B)

End user	Qualifications	Experience in mining industry	Experience in condition-monitoring field
1	B. Eng, M. Eng, PhD	6	1
2	B. Eng, M. Eng, PhD, Pr. Eng, MBA	16	5
3	B. Eng, M. Eng, PhD	8	4

The results show that all qualitative factors received high ratings. This in turn, highlighted the end users' overall satisfaction with the reporting application. The high ratings for actionability, usability, and accessibility of the report indicate that end users used the report, while the high data quality ratings for data source reliability, data accuracy, and up-to-date data indicate that the end users trusted the information provided to them.

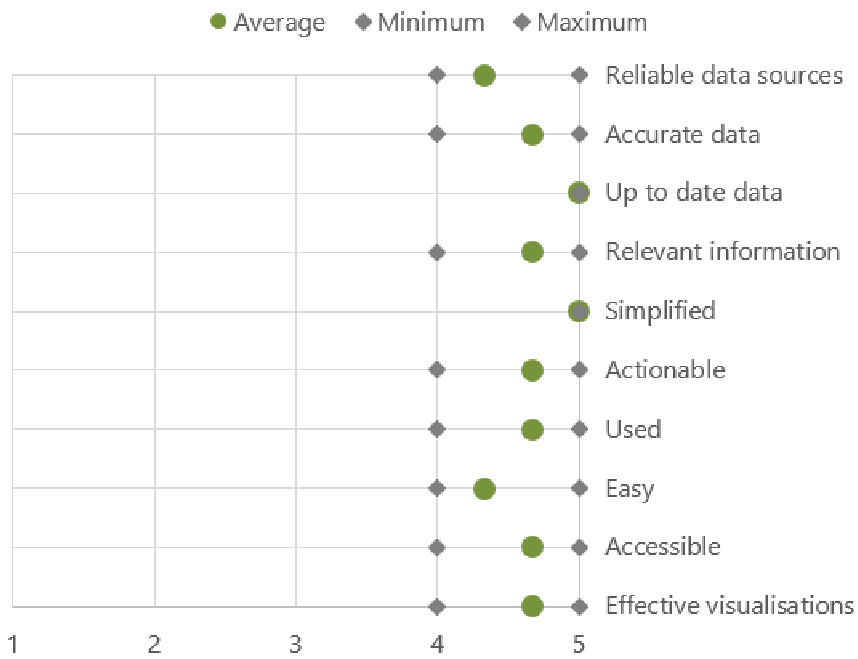


FIGURE 4-16: QUALITATIVE IMPACT EVALUATION RESULTS (CASE STUDY B)

The quantitative survey results are shown in Figure 4-17. End users agreed that the reporting application resulted in time and productivity savings. Time was saved since the report was readily available and no data had to be collected or analysed manually. Productivity savings arose due to the prioritisation concept of the reporting application. Since end users knew what the most critical equipment was, they could spend their time maintaining those pieces equipment as opposed to all equipment, which increased their productivity. The time and productivity results obtained from the surveys were converted to monetary savings by using the average salary of a mining engineer in South Africa. This amounted to a R200 00 annual saving.

A variety of direct and indirect impacts were obtained from the end-user surveys. The direct impacts included avoided costs due to equipment failures since the highest priority maintenance could be completed and emergency call-outs for maintenance were reduced. This amounted to a saving of R15.4 million annually for the mining operations. The indirect impacts from the end-user surveys included the avoidance of stoppages that could have influenced production, improvement in resource management, and positive effects in mine health and safety. These impacts amounted to R6.1 million according to the end-user surveys. The accumulated quantitative impact amounted to R21.7 million annually.

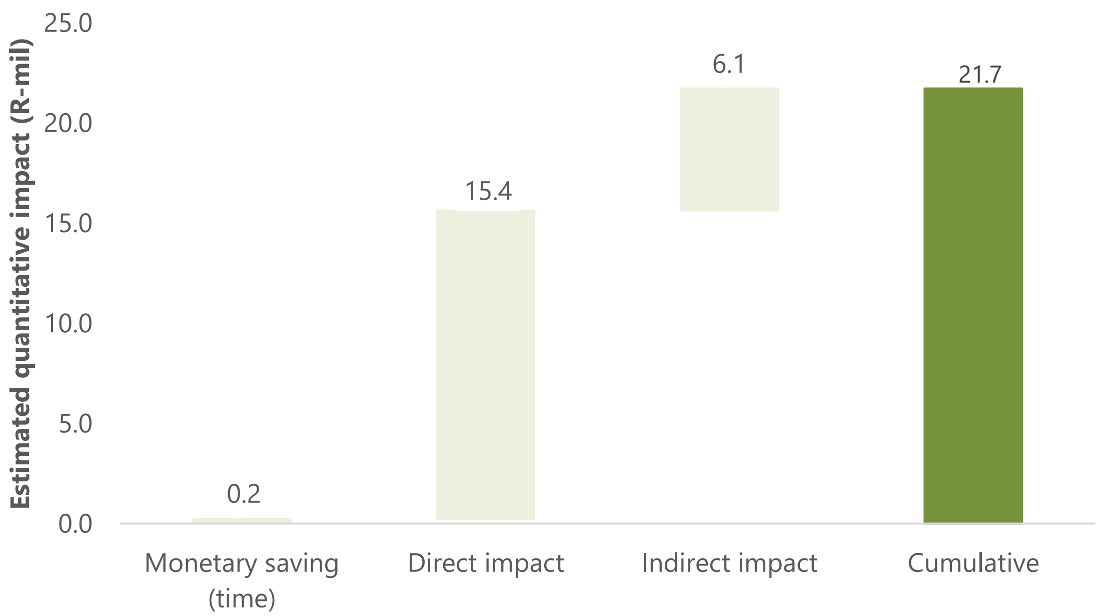


FIGURE 4-17: QUANTITATIVE IMPACT EVALUATION RESULTS (CASE STUDY B)

The impact evaluation survey results show that the report had a high qualitative impact and significantly high direct quantitative impacts. This supports the continuation of the reporting application and the motivation for future developments. Alternatively, the high qualitative ratings and high quantitative impacts may further indicate that reporting resources could spend time on other reporting applications to get them on the same standard as the reporting application in this case study.

Succeeding assessment

Each of the reporting qualities were improved during the iterative objective completion. The newly developed reports did not replace the existing SMS and daily exception reporting, but rather aided in obtaining more valuable information for data-driven maintenance decision-making. This was done by using reporting on an enterprise level, long-term data, diagnostic analytics, and observational visualisation. The succeeding assessment is shown in Figure 4-18 and discussed thereafter.

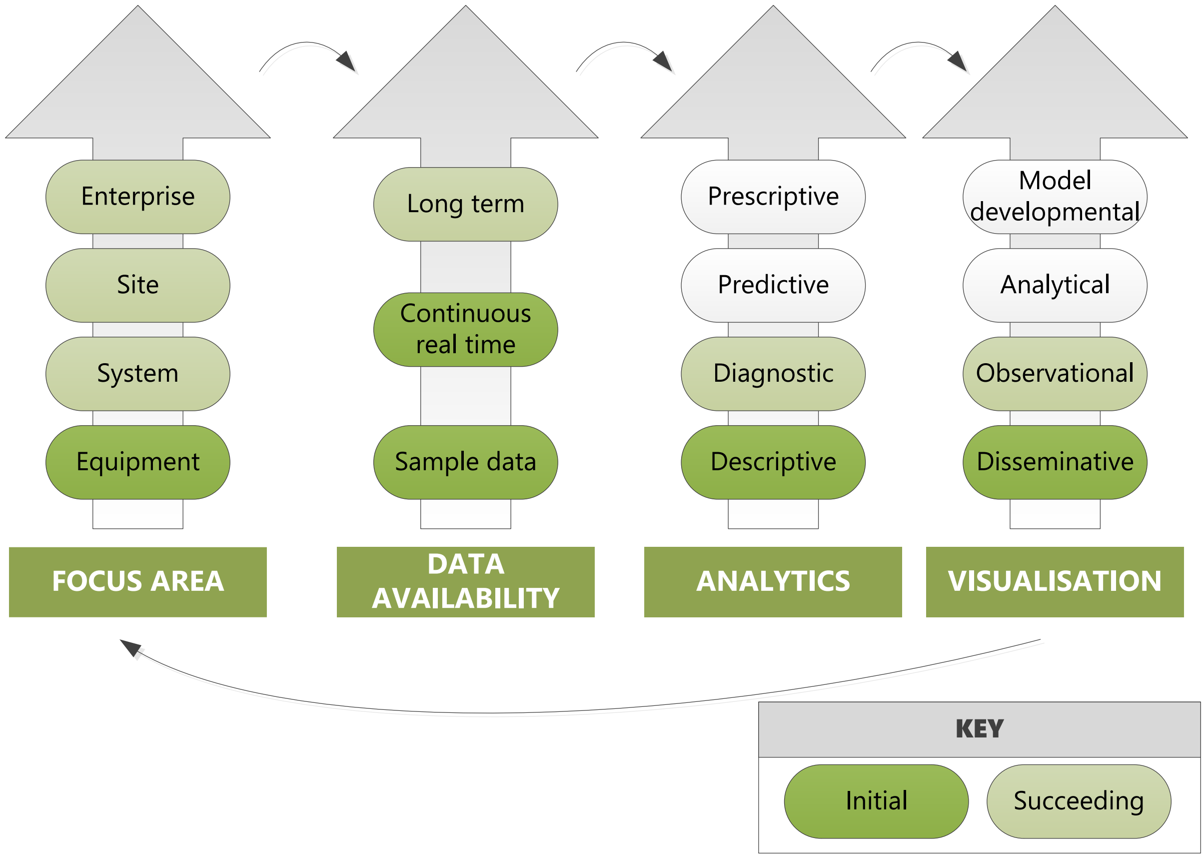


FIGURE 4-18: SUCCEEDING ASSESSMENT (CASE STUDY B)

By prioritising the risk of failure scores and reporting on the top five critical equipment per system over the entire enterprise, reporting could be done on an enterprise level. This information could notify high-level management about equipment that critically needed maintenance. The use of a 30-day period of data when calculating the risk scores enabled a longer indication of the deterioration of equipment condition. Thus, reporting was done on a long-term basis.

The calculation of risk of failure scores per equipment instead of analysing each condition-monitoring parameter moved the level of analytics from descriptive to diagnostic. Trending the cumulative risk scores gave an indication of the deterioration of equipment, while a bar chart showing the contribution of each condition-monitoring parameter served as a speedy observation of the cause of deterioration. This allowed for observational level of visualisations. A summary of the succeeding assessment is given in Table 4-9.

TABLE 4-9: SUMMARY OF SUCCEEDING ASSESSMENT (CASE STUDY B)

Initial assessment	Succeeding assessment	Changes implemented
Focus area: *Reporting and monitoring focussed on equipment level*	Reporting rolled up to enterprise level	Prioritised risk to failure scores and reporting on the top five critical equipment per system for all business units

Initial assessment	Succeeding assessment	Changes implemented
Data availability: *Continuous real-time reporting*	Continuous real-time reporting with long-term data	Use a 30-day period of data
Analytics: *Vast amount of descriptive information conveyed*	Diagnostic analytics utilised to identify critical equipment	Determined risk to failure scores for all equipment
Visualisation: *Utilisation of numerous daily single variable trends*	A decreased number of trends that are observational of equipment condition	Trended cumulative risk scores and a bar chart showing the contribution of each condition-monitoring parameter

From the succeeding assessment, the next step for improvement was identified as predictive analytics, which included predicting equipment failures or lifetime. This further enhanced maintenance planning. Furthermore, the use of analytical visualisation was identified as a future step, which could include showing the relationship between predicted equipment lifetime and respective influencing variables.

4.4 CASE STUDY C: CARBON TAX LIABILITY

4.4.1 CASE STUDY SELECTION AND BACKGROUND

The importance of carbon tax liabilities

Greenhouse gases (GHGs) emitted to the atmosphere are a main contributor to climate change, which adversely affects the earth's sustainability [126]–[129]. GHG mitigation strategies have been implemented globally to reduce carbon emissions and mitigate the effect of climate change [128], [130], [131]. South Africa has shown its commitment to reduce its GHG emissions by formally consenting to two of the most significant international treaties. The first is the Kyoto Protocol that came into effect in 1997. In 2002, South Africa ratified the Protocol and it came into effect in 2005 [132]. This Protocol legally obligates multiple countries to reduce their GHG emissions [130]. Additionally, South Africa ratified the Paris Agreement in 2016, which is to be legally enforced post-2020 [133].

Despite the fact that South Africa does not have set targets for the Kyoto Protocol as a developing country [134], the government committed to implement mitigating actions in the *South African National Climate Change White Paper*. The country aims to reduce its GHG emissions by 34% by 2020 and 42% by 2025 [134], [135].

One of the most recent strategies initiated by the South African government towards reducing its GHG emissions is the carbon tax system. This environmental tax system aims to tax GHG emissions at R120 per tonne of carbon dioxide (CO_2) [129], [136]. The carbon tax system is, however, still a new legislation that presents various uncertainties and risks [137], [138].

South Africa is one of most CO_2 intensive countries [139] with the biggest culprits being energy-intensive industries. One of the large industries that will be affected by the carbon tax system is the mining industry. Industries need to adapt to ensure sustainability and competitiveness. Monitoring the carbon tax liability as well as its uncertainties is thus crucial for the industry to prepare for the financial implications.

Case study background

This case study focussed on a gold mining company that consists of 13 underground mining shafts, one open pit surface mine, and ore processing plants. To ensure continuous operation, this mining company uses various vehicles, machinery and offices. The basic layout of the company and its carbon emissions are illustrated in Figure 4-19.

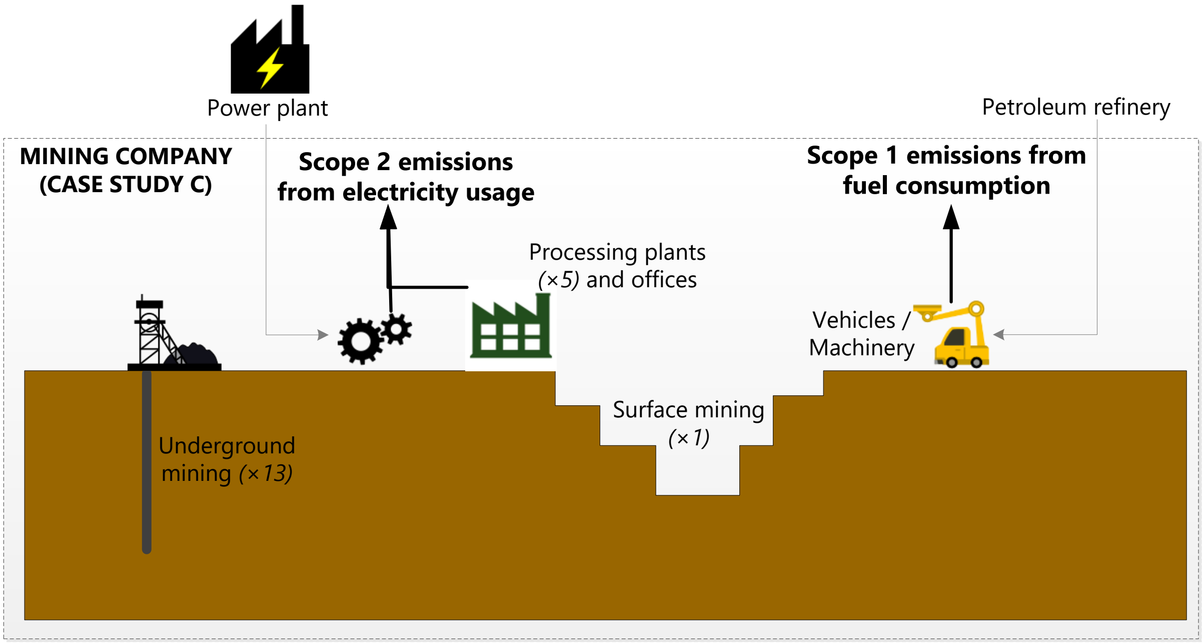


FIGURE 4-19: BASIC ILLUSTRATION OF CARBON EMISSIONS FROM A MINING COMPANY (CASE STUDY C)

Electricity is purchased from the national grid and used for office buildings and various energy-intensive machinery related to gold ore production. Carbon energy sources are used to produce the electricity purchased by the mining company from the national grid. The mining company is responsible for the carbon tax related to the electricity used from the carbon energy sources. These emissions are referred to as scope 2 carbon emissions.

Fuels such as diesel, petrol, jet fuel, and polyfuel are purchased from petroleum refineries and used for various vehicles and machinery required for gold ore production. These fuels are carbon energy sources that are directly used and emitted by the mining company. These emissions are referred to as scope 1 carbon emissions.

The main end-user in this case study is a carbon tax analyst who is responsible for future estimates of the mining company's carbon tax liability. A single project lead and contributor were identified, respectively.

4.4.2 PHASE 1: STRUCTURED PLANNING

Evaluate preliminary impact

A preliminary discussion between the project lead and end user revealed that the end user required a report for forecasting carbon tax liability estimates that takes multiple uncertainties into consideration. One of the largest uncertainties included the scope 2 emissions related to electricity purchased from the national grid. Since the national grid is under strain to remain profitable and deliver continuous electricity supply, the financial impact on allowances related to scope 2 emissions was concerning to the end user. It was expected that a reporting mechanism could identify the uncertainty range and assist with budget planning.

Define structured objectives

The data related to the carbon emissions are obtained from manual sources such as invoices and manual meter readings. This data is generally collected from various data sources and collated in sheets. When carbon emissions need to be quantified, ad hoc calculation sheets are generated. The existing carbon emissions, data pipeline, and reporting structure are depicted in Figure 4-20.

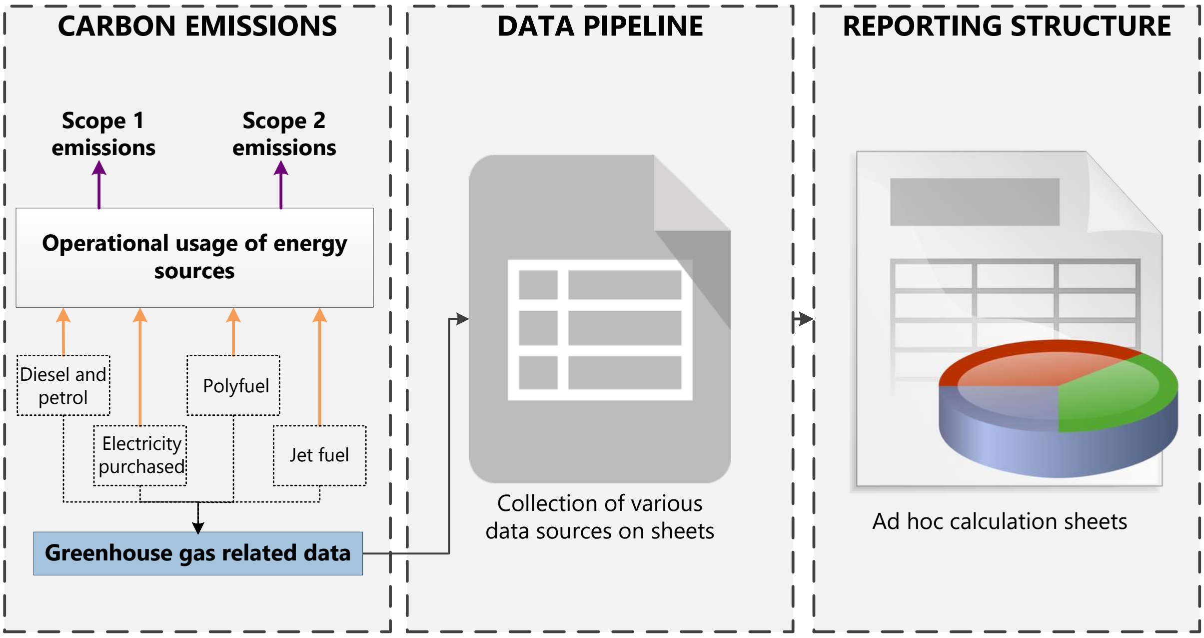


FIGURE 4-20: EXISTING CARBON EMISSIONS, DATA PIPELINE AND REPORTING STRUCTURE (CASE STUDY C)

The data collected comprised data for all the mining operations; thus, the focus area was ranked on the enterprise level during the initial report assessment. The data has been collected and collated in the sheets for long periods of time. Although not in real time, this data was retrieved at regular intervals. For this reason, the data availability quality for the initial reporting was ranked on the long-term level. Although it is recommended that data be collected automatically for future applications, this did not affect the need for the current reporting application (based on preliminary impact evaluation).

The ad hoc calculation sheets only contained a single value for the carbon tax liability. Therefore, the analytics and visualisation reporting qualities were ranked on the descriptive and disseminative levels, respectively. The initial reporting assessment is depicted in Figure 4-21.

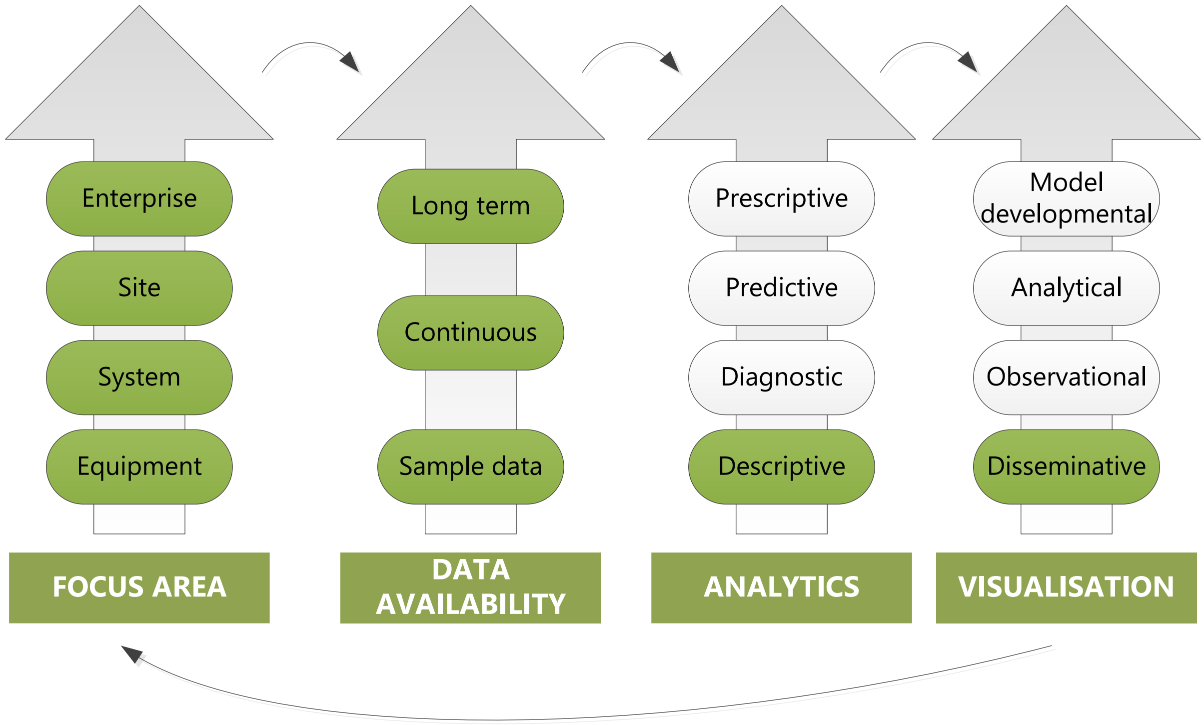


Figure 4-21: Initial reporting assessment (Case Study C)

Table 4-10 summarises the initial reporting assessment with the features required for improvement per reporting quality. The KPI to be reported on in this reporting application was clear and relevant, and included the carbon tax liability. No recommendations were made for the focus area and data availability quality since all carbon emitters were considered and long-term data was available.

On the analytics level, only the calculated carbon tax liability answer was presented on a descriptive level. The descriptive level did not consider any changes to the carbon tax system that could have led to uncertainties in the calculated carbon tax liability estimate. Therefore, it was recommended to provide a forecasting model to estimate the future carbon tax liabilities based on various possible uncertainties.

During the initial reporting assessment, the visualisation consisted of displaying the calculated carbon tax liability as a single value. This descriptive level of visualisation restricted the intuitive assessment of how uncertainties affected the carbon tax liability. Thus, it was recommended to provide interactive visualisation where different scenarios of the carbon tax uncertainties had to be evaluated.

Table 4-10: Summary of initial assessment (Case Study C)

Initial assessment	Lacking features	Required feature for improvement
Focus area: *All carbon emitters in mining enterprise are considered*	None	None required

Initial assessment	Lacking features	Required feature for improvement
Data availability: *Data collected from manual meter readings on regular intervals*	None	None required for this reporting application
Analytics: *Only raw data or calculated carbon liability is provided on a descriptive level*	Descriptive does not take uncertainties into account for future estimates	Predictive analytics required
Visualisation: *Only a single end value is calculated and displayed*	Single value makes it difficult to examine the impact of uncertainties intuitively	Interactive visualisation is required to evaluate scenarios of uncertainty

Prioritise objectives

From Table 4-10 it can be seen that two objectives were required. The first was to build a forecasting carbon tax liability model and the second was to provide the interactive visualisation thereof based on various uncertainties. Although more time would be required to compile the forecasting model than the interactive visualisation, the forecasting model was required to obtain the results to visualise. The forecasting model further had the largest impact on the quality of the reporting application since the answers could be used by the end user while the visualisation was still being compiled. Therefore, the forecasting model was prioritised as the first objective while the interactive visualisation was prioritised as the second objective. The prioritised list of objectives is shown in Figure 4-22.

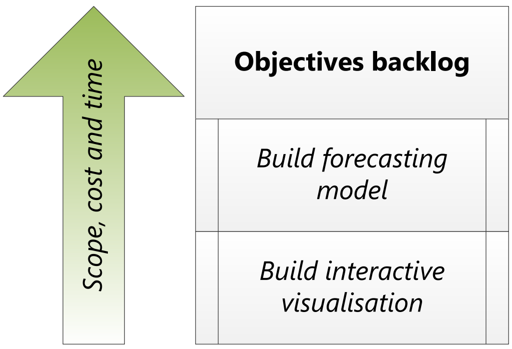


FIGURE 4-22: PRIORITISED LIST OF OBJECTIVES (CASE STUDY C)

4.4.3 PHASE 2: ITERATIVE EXECUTION

Objective 1: Build forecasting model

The first objective aimed to improve the analytics from a descriptive level to a predictive level, which was a reporting quality specific objective. Carbon emission relevant data was collected for all mining operations, which was used to compile a model to forecast the carbon tax liability through three iterations. The iterations were based on obtaining a valuable output that could be used by the end user after each iteration.

During the first iteration, the contributor focussed on obtaining a model to forecast the scope 1 emissions of the enterprise accurately. After approval by the project lead and end user, the focus was on the scope 2 emissions during the second iteration. Thereafter, the model was investigated to identify the parameters that affect the forecasted carbon tax liability the most. Realistic ranges for the variable parameters were researched and built into the model. After completion of Objective 1, an ad hoc calculation sheet was available to the end user with the forecasting model built in.

Objective 2: Build interactive visualisation

Objective 2 focussed on improving the visualisation of the reporting application, which was a reporting quality specific objective. The aim was to evaluate the carbon tax forecasting intuitively. To achieve this, the variables that most affected the uncertainty of the carbon tax liability were divided into various possible scenarios on both the scope 1 and scope 2 emissions. The results from the various possible scenarios were visualised in an interactive report by using Microsoft Power BI. The end user approved the interactive report with the forecasting model results that showed the uncertainties related the future carbon tax liabilities. An example of the completed report is shown in Appendix E and Figure 4-23.

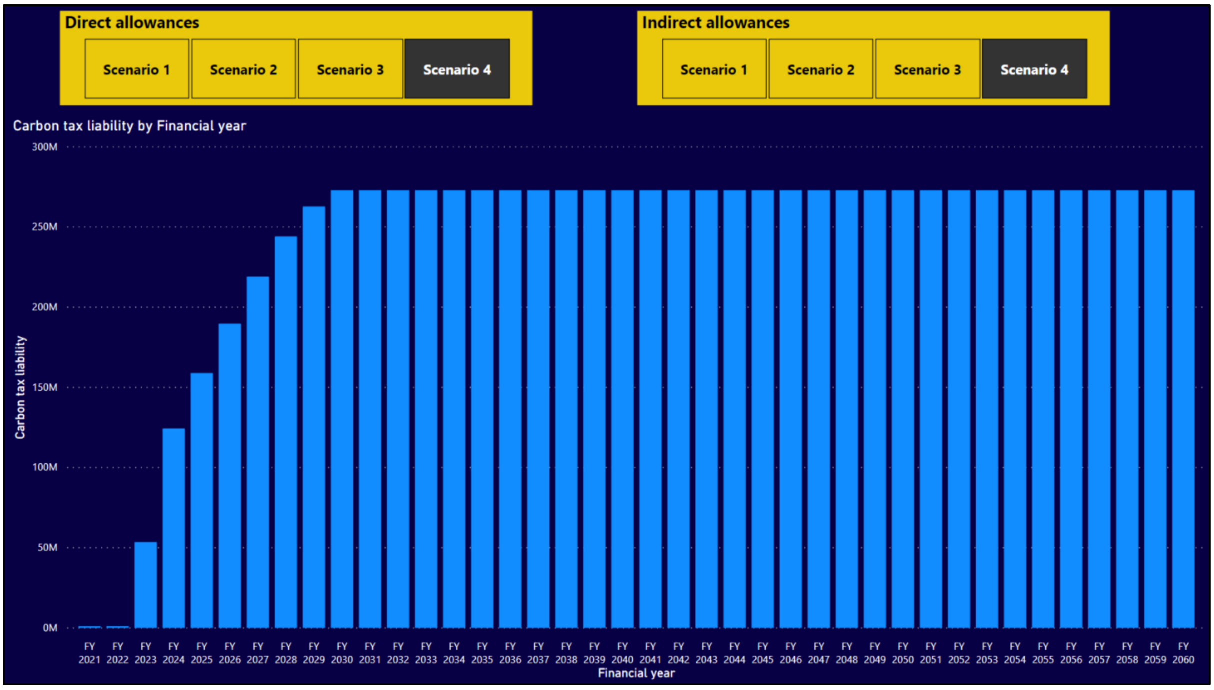


FIGURE 4-23: EXAMPLE OF SELECTED VISUALISATION (CASE STUDY C)

4.4.4 PHASE 3: EVALUATION

Impact evaluation

After completing Phase 1 and Phase 2 of the framework, the impact evaluation survey was sent out to the end users, including the carbon tax analyst as described in the case study selection and background (Section 4.4.1) as well as two colleagues. The end users' details are shown in Table 4-11. The end users' qualifications and experience in the field of mining as well as carbon tax were deemed sufficient to obtain survey results.

TABLE 4-11: DETAILS OF END USERS WHO COMPLETED THE IMPACT EVALUATION SURVEYS (CASE STUDY C)

End user	Qualifications	Experience in mining industry	Experience in carbon tax field
1	B. Eng, M. Eng, PhD, accredited carbon footprint analyst	7	6
2	B. Eng, accredited carbon footprint analyst	1	1
3	B. Eng	1	1

The qualitative survey results are presented in Figure 4-24. Minimum and maximum ratings obtained from end users are indicated by the grey diamond shapes while the average score is indicated by the green dots. Overall, all qualitative factors received high ratings from end users, with actionability receiving the highest and consistent rating. In the preliminary impact evaluation meeting in Phase 1 of the framework, it was discussed that a carbon tax liability report was required to estimate carbon tax uncertainties. To achieve confidence in the reported values, it is important that data of good quality is used. From the qualitative survey results, it can be seen that high ratings were given to the data quality factors, such as reliable data sources, accurate data, and up-to-date data. This increased confidence in the reported carbon tax liabilities.

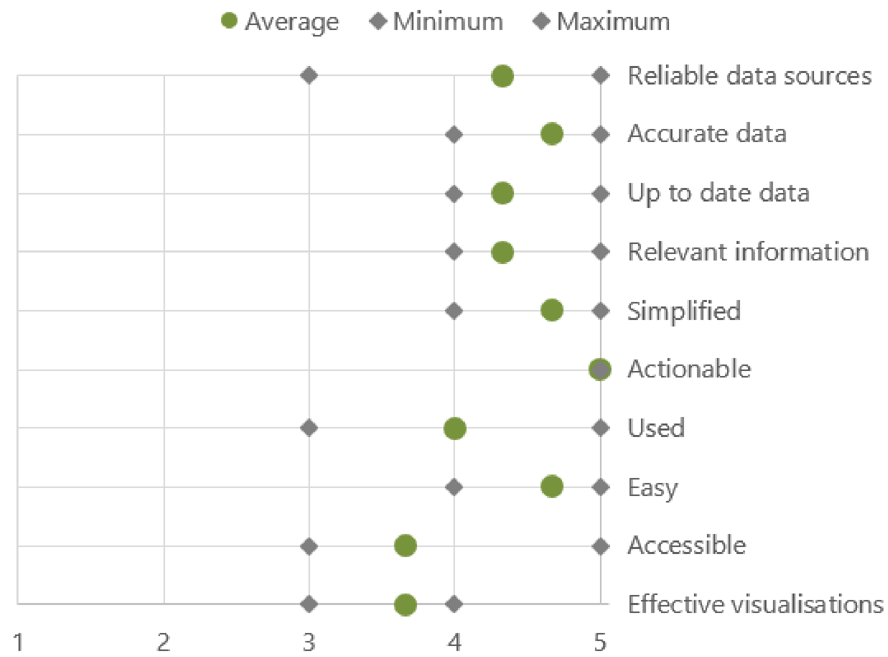


Figure 4-24: Qualitative impact evaluation results (Case Study C)

The quantitative survey results are shown in Figure 4-25. The end users indicated that the carbon tax liability is reviewed four times a year and that using the report developed in this case study time would save analysis time. The time savings obtained from the end-user surveys were converted to an annual monetary saving by using the average salary of a mining engineer in South Africa. This amounted to R17 000 annually.

The end-user surveys further indicated that there was no direct impact as a result of the report because the report only quantifies carbon tax liabilities but does not affect the actual liability. The quantitative impact of value is the indirect impact. Since the report indicates the uncertainty associated with the carbon tax liability, which can result in accurate budgeting, it can be seen as an indirect impact. This amounted to R13.91 million. The cumulative quantitative impact thus amounted to R13.93 million.

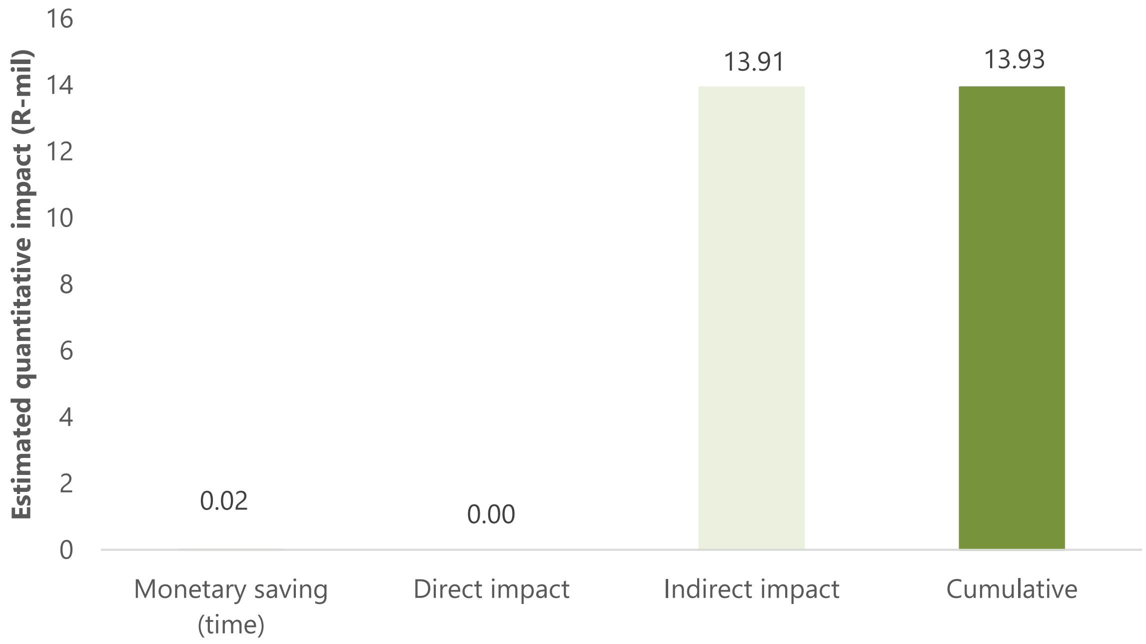


Figure 4-25: Quantitative impact evaluation results (Case Study C)

Although the report did not result in significant time savings or any direct impacts, the significantly high indirect impact justified the need for this report. This further aligned with the end user's need for the report as highlighted in the preliminary impact evaluation during Phase 1. From the end-user surveys it can, however, be suggested to investigate whether more value can be added to real-world operations by expanding the reporting application in ways that will have direct quantitative impacts.

Succeeding assessment

During Phase 1 of the framework (Section 4.4.2), objectives were identified to improve the reporting application. During Phase 2 (Section 4.2.3), these objectives were executed iteratively. This section describes how a succeeding assessment of the report was completed to assess the improvement of the report and identify future areas of improvement. The succeeding assessment is shown in Figure 4-26.

No changes were required on the focus area and data availability reporting quality; thus, they were ranked on the same levels as in the initial reporting assessment. The analytics moved from the calculation of a single carbon tax value to forecasting future liabilities by incorporating various uncertainties associated with the carbon tax system. This moved the analytics quality from a descriptive level to a predictive level.

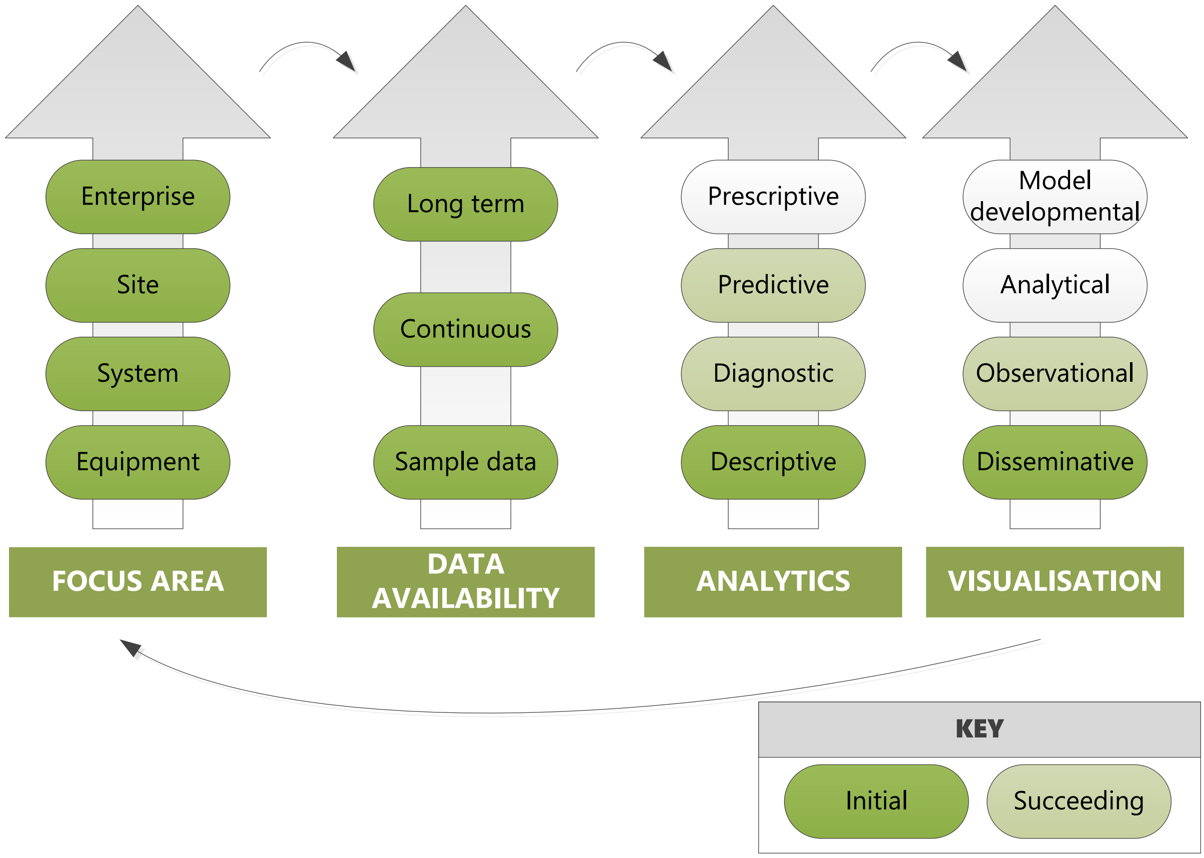


Figure 4-26: Succeeding report assessment (Case Study C)

Before implementation of the framework, ad hoc calculation sheets were created that showed the carbon tax liability value. After implementation of the framework, an interactive report was available that displayed the carbon tax liability for future periods. In this report, various scenarios of uncertainty can be explored related to the scope 1 and scope 2 emissions. The interactive nature of the report allows for an intuitive observation of carbon tax liability and provides relevant information to compile budgets accurately. Therefore, the visualisation was ranked on the observational level in the succeeding assessment. A summary of the succeeding assessment is shown in Table 4-12.

Table 4-12: Summary of succeeding assessment (Case Study C)

Initial assessment	Succeeding assessment	Changes implemented
Focus area: *All carbon emitters in mining enterprise are considered*	All carbon emitters in mining enterprise are considered	None required
Data availability: *Data is collected from manual meter readings on regular intervals*	Long-term and continuous data is used	None required

Initial assessment	Succeeding assessment	Changes implemented
Analytics: *Only raw data or calculated carbon liability is provided on a descriptive level*	Future estimates of carbon tax liability are available that consider various uncertainties	Development of carbon tax liability forecast model
Visualisation: *Only a single end value calculated and displayed*	Speedy observation of carbon tax liability and uncertainties can be made	Development of an interactive visualisation report

From the succeeding assessment it was evident that the next step for improvement of the reporting application is to provide prescriptive analytics. Many possible methods exist to achieve this – one example would be to not only forecast the carbon tax liabilities, but also place more focus on the largest GHG emitters that provide the carbon tax liability and suggest methods to decrease the GHG emissions. This will add value by assisting with the decision of which GHG-reducing methods to implement, which will result in a smaller financial carbon tax liability and ultimately assist to achieve South Africa's GHG-reducing goals.

4.5 RESEARCH VALIDATION

4.5.1 REVIEW OF THE NEED FOR THIS STUDY

Chapter 1 explained that the South African mining industry is in the early stages of BI adoption and proposed the utilisation of data for value creation. It was thus highlighted that a new report development framework is required for the mining industry to add practical value. The new framework requirements were to evaluate the impact of reports, provide structure, and provide practical guidance. Chapter 3 combined the literature from Chapter 2 into a new value-add driven report development framework. It was further shown that the new framework achieved the requirements (Section 3.4).

In this chapter, the framework was applied to relevant case studies in the mining industry. End-user surveys were used to evaluate the qualitative and quantitative impact of the developed reports. This section aims to validate the research of this study by independently evaluating the value added to real-world operations after applying the newly developed framework. This will validate that the use of data adds value to real-world operations and, ultimately, that the framework addresses the original need for the study.

The qualitative impact is not evaluated in this section since it remains a factor that is perceived by end users. This section specifically evaluates the highest quantitative value added to each case study, respectively, by comparing the quantitative end-user survey results with associated literature. Additionally, this section reviews how the novel contributions of this study as stated in Chapter 1 were achieved.

4.5.2 INDEPENDENT EVALUATION OF VALUE ADDED

Case Study A

Case Study A focussed on operational water management. The end-user survey highlighted that extreme water incidents may lead to a loss in shifts, which has significant financial repercussions of R6.6 million per shift. According to the 2020 annual report, the specific mining operation in Case Study A produced about 7 000 kg of gold, which equates to approximately 10 kg of gold per shift (for a mining operation that has two shifts a day).[*] Please note that the reference for the annual report has been altered for confidentiality purposes. Based on the production and gold price information from the annual reports, the quantitative value of a single gold producing shift is amounts to R7.4 million.

The availability of the report allows for continuous monitoring and management of the water reticulation of the mining operation. Although the above-mentioned value add will only take place in extreme cases, it highlights the importance of a water management report as developed in this study with a high financial impact.

Case Study B

Case Study B considered condition-based equipment monitoring. In this case study, a report was developed that used numerous condition-monitoring data values to prioritise critical equipment. The end-user surveys indicated that an annual cost saving of R15.4 million was obtainable as a result of avoiding critical failure of equipment and reducing emergency maintenance.

A study by Stols [122] focussed on the implementation of a condition-monitoring system for South African gold mines. According to this study, a R20.0 million cost saving was obtained due to the prevention of equipment critical failures over a one-year period. This value is deemed comparable for the selected case study since the mines considered in the study by Stols [122] included a similar number of gold mines.

[*] Mining Company A, "2020 Operational report," 2020.

Case Study C

In Case Study C, a report was developed regarding future carbon tax liability uncertainties for a gold mining company. The end-user surveys indicated that the report allows for uncertainty management for their carbon tax liability that can be up to R13.9 million for the year 2023 (which is referred to as the difference between the highest possible carbon tax liability and the lowest possible carbon tax liability). This uncertainty is composed of R80 000 scope 1 emissions uncertainty and R13.8 million scope 2 emissions uncertainty.

Gous [140] calculated possible tax liabilities and uncertainties for GHG-intensive industries in South Africa. According to Gous [140], the mining industry may face an uncertainty of 6% annually regarding scope 1 emissions. For Case Study C, this percentage is equivalent to a R70 00 annual scope 1 emissions uncertainty. This gives a good comparison of the uncertainty obtained from the end-user surveys. Thus, it is expected that the same comparison would be obtained for scope 2 emissions.

The report developed in this study estimates the uncertainty that can manage expectations and allows for accurate budgeting processes.

Summary

Table 4-13 compares a summary of the independent evaluation of the value add per case study with the survey results. From Table 4-13 it can be seen that value add for each case study could be evaluated independently and that the difference between the end-user survey results and the independent evaluations vary between 11% and 23% for the three case studies. All real-world operations are different, and it is therefore not expected to obtain a perfect comparison between the survey results and associated literature. However, the independent evaluation shows that the value add as given in the end-user surveys compare relatively well with the associated literature. These results validate that the developed reports have added value to real-world operations. In summary, a total value add of between R80 000 and R15.4 million was achieved.

TABLE 4-13: SUMMARY OF INDEPENDENT EVALUATION OF VALUE ADD PER CASE STUDY

Case study	Value add (End-user survey)	Value add (Independent)	Difference (%)
Case Study A	R6.6 mil	R7.4 mil	11%
Case Study B	R15.4 mil	R20.0 mil	23%
Case Study C	R0.08 mil	R0.07 mil	14%

In this chapter, case studies were selected that are relevant to the mining industry. However, multiple additional relevant use cases exist in real-world applications. The developed framework in Chapter 3 is generic and could be applied to any of these use cases. It is therefore expected that the application of the developed framework would assist with value creation in the mining industry in general.

4.5.3 REVIEW OF NOVEL CONTRIBUTIONS

The main objective of this study was to develop a new value-add driven report development framework. This objective was supported by four contributions listed in Chapter 1. Figure 4-14 summarises how each contribution was achieved throughout this study.

TABLE 4-14: REVIEW OF NOVEL CONTRIBUTIONS

Novel contribution	Achieving novel contribution		
	Need for contribution	**Literature review conducted**	**Inclusion in newly developed framework**
Evaluating the impact of operational reports	Chapter 1 identified that none of the existing BI implementation guidelines allow for the impact evaluation of reports on real-world operations.	An SLR conducted in Section 2.2 identified how impact is evaluated in literature. It was seen that although qualitative and quantitative impact evaluation factors exist, little was done to quantify these impacts. It was further identified that end-user surveys are the most commonly used method for evaluating impact.	The literature was used to develop a new end-user survey to evaluate the qualitative and quantitative impact of reports (Chapter 3). This survey was incorporated into the third phase of the newly developed framework. In Chapter 4, the framework was applied to case studies in the mining industry, where the end-user surveys were used to evaluate the impact of reports on real-world applications.
Identification of structured reporting qualities	Chapter 1 identified that the steps in existing BI implementation guidelines are too high level and do not provide sufficient structure to allow incremental improvement in reporting applications.	Section 2.3 presented a comprehensive literature review. Firstly, four research questions were formulated regarding the structure provided by the high-level steps in existing BI implementation guidelines. These research questions were addressed by four individual and relevant research fields. From the research, four structured reporting qualities with associated levels were identified.	The four reporting qualities were incorporated into all three phases of the newly developed framework in Chapter 3 to provide incremental structure to the report development process.

Novel contribution	Achieving novel contribution		
	Need for contribution	**Literature review conducted**	**Inclusion in newly developed framework**
A new value-add driven report development framework	Chapter 1 identified that a new report development framework was required to evaluate impact, provide structure, and provide practical guidance.	In Chapter 2, a literature review was conducted to address each requirement of the new framework. Firstly, impact evaluation methods were reviewed. Secondly, structured reporting qualities were investigated and identified. Thirdly, project management methodologies were reviewed to aid with practical guidance.	The knowledge gained from literature was used to develop a new value-add driven report development framework in Chapter 3. Section 3.4 further addressed how each requirement of the new framework was achieved.
Practical implementation of BI concepts on mining case studies	Chapter 1 identified that the South African mining industry is in the early stages of BI adoption and utilisation of data for value creation.	A literature review was conducted to ensure that each case study selected in this study was a relevant issue faced by the mining industry.	The newly developed framework was applied to three diverse and relevant case studies in the South African mining industry in Chapter 4. This resulted in the successful development of reports that contributed to value creation in real-world-operations. The end-user surveys were used to evaluate the qualitative and quantitative value added to each case study, respectively.

4.6 CONCLUSION

In Chapter 3, a new value-add driven report development framework was developed. In this chapter, the framework was applied successfully to relevant case studies in the mining industry. Case Study A focussed on operational water management, Case Study B on condition-based equipment monitoring, and Case Study C on carbon tax liabilities. For each case study, specific objectives were identified by means of structured reporting qualities. These objectives were executed incrementally by specific role players. After the report development, the qualitative and quantitative impact were evaluated by the use of end-user surveys.

The clear communication of the end-user surveys together with a succeeding evaluation of reporting qualities allowed for continuous improvement of reporting to improve the value added by reports. The structured nature of the framework showed what was required next while the impact evaluation showed whether it was worthwhile. This aided with fully utilising reports for value addition.

Lastly, the value-add information obtained from the end-user surveys was evaluated and compared independently. This amounted to between R80 000 and R15.4 million for the three case studies. The impact evaluation validates that value was added to real-world operations due to report development. The possibility exists to apply the framework to additional real-world use cases, which is expected to assist with value creation in the mining industry in general.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5. CONCLUSION AND RECOMMENDATIONS

5.1 SUMMARY OF WORK

The South African mining industry has a significant impact on the country's economy. However, it is experiencing unique challenges and need to use all available tools to add value to operations and to remain sustainable and profitable. BI uses data for valuable data-driven decision-making to add value to businesses and is widely used in other industries. The South African mining industry is, however, still in the early stages of BI adoption.

The first levels of BI adoption involve developing various reporting mechanisms. Therefore, this study proposed the use of reports to add practical value to the mining industry. To do this, key requirements of BI implementation were investigated and evaluated against existing BI implementation guidelines in literature. It was found that existing BI implementation guidelines do not evaluate the impact on real-world operations and lack structure for incremental improvement and practical guidance. Report impact evaluation is required to fully gauge the value that reports add to real-world operations. Structure is required to ensure incremental improvement to reports and allow for the identification of areas of improvement. Practical guidance is vital to ensure that practical results are obtained.

The shortcomings from available BI implementation guidelines identified the need for a new value-add driven report development framework for mining industries. This framework had to evaluate the impact of reports, be structured, and provide practical guidance. Chapter 2 presented a comprehensive literature review to address each shortcoming identified from existing BI implementation guidelines. First, report impact evaluation methods were reviewed. It was explained that both the quantitative and qualitative impact of reports had to be evaluated to fully gauge the impact of reports. Although existing literature showed that end-user surveys are most commonly used for impact evaluation of BI systems, limited information was found regarding the quantitative impact of reports.

Second, the steps involved in existing BI implementation guidelines were evaluated critically to identify whether sufficient structure was provided by these high-level steps. It was found that additional structure was required to allow incremental progress. With the support of four research fields, four structured reporting qualities were identified with associated incremental levels. These reporting qualities included focus, data availability, analytics, and visualisation.

Third, project management methodologies were reviewed to identify the critical concepts required to provide practical guidance to the report development process. These concepts included that report development should be agile to adapt continuously to the end users' needs in an iterative nature while delivering a usable report throughout the process. Other critical concepts included identifying specific role players, producing a product backlog, and doing a sprint backlog. Two of the three literature studies presented in Chapter 2 were published in peer-reviewed journal articles to support the subsequent framework development [1], [2].

In Chapter 3, the knowledge gained from literature was used to develop a new value-add driven report development framework for mining industries. The framework consisted of three phases that addressed the original shortcomings identified from the BI implementation guidelines.

The first phase was structured planning. In this phase, the reporting qualities with their associated levels were used to assess the initial state of a reporting application. The assessment allowed for the identification of specific objectives that met the end users' needs. Thereafter, the objectives were prioritised and placed in an objectives backlog.

The second phase was called iterative execution. In this phase, each of the objectives was executed in an iterative nature according to their priority in the objectives backlog. The structured reporting qualities with their associated levels once again provided guidance during execution.

The third phase was evaluation. In this phase, both the qualitative and quantitative impact of the reports were evaluated by means of end-user surveys. Additionally, the structured reporting qualities were used to assess the completed reporting application to ensure that the initial objectives were achieved and enabled continuous improvement.

In Chapter 4, the newly developed framework was verified by applying it to three real-world case studies. Each case study delivered practical reports to address a variety of relevant problems in the South African mining industry. Case Study A focussed on a report to assist mining personnel to manage operational water by using data that has not been used previously. In Case Study B, a report was developed to prioritise the condition of mining equipment to assist with maintenance planning and present a data-rich problem that required prioritisation. Case Study C focussed on carbon tax liabilities and converted ad hoc calculations to an interactive report to assist with budgeting processes by assessing future uncertainties regarding carbon tax liabilities.

The qualitative and quantitative impacts of each reporting application for the three case studies were identified via end-user surveys. To validate the research in this study, the quantitative value add of each case study as reported in the end-user surveys was compared independently with associated literature.

A total value add for the three case studies varied from R80 000 to R15.4 million. This validates that increased data utilisation in the developed reports added value to the respective mining operations.

5.2 ACHIEVING NOVEL CONTRIBUTIONS

The main objective of this study was to develop a new value-add driven framework for report development in the mining industry. This objective was important as no existing frameworks were applicable to specific shortcomings relevant to the mining industry. Achieving this objective was supported by the four novel contributions listed in Chapter 1. The following sections discuss how these novel contributions were achieved.

Contribution 1: Evaluation of the impact of operational reports

Chapter 1 identified that none of the existing BI implementation guidelines allow for the evaluation of the impact that reports have on real-world operations. This is deemed critical to justify the expenditure of time and resources on report development and truly evaluate the value that reports add in practical environments.

In Section 2.1, an SLR was completed to assess how impact is evaluated in existing literature. It was shown that although qualitative factors are generally evaluated by means of end-user surveys, limited quantitative evaluations are done. The available literature was used to compile a new end-user survey to evaluate both the qualitative and quantitative impacts of operational reports. This end-user survey was incorporated in the third phase of the newly developed report development framework presented in Chapter 3.

In Chapter 4, the framework was applied to three case studies in the mining industry. A report was developed for each case study and the impact thereof evaluated via the end-user survey. The end-user survey allowed for clear communication regarding the impact that reports have on real-world operation. The qualitative and quantitative impacts of reports were compared to identify areas where reports have an effect and where they do not. This value can be used to justify report development, improvement, or discontinuation.

This contribution was published in a peer-reviewed journal [2] (the manuscript of this article is provided in Appendix B). It was also presented at the annual conference of the South African Institute of Industrial Engineering (held virtually from 5–7 October 2020).

Contribution 2: Identification of structured reporting qualities

Chapter 1 evaluated the existing BI implementation guidelines and identified that the steps were too high-level and lacked structure for incremental improvement in reporting applications. To address this shortcoming, a comprehensive literature review was done by formulating research questions regarding the incremental implementation of BI guidelines. This literature review was presented in Section 2.2.

Individual research fields were evaluated to address each research question. From this research, four structured reporting qualities with associated levels were derived. These qualities included focus area, data availability, analytics, and visualisation. Each reporting quality was verified by practical application of data-driven studies.

The structured reporting qualities were included in all three phases of the new value-add driven report development framework presented in Chapter 3. In the first phase, the reporting qualities were used to assess the initial state of the reporting application. This allowed for the identification of the precise objectives required to improve the reporting application.

In the second phase of the framework, each objective was completed by focussing on improving a specific or multiple reporting qualities. This provided focus and structure to the execution of reporting development. In the third phase, the completed reporting application was assessed once again according to the reporting qualities to ensure that objectives that enabled continuous improvement were met.

This contribution was published in a peer-reviewed journal [1] (the manuscript of this article is provided in Appendix C). It was also presented at the annual conference of the South African Institute of Industrial Engineering (held during 1–3 October 2019 in Port Elizabeth, South Africa).

Contribution 3: Creation of a new value-add driven report development framework

Existing BI implementation guidelines were critically analysed in Chapter 1. Three shortcomings were identified for report development, namely: the lack of impact evaluation, structured implementation guidelines, and practical guidance. It was thus highlighted that a new value-add driven report development framework was required to address these shortcomings.

Chapter 2 presented a comprehensive literature review to address each shortcoming. The knowledge gained from literature was combined into the new report development framework, which consisted of three phases (Chapter 3), namely: structured planning, iterative execution, and evaluation. Section 3.4

described how the new framework addresses each of the shortcomings identified from existing BI implementation guidelines.

Firstly, literature was used to compile an end-user survey to evaluate the qualitative and quantitative impact of reports. This survey was incorporated into the third phase (evaluation) of the report development framework. The end-user survey allowed for report end users to evaluate the impact that the reporting application had on real-world operations.

Secondly, structure was provided to the report development framework by using the four structured reporting qualities identified from literature. These qualities were incorporated in all three phases of the framework. This allowed for the identification of precise objectives, structured execution, and continuous identification of areas of improvement.

Thirdly, critical concepts for providing practical guidance to the report development framework were identified in the literature review. It was identified that the framework had to be agile. This was included in the second phase of the framework where objectives were completed in an iterative manner. Other critical concepts included the identification of specific role players and the product backlog. An objectives backlog was created in Phase 1 of the framework. In this study, three generic role players were identified, namely the project lead, contributor(s), and end user(s). These role players were involved with various tasks in all three phases of the framework.

The framework was verified and validated further in Chapter 4 by applying it to three diverse case studies in the mining industry. The framework delivered quantifiable value to real-world operations, which amounted to between R80 000 and R15.4 million for all three case studies.

Contribution 4: Practical implementation of BI concepts on mining case studies

The developed framework was applied to three case studies in the South African mining industry in Chapter 4. Each case study addressed a relevant issue faced by the South African mining industry, including operational water management, condition-based equipment monitoring, and carbon tax liability. The application of the framework allowed the development of a report for each case study. Both the qualitative and quantitative value added by these reports were assessed by means of end-user surveys. This validated that the reports added value to real-world operations.

5.3 RECOMMENDATIONS FOR FUTURE WORK

Recommendations for future work are discussed below. These recommendations are suggested to improve the results obtained in this study further.

Consideration of change management

This study focussed on a framework for report development in the mining industry that will add value. Change management is important to realise the potential value that could be added by using reports. The reporting qualities with their associated levels in this study allow for a more incremental approach to reporting. Although this already assists with change management, it is recommended that the given framework be elaborated to include how change management can be achieved even further.

Expanding on chosen case studies

The chosen case studies discussed in Chapter 4 verified the use of the developed framework to add value to real-world operations. This study was further found to be applicable to multiple possible use cases (in addition to the three case studies presented in Chapter 4). However, the type of case studies can be expanded. As an example, all the case studies were implemented in the gold mining industry. The case studies selected were, however, deemed sufficient to verify the developed framework since they included underground mining, surface mining, and process plants, which are applicable to most mining industries. The case studies further covered relevant issues faced by all South African mining industries and not just the gold mining industry. The framework was developed to be generic and should suffice for other mining industries. However, the chosen case studies could be expanded to other industries as well.

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A. APPENDIX: CRITICAL ANALYSIS OF EXISTING GUIDELINES

This appendix contains supplementary information regarding the critical analysis of available business intelligence (BI) implementation guidelines (Section 1.3). More specifically, this appendix provides a detailed critical analysis and description of each guideline by first providing an overview of each BI implementation guideline and second by analysing how the guideline addresses the key requirements for BI implementation for report development (identified in Section 1.2).

Life cycle of BI System

Conference proceedings by Gangadharan and Swami [34] describe the various phases of BI development. These phases include analysis, design, development, deployment, and evolution. The full life cycle is depicted in Figure A-1 and described thereafter.

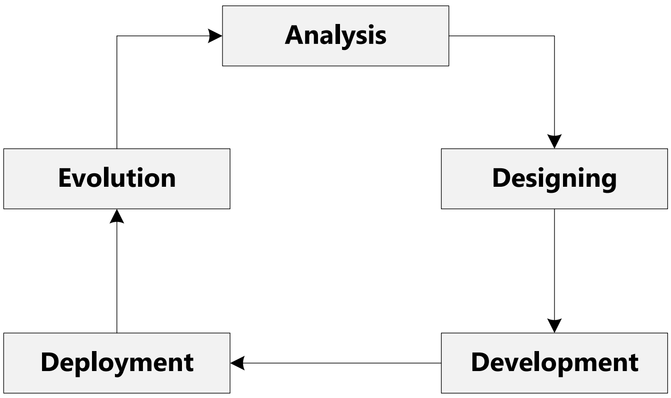

FIGURE A-1: LIFE CYCLE OF BI SYSTEM (ADAPTED FROM [34])

In the analysis phase, the business problem is analysed by considering the end-user requirements and producing a high-level design of the solution. In the design phase, the appropriate BI technologies are selected for the solution and prototypes are delivered of any functional deliverables. In the development phase, the full process flow of information is modelled. This may also include factors such as metadata repositories and data pre-processing. After testing all components during the development phase, the application is deployed to end users in the deployment phase. Interactive training and support are vital in this phase. During the evolution phase, the application is extended across the enterprise, the success of the application is measured, and cross-functional information sharing is enabled.

Table A-1 shows a critical analysis of this guideline according to the requirements for BI implementation identified in Chapter 1. Additional notes are included to assess if the guideline is industry specific or focusses on report development specifically.

TABLE A-1: CRITICAL ANALYSIS OF GUIDELINE: LIFE CYCLE OF A BI SYSTEM

BI requirement for report development	Life cycle of BI system analysis	
Impact evaluation	Although this guideline states that the application success should be measured in the evolution phase, it does not provide guidance on how the impact should be evaluated or what is considered to be a successful impact.	×
Structured	All phases in the life cycle are high level with no indication of how to achieve the outcomes incrementally.	×
Practical guidance	No practical guidance is given.	×
Additional notes	The guideline is not industry specific and does not focus on report development specifically, but rather BI overall.	

Methodology of Implementing BI Systems

A journal article by Olszak and Ziemba [25] describes the process of creating BI systems. According to Olszak and Ziemba [25], there are two main stages involved with BI building and implementation, namely BI creation and BI consumption. Their study mainly focussed on BI creation, which involves the following steps:

- Defining the BI undertaking
- Identifying and preparing source data
- Selecting BI tools
- Designing and implementing BI
- Discovering and exploring new informational needs and other business applications and practices

In the first step, the vision of the BI system that relates to business objectives is defined. The requirements of the BI system within the business are also defined in this step. During the second step, data is identified and prepared to address business needs as described in the first step. In the second step, any required processes take place to ensure that the data is ready for further analysis. In the third step, BI tools are selected based on their functionality, complexity of solutions, and compatibility. During the fourth step, the BI system is designed and implemented. This may include various tasks depending on the definition of the BI undertaking in the first step. These tasks may include building a data warehouse, creating mechanisms of data import, and setting up of predefined reports. In the fifth step, it is noted that new business needs arise over time and, therefore, the BI system needs to be adapted accordingly.

Table A-2 shows the critical analysis of this guideline according to the requirements for the BI implementation as identified in Chapter 1. Additional notes are included to assess if the guideline is industry specific or focusses on report development specifically.

TABLE A-2: CRITICAL ANALYSIS OF GUIDELINE: METHODOLOGY OF IMPLEMENTING BI SYSTEMS

BI requirement for report development	Methodology of implementing BI systems analysis	
Impact evaluation	No impact evaluation is given.	✗
Structured	Only high-level steps are given with no indication of how to achieve the outcomes incrementally.	✗
Practical guidance	No practical guidance is given.	✗
Additional notes	The guideline is not industry specific and does not focus on report development specifically, but rather BI overall. Report development is only mentioned as a part of the entire guideline.	

Snail Shell KDDA Process Model

A journal article by Li, Thomas and Osei-Bryson [21] proposes a snail shell model for knowledge discovery via data analytics (KDDA) to overcome challenges faced by the traditional knowledge discovery and data mining (KDDM) process models. The snail shell model of the KDDA process consists of eight phases, which are presented in Figure A-2.

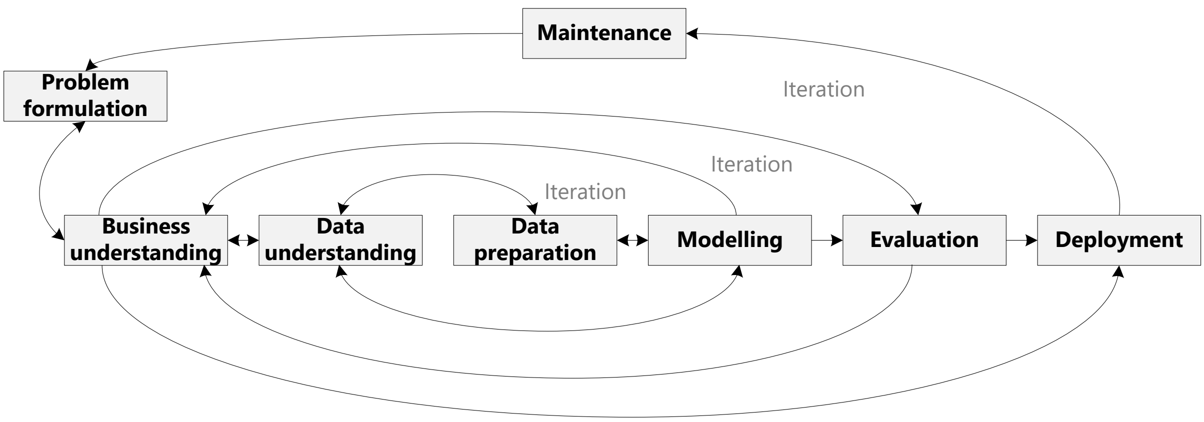

FIGURE A-2: THE SNAIL SHELL KDDA PROCESS MODEL (ADAPTED FROM [21])

The business understanding, data understanding, data preparation, modelling, evaluation, and deployment phases originate from the traditional KDDM model. The snail shell KDDA model, however, has the addition of the maintenance and problem formulation phase. In the problem formulation phase, problem formulation strategies are used to identify business challenges that the KDDA application should address. These challenges are transformed to actionable analytic problem statements.

During the business understanding phase, an organisation's analytic capability is assessed along three dimensions: organisational analytics maturity, data maturity, and decision style maturity. Organisational analytics maturity assesses the analytic environment in the organisation, while data maturity evaluates data suitability for analytics. Decision style maturity evaluates whether the end users' decision styles will allow the use of analytics results.

In the data understanding phase, all data required to address the analytic problem is evaluated. This includes assessing the data quality, understanding its metadata and source systems, and updating frequencies. The data preparation phase involves data integration and transformation for further use. In the modelling phase, modelling techniques are selected and multiple analytic models built to address the business challenges.

During the evaluation phase, the multiple analytic models are evaluated against the original problem statements defined in the problem formulation phase. In the deployment phase, a deployment plan is created and executed. In the maintenance phase, the analytics model is maintained, usage monitored, and replaced if required.

The arrows in Figure A-2 indicate a highly iterative nature between the different phases of the snail shell KDDA process model. Although there is no particular defined sequence of phases, most projects start with the problem formulation phase. Thereafter, the outcome of each phase determines which phase to perform next. The arrows indicate the direction from one phase to another, while bi-directional arrows indicate that movement can be to and from a phase.

Table A-3 shows the critical analysis of this guideline according to the requirements for BI implementation as identified in Chapter 1. Additional notes are included to assess if the guideline is industry specific or focusses on report development specifically.

TABLE A-3: CRITICAL ANALYSIS OF GUIDELINE: SNAIL SHELL KDDA PROCESS MODEL

BI requirement for report development	Snail shell KDDA process model analysis	
Impact evaluation	No impact evaluation is given. Only an analytical model evaluation phase is discussed in this guideline.	×

Structured	Only high-level phases are given with no indication of how to achieve the outcomes incrementally.	×
Practical guidance	Practical guidance does not form part of the guideline.	×
Additional notes	The guideline is not industry specific and does not focus on report development specifically, but is rather focusses on data exploration.	

Big Data Analytics Process

A journal article by Ur Rehman *et al.* [46] describes a big data analytics process. The process consists of six steps, namely data collection, data preparation, modelling, evaluation, deployment, and monitoring. This process is depicted in Figure A-3 and discussed thereafter.

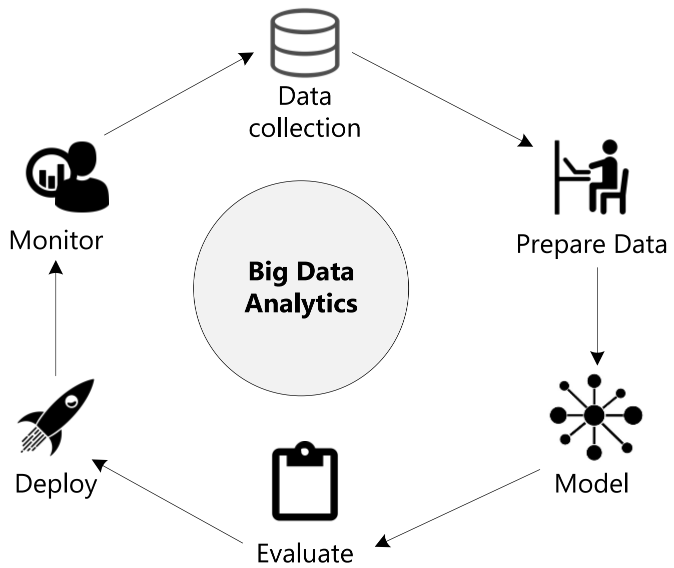

FIGURE A-3: BIG DATA ANALYTICS PROCESS (ADAPTED FROM [46])

During the data collection step, relevant big data is collected from various data sources. Thereafter, the data is pre-processed and integrated to improve data quality during the second step. This may include reducing data noise, detecting outliers, removing anomalies, and handling missing values. In the third step, learning models are generated based on statistical methods and machine learning-based data mining techniques. These models are evaluated with test data in the fourth step. In the fifth step, the models are deployed in real-world applications. In the sixth step, the prediction of the models is monitored and improved continuously.

Table A-4 shows the critical analysis of this guideline according to the requirements for BI implementation identified in Chapter 1. Additional notes are included to assess if the guideline is industry specific or focusses on report development specifically.

TABLE A-4: CRITICAL ANALYSIS OF GUIDELINE: BIG DATA ANALYTICS PROCESS

BI requirement for report development	Big data analytics process analysis	
Impact evaluation	No impact evaluation is given. Only the analytical model performance is evaluated in the given guideline.	×
Structured	Only high-level steps are given with no indication of how to achieve the outcomes incrementally.	×
Practical guidance	No practical guidance is given.	×
Additional notes	The guideline is not industry specific and does not focus on report development specifically, but rather focusses on data exploration.	

Cross-Industry Standard Process for Data Mining

The Cross-industry Standard Process for Data Mining (CRISP-DM) is covered in Larose's [47] book titled *Data Mining: Methods and Models*. CRISP-DM describes a project as having a life cycle with six phases. The CRISP-DM life cycle is presented in Figure A-4 and discussed thereafter.

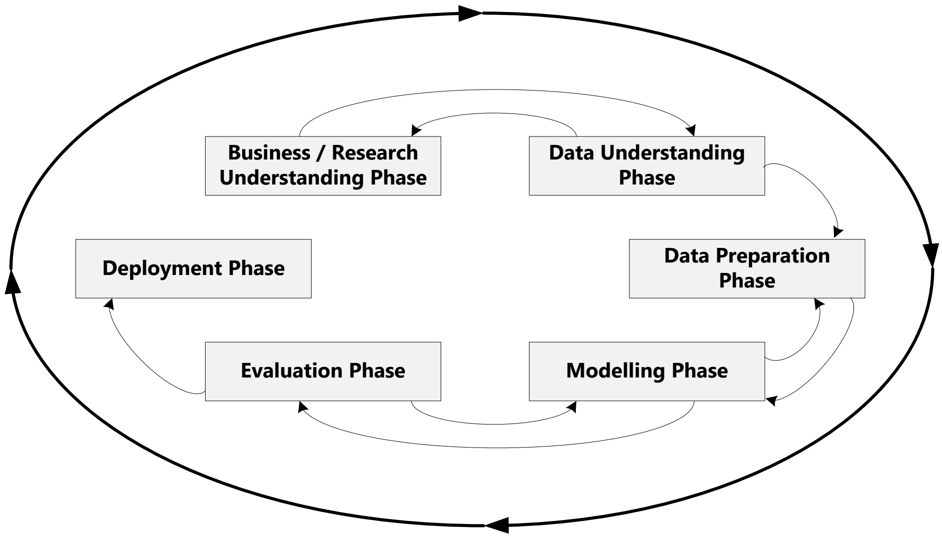

FIGURE A-4: CRISP-DM LIFE CYCLE

CRISP-DM is an adaptive and iterative process, where the next phase depends on the outcome of the previous phase. In the business understanding phase, a business objective is identified, which is translated to a data mining problem definition, and a preliminary strategy for achieving the objective is prepared.

In the data understanding phase, data is collected, data quality evaluated, and exploratory data analysis performed to get familiarised with the data. During the data preparation phase, the data is prepared to be used as the final data set, which may include data transformation and cleaning the data. In the modelling phase, a modelling technique is selected, applied, and calibrated. Several different modelling techniques may be applied in this phase. In the evaluation phase, the different models are evaluated for their quality and effectiveness. They are further compared to determine whether the model addresses the original business objective. In the deployment phase, the model is used according to the business objective.

Table A-5Table A-1 shows the critical analysis of this guideline according to the requirements for BI implementation as identified in Chapter 1. Additional notes are included to assess if the guideline is industry specific or focusses on report development specifically.

TABLE A-5: CRITICAL ANALYSIS OF GUIDELINE: CRISP-DM

BI requirement for report development	CRISP-DM analysis	
Impact evaluation	No impact evaluation is given. Only the analytical model performance is evaluated in the given guideline.	✗
Structured	Only high-level phases are given with no indication of how to achieve the outcomes incrementally.	✗
Practical guidance	No practical guidance is given.	✗
Additional notes	The guideline is not industry specific and does not focus on report development specifically, but rather focusses on data exploration.	

Big Data Analytical Framework for Energy-Intensive Industries

A journal article by Zhang *et al.* [48] proposes a big data driven analytical framework for energy-intensive industries to reduce energy consumption and emissions. The framework is presented in Figure A-5. The big data analytical framework for energy-intensive industries consists of four main steps, namely: energy big data perception and acquisition, energy big data storage and pre-processing, energy big data mining and energy-efficiency decision-making, and application services of energy big data.

In the first step (energy big data perception and acquisition), various metering instrumentation is used to capture heterogeneous energy-related data from multiple sources. In the second step (energy big data storage and pre-processing), the captured data is stored using various data storage and processing technologies and tools. Data pre-processing such as data cleaning, data integration, data reduction, and data transformation also take place in this step.

In the third step (energy big data mining and energy-efficiency decision-making), data mining, such as clustering, association and classification, is applied to the data. The results can be used for energy-efficiency decision-making. In the fourth step (application services of energy big data), several application services are designed, which will further assist with energy conservation and emission reduction in real-world operations.

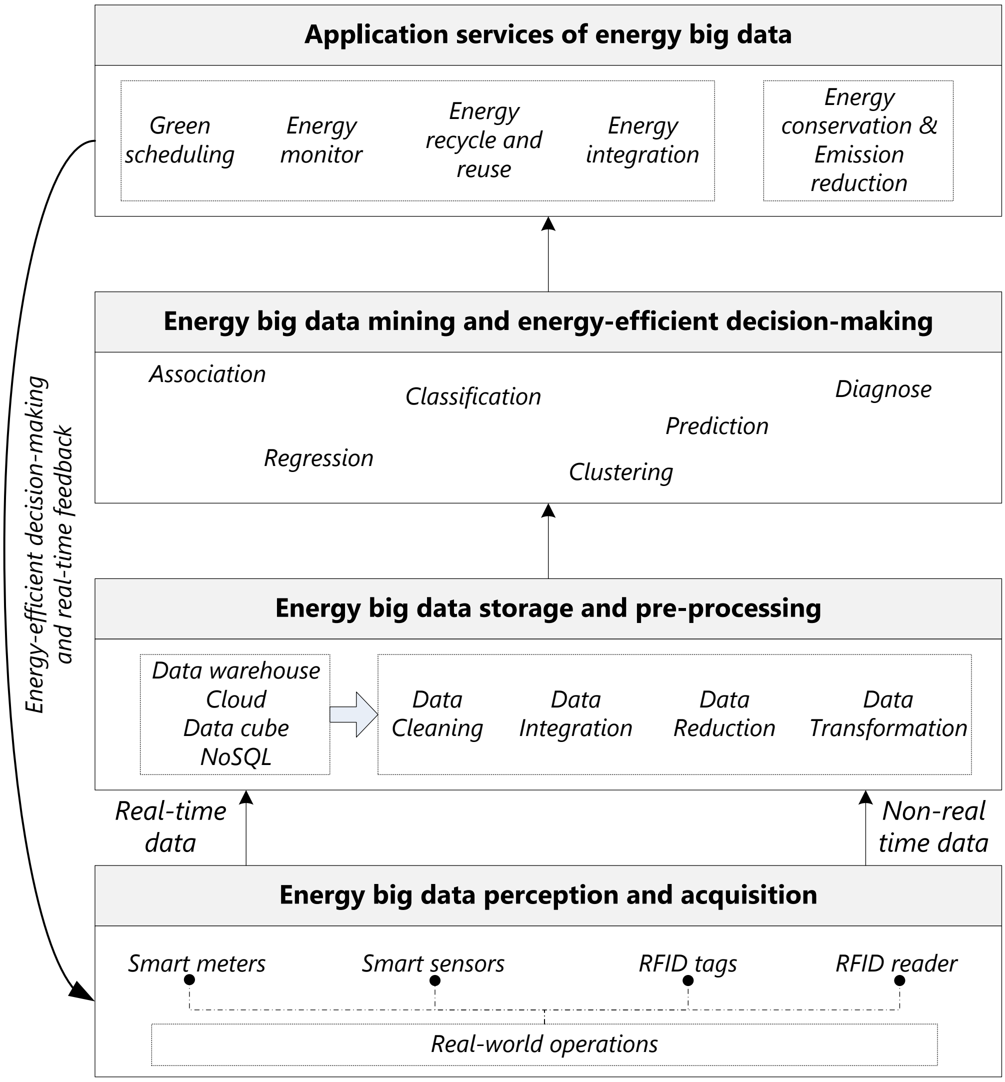

FIGURE A-5: BIG DATA ANALYTICAL FRAMEWORK FOR ENERGY-INTENSIVE INDUSTRIES (ADAPTED FROM [48])

A case study is provided in the journal article by Zhang *et al.* [48], which is based on the ceramics industry. It is shown that the energy costs could be reduced with up to 4% for the selected case studies after applying the framework.

Table A-6 shows the critical analysis of this guideline according to the requirements for BI implementation as identified in Chapter 1. Additional notes are included to assess if the guideline is industry specific or focusses on report development specifically.

TABLE A-6: CRITICAL ANALYSIS OF GUIDELINE: BIG DATA ANALYTICAL FRAMEWORK FOR ENERGY-INTENSIVE INDUSTRIES

BI requirement for report development	Big data analytical framework for energy-intensive industries analysis	
Impact evaluation	Although a case study is given where the energy intensiveness was reduced after applying the framework, the framework itself does not consider impact evaluation and does not provide guidance on how the impact should be evaluated.	✗
Structured	Only high-level steps are given with no indication of how to achieve the outcomes incrementally.	✗
Practical guidance	No practical guidance is given.	✗
Additional notes	The guideline is focussed on energy-intensive manufacturing industries and does not focus on report development specifically, but rather focusses on data exploration from an energy conservation perspective.	

Data Science Process

A data science process is given in Byrne's [49] book titled *Development workflows for data scientists*. This process is presented in Figure A-6 and discussed thereafter.

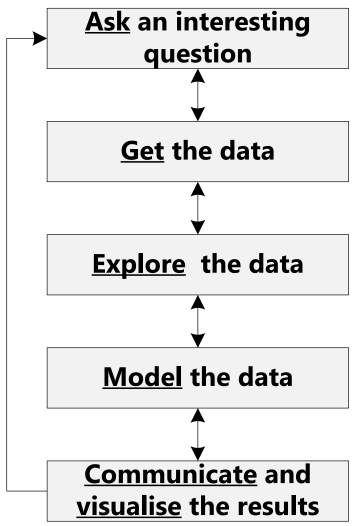

FIGURE A-6: DATA SCIENCE PROCESS (ADAPTED FROM [49])

In the first stage, an interesting question is asked that considers both the business goals and data science team limitations. Thereafter, relevant data is collected in the second stage, while the data is explored in the third stage. Data exploration may include creating quick visualisations or computing statistics. In the fourth stage, the data is used to build an analytical model and to test the model. The selected model will depend on the goal of the analysis as well as the characteristics of the data. In the fifth stage, the model results are communicated in an understandable manner by using visualisations.

Byrne [49] mostly focusses on predictive modelling and elaborates further on GitHub's software development tools and techniques that could be incorporated into the data science process.

Table A-7 shows the critical analysis of this guideline according to the requirements for BI implementation as identified in Chapter 1. Additional notes are included to assess if the guideline is industry specific or focusses on report development specifically.

TABLE A-7: CRITICAL ANALYSIS OF GUIDELINE: DATA SCIENCE PROCESS

BI requirement for report development	Data science process analysis	
Impact evaluation	No impact evaluation is given.	×
Structured	Only high-level stages are given with no indication of how to achieve the outcomes incrementally.	×
Practical guidance	No practical guidance is given within the guideline.	×
Additional notes	The guideline is not industry specific and does not focus on report development specifically, but rather focusses on predictive data exploration.	

Industrial Analytics Process

A journal article by O'Donovan, Bruton and Sullivan [50] proposes an industrial analytics methodology that involves six steps, namely: operational question, historical data, data ingestion, data preparation, model building, and model operationalisation. The process steps involved with this methodology are depicted in Figure A-7 and discussed thereafter.

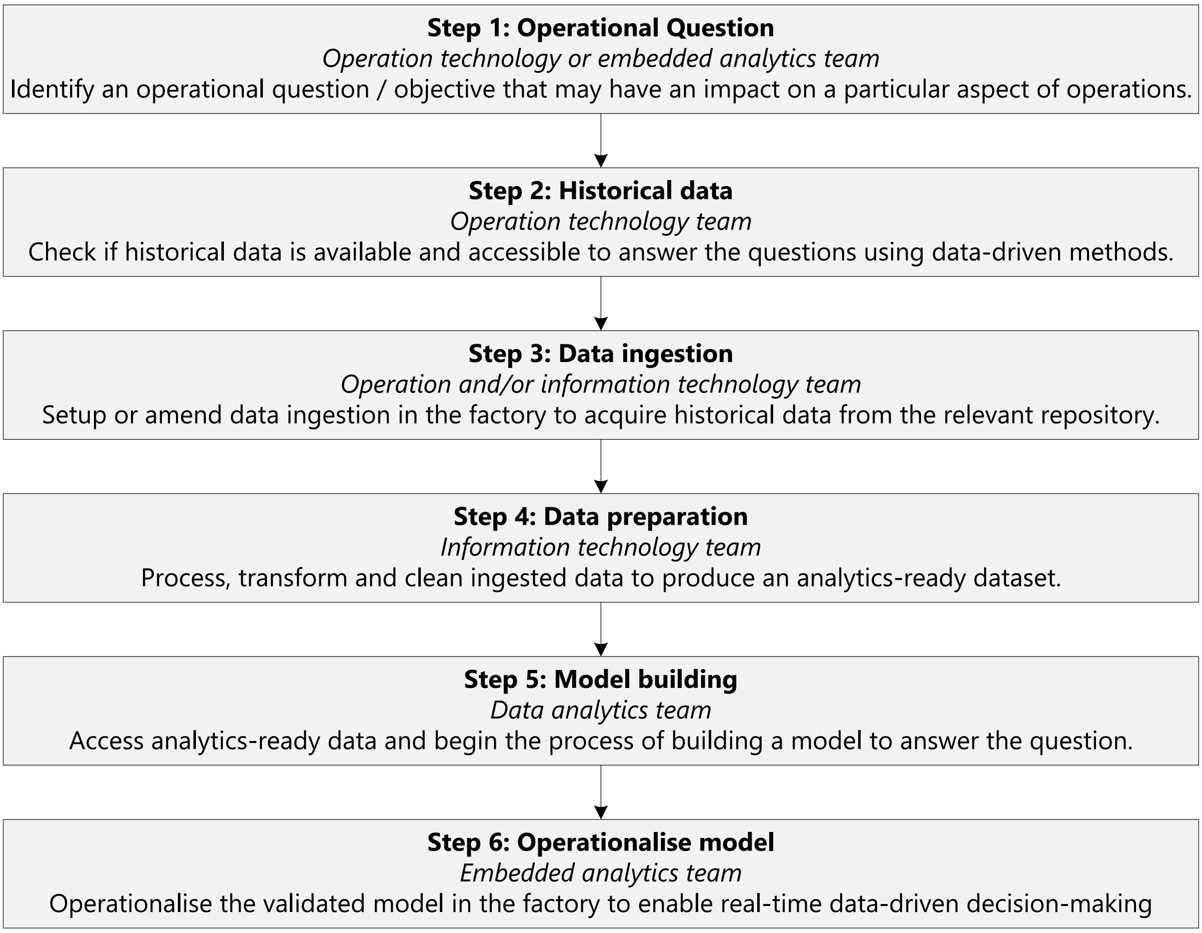

FIGURE A-7: INDUSTRIAL ANALYTICS PROCESS STEPS (ADAPTED FROM [50])

In Step 1, an operational question is identified based on operational needs. Thereafter, historical data is collected in Step 2. In Step 3, data ingestion is set up in real-world operations if required. In Step 4, all of the collected data is prepared, transformed, and cleaned. In Step 5, the data is used to build and test an analytical model. In Step 6, the model is deployed to real-world operations data to aid decision-making.

Table A-8 shows the critical analysis of this guideline according to the requirements for BI implementation as identified in Chapter 1. Additional notes are included to assess if the guideline is industry specific or focusses on report development specifically.

TABLE A-8: CRITICAL ANALYSIS OF GUIDELINE: INDUSTRIAL ANALYTICS PROCESS

BI requirement for report development	Industrial analytics process analysis	
Impact evaluation	No impact evaluation is given.	✘
Structured	Only high-level steps are given with no indication of how to achieve the outcomes incrementally.	✘

BI requirement for report development	Industrial analytics process analysis	
Practical guidance	Role players are identified and incorporated into each step in the guideline.	✓
Additional notes	The guideline is focussed on manufacturing industries and does not focus on report development specifically, but rather focusses on data exploration.	

Data Value Chain for Predictive Maintenance

A journal article by Åkerman [51] describes how a data value chain was built with the aim of doing predictive maintenance in the manufacturing industry. The steps involved are data acquisition, data transfer, pre-processing and storage, data analytics, and system feedback to the production system. The data value chain is depicted in Figure A-8 and discussed thereafter.

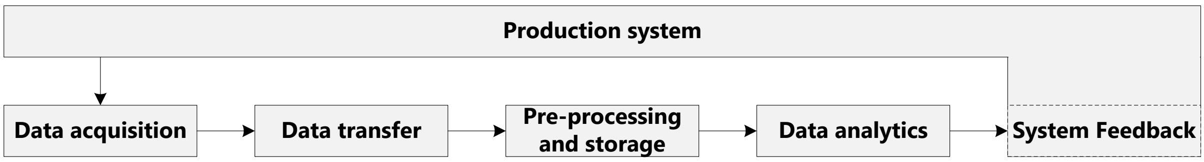

FIGURE A-8: DATA VALUE CHAIN FOR PREDICTIVE MAINTENANCE (ADAPTED FROM [51])

In the data acquisition step, data is collected from various sensors in real-world applications. A few factors to consider during this step are the frequency at which data is collected and if only key data sources relevant to the application or all data sources will be collected to test connectivity and ensure synergy in the data processing procedure.

In the data transfer step, data is transferred to a data centre via communication protocols. These protocols will differ from case to case since digital systems support different types of communication protocols. During the pre-processing and storage step, all of the data in the data centre is stored in a database. In this step, it is also important to identify metadata associated with the data.

In the data analytics step, the correct data and analytical methods are chosen for predictive maintenance. Thereafter, in the systems feedback step, feedback is provided to the relevant personnel in the real-world manufacturing industry. In this step it is important to consider the communication platform used and the visualisations of the data. The aim of feedback is to give relevant information to assist personnel to do proactive equipment maintenance.

Table A-9 shows the critical analysis of this guideline according to the requirements for BI implementation as identified in Chapter 1. Additional notes are included to assess if the guideline is industry specific or focusses on report development specifically.

TABLE A-9: CRITICAL ANALYSIS OF GUIDELINE: DATA VALUE CHAIN ARCHITECTURE FOR PREDICTIVE MAINTENANCE

BI requirement for report development	Data value chain and architecture for predictive maintenance analysis	
Impact evaluation	No impact evaluation is given.	×
Structured	Only high-level steps are given with no indication of how to achieve the outcomes incrementally.	×
Practical guidance	No practical guidance is given within the guideline.	×
Additional notes	The guideline is focussed on manufacturing industries and does not focus on report development specifically, but rather focusses on data exploration.	

Process of Knowledge Discovery in Databases

The book titled *Data Mining and Knowledge Discovery Handbook* by Maimon and Rokach [52] describes the process of knowledge discovery in databases (KDD). The KDD process is iterative and consists of nine steps, starting with the determination of KDD goals and ending with the implementation of gained knowledge. The process is depicted in Figure A-9 and discussed thereafter.

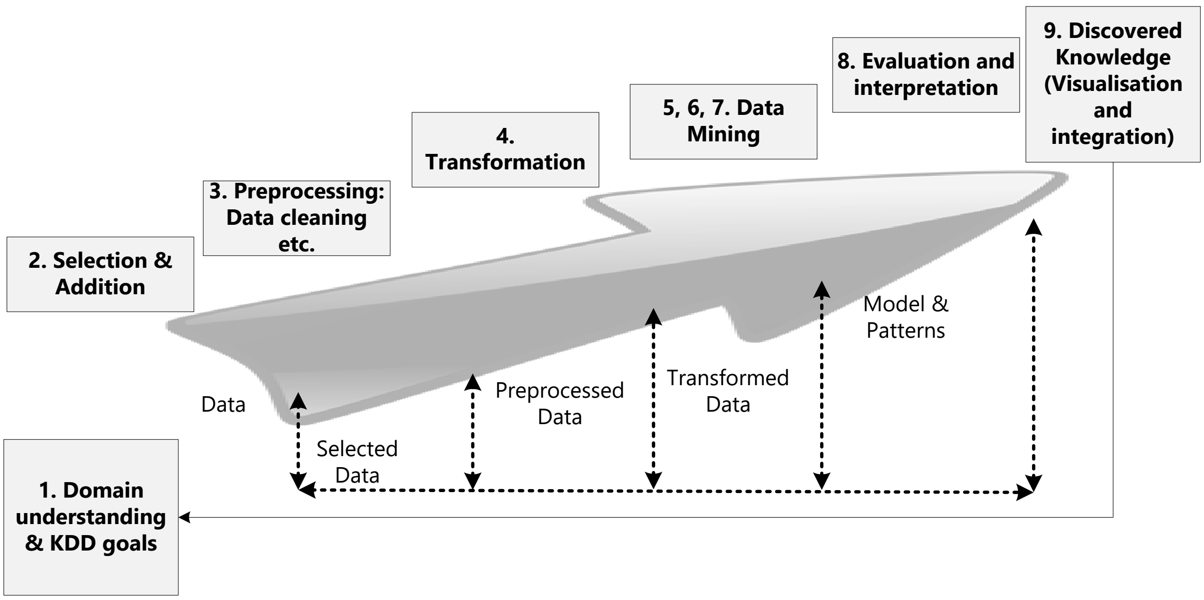

FIGURE A-9: THE PROCESS OF KDD (ADAPTED FROM [52])

In Step 1, the goals of the KDD process are defined within the environment where the process will take place. Thereafter in Step 2, a data set is selected on which KDD will be performed. This includes the identifying available data, adding data if necessary, and integrating all the data into one data set. In Step 3, the reliability of the data set is enhanced by handling missing values and removing noise and outliers. During Step 4, the data is transformed as required. Steps 5, 6, and 7 form part of the data mining process. In Step 5, the appropriate data mining method, such as classification or regression, is selected. In Step 6, a data mining algorithm is selected, e.g. will precision or understandability be used to evaluate the process. In Step 7, the chosen data mining algorithm is deployed, which may include multiple iterations until desired results are obtained. In Step 8, the results are evaluated with respect to the original KDD goals as defined in Step 1. In Step 9, the discovered knowledge is used by incorporating it into other systems for further action.

Table A-10 shows the critical analysis of this guideline according to the requirements for BI implementation as identified in Chapter 1. Additional notes are included to assess if the guideline is industry specific or focusses on report development specifically.

TABLE A-10: CRITICAL ANALYSIS OF GUIDELINE: PROCESS OF KDD

BI requirement for report development	Process for KDD analysis	
Impact evaluation	No impact evaluation is given.	×
Structured	Only high-level steps are given with no indication of how to achieve the outcomes incrementally.	×
Practical guidance	No practical guidance is given within the guideline.	×
Additional notes	The guideline is not industry specific and does not focus on report development specifically, but rather focusses on data exploration.	

Framework for Implementation of Big Data Projects in Firms

A journal article by Dutta and Bose [53] describes how a framework was developed to implement big data projects in firms. The framework is organised into three main phases, namely strategic groundwork, data analytics, and implementation. This framework is shown in Figure A-10 and discussed thereafter.

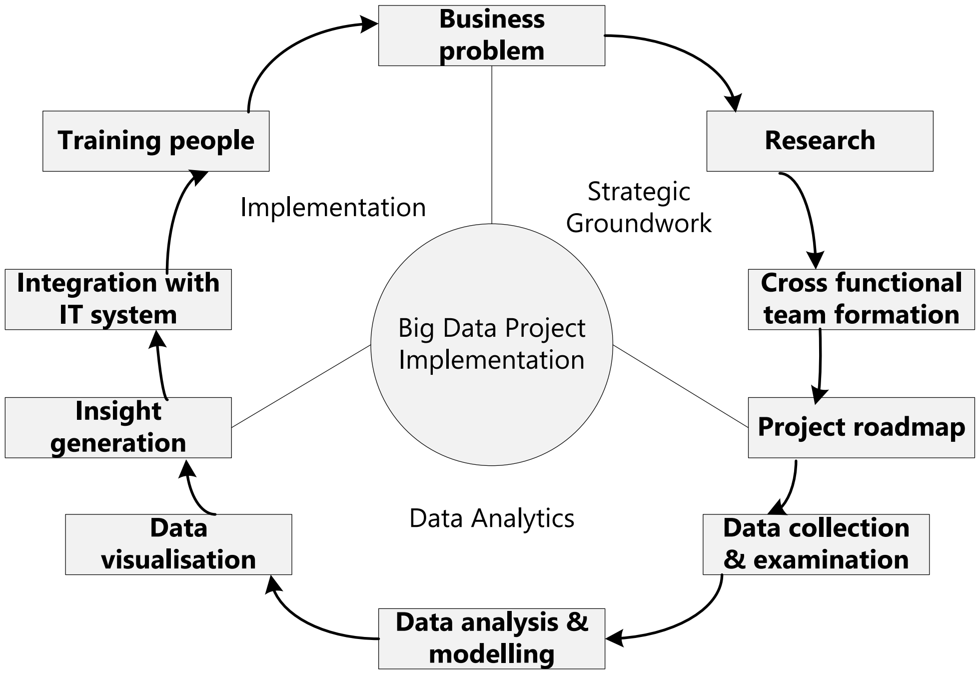

FIGURE A-10: FRAMEWORK FOR IMPLEMENTATION OF BIG DATA PROJECTS IN FIRMS (ADAPTED FROM [53])

The strategic groundwork phase consists of the four steps: business problem, research, cross-functional team formation, and project road map. In the business problem step, the business problem is understood. Thereafter, it is researched in the research step how other companies have addressed similar problems. In this step, the information technology (IT) and analytics infrastructure of the organisation are also understood. During the cross-functional team formation step, a team is instituted that consists of people from various stakeholders, business units, IT experts, data modellers, and relevant decision makers. This team will be involved with the various steps throughout the framework. Next a project road map is developed that contains main activities throughout the process, timelines, and responsible persons.

The data analytics phase consists of four steps: data collection and examination, data analysis and modelling, data visualisation, and insight generation. In the data collection and examination step, all data captured by the organisation is examined. This includes evaluating metadata and analysing structured and unstructured data. In the data analysis and modelling step, an analytical method is chosen to analyse the data with respect to the business problem. This may include regression, factor analysis, and discriminant analysis for structured data. For unstructured data, this may include methods such as text mining. In the data visualisation step, the data and analytics results are visualised to assist with insight generation. During the insight generation step, the visualised data is analysed to uncover insights that could lead to actionable business outputs.

The implementation phases consist of two steps: integration with IT system and training people. In the integration with IT system step, the data, analytic models, and visualisation are deployed and integrated with the existing IT system. Thereafter, people such as managers obtain training on how to use the system for day-to-day decision-making. This step provides a platform for change management to ensure usability of the system.

Table A-11 shows the critical analysis of this guideline according to the requirements for BI implementation as identified in Chapter 1. Additional notes are included to assess if the guideline is industry specific or focusses on report development specifically.

TABLE A-11: CRITICAL ANALYSIS OF GUIDELINE: FRAMEWORK FOR IMPLEMENTING BIG DATA PROJECTS IN FIRMS

BI requirement for report development	Framework for implementation of big data projects in firms analysis	
Impact evaluation	No impact evaluation is given.	✗
Structured	Only high-level steps are given with no indication of how to achieve the outcomes incrementally.	✗
Practical guidance	The importance of role players, project road map and system training are highlighted within the given steps of the framework.	✓
Additional notes	The guideline is not industry specific and does not focus on report development specifically, but rather focusses on data exploration within an existing IT system.	

Process Model for Big Data Driven Smart Energy Management

A journal article by Zhou, Fu and Yang [54] proposes a process model for big data driven smart energy management, which consists of seven steps. The process is depicted in Figure A-11 and discussed thereafter.

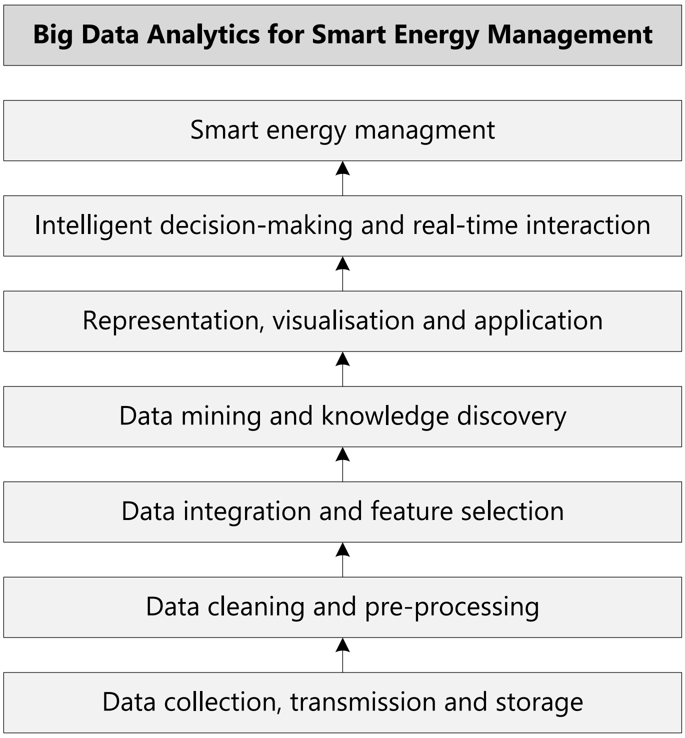

FIGURE A-11: PROCESS MODEL OF BIG DATA DRIVEN SMART ENERGY MANAGEMENT (ADAPTED FROM [54])

In preparation of the process, the first three steps include data collection, transmission and storage; data cleaning and pre-processing; and data integration and feature selection. Data mining and knowledge discovery take place subsequently as a core step in the process. Thereafter, results are represented with visualisation and used to support decision-making. Finally, the entire system is used to achieve various energy management objectives. These objectives include energy efficiency, real-time monitoring, demand response intelligent control.

Table A-12 shows the critical analysis of this guideline according to the requirements for BI implementation identified in Chapter 1. Additional notes are also included to assess whether the guideline is industry specific or focusses on report development specifically.

TABLE A-12: CRITICAL ANALYSIS OF GUIDELINE: PROCESS MODEL FOR BIG DATA DRIVEN SMART ENERGY MANAGEMENT

BI requirement for report development	Process model for big data driven smart energy management analysis	
Impact evaluation	No impact evaluation is given.	✗
Structured	Only high-level steps are given with no indication of how to achieve the outcomes incrementally.	✗
Practical guidance	No practical guidance is given within the guideline.	✗
Additional notes	The guideline is not industry specific and does not focus on report development specifically, but rather focusses on data exploration for energy management and control.	

Team Data Science Process

A conference paper by Saltz and Suthrland [55] explores data science project management. During this process, Saltz and Suthrland [55] describe the Team Data Science Process (TDSP) that was launched by Microsoft.* An overview of the TDSP life cycle is shown in Figure A-12 and described thereafter.

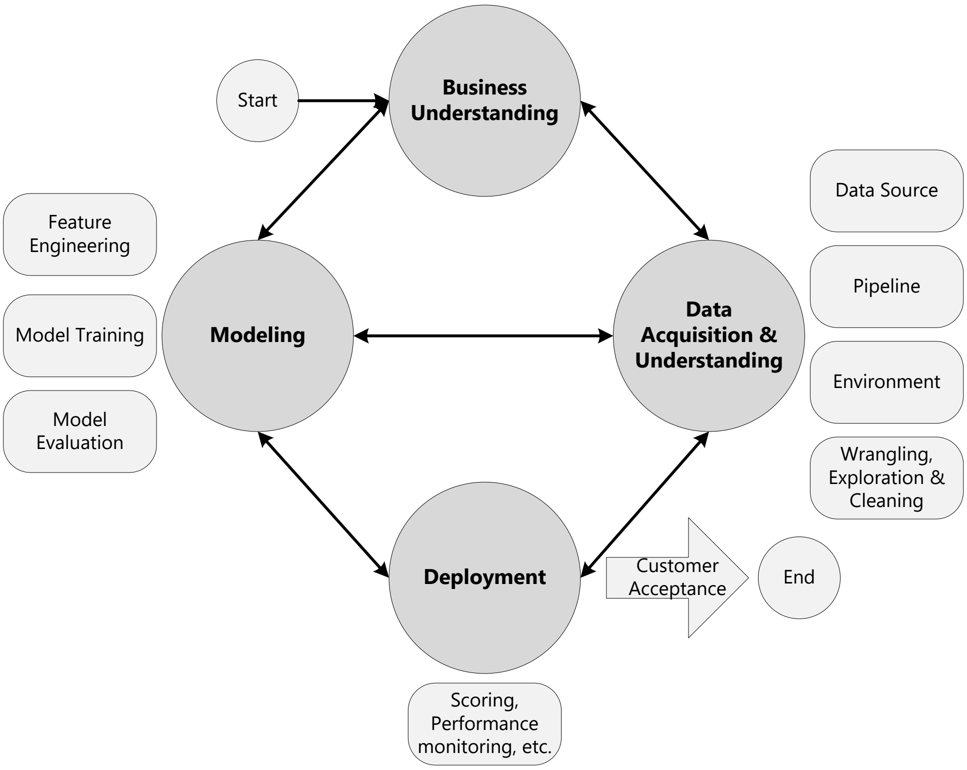

FIGURE A-12: TDSP†

The TDSP has five iterative stages. In the first stage, business understanding, the business problem is understood, objectives are defined to address the problem, and required data sources are identified. In the second stage, data acquisition and understanding, the required data is ingested and explored to see if it could address the business problem. During the third stage, modelling, analytical models are trained and any required features are engineered. In the fourth stage, deployment, the results are deployed into a production environment. Lastly, in the fifth stage, customer acceptance, it is confirmed whether the project meets customer needs.

The TDSP combines agile principles with the steps involved with CRISP-DM. Each iteration of the life cycle is kicked off with a sprint planning. Additionally, distinct role players are identified and assigned

* Microsoft. What is the Team Data Science Process? 2020. [Online]. Available: https://docs.microsoft.com/en-us/azure/machine-learning/team-data-science-process/overview [Accessed: 19-Feb-2021].
† Microsoft. What is the Team Data Science Process? 2020. [Online]. Available: https://docs.microsoft.com/en-us/azure/machine-learning/team-data-science-process/overview [Accessed: 19-Feb-2021].

specific responsibilities throughout the process. Microsoft further provides resources on GitHub to incorporate additional project management principles into TDSP.

Table A-13 shows the critical analysis of this guideline according to the requirements for BI implementation as identified in Chapter 1. Additional notes are included to assess if the guideline is industry specific or focusses on report development specifically.

TABLE A-13: CRITICAL ANALYSIS OF GUIDELINE: TDSP

BI requirement for report development	Team Data Science Process analysis	
Impact evaluation	No impact evaluation is given.	×
Structured	Only high-level steps are given with no indication of how to achieve the outcomes incrementally.	×
Practical guidance	Agile principles are used and distinct role players are identified with specific responsibilities.	✓
Additional notes	The guideline is not industry specific and does not focus on report development specifically, but rather BI overall.	

Sample, Explore, Modify, Model, Assess

A journal article by Tariq *et al.* [56] describes how the sample, explore, modify, model and assess (SEMMA) methodology was used to predict loan defaults. Additionally, in a conference paper by Azevedo and Santos [82], a comparative study was done between the SEMMA, CRISP-DM, and KDD processes. These two references are used to describe the SEMMA process in this section.

The SEMMA process consists of five stages, namely sample, explore, modify, model and assess [56], [82]. The sample stage is described as optional and includes extracting a portion of significant data from a larger data set. In the explore stage, the data is explored to understand the structure of the data and detect any anomalies. During the modify stage, the data is modified in preparation of modelling, which includes tasks such as transforming the data and handling missing values. In the model stage, various data mining methods are deployed to achieve the desired outcomes. This stage aims to obtain meaningful insights from the pre-processed data set. Lastly, in the assess stage, the model is assessed according to its reliability. This could include parameters such as model accuracy, sensitivity, and error rate.

Table A-14 shows the critical analysis of this guideline according to the requirements for BI implementation as identified in Chapter 1. Additional notes are included to assess if the guideline is industry specific or focusses on report development specifically.

TABLE A-14: CRITICAL ANALYSIS OF GUIDELINE: SEMMA

BI requirement for report development	SEMMA analysis	
Impact evaluation	No impact evaluation is given.	×
Structured	Only high-level stages are given with no indication of how to achieve the outcomes incrementally.	×
Practical guidance	No practical guidance is given within the guideline.	×
Additional notes	The guideline is not industry specific and does not focus on report development specifically, but rather focusses on data exploration.	

B. APPENDIX: EVALUATING THE IMPACT OF OPERATIONAL REPORTS

South African Journal of Industrial Engineering November 2020 Vol 31(3) Special Edition, pp 156-169

EVALUATING THE IMPACT OF OPERATIONAL REPORTS

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ARTICLE INFO

Article details
Presented at the 31st annual conference of the Southern African Institute for Industrial Engineering (SAIIE), held virtually from 5-7 October 2020.

Available online 11 Nov 2020

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DOI
http://dx.doi.org/10.7166/31-3-2428

ABSTRACT

New technological developments allow for an increase in data generation. There is a parallel increase in business intelligence systems. As a result, numerous operational reports are continuously developed to measure operational performance. Many studies state that data-driven reporting aids valuable decision-making. However, reports need to be evaluated to identify the extent of their impact on operations. This paper provides a review of current evaluation methods, which shows that user surveys are most commonly used. These surveys are limited, as they only indicate reporting quality. Little has been done to quantify the impact of reporting. In this paper, an evaluation method is developed that assesses both the qualitative and quantitative impacts of operational reports. This method is then applied to water management and energy management reporting case studies in the mining industry. The quantitative impact ranged from R0.5-million to R7.3-million and from R0.3-million to R65.0-million for the two case studies respectively.

OPSOMMING

Nuwe tegnologiese ontwikkelinge maak voorsiening vir 'n toename in die generering van data. Daar is 'n parallelle toename in sake-intelligensie stelsels. As gevolg hiervan word talle operasionele verslae deurlopend ontwikkel om bedryfsvertoning te evalueer. Baie studies noem dat data-gedrewe verslaggewing waardevolle besluitneming bevorder. Verslae moet egter evalueer word om die omvang van hul impak op bedrywighede te bepaal. Hierdie artikel gee 'n oorsig van huidige evalueringsmetodes, wat toon dat gebruikersopnames die meeste gebruik word. Hierdie opnames is beperk, aangesien dit slegs die gehalte van verslae aandui. Daar is min gedoen om die impak van verslaggewing te kwantifiseer. In hierdie artikel word 'n evalueringsmetode ontwikkel wat die kwalitatiewe en kwantitatiewe impak van operasionele verslae beoordeel. Hierdie metode word dan op gevallestudies van die bestuur van water en energie in die mynbedryf toegepas. Die kwantitatiewe impak het gewissel van R0.5 miljoen tot R7.3 miljoen en van R0.3 miljoen tot R65.0 miljoen onderskeidelik vir die twee gevallestudies.

1 BACKGROUND AND PROBLEM STATEMENT

Data is collected and used by information systems to produce data-driven reports and analyses, which in turn are used for managerial decisions [1]. There has been a rapid increase in data generation, and this trend will continue [2]. This increase is supported by the availability of various technologies that make data available from a variety of sources, allow data generation at high velocities, and so cause data to expand in volume [3]. Therefore it is expected that the development of reports to represent that data will increase too.

Vallurupalli and Bose [4] confirm the increase in performance measurement systems in recent times, and acknowledge the impact of the increased adoption of business intelligence (BI) on these systems. BI transforms raw data into valuable information [5], [6] by making use of various technologies to gather, analyse, and present data [7]. Presenting data can take place in various forms of reporting [7] (noon-reports / automated reports / dashboards and platforms) that are generally used to measure performance.

Figure 1 below shows a 99 per cent increase in studies with the key words 'business intelligence', and a 212 per cent increase in studies with the key words 'performance measurement' over the past decade. This supports the expected increase in reporting.

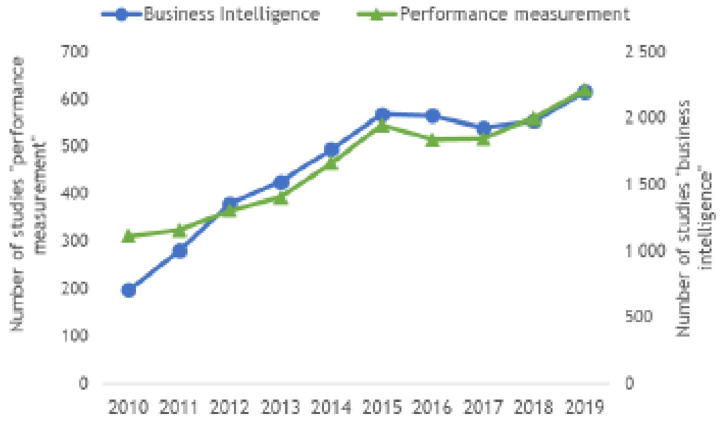

Figure 1: Increase in studies with the key words 'business intelligence' and 'performance measurement' over the past decade [Science Direct database]

As data becomes more accessible, it becomes easier to compile reports (especially automated reporting and dashboards). If left unchecked, there may be multiple reporting products in an organisation without any way of evaluating whether such platforms are contributing to business objectives. It may also be difficult to determine whether reporting that is intended to achieve certain objectives is effective in doing so.

Numerous studies indicate that business advantages can be obtained by exploiting performance measurement methods [2], [8]-[12]. However, with the increase in available data and reporting measures, their impact needs to be assessed. Although many studies suggest that these measures aid in decision-making [1], [2], [10], they do not evaluate the impact of those decisions.

Mesaros *et al.* [1] highlight the importance of BI systems for quantitative measures such as business cost and profit. So the extent of the impact of operational reporting on operations need to be comprehensively assessed by considering both qualitative and quantitative measures. Figure 2 highlights the scope of this study in a basic reporting structure.

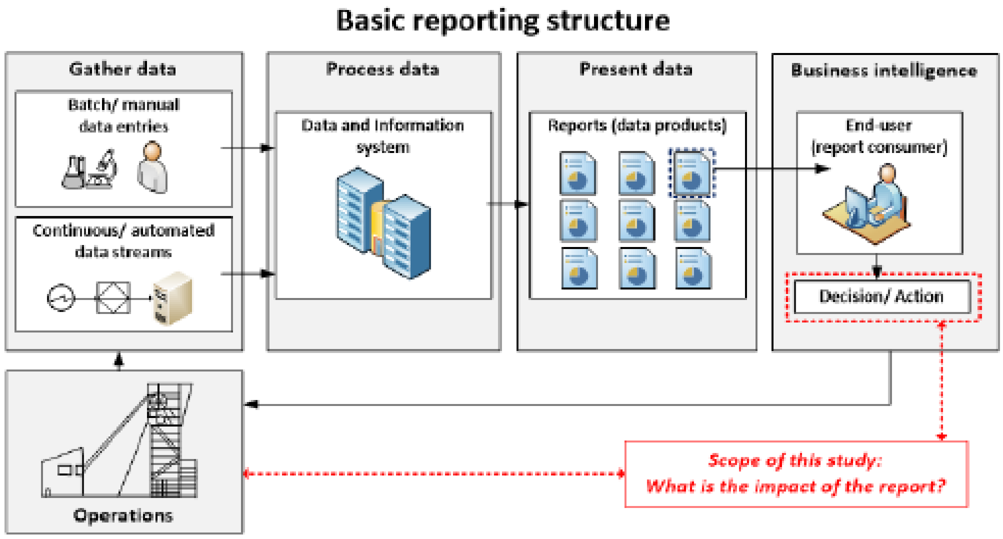

Figure 2: Basic reporting structure highlighting the scope of this study

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As shown in Figure 2, BI has three basic steps: gathering data, processing data, and presenting data [7]. Numerous technologies and forms of systems architecture can be applied to enable BI. The workings and design of these systems have been extensively described in the literature [13]-[15].

The scope of this study is focused on the consumer of operational reports and the actions that are enabled thereby. This paper is also focused on the mining sector, considering its importance in South Africa and its impact on the environment. Reports have been developed in several studies that are widely used for operational efficiency, including water [16] and energy management [17].

Reporting will need to have a traceable impact on operations if it is to be regarded as valuable. However, evaluating these impacts can be challenging, as described in the literature review in the next section.

This paper describes the development of a method to evaluate the impact of operational reports, based on the existing and relevant literature. The objectives of the developed method are to identify existing report evaluation methods and to combine them into a comprehensive evaluation method to gauge fully the qualitative and quantitative impact of operational reports. Finally, the evaluation method is applied to two reporting case studies to determine whether it is useful in practice.

2 RESEARCH METHODOLOGY

The problem statement was discussed in Section 1: to evaluate the qualitative and quantitative impact of operational reports. To address this problem, this study makes use of the systematic literature review (SLR) method. An SLR is completed to obtain relevant information on how operational reports are evaluated in the literature (Section 2). The knowledge gained from the literature review is used to develop a new method to evaluate the impact of operational reports that consider both qualitative and quantitative aspects (Section 3). Last, the newly developed method is verified with real-world case studies (Section 4).

3 SYSTEMATIC LITERATURE REVIEW

A systematic literature review (SLR) is a procedural method used to identify and critically evaluate available research on a specific research topic [18]. An SLR is used in this paper to identify and assess how the impact of reports is evaluated in the literature. The knowledge gained from the SLR was then incorporated into a method to evaluate fully the impact of reports on operations (described in the next section).

During an SLR, a step-by-step process is followed. These steps include conducting a search in databases based on relevant key words, filtering the results to ensure their relevance to the research topic, and summarising the final results [18], [19]. The SLR method followed in this paper is shown in Figure 3 and discussed thereafter.

Throughout the SLR the goal was to obtain studies relating to the impact of reports in the BI field. Therefore the chosen keywords were 'report', 'impact' or 'effect' or 'value', and 'business intelligence' or 'performance measurement'. The keywords were used to search four different credible databases (Scopus, IEEEXplore, EBSCO, and Science Direct). To ensure high-quality results, only journal articles and conference papers were considered. Results from 2015 to 2020 were considered to ensure that the latest studies were included. Last, only studies in English were included.

After the initial search, a large number of results was obtained. To refine this search to the most relevant studies, the database results were sorted according to relevance, and only the top 50 results per database were considered. Thereafter duplicate results were removed, which yielded a total of 111 results.

The title and abstract of each study were evaluated to establish their relevance before doing a full text analysis. Only studies in which a report was developed or evaluated or the impact of a BI system was evaluated were considered relevant. This delivered a total of 17 relevant studies. The low number of relevant studies indicate a gap in the evaluation of reports in the published literature.

A full text analysis was done for each of the 17 relevant studies. The full text was screened to identify 1) whether a report was developed, 2) what method of evaluation was used, if any, 3) what reporting factors were considered during the evaluation, and 4) listed benefits or value achievable from the reporting / BI system. The full text analysis is shown in Appendix A, while a summary of the results is shown in Figure 4.

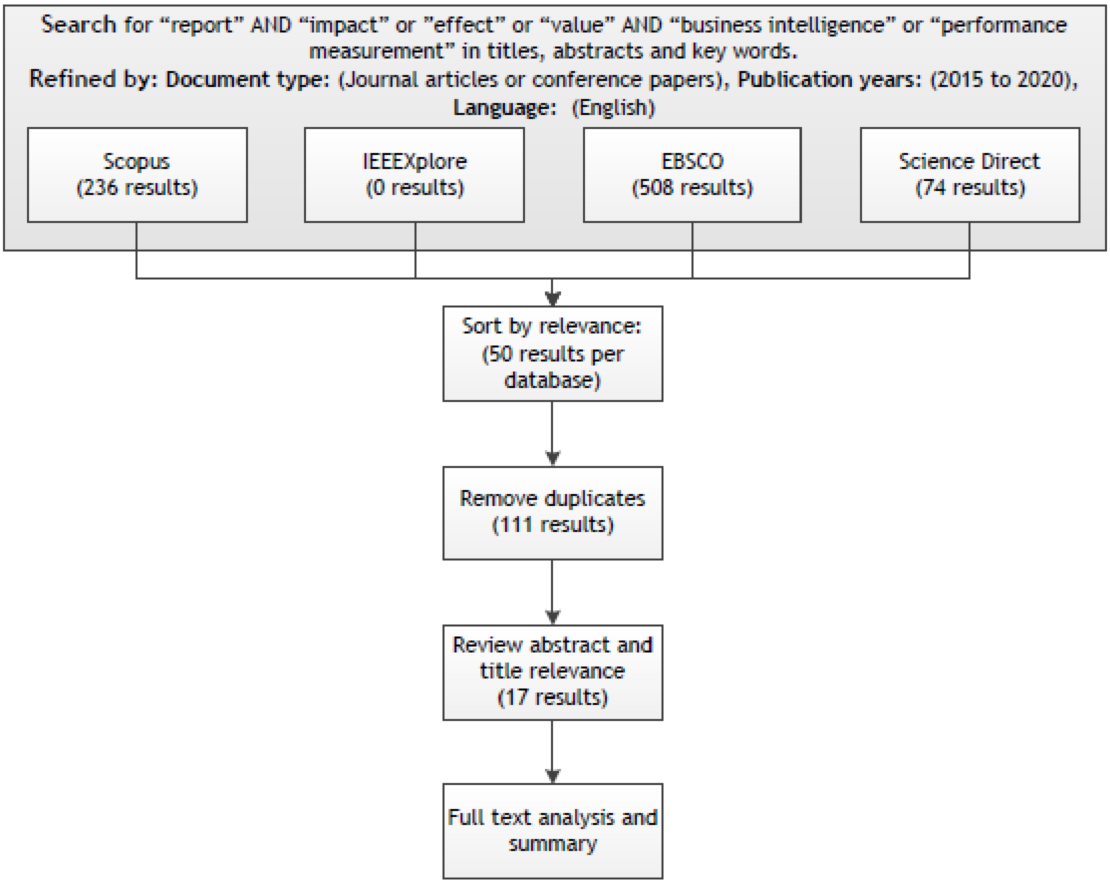

Figure 3: SLR method and results

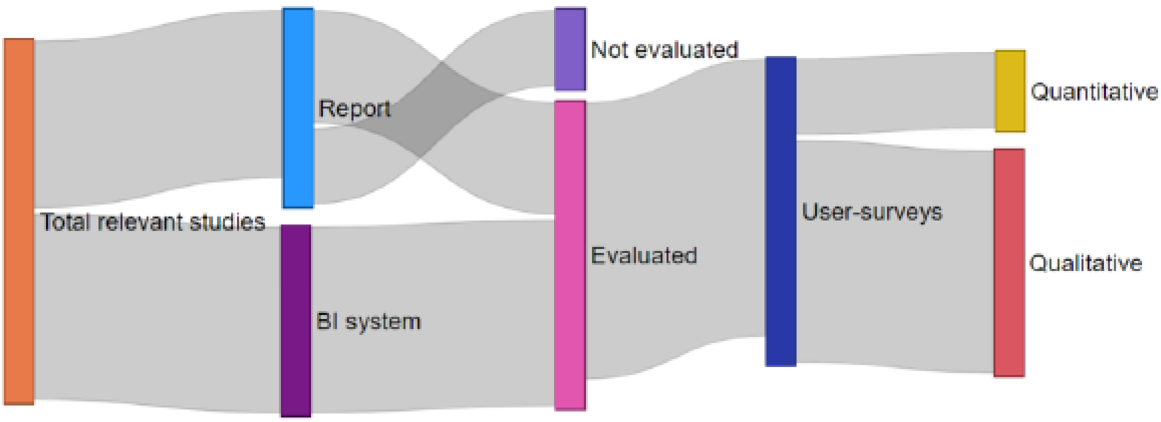

Figure 4: Summary of SLR full text analysis results

Of the 17 relevant studies, nine evaluated BI systems, and the remainder either developed a report or evaluated a report. While all BI systems were evaluated, not all reports were evaluated. This means that reports were developed but not evaluated afterwards. Where reports or BI systems were evaluated, the evaluation methods consisted exclusively of user surveys, questionnaires, and interviews.

Most factors considered in the evaluations were qualitative. Although some studies evaluated quantitative factors – such as time savings, profitability, and costs – they were all evaluated in a qualitative manner (e.g., whether profitability increased or decreased, without indicating by how much).

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The evaluated qualitative factors can be grouped into three groups: data quality, information, and representation. Data quality factors are concerned with the quality of the data used in reports and BI systems. Information considers the relevance and actionability of the information displayed in reports. Representation factors evaluate the visualisations and interaction with the reporting measure.

Peters, M.D., Wieder, B., Sutton, S. & Wakefield, J. [20] considered quantitative factors in their evaluation, such as sales growth, market share, and profitability. However, these factors were still evaluated in a qualitative way and were not quantified. Most of the studies discuss the importance of reports to aid operational and managerial decision-making (Appendix A). However, none of these studies quantify the impact of the possible decision-making.

The reports have a direct impact on some of these decisions, such as beneficial operational changes and monitoring savings. Other impacts, such as compliance with guidelines and ensuring sustainable operations, are indirect. Thus, when quantifying the impact of operational reports, all possible decisions and benefits should be considered.

The SLR highlights that there is a need for a new report evaluation method that considers both the qualitative and the quantitative factors of reporting. In addition, quantitative factors should be quantified by considering the possible decisions and actions taken as a result of the report analysis. These evaluation aspects are necessary to gauge the impact of operational reporting fully. Such a method is developed in the next section.

4 DEVELOPMENT OF SOLUTION

The SLR showed that current evaluation methods mainly consist of user surveys. These surveys provide an indication of how useful the end-user finds the report in achieving certain objectives (i.e., the quality of a report). This study proposes the addition of quantitative evaluations to provide an indication of the actual business value of a report.

The combination of qualitative and quantitative evaluations identifies any mismatch between the two aspects of a report, and helps report developers to improve the reporting. For example, it is expected that a report that has high quantitative impact will also have a good qualitative score in order to be effective. Lower quality reports with a high quantitative impact give a clear indication of where improvements are required. Conversely, lower impact reports should have a lower priority when allocating development time and resources.

In this study, the impact of a report was evaluated with a survey, as suggested by multiple studies in the SLR. The survey was compiled to evaluate both qualitative and quantitative impacts of reports. The factors evaluated in the survey are shown in Table 1, and then discussed.

Table 1: Description of factors evaluated in survey

Evaluating factor	Description
Qualitative	
Data quality	Data source reliability, data accuracy, data refresh time.
Information	Information relevance, assistance in process assessment, information actionability, usability.
Representation	Report understandability, report accessibility, effectiveness of visualisations.
Quantitative	
Time savings	Increase in productivity or data analysis time savings.
Direct impacts	Direct impacts associated with specific report – e.g., operational changes and incentives.
Indirect impacts	Indirect impacts associated with specific report – e.g., compliance to guidelines and avoided costs.

First, the survey considered the qualitative impact. In this study, 'qualitative impact' refers to the overall satisfaction of a user or consumer of a report. Questions were compiled from the qualitative factors evaluated in the literature. This included the data quality, information, and representation. A semantic differential scale was used to evaluate each qualitative factor (as proposed by Jetter, Eimecke & Rese, [21]). The scale consisted of a five-point rating scale with the direct opposites of each qualitative factor at each end.

Second, the survey evaluated the quantitative impact. In this study, 'quantitative impact' refers to a measurable benefit arising from reporting. Quantitative impacts consider time savings and impacts related to decision-making. Time savings can be a result of increased productivity or a decrease in the time spent in process analyses owing to the availability of the reports. All time savings will then be correlated with savings in wages in order to obtain a quantitative impact.

The survey also evaluated the quantitative impact of possible decisions made, or benefits obtained, as a result of the report. The possible decisions or benefits will vary for each specific report. The user was thus allowed to elaborate on these impacts in the survey, being asked to list both the direct and the indirect impacts arising from the report, and to indicate the estimated monetary impact.

Both the direct and the indirect impacts were included to obtain an indication of the cascading effects of the quantitative impact of reports. This resulted in a range of monetary impacts, from direct to indirect, associated with the report.

The method discussed in this section can be used to estimate the quantitative impacts of reports to evaluate their feasibility before they are developed. However, it can also be used after development to ensure that reports achieves their original intended purpose. An additional impact can then be added to the already-developed reports, based on actual events. This information can be used to motivate changes or expansions (or curtailment, in the case of over-reporting) to the existing reports.

In the next section, the method developed in this study is applied to case studies. This will show how the method is applied to actual situations in the South African mining industry.

5 EVALUATING THE IMPACT OF ACTUAL REPORTING CASE STUDIES

5.1 Overview of case studies

The primary sectors — such as farming, fishing, and mining — form a crucial part of the South African economy. Owing to the importance of these sectors, the case studies in this paper focus on one of them, the mining industry. The environmental impact of the mining industry, which is very resource-intensive, is undeniable [22].

In 2019, the South African mining industry contributed more than 38 per cent of the total industrial energy use [23]. According to Haggard, E.L., Sheridan, C.M. & Harding, K.G. [24], the total water consumption of the mining industry in 2010 was three per cent of all water used, and although it is not the highest consumer of water, the industry's effect on water quality is severe.

The mining industry needs to manage these resources to remain sustainable and to reduce its environmental impact. Accurate reporting can enable operations to monitor these valuable resources and identify opportunities to improve operations. Therefore the two case studies in this paper consider water management (Case study A) and energy management (Case study B).

5.2 Case study A: Water management

Water is a valuable resource, and industries need to manage it to enable sustainable use. This case study focused on an operational water reticulation report for a deep-level gold mine. In this study, water is cooled on the surface by chillers before being sent underground for various uses. These include cleaning stope faces, cooling hot air, cooling, and lubricating drilling equipment. The water is then stored and pumped back to the surface to maintain accessible and safe working conditions.

The basic reporting structure is shown in Table 2 (analogous to Figure 2). Throughout the water reticulation system, various water-flow and storage-level measurements are installed. The data is captured by the mine's supervisory control and data acquisition system (SCADA), from where the data is stored in a cloud-based database via an open platform communications (OPC) connection. An established reporting system can access the data, perform data analytics, and develop reports.

Table 2: Basic reporting structure of Case study A

	Description
Operations	Underground water reporting of a deep-level gold mine
Gather data	Water-flow and storage-level measurements
Process data	Reporting system with access to a cloud-based database
Present data	Daily automated portable document format (PDF) report via email
End-user	Shaft and services engineer, project engineers, and shaft senior engineering manager

An automated PDF report was developed to monitor water use throughout the operation. The end-users receive the report daily via email. The main end-users are the shaft and services engineer, the energy management engineers, and the shaft senior engineering manager. Project engineers form part of the end-users, since they use the report to focus on the optimal and efficient operation of critical equipment that uses water.

Certain parameters are reported on, such as water usage intensity, volumes of water sent underground and back to the surface, water flow to various mining levels, water use in critical equipment, and exceeded water storage limits.

Survey results

To test the functionality of the survey, it was sent to selected main end-users — three project engineers. The qualitative survey results are shown in Figure 5, with the minimum and maximum indicated. The results show that the qualitative factors are rated high by report users. The survey questions were derived from the SLR (listed in Table 1).

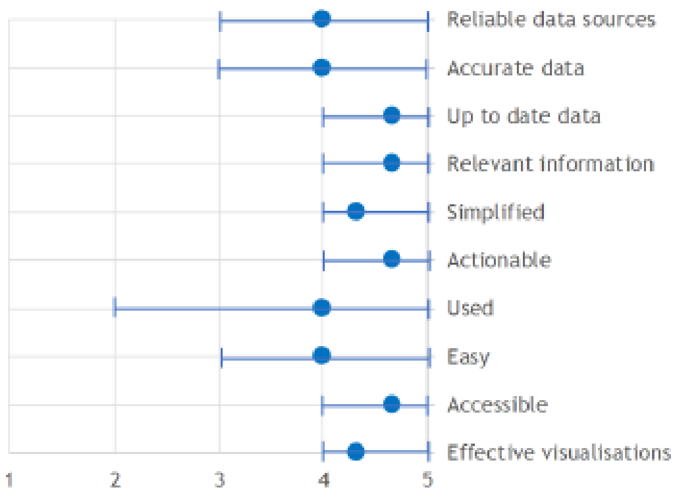

Figure 5: Case study A — qualitative survey results

All the end-users agreed about the time saved by using the report to analyse operations and to do fault finding. The average time savings were converted to an annual monetary saving by considering the average salary of a mining engineer in South Africa. This amounted to R 0.5-million annually. Overall, the end-users gave a high rating to the report's quality, which indicated that the report likely had a time-saving impact for the users.

Using the report for fault finding had a significant direct impact on energy savings for pumping and cooling, which can be up to R 0.3-million per incident. In extreme cases, when faulty operations can lead to a loss in production shift and the report could be used to rectify the problem in time, an avoided cost of R 6.6-million per day could be obtained. The cumulative impacts are presented in Figure 6.

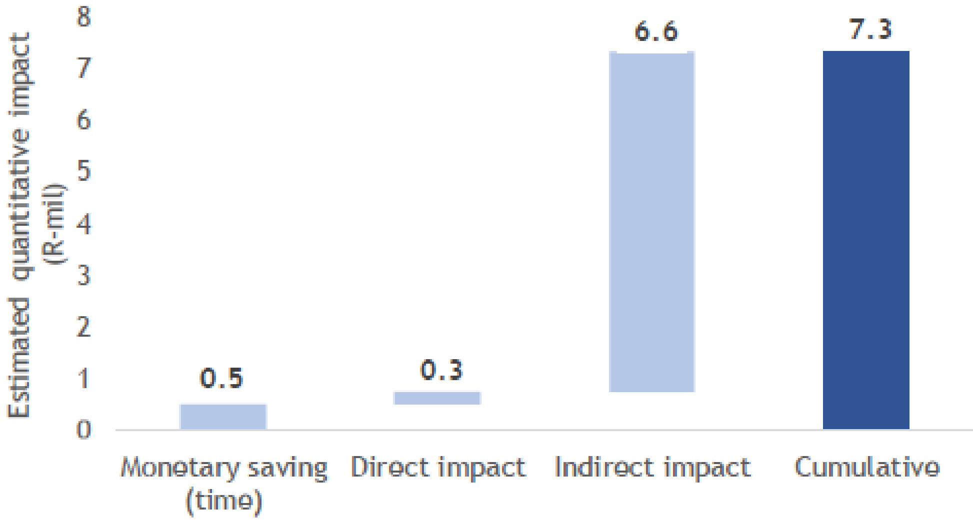

Figure 6: Case study A — quantitative impacts (cumulative)

It is important to note that the values in Figure 6 are the perceived benefit from the survey's respondents. Although potentially subjective, the values are considered reliable, since the survey's respondents were relevant, qualified, and experienced personnel.

From Figure 6 it can be seen that the direct and monetary impact of the report is much lower than the indirect impact. Note that the indirect impact shown above is for extreme cases, which means that the monetary and direct impacts are more likely to be achieved on a day-to-day basis.

The high possible indirect impact motivates the continued use of the report, while the lower direct impact indicates that report usability should be improved to increase this value. This is motivated by the qualitative evaluation (Figure 5), which indicates that the report is not used as much by all the survey's respondents (the largest difference between maximum and minimum rating).

It is recommended to meet regularly with all report end-users and to discuss value-added incidents from the report to improve the report's usability in future. This is expected to lead to an increase in the direct impacts of the report.

5.3 Case study B: Energy management

South African deep-level gold mines have faced a decrease in productivity and an increase in operational costs in recent years [25], [26]. A significant contributor to the increased costs is the industry's dependence on electricity, together with increases in electricity prices [26]. This makes electricity an important resource to manage in deep-level gold mines. Case study B therefore considers energy management reporting for a range of deep-level gold mines.

The basic reporting structure is shown in Table 3 (analogous to Figure 2). Numerous electricity meters are installed to monitor the use of critical equipment. The data is captured by various electricity meters, and is ultimately stored in a cloud-based database. The database is accessible via a reporting system that is used to develop energy management reports.

Table 3: Basic reporting structure of Case study B

	Description
Operations	Energy management of deep-level gold mines
Gather data	Numerous electricity meters
Process data	Reporting system with access to cloud-based database
Present data	Automated PDF project savings and month-to-date performance tracking reports via email
End-user	Shaft and services engineers, energy management engineers, and shaft senior engineering managers

As part of the reporting initiative, two types of report are automatically generated in PDF and sent to end-users via email. The first is project savings reports that are generated once a month and used to provide feedback on the performance of specific energy-saving projects. These reports include parameters such as average daily electricity profiles, daily cost savings, daily energy use, and a distribution of electricity consumption according to Eskom's time-of-use periods.

The second is month-to-date budget tracking reports that are mainly used to monitor how far under or over budget a shaft's electricity use is for each of its critical consumers. The reports are sent to end-users once a week. These reports contain electricity consumption information, which is compared with the budgets for each critical consumer of a shaft.

This reporting initiative provides end-users with an overview of the electricity consumption of their operations. The main end-users of the reports include shaft and services engineers, energy management engineers, and shaft senior engineering managers.

Survey results

Three energy management engineers were asked to complete the surveys in order to test their functionality. From the qualitative survey results in Figure 7 it can be seen that most of the qualitative factors were rated high. The actionability and usability of the reports received the lowest rating among the qualitative factors. This indicates that, although the reports consist of relevant information that is easily interpreted to provide energy awareness, they are not exclusively used to develop action plans or make decisions.

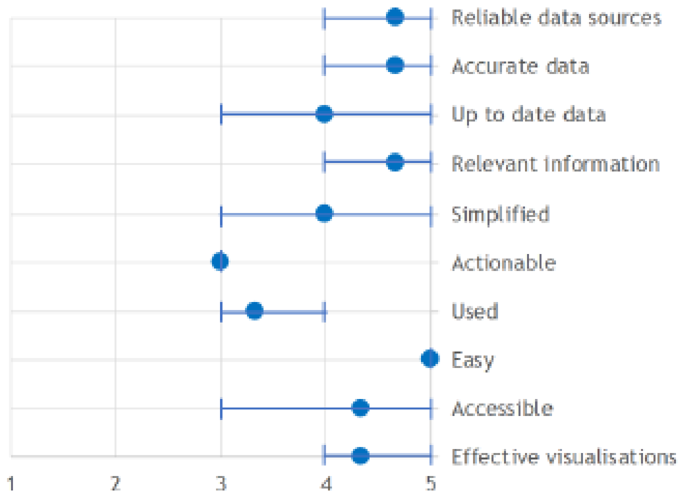

Figure 7: Case study B – qualitative survey results

The survey results show that end-users indicated that the availability of reports results in time savings when gathering, processing, and analysing the energy-related data. This was converted to a monetary saving, considering the average salary of a South African mining engineer. This resulted in an estimated R 0.3-mil annual impact as a result of time savings. Although the usability of the report was not rated very high, the estimated impact owing to time savings is deemed conservative, considering that the reports go out to multiple shafts and have multiple end-users.

The survey results indicated that the weekly month-to-date performance tracking reports have been used to identify abnormal energy use so that immediate action could be taken. The reports have also been used to maintain the performance of energy-saving initiatives. This results in an annual total cost savings of R 62.5-million, and is a direct impact of the reporting.

As an indirect impact of the reports, the results have also been used to verify electrical metering anomalies – one of three systems used to track electricity consumption. In a specific case, this resulted in finding a billing mistake that, when corrected, resulted in a recovered cost of R 2.2-million. The cumulative impacts related to the energy reporting discussed in this section are shown in Figure 8.

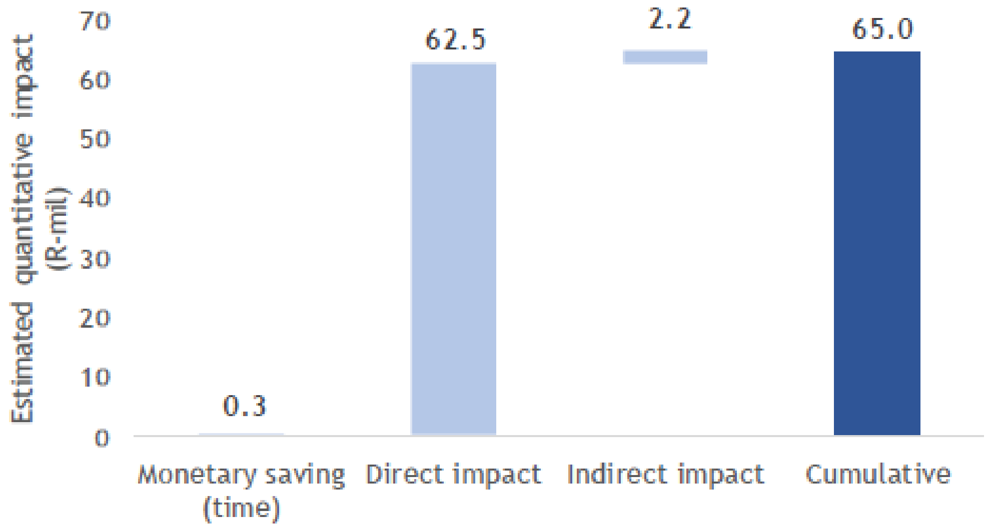

Figure 8: Case study B — quantitative impact (cumulative)

Figure 8 shows a high direct impact and lower monetary and indirect impacts. This indicates that the impacts on a day-to-day operational basis are significant for these reports. And this direct impact may be even higher when report developers aim to improve the lower qualitative rating received for report actionability (Figure 7).

Alternatively, the high direct impact indicates that development resources can be spent elsewhere instead of improving report actionability, since the direct monetary impact is already significant.

6 DISCUSSION OF RESULTS

The survey developed in this paper can easily be used by report end-users to evaluate operational reports. This method allowed the impact of a water management report and energy management reports in the mining industry to be evaluated. First, qualitative factors were evaluated, providing a clear indication of the reports' strengths and weaknesses, and allowing report developers to identify where improvements were required.

Second, quantitative impacts were also evaluated. Quantifying this impact was valuable for the stakeholders involved to help them understand the function and intended effects of the reports. And by evaluating both the qualitative and the quantitative impacts, a mismatch was identified that also indicated areas for improving the reports.

Case study A identified that report usability could be improved on, leading to increased direct monetary impacts. Case study B's results showed a low report actionability qualitative rating, but a high quantitative direct impact. This indicated that development resources could rather be spent elsewhere, since high quantitative impacts were already obtained.

It should also be noted that quantifying the impacts related to reporting is a challenging task, and impacts such as avoided costs remain subjective. In this paper, highly relevant, qualified, and experienced end-users provided these quantitative measures of impact, and so they can be seen as a sufficient indication of the quantitative impacts.

As a recommendation for further work, standardised performance quantification methods can be used to improve the objectivity of the results (which can be based on established protocols [27]). The sample size of the survey can also be increased to verify the functionality of the survey. In this study, the case study reports had very specific end-users, and only three end-users were considered per case study. More end-users should be considered to obtain more accurate results.

7 CONCLUSION

The objective of this paper was to develop a comprehensive method to evaluate the qualitative and quantitative impact of operational reports. A systematic literature review was completed to identify how the existing literature evaluates the impact of reports. It was found that surveys are the most common method of report evaluation. However, most studies focused on the qualitative factors of reports, and rarely considered the quantitative factors.

A survey was therefore developed for this paper to evaluate both the qualitative and the quantitative factors of operational reports. The survey was tested on two case studies in the South African deep-level gold mine industry. First, an underground water management report was considered. It was found that this report had highly rated qualitative factors that could be used to develop action plans and assist decision-making. This resulted in cumulative quantitative impacts ranging from R 0.5-million to R 7.3-million.

Second, the energy management reporting of multiple shafts was evaluated. The evaluation showed that most qualitative factors were rated high, with the actionability and usability of the reports obtaining an average rating. However, the quantitative evaluation indicated that, when the reports were actioned, significantly high quantitative impacts could be obtained. These impacts ranged from R 0.3-million to R 65.0-million.

In conclusion, a method was derived to evaluate both the qualitative and the quantitative impacts of operational reports. The method provides clear communication with involved stakeholders, and allows report developers to identify areas for improvement.

ACKNOWLEDGEMENTS

This work was sponsored by ETA Operations (Pty) Ltd.

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APPENDIX A: FULL TEXT ANALYSIS OF SLR RELEVANT STUDIES

Ref.	Report/BI system	Evaluation method	Factors evaluated	Benefits / value
[4]	Dashboard developed	Interview with vice president	Productivity, time savings, standardised KPIs, reliable data sources, effective visualisation, managerial control	Increased productivity of review meetings, less time on data and more time making action plans.
[20]	Business intelligence system	Hypotheses made and tested with questionnaire to senior managers	Performance measurement capabilities: profit-planning information and non-financial key performance indicators. Competitive advantage: sales growth, market share, profitability	Competitive advantage (increase in business effectiveness and efficiency)
[28]	Business intelligence system	Hypotheses made and confirmed by surveys	Strategic and operational capabilities	Strategic and operational business value
[29]	Business intelligence system	Hypotheses tested by partial least squares from surveys	Sophisticated formats and presentation features, interactive reporting, easy to use, rapid refresh times	Management control activities
[30]	Business intelligence system	Model built based on hypotheses and surveys completed	Data quality (accurate, comprehensive, correct, consistent), representational fidelity (understandable, easy to interpret, not overwhelming), actionability (applicable, usable), and transparent interactions (easy to access, available when needed, easy to extract)	Decision-making or actionability that leads to performance benefits
[31]	Dashboard and scorecard developed	Surveys	Effectiveness, user involvement and usability	Communicate strategic goals, guidelines development decisions, identify improvement opportunities
[32]	Existing dashboards	Interviews	Dashboard system quality (accessibility and viewpoint integration) and information quality (completeness and currency – how current is the information?)	Facilitates decisions, strategy surrogation
[33]	Business intelligence system	Decision support tool facilitated by a questionnaire	Reliability, responsiveness, costs, asset management, agility	-
[34]	Dashboard developed	Questionnaire	Visibility, flexibility, leanability, operability, error control and help, effectiveness and efficiency	Makes integrated information available, improves organisational performance, improves support for managing strategic goals, better decision-making, provides more and better information
[35]	Business intelligence system	Questionnaire	Availability of data, completeness of information, information management strategy, integration in reporting systems, analytical capability, actionability, information suitability for decision-making, information presentation, accessibility and availability, pre-determined formats	Strategic planning
[36]	Report developed	None	-	Improve educational quality, avoid student dropouts
[37]	Dashboard developed	None	-	Decision-making, identification of problematic areas, and deciding whether improvement measures should be taken
[38]	Report developed	None	-	Assists auditor's work

Ref.	Report/BI system	Evaluation method	Factors evaluated	Benefits / value
[39]	Business intelligence system	Surveys	Overall performance, ROI, cost savings, increased sales, customer service quality, data quality, time savings, access to data, decision-making, user interface, business process efficiency, number of active solvers, satisfaction of employees	Increase in overall performance and competitiveness of business
[40]	Existing healthcare reporting	Interviews	Specific use of reports	Health system decision-making, assists with selecting health care providers, community advocacy, creates users' trust in good health care provision
[41]	Business intelligence system	Surveys	Emotional factors influencing the intention to use BI systems	-
[42]	Business intelligence system	Questionnaire	System quality, information quality, task compatibility, task significance, task interdependence, task specificity, tsk significance, use, user satisfaction	Improve patient progress, improve financial reporting, and enhance learning in hospitals

C. APPENDIX: FINDING THE FOUR QUALITIES OF INTELLIGENT INDUSTRIAL REPORTING

South African Journal of Industrial Engineering November 2019 Vol 30(3) Special Edition, pp 262-276

FINDING THE FOUR QUALITIES OF INTELLIGENT INDUSTRIAL REPORTING

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ARTICLE INFO

Article details
Presented at the 30th annual conference of the Southern African Institute for Industrial Engineering (SAIIE), held from 30 September - 2 October 2019 in Port Elizabeth, South Africa

Available online 15 Nov 2019

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DOI
http://dx.doi.org/10.7166/30-3-2235

ABSTRACT

Internationally, innovation and technology are driving change through concepts such as 'Industry 4.0'. However, due to various constraints, South Africa is lagging behind in this transformation. Furthermore, local industry generates large amounts of data that could contribute to a positive transformation. Data analytics, in the form of reporting, may therefore present a workable alternative to understand better the intricate nature of real-world operations. This paper identifies four qualities for the practical application of data analytics, with the aim of intelligent reporting. The four qualities are focus area, data availability, analytics, and visualisation. Research on each quality shows that they have various levels. A comprehensive literature review supports these findings. Forty studies are included that were selected through a process of relevant research criteria. A case study is presented to show how the four qualities contribute to the development of intelligent reports as an objective representation of industry performance.

OPSOMMING

Internasionaal dryf innovasie en tegnologie verandering deur konsepte soos Industrie 4.0. Weens verskeie beperkings is Suid-Afrika egter agter in hierdie transformasie. Verder genereer die plaaslike industrie groot hoeveelhede data wat kan bydrae tot 'n positiewe transformasie. Data analise, in die vorm van verslaggewing, kan 'n werkbare alternatief bied om die ingewikkelde aard van werklike prosesse beter te verstaan. Hierdie artikel identifiseer vier kwaliteite vir die praktiese toepassing van data analise met die doel van intelligente verslaggewing. Die vier eienskappe is onderskeidelik fokusarea, beskikbaarheid van data, data analise en visualisering. Navorsing oor elke kwaliteit toon dat hulle uit verskillende vlakke bestaan. 'n Deeglike literatuurstudie ondersteun hierdie bevindings. Veertig studies is ingesluit wat geselekteer is deur 'n proses van toepaslike navorsingskriteria. 'n Gevallestudie word aangebied om te illustreer hoe die vier eienskappe bydrae tot die ontwikkeling van intelligente verslae.

1 INTRODUCTION

1.1 The growing role of data and analytics in industry

Globally there is a drive for change in the technological innovation field. This change, known as the fourth industrial revolution, is becoming increasingly popular [1]-[3]. It follows the first, second, and third industrial revolutions, each of which significantly impacted production processes. The first industrial revolution made use of water- and steam-powered mechanical production facilities. Thereafter, during the second industrial revolution, the introduction of electricity enabled mass production processes. The third industrial revolution further automated production by using electronics and information technology. Today we are experiencing the fourth industrial revolution, also known as Industry 4.0 (I4.0). This revolution is based on cyber-physical-systems [1]-[3].

Unfortunately, South African industries are falling behind in implementing I4.0. In a study that set out to evaluate I4.0 readiness [4], South African industries were ranked as 'beginners'. This ranking was obtained through a survey that considered the awareness and implementation of I4.0.

South Africa's lag in this transformation may be attributed to various constraints — the top three being a lack of digital culture, insufficient talent, and the requirement of high financial investment [2]. Due to these constraints, the implementation of advanced technologies may be seen as a strenuous and inopportune task for South African industries.

Despite this lag, South African industries generate a large amount of data that is increasing in volume, velocity, and variety. However, many industries only make use of a fraction of their captured data for valuable decision-making [5], [6]. This leaves scope to use this data as a positive contribution to I4.0. Data analytics has been identified as a powerful tool in I4.0 [7], [8]. Industries producing large amounts of data can thus implement data analytics despite the inhibiting factors. This would serve as an initiating step towards I4.0 readiness.

The application of data analytics in the form of reporting will present data as an alternative to real operations and analytics as an alternative to real performance, and enhance data-driven decision-making as an alternative to conventional practices. Business intelligence can therefore be improved by more intelligent reporting. This study will focus on identifying the qualities that can be used to evaluate reporting intelligence to assist with practical applications.

1.2 Research questions towards practical application

In industry, the term 'business intelligence' is used to describe the use of technology to gather, analyse, and present data for managerial purposes [9]. These generic steps are shown in the first column of Table 1. They can be aligned with the steps required by the cross-industry standard process for data mining (CRISP-DM) [10], as shown in the second column of Table 1. The steps from both of these fields were used to identify the core questions that need to be addressed in their practical application in industry. Therefore, the third column in Table 1 summarises four research questions for further evaluation.

Table 1: Data analytics application steps and further research questions

Business intelligence	CRISP-DM	Research questions
Gather data	Business / Research understanding	1. Where should focus be placed?
	Data understanding	2. How to make maximum use of available data?
	Data preparation	
Analyse data	Modelling and evaluation	3. How to calculate results?
Present data	Deployment	4. How to communicate results?

This study proposes that data-driven decision-making needs to be promoted as a first step towards implementing I4.0 initiatives in established industries. An opportunity exists to use existing data sources that are currently underused. The challenge is to make this practically applicable for industries that are comfortable with conventional data applications.

This paper therefore aims to identify the qualities for intelligent reporting based on the research questions above. This is done by conducting a comprehensive literature review on each of the research questions. From this review, the four qualities associated with intelligent reporting are described. Practical applications from the literature are then reviewed to test the relevance and occurrence of the identified qualities (Section 2). Lastly, the identified qualities are tested and validated by a case study (Section 3).

2 RESEARCH METHOD

This section attempts to address the research questions (identified in Table 1) while aiming to identify the qualities of intelligent reporting. Firstl individual fields of the literature about each of the questions are evaluated. Second, studies focusing on the practical application of analytics are reviewed according to each of the research questions, as well as the information obtained in each of the individual research fields. The research method is depicted in Figure 1.

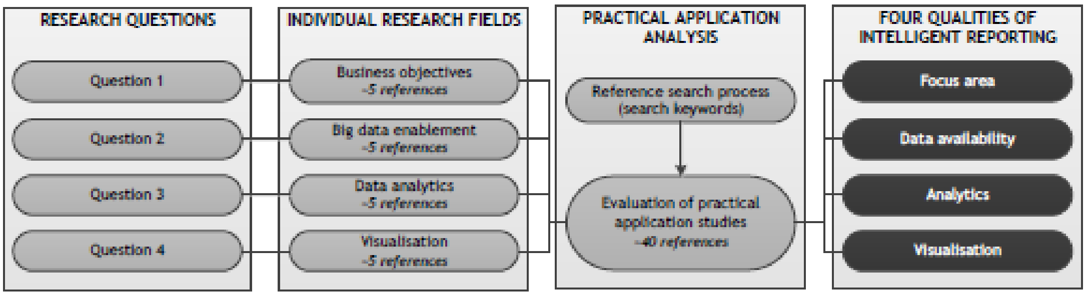

Figure 1: Research method for identifying the qualities of intelligent reporting

2.1 Individual research fields

Four individual research fields were evaluated to address the four research questions. The four fields include business objectives, big data enablement, data analytics, and visualisation.

Establishing focus areas through business objectives (Question 1)
A suitable focus area should be driven by business objectives [11], [12]. In a study undertaken by Kritzinger [11], it was stated that performance measurement should be linked to key business goals and drivers. Sondalini [12], in another study, highlighted that key performance indicators (KPIs) should match corporate goals. Business objectives thus form a crucial part in developing intelligent and functional reporting.

A review of the relevant literature [11], [12] emphasised the necessity to link a strategic objective to an executable task at an operational level. It is therefore practical to divide the business into a hierarchy of levels to illustrate the focus area. Furnham [13] stated that, through performance measurement, management is possible through a holistic view of complex underlying systems. A hierarchy of levels would thus ensure traceability from a management level to a parameter that is measured or manipulated at the level of execution (i.e., each complex underlying system).

Sondalini [12] suggested that KPIs should be created by a 'top-to-bottom' approach of an organisation. Three levels of an organisation are suggested to achieve this: corporate, site, and department and individual. It is suggested that corporate goals be used to establish the purpose of KPIs (top-to-bottom). Meanwhile, the bottom-up approach is used to achieve the goals and KPIs from the department and individual level.

In the studies referenced above, the focus is placed on various levels of an organisation, depending on the specific business objectives. A detailed analysis of performance measurement and business objectives was performed, and is summarised in Table 2. The analysis of various studies [11], [12], [14]-[16] revealed that different levels of focus areas or objectives are suggested. The different levels suggested by these studies were consolidated into four levels, and are referred to in this study as the enterprise, site, system, and equipment levels.

'Enterprise' refers to the highest level of an organisation. On this level, strategic business objectives are set and high-level management decisions are made. The second-highest level includes the different sites within an organisation. Within a site, different systems and kinds of equipment are used. 'System' refers to individual departments or systems within a site. The lowest management level is the equipment level. This refers to the specific level of execution, and contains the highest amount of detail.

Establishing these levels of focus areas is critical to ensure that reports are traceable from strategic goals to a specific execution level. The various levels also aid in the practical functionality of reports by reporting to various levels within an organisation, according to their specific business objectives.

Table 2: Levels of focus for business objectives identified from the literature

Description used in this study	Levels of business objectives in the literature
Enterprise	Corporate goals [12], Organisation [14], Top management [15], Organisational [11], Strategic [16]
Site	Site goals [12], Business [14], Middle management [15], Business unit [11], Operational [16]
System Equipment	Department & individual [12], Functional [14],Operational employees [15], Individual [11], Team [16]

Identifying data availability through big data enablement (Question 2)
The big data enablement research field was evaluated to understand the flow of data within big data platforms. This helps to understand what data is available in order to know how to make maximum use of it, thus addressing the second research question.

'Big data' is used to refer to the speedy capturing (high velocity collection) of data that consists of large volumes of varyingly complex datasets [17] [18]. The term 'big data' has become relevant in recent times due to the increased volume of data generation in industry. As an example, it is predicted that by the year 2020 the amount of data in China will be ten times the amount it was in 2013 [19]. Big data platforms are necessary to manage this variety and volume of generated data, by making use of specific technologies and tools [17] [18] [19].

Various studies concerning big data platforms [18]-[23] were evaluated. From these studies it was found that measurement instrumentation installed on equipment forms the initial stage in the data pipeline. The data can be viewed in real-time on a Supervisory Control and Data Acquisition (SCADA) system, and local data historians are generally used to store the data for a short period of time. The local historian typically stores the data for a three- to six-month period. This enables the collection of sample data from the local historians. An Open Platform Communication (OPC) connection can be configured to enable data loggers to collect the data continuously (an increase in the velocity of data acquisition). This process allows users to view and analyse a variety of measurement variables from remote locations (an increase in data variety). The data can also be stored in a database, which then creates the long-term availability of data (an increase in data volume).

The studies evaluated make use of different structures and techniques within their big data platforms; however, the data pipeline remains consistent. Table 3 summarises three generic types of data available within the data pipeline identified from the various studies. The available data consist of sample data, continuous real-time data, and long-term data. These generic types of data availability identified from the literature [18]-[23] are used as the levels of data that can be used in reporting applications.

Table 3: Generic types of data availability identified from the literature

Description used in this study	Data pipeline of big data platforms
Sample data	Equipment and measurement devices [18], equipment measurement [20], equipment measurements [21], data collection on-site [22], measurement [19], data generation [23]
Continuous real-time	Real-time [18], acquire data [20], OPC communication [21], database server via internet [22], real-time data submission [19], data acquisition [23]
Long-term	Data warehousing [18], transfer and storage [20], store and archive data in database [22], data storage [19], data storing [23]

The different forms of data availability will influence reporting intelligence. Sample and continuous availability of data distinguishes whether reports will be a once-off or a continuous application. This in turn influences the ease of reporting, since sample data will be a manual process, while a continuous inflow of data can be used to develop automated reports. Furthermore, the use of long-term data will allow the evaluation of the trend of performance (i.e., improvement or deterioration).

Calculations through analytics (Question 3)
Analytics are used to convert raw data to knowledge and wisdom. This conversion enhances the value of the data [24], while also reducing the level of detail. Reporting on raw data trends

containing too much detail restricts the data from being used in valuable decision-making. Therefore, analytics are crucial in intelligent reporting.

Numerous analytical methods exist, and are covered extensively in the available literature[14], [25]-[27]. Some common methods include counts, statistical methods, classification, regression analyses, decision trees, and artificial intelligence. Each of the analytical methods varies not only in computational complexity, but also in the complexity of the questions it addresses.

Therefore, the various types of analytical methods are classified into different types of analytics. Various studies have a different classification of analytics. However, this classification generally includes descriptive, diagnostic, predictive, and prescriptive analytics. Each of the classifications increases in complexity and value. Table 4 summarises the classification of analytics by various studies, as well as by the description used in this study.

Table 4: Levels of analytics identified from the literature

Description used in this study	Types of analytics used in the literature
Descriptive	Descriptive [28]-[30], historical view [31], reporting and trending [14], simple data analysis and statistical methods [25], statistical methods [26], samples and comparisons [27], characterisation [11]
Diagnostic	Inquisitive [28], descriptive [31], segmentation [14], graph analysis [25], diagnostic [30], data mining [26], relationships [27], evaluation [11]
Predictive	Predictive [27]-[31], predictive modelling [14], artificial intelligence [25], machine learning [26], prediction and preparation [11]
Prescriptive	Prescriptive and pre-emptive [28], prescriptive [30], improvement [11]

Descriptive analytics is used in reporting simply to describe occurrences by making use of past and present data without addressing complex questions. Diagnostic analytics, however, investigates what has happened by highlighting the causes and effects of occurrences. This level of reporting is useful in providing actionable information and transferring knowledge about influencing factors to real operations. Predictive analytics aims to identify what will happen in the future by making use of historical data to predict future outcomes. Reporting on predictive analytics is valuable for planning ahead. Prescriptive analytics is a form of predictive analytics, but also prescribes actions to the decision-maker about multiple possible predictions. A report's intelligence can be improved by addressing more complex questions to aid with specific decision-making scenarios by specifying the level of analytics.

Communicate through visualisation (Question 4)

The visualisation of the completed data analysis is critical when reporting on an organisation's performance. Visualisation forms part of information processing. It assists in extracting information from data to enable decision-making which, in turn, leads to action.

Similar to analytical methods, numerous visualisation methods are widely used. These methods are available in the existing literature [27], [32]-[34]. The literature [27], [34], [32] has shown that typical methods include bar charts, line graphs, histograms, waterfall charts, pie charts, scatter plots, and bubble plots.

A study done by Chen and Golan [35] identified four levels of typical visualisation methods. These levels are disseminative, observational, analytical, and model-developmental. Each level of visualisation increases in the complexity of the question it addresses, as well as the number of variables considered. Disseminative visualisation does not address any questions — it informs users about the data (e.g., single variable line graphs). The aim of observational visualisation is the speedy and intuitive observation of the data; this visualisation answers what has happened. Analytical visualisation shows the relationship between variables, and thus answers what the variable relates to. The fourth level of visualisation — model-developmental — aids in the development of existing and new models or methods. It answers what the steps are from one situation to the next.

The first column of Table 5 lists the four levels identified by Chen and Golan [35]. These are also the levels used in this study. The second column summarises the visualisation methods identified by other studies. These methods are grouped according to the questions they address, as recommended by Chen and Golan. Each of the levels identified by Chen and Golan were verified by other studies.

Therefore, the levels recommended by Chen and Golan are also used to describe the levels of visualisation available in this study.

Table 5: Levels of visualisation identified from the literature

Description used in this study	Types of visualisation in the literature
Disseminative	Bar chart, line chart, histogram and pie chart [32], samples [27], dials, iconic representation, Chernoff face, and test [34]
Observational	Funnel plot, maps and tree maps [32], comparison, distribution and composition [33], comparisons [27], point representation, star plots, magnification and mosaic plots [34]
Analytical	Bubble plot and dynamic plot [32], relationship [27], [33], scatter plots and parallel coordinate plots [34]
Model-developmental	Multidimensional scaling plot, maps and dynamic plots [32], patterns and theme river [34]

The usability of a report can be improved by making use of the appropriate level of visualisation. For instance, a focus on disseminative visuals may cause an information overload when used in the incorrect context. It is therefore critical that the chosen level of visualisation displays information and knowledge in such a way that it aligns with the overlying need of the report.

Summary

In this section, the four research questions (identified in Section 1) were addressed by evaluating four individual research fields. This review identified the four qualities attributed to intelligent reporting. It was also noted that each of the qualities consists of various levels that influence reporting intelligence. The use of these qualities and their associated levels in practical applications should, however, still be tested and verified. This will be addressed in the next section.

2.2 Practical application analysis

In this section, a literature review is presented to support the identified qualities and levels from the previous sections. This is done by evaluating how these qualities are addressed in practical applications. Studies of the practical application of data analytics were obtained by making use of the following key words:

- Analytics
- Practical application
- Industrial
- Data-driven
- Performance measurement / metric

The references obtained were filtered according to their titles and abstracts to ensure relevance. Forty references were used in the final review. Figure 2 shows the timeline and type of references used. The majority of the references (86 per cent) consist of journal articles.

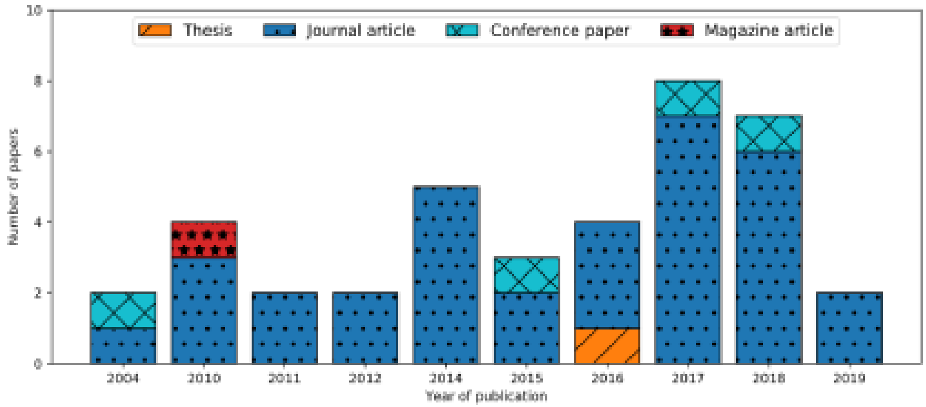

Figure 2: Timeline and type of references (practical application studies)

Each reference was evaluated according to the qualities described in the previous section, as well as the levels identified. The four qualities include focus area, data availability, analytics, and visualisation. The detailed review can be seen in Appendix A. A summary of the review is shown in Figure 3.

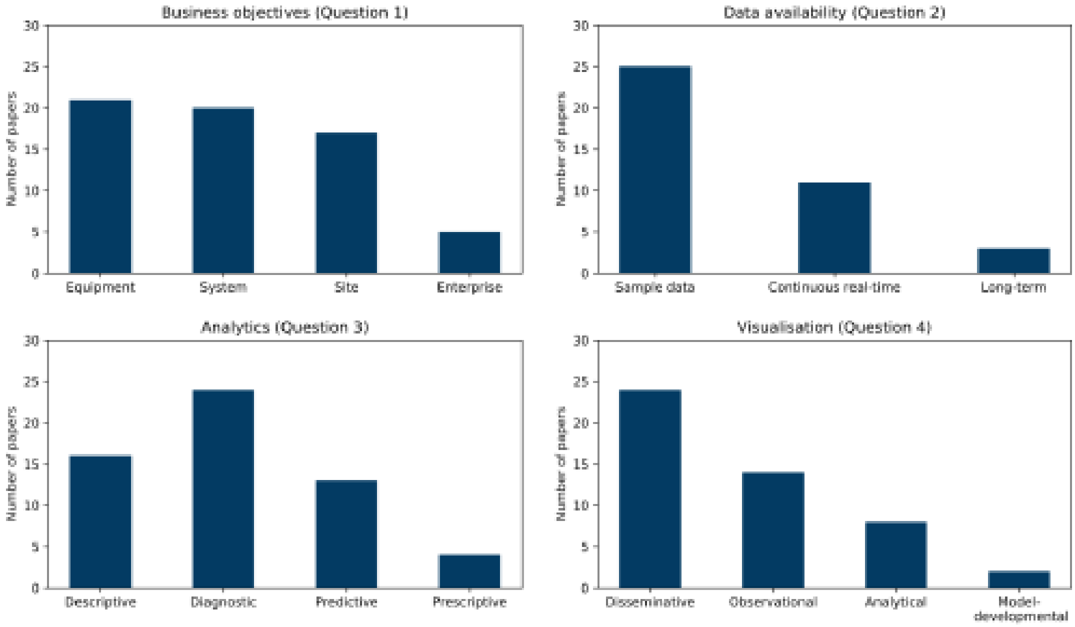

Figure 3: Summary of critical analysis of practical data analytics applications

Figure 3 shows that the application of data analytics takes place across the four qualities and their respective identified levels. This verifies the identified qualities and levels. During the review, however, it was noted that none of these studies provides a framework that considers the various qualities with their associated levels. Therefore, providing guidelines for the use of the four qualities and their respective levels for intelligent report development can be evaluated in future work.

2.3 Four qualities of intelligent reporting

Evaluation of the research fields aided in identifying the qualities of intelligent reporting: focus area, data availability, analytics, and visualisation.

The evaluation also identified that each of the qualities could be divided into various levels. The identified qualities, as well as their respective levels, were verified by 40 studies related to practical applications. The levels associated with each quality add an additional level of complexity to the generic steps recommended by the CRISP-DM and business intelligence. Due to this additional level of complexity, it is recommended that implementation guidelines of data analytics be evaluated in future work. The multiple levels would lead to multiple analytical application options. Therefore, it is recommended that the proposed guidelines be of an iterative / agile nature in order to achieve rapid results.

The qualities and their respective levels identified in this section are summarised in Table 6.

Table 6: Summary of four qualities for intelligent reporting

Business intelligence	Data availability	Analytics	Visualisation
Equipment	Sample	Descriptive	Disseminative
System	Continuous real-time	Diagnostic	Observational
Site	Long-term	Predictive	Analytical
Enterprise		Prescriptive	Model-developmental

The four qualities are necessary for intelligent reporting of industrial processes. The identified levels are valuable in evaluating the status of an existing application. It should, however, be investigated whether these qualities can be practically used to improve existing applications. The next section will therefore illustrate how the four qualities and their respective levels can be used to aid in the improvement of reporting intelligence in a case study.

3 CASE STUDY & DISCUSSION

3.1 Case study selection

Numerous data applications exist in practice. For the purpose of this paper, a case study from the South African mining industry was selected to test the four qualities identified and described in the previous section. The pressure the mining industry is under to improve the uptake of new technology in order to improve operations and sustainability [6], [36] provides excellent opportunities for I4.0-based implementations.

In this section, a condition monitoring application in the mining industry is evaluated. Condition monitoring entails monitoring parameters that directly relate to the condition of equipment. Condition monitoring forms a crucial part of condition-based and predictive maintenance. This allows corrective actions on faulty equipment before critical failures occur, as opposed to reactive maintenance where equipment is maintained as a result of a failure.

The existing status of the condition monitoring application is depicted in Figure 4. The critical mining equipment is shown in the left block, while the data flow of the condition monitoring data is shown in the second block. This data is then used for various reporting applications, which are shown in the third block.

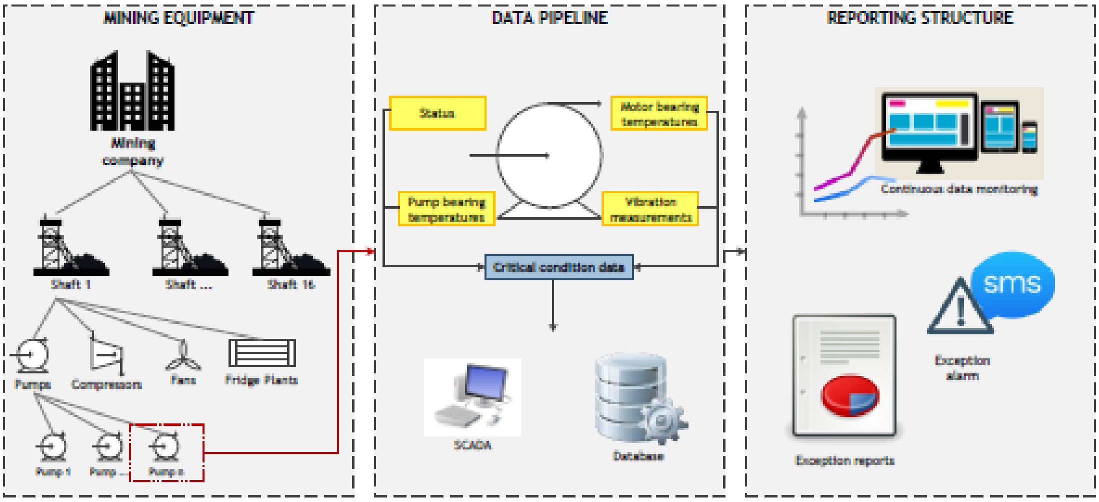

Figure 4: Existing status of condition monitoring application (see online version for colour)

As indicated in the left block of Figure 4, condition monitoring parameters are measured on various items of equipment on sixteen mine shafts. This equipment includes pumps, fans, compressors, fridge plants, and mills. This equipment forms part of the main systems necessary for daily mining activities to take place. As an example, the measured condition monitoring parameters of a pump are indicated in the middle block of Figure 4.

The measured data is available locally via the on-site SCADA system. An OPC connection then facilitates the data acquisition process, which provides users access to the condition monitoring data in continuous real-time. Finally, as data is acquired, it is stored in a cloud database. The stored data is used for various reporting purposes, as indicated in the right block of Figure 4.

The data is used to develop continuous real-time graphs of the condition monitoring parameters. 2100 graphs are continuously available on a daily basis for the various mining shafts. Upper limits are set for each parameter, and once a parameter exceeds a given limit, an SMS is sent to relevant mining personnel. On average, 4 400 SMSs are sent per month. Daily reports are also sent out for each of the mining shafts. This report summarises the exceptions of limits that occurred the previous day.

It is noted that the case study in its existing form already provides a basis for data-driven decision-making. However, it is not clear to what extent the existing application provides the end-user with actionable information. It is also not clear whether the reports being generated are usable to their full extent. This case study application is therefore evaluated in the next section according to the four qualities. This evaluation will then be used to identify the possible improvements relevant to each of the four qualities. Lastly, the information gained is used to discuss the potential value of the condition monitoring application.

3.2 Initial evaluation of reporting intelligence qualities

In this section, the existing condition monitoring reporting is evaluated according to the four qualities identified in this study. A large amount of information is available due to the numerous limit exceptions on a daily basis. This information is available in the form of single variable trends in the existing application. The graphs only describe what is already happening with each parameter. Therefore, the analytics and visualisation qualities will be descriptive and disseminative respectively. Furthermore, although data is reported in a real-time manner, there is no long-term indication of equipment deterioration. Lastly, the condition monitoring parameters are measured and reported on an equipment level. Table 7 shows the levels to which the existing application adheres (indicated by shaded cells).

Table 7: Initial evaluation of reporting intelligence qualities

Business intelligence	Data availability	Analytics	Visualisation
Equipment	Sample	Descriptive	Disseminative
System	Continuous real-time	Diagnostic	Observational
Site	Long-term	Predictive	Analytical
Enterprise		Prescriptive	Model-developmental

In a study focusing on the condition monitoring of gold mining equipment [20], it was suggested that the condition monitoring data be evaluated on a system level, making use of long-term data and using risk scores to identify the severity of equipment condition. From the evaluation in Table 7, it can be seen that each of the suggestions made by van Jaarsveld [20] would improve the intelligence of the existing method of reporting. These suggestions are therefore also used in this study. The risk scores are, however, cumulated over a thirty-day period in this study to indicate the trend of deterioration. Furthermore, the cumulated risk scores are used to rank and prioritise the various equipment's conditions. Only the top five critical equipment items are reported on. The reporting is done per system: reports are generated per shaft (i.e., top five per system for specific shaft) and enterprise (i.e., top five per system between all sixteen shafts). Table 8 presents the initial evaluation, the qualities lacking, and the implemented changes needed for improvement. Table 8 illustrates how each of the four qualities is used to evaluate the existing report, and how the levels within each focus area are used to identify areas of improvement.

Figure 5 shows an example of an enterprise-level report for a pumping system. The two graphs in Figure 5 present the cumulative risk scores (Figure 5a) and the contribution of each condition monitoring parameter to the cumulated risk score (Figure 5b). Similar graphs can be obtained for each of the mining systems (e.g., pumps, fans, compressors, fridge plants, and mills).

3.3 Succeeding evaluation of reporting intelligence qualities

After implementing the changes described in Section 3.2, the analytics and visualisation qualities changed to a diagnostic and observational level respectively. This enabled actionable information that could be used to make decisions about equipment maintenance. The data availability not only made use of continuous data, but also a longer period of data to indicate deterioration over time. Lastly, the condition monitoring could be reported on an equipment, system, site, and enterprise level by prioritising the risk scores. Table 9 shows the succeeding evaluation of reporting intelligence qualities, indicated in lightly shaded cells.

Table 8: Improvement on existing reporting intelligence

Quality	Initial evaluation	Lacking qualities	Changes implemented
Focus area: *Extend the focus area from equipment level to roll-up to enterprise level*	Reporting and monitoring focused on equipment level	Difficulty in making high-level decisions based on equipment level evaluations	Prioritisation of risk scores and only reporting on the top five critical equipment per system. The top five per system can be reported on a site level (e.g., top five for each system per shaft). Furthermore, reporting on the top five per system can be done on enterprise level (i.e., reporting on top five per system between all sixteen shafts).
Data availability: *Make use of long-term data*	Continuous reporting done	No long-term indication of equipment deterioration	Cumulate risk scores over a thirty-day period to observe the trend of deterioration
Analytics: *Move from descriptive analytics to diagnostic analytics*	Descriptive reporting is done, which provides ample information about the condition monitoring parameters	All of the information may become overwhelming and difficult to interpret	Calculation of risk scores for each equipment item based on all of its condition monitoring parameters
Visualisation: *Use visuals that are observational instead of disseminative*	Single variable trends are reported on	The numerous daily single variable trends obstruct speedy observation of the condition of equipment and the trend of its deterioration	Trending cumulative risk scores may give an indication of deterioration, while a bar chart showing the contribution of each condition monitoring parameter may serve as a speedy observation of the cause of deterioration

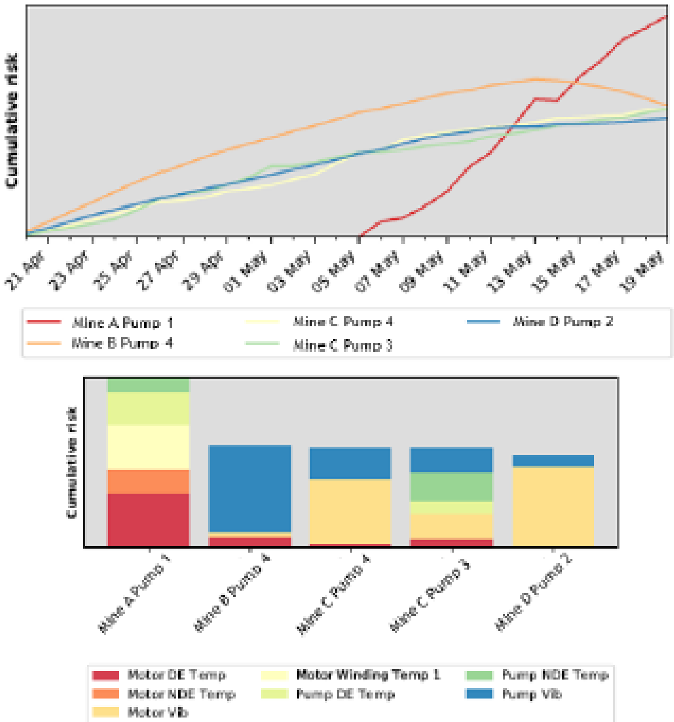

Figure 5: Example of enterprise-level cumulative risk score and distribution (see online version for colour)

Table 9: Succeeding evaluation of reporting intelligence qualities

Business intelligence	Data availability	Analytics	Visualisation
Equipment	Sample	Descriptive	Disseminative
System	Continuous real-time	Diagnostic	Observational
Site	Long-term	Predictive	Analytical
Enterprise		Prescriptive	Model-developmental

The resultant evaluation in Table 9 clearly indicates that the next steps include predictive analytics and analytical visualisation. Predictive analytics for this specific case study would include predicting equipment failures or lifetimes, to enhance maintenance planning. Analytical visualisation would be useful to indicate the relationship of the predicted lifetime and the respective influencing variables, which would enhance awareness of knowledge. The identified qualities and associated levels can therefore be used as criteria to motivate further improvements. Intuitively, the levels show what can be done incrementally to guide and motivate more intelligent reporting.

In this application, the condition monitoring data served as an alternative to real equipment conditions. Decisions could be made based on data analytics instead of intuition. Implementation did not require capital expenditure, since a big data framework was already available. The application of data analytics in the form of reporting showed the value of relying on digital concepts, thus enhancing the growth of a digital culture — both of which are seen as inhibiting factors towards I4.0 in SA. Therefore, the application of data analytics can be seen as an initiating step towards I4.0.

3.4 Potential value of application

In the presented case study, the awareness of equipment condition was prioritised and rolled up to enterprise level. Reporting at this level is valuable, since most decisions on the expenditure of capital, time, and resources are made at this level. Using these resources on equipment maintenance can thus be based on informed decisions. Additionally, being unaware of the most critical equipment could have various consequences, the severity and financial implications of which may vary according to specific situations. Figure 6 illustrates the possible extent of these consequences.

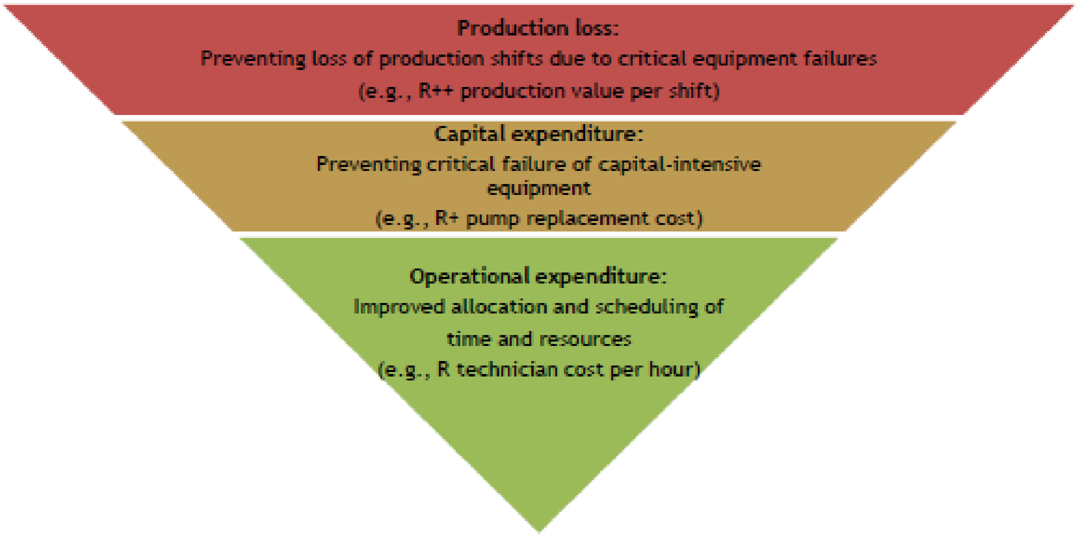

Figure 6: Possible extent of consequences of improved data-driven decision-making (see online version for colour)

The lowest level in Figure 6 represents operational expenditure, which refers to the improved allocation and scheduling of time and resources by maintaining the correct equipment. The second level in Figure 6 represents the prevention of large capital expenditure. This can be achieved by maintaining the relevant equipment and, in turn, preventing the critical failure of capital-intensive equipment. The most financially intensive consequence will be the loss of production. Prevention of production loss can be achieved by preventing the critical failure of equipment that directly influences production. These consequences validate the necessity of prioritising equipment condition.

4 CONCLUSION

Four research questions were identified from the CRISP-DM and general steps of business intelligence. Individual research fields were investigated to address the research questions. From these critical reviews, the four qualities contributing to intelligent reporting were identified. These qualities include establishing a focus area, data availability, analytics, and visualisation. The individual research fields further showed that each quality consists of various levels of implementation. A comprehensive literature review of practical application studies supports the qualities and the applicability of the defined levels.

A case study was presented to test and validate the four qualities. The selected case study made use of mine condition monitoring data as an alternative to the real equipment's condition. This data is used to improve condition-based maintenance strategies. The four qualities were used to evaluate the current intelligence of the case study's reporting. It could also be used to identify areas for improvement. The results indicate that the four qualities can be used to evaluate the intelligence of an existing data application so that it can intuitively show how it can be expanded to improve data-driven decision-making.

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APPENDIX A: CRITICAL ANALYSIS OF PRACTICAL DATA ANALYTICS APPLICATIONS

No.	Ref	Question 1 Business objectives				Question 2 Analytics				Question 3 Visualisation					Question 4 Data availability			
		Equipment	System	Site	Enterprise	Descriptive	Diagnostic	Predictive	Prescriptive	None	Disseminative	Observational	Analytical	Model-developmental	Not disclosed	Sample data	Continuous real-time	Long-term
1	[37]		□			□	□	□					□			□		
2	[38]			□				□			□					□		
3	[39]	□	□			□					□						□	
4	[40]	□					□	□					□			□		
5	[41]	□						□			□					□		
6	[42]	□		□			□			□						□		
7	[43]	□		□	□		□				□				□			
8	[44]	□	□			□	□	□			□	□	□			□		
9	[45]	□	□					□					□			□		
10	[46]			□	□		□			□						□		
11	[47]		□	□		□	□				□	□	□	□		□		
12	[48]		□	□			□					□				□		
13	[49]	□	□			□					□						□	
14	[50]	□				□	□				□	□				□		
15	[51]	□							□			□	□			□		
16	[52]			□		□					□	□	□			□		
17	[53]	□						□	□		□					□		
18	[54]		□					□			□	□				□		
19	[55]	□		□					□	□						□		
20	[56]	□	□	□		□	□				□	□					□	
21	[57]			□			□			□						□		
22	[58]	□					□	□			□					□		
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24	[60]	□						□			□					□		
25	[61]			□	□	□											□	
26	[62]		□	□		□	□				□	□		□			□	□
27	[63]	□		□			□				□	□				□		
28	[64]	□	□	□	□	□	□				□	□					□	□
29	[65]		□		□	□				□					□			
30	[66]	□	□			□	□	□		□							□	
31	[67]		□					□			□				□			
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33	[69]	□	□			□	□					□					□	□
34	[70]		□			□					□					□		
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38	[74]	□					□				□					□		
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40	[18]			□			□				□						□	

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D. APPENDIX: REPORT IMPACT EVALUATION END-USER SURVEY

This survey evaluates the impact of the "report name"

Data quality

1. Is the data used in the report from reliable sources?

Unreliable data sources	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	*Reliable data sources*

2. Is the data used in the report accurate?

Inaccurate data	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	*Accurate data*

3. Is the data used in the report up to date (i.e. sufficient refresh time)?

Outdated data	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	*Up to date data*

Information

4. Does the report show relevant information?

Irrelevant information	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	*Relevant information*

5. Does the information in the report simplify process assessment?

More effort / no change	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	*Simplified*

6. Does the information in the report assist with developing action plans and decision making?

Non-actionable	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	*Actionable information*

7. Is the report used?

Not used	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	*Used*

Representation

8. Is the report easy to understand?

Complex	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	*Easy*

9. Is the report easily accessible?

Inaccessible	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	*Accessible*

10. Are the visualisations in the report effective?

Overwhelming or ineffective visualisations	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	*Effective visualisations*

Value adds

11. Does the report result in increased productivity and time savings? If so, indicate how much.

12. List any possible direct impacts as a result from decisions made or benefits obtained associated with the report? Also indicate estimated monetary values for each impact.

13. List any possible indirect impacts as a result from decisions made or benefits obtained associated with the report? Also indicate estimated monetary values for each impact.

E. APPENDIX: CASE STUDIES EXAMPLE REPORTS

Case Study A

1 WATER RETICULATION LAYOUT

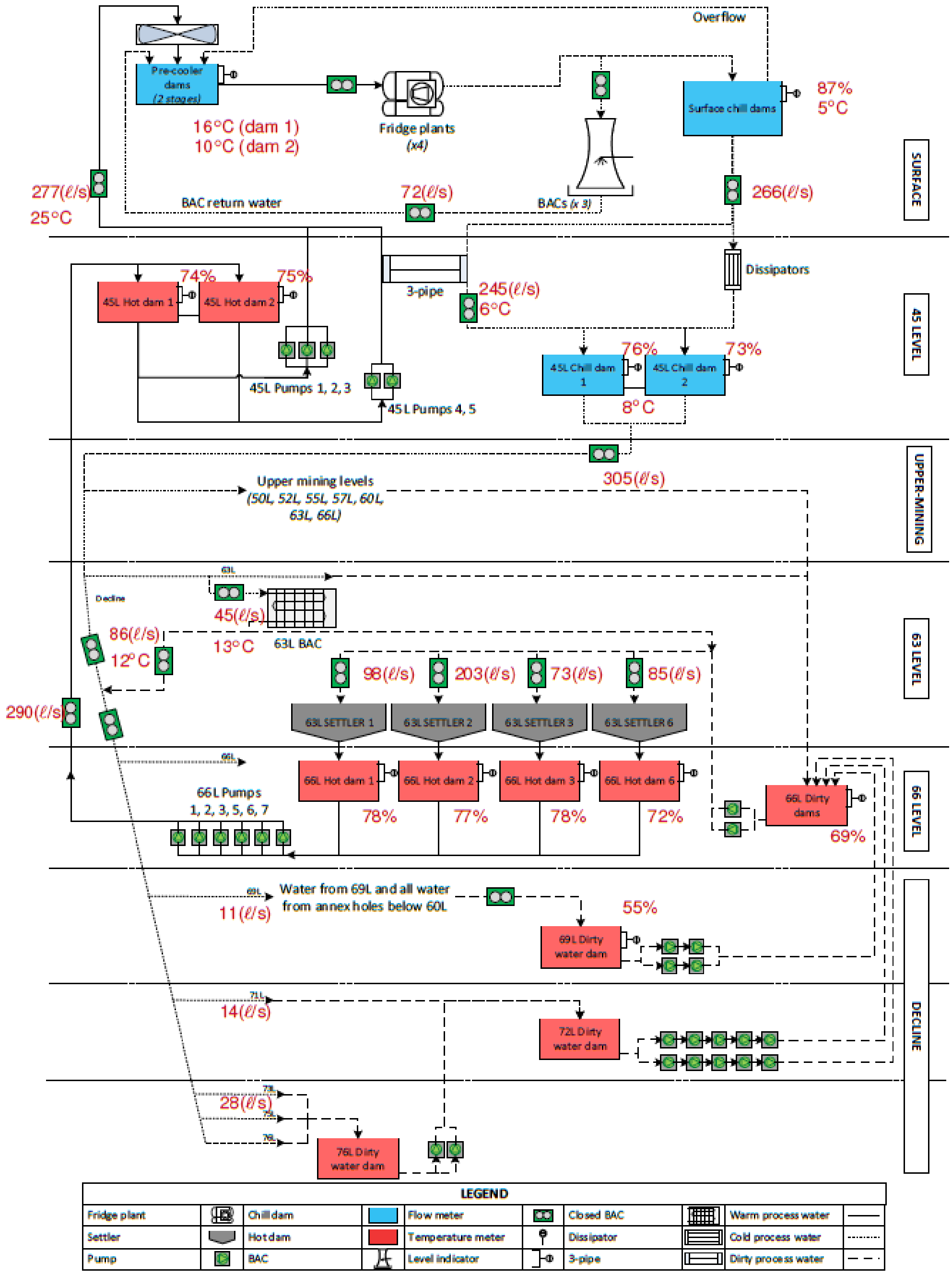


Figure 1.1: *Operational water reticulation layout with daily average flows indicated*

2 OVERVIEW OF WATER RETICULATION

2.1 Service water usage intensity

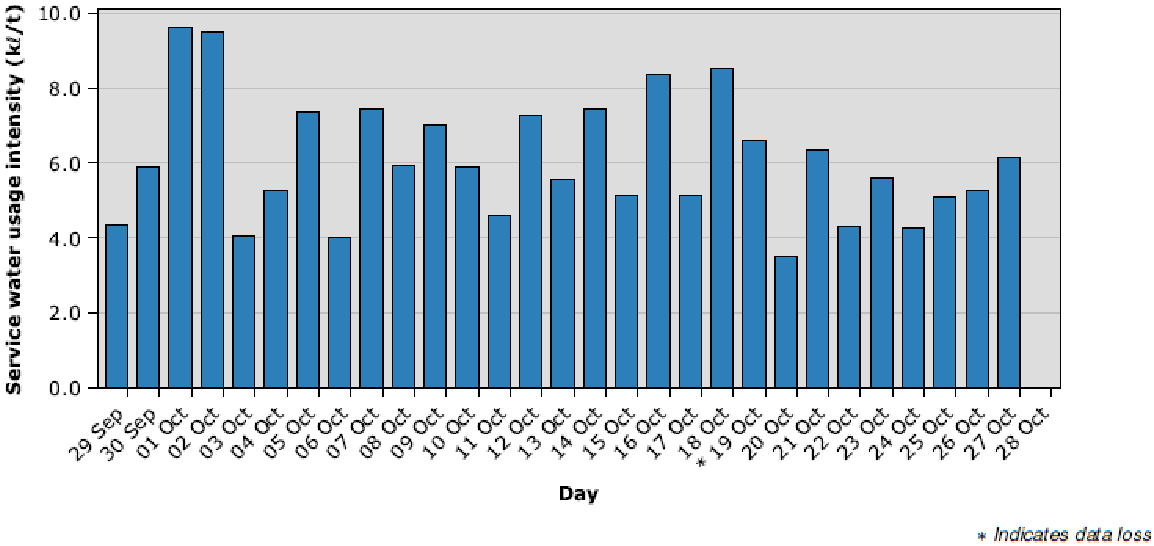


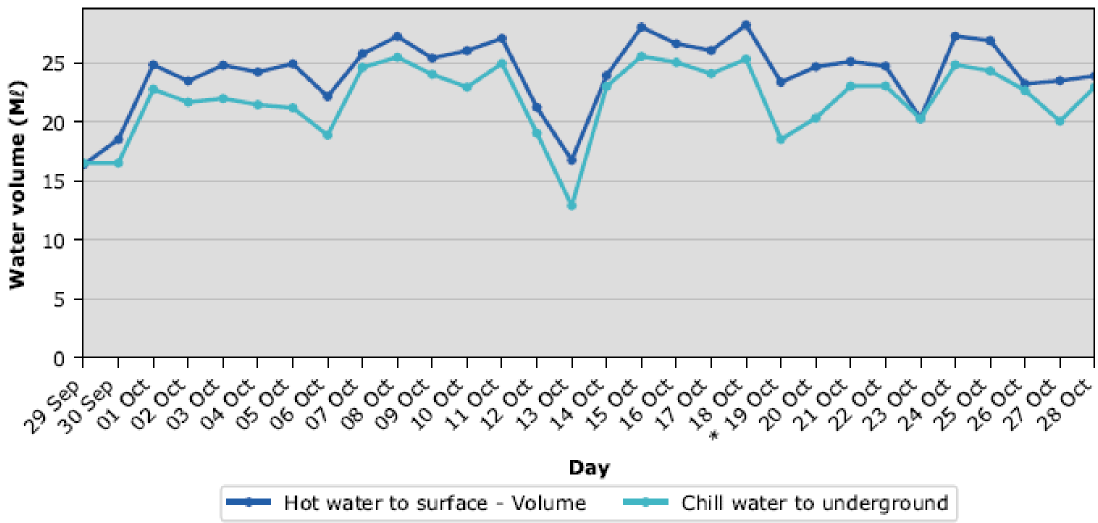
Figure 2.1: *Service water usage intensity*

2.2 Surface water balance

Table 2.1: *Summary of surface water balance (Mℓ/day)*

Description	22 Oct	23 Oct	24 Oct	25 Oct	26 Oct	27 Oct	28 Oct
Chill water to underground	23.1	20.3	24.9	24.3	22.7	20.1	23.0
Hot water to surface	24.8	20.3	27.3	26.9	23.2	23.5	23.9
Surface balance (calc)	1.7	0.0	2.4	2.6	0.6	3.4	0.9

Surface water balance volume scale (Mℓ)



** Indicates data loss*

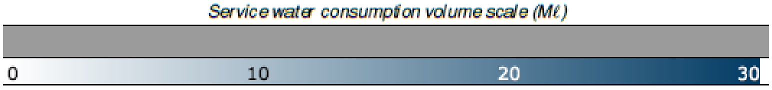
Figure 2.2: *Surface water balance over the past 30 days*

2.3 Breakdown of service water consumption

Table 2.2: *Summary of service water consumption per level (Mℓ/day)*

	Level	22 Oct	23 Oct	24 Oct	25 Oct	26 Oct	27 Oct	28 Oct
Total chill water to mining	Total chill water to mining	25.1	25.0	26.2	26.8	25.0	22.5	26.4
Decline	Total decline	10.1	10.2	10.7	10.5	10.8	10.3	10.9
	69L	0.9	1.1	1.1	0.9	0.9	0.9	1.0
	71L	1.4	1.5	1.5	1.2	1.2	0.9	1.2
	73L	2.3	2.2	2.4	2.3	2.6	2.2	2.4
Upper mining	52L East	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	55L East	0.9	1.0	0.9	1.0	0.9	0.7	0.9
	55L West	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	57L East	0.1	0.1	0.1	0.1	0.0	0.0	0.1
	57L West	4.0	3.9	4.2	4.6	4.2	3.3	4.4
	60L East	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	60L West	0.7	0.7	0.7	0.6	0.7	0.7	0.7
	63L East	1.2	1.1	1.1	1.7	1.1	1.0	1.1
	63L BAC	4.1	4.1	4.4	4.4	4.5	4.4	3.9
	63L West	3.3	3.3	3.3	3.2	3.3	3.3	3.3
	66L East	-3.6	-3.7	-4.0	-4.1	-4.2	-4.0	-3.4

Service water consumption volume scale (Mℓ)



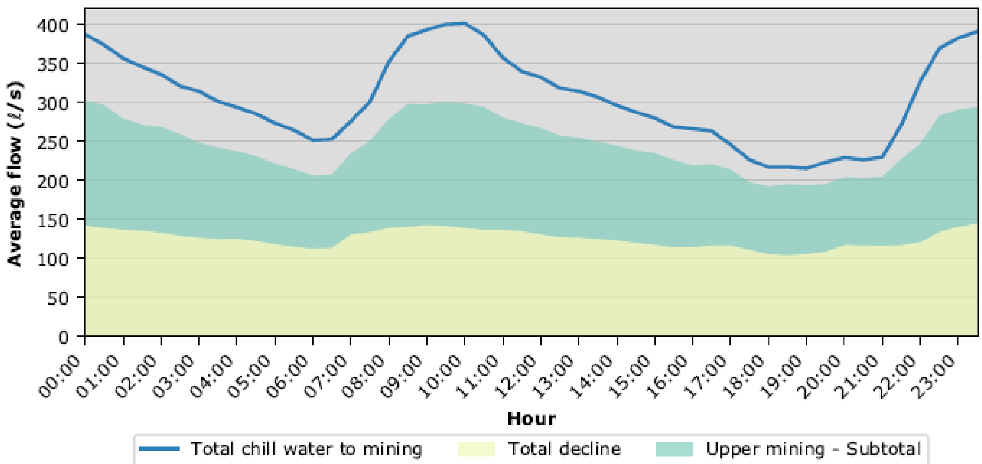


Figure 2.3: *Hourly profile of chill water to mining levels*

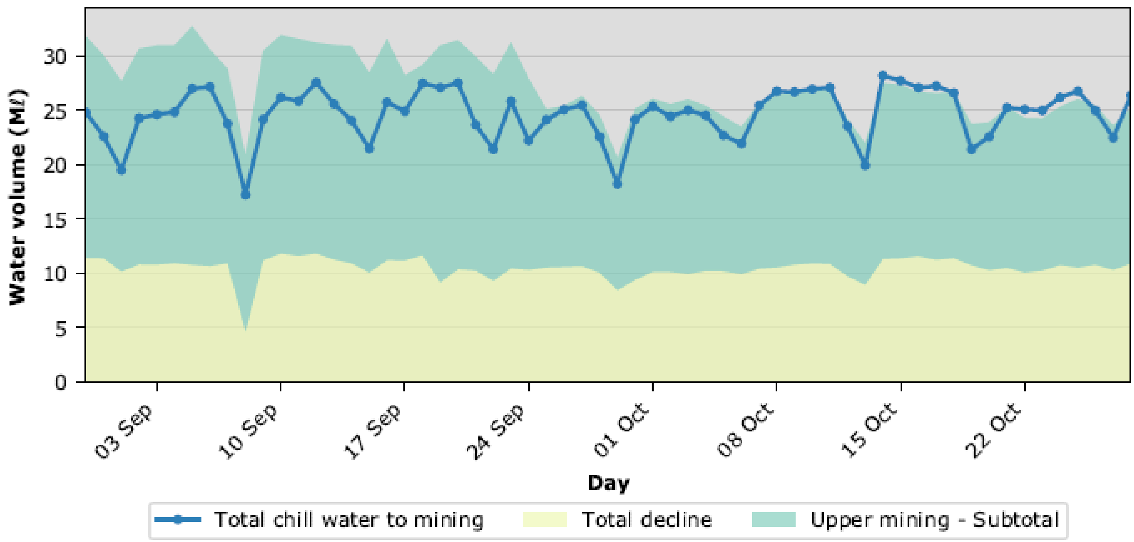


Figure 2.4: *Historic chill water volumes to mining levels*

2.4 Exception of dam limits

Table 2.3: *Hours exceeding upper limit*

Description	22 Oct	23 Oct	24 Oct	25 Oct	26 Oct	27 Oct	28 Oct
Surface pre-cooling dam 1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Surface pre-cooling dam 2	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Surface chill dam	0.0	0.0	0.0	0.0	0.0	0.0	0.0
45L Chill dam 1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
45L Chill dam 2	0.0	0.0	0.0	0.0	0.0	0.0	0.0
45L Hot dam 1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
45L Hot dam 2	0.0	0.0	0.0	0.0	0.0	0.0	0.0
66L Hot dam 1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
66L Hot dam 2	0.0	0.0	0.0	0.0	0.0	0.0	0.0
66L Hot dam 3	0.0	0.0	0.0	0.0	0.0	0.0	0.0
66L Hotdam 6	0.0	0.0	0.0	0.0	0.0	0.0	0.0
66L Dirty dam	0.5	0.0	0.0	3.0	0.5	2.5	1.0
69L Dirty dam	0.0	0.0	0.5	1.5	0.0	0.0	0.0

Table 2.4: *Hours exceeding lower limit*

Description	22 Oct	23 Oct	24 Oct	25 Oct	26 Oct	27 Oct	28 Oct
Surface pre-cooling dam 1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Surface pre-cooling dam 2	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Surface chill dam	0.0	0.0	0.0	0.0	0.0	0.0	0.0
45L Chill dam 1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
45L Chill dam 2	0.0	0.0	0.0	0.0	0.0	0.0	0.0
45L Hot dam 1	1.0	0.5	0.0	0.0	1.0	0.0	0.0
45L Hot dam 2	0.0	0.0	0.0	0.0	0.0	0.0	0.0
66L Hot dam 1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
66L Hot dam 2	0.0	0.0	0.0	0.0	0.0	0.0	0.0
66L Hot dam 3	0.0	0.0	2.0	9.0	0.0	0.0	0.0
66L Hotdam 6	0.0	0.0	0.0	0.0	0.0	0.0	0.0
66L Dirty dam	0.0	0.0	0.0	0.0	0.0	0.0	0.0
69L Dirty dam	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Hours exceeding upper / lower limit scale (Hours)

0 6 12 18 24

Case Study B

1 Summary

1.1 Plant prioritised summary

Table 1.1: *Plant prioritised summary of critical components per system for 24 September 2019 - 24 October 2019*

Ranking	Mill	
	Name	Util*
1	Mill 1	83%
2	ROM Mill	86%
3	Mill 2	70%
4	Mill 3	75%
5	Mispah Mill	91%

** Utilisation (% time running in reporting period)*

1.2 Shaft prioritised summary

Table 1.2: *Shaft prioritised summary of critical components per system for 24 September 2019 - 24 October 2019*

Ranking	Compressor		Fan		Fridge plant		Pump	
	Name	Util*	Name	Util*	Name	Util*	Name	Util*
1	Compressor 3	62%	85L Booster Fan	97%	100L Fridge Plant 2	95%	102L Pump 1	56%
2	GHH Compressor 2	35%	88L Booster Fan	97%	Ammonia Plant 5	85%	102L Pump 2	29%
3			100L BAC Fan 1	96%	Ammonia Plant 1	26%	75L Pump 3	34%
4			102L Booster Fan	100%	Ammonia Plant 2	78%	75L Pump 5	73%
5			Main Fan 1	12%				

** Utilisation (% time running in reporting period)*

1.3 Abbreviations

Table 1.3: *List of abbreviations*

Abbreviation	Description
Comp	Compressor
DE	Drive End
F	Fan
G/B	Gearbox
NDE	Non Drive End
P	Pump
Temp	Temperature
Vib	Vibration

2 Plant mills

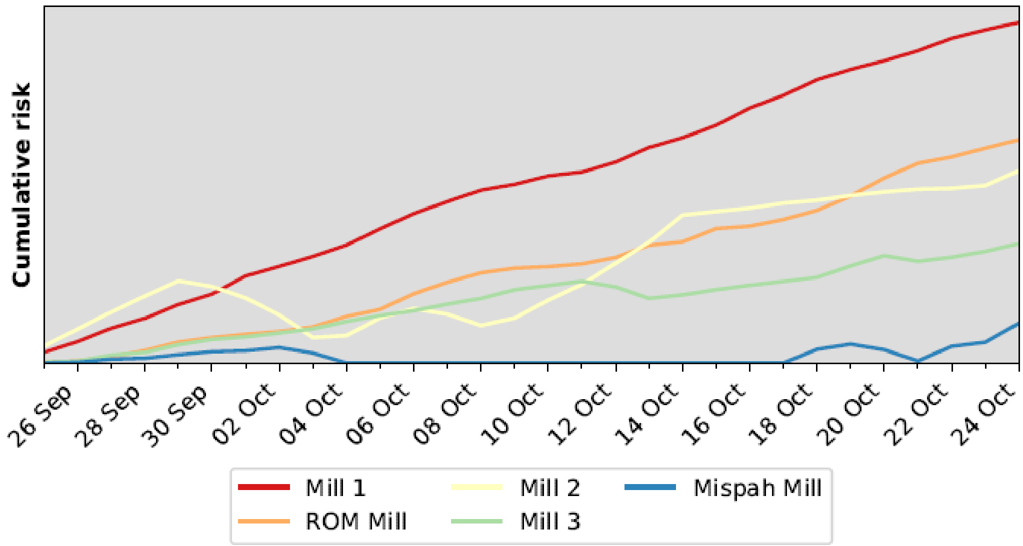


Figure 2.1: *Mill cumulative risk indication*

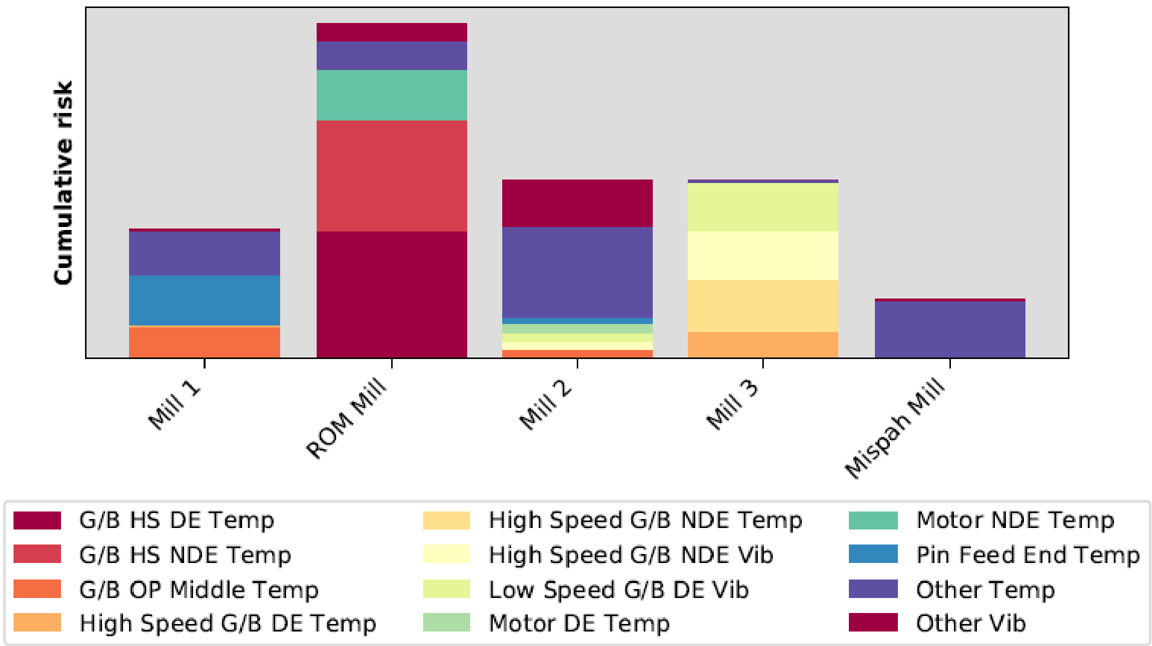


Figure 2.2: *Mill distribution of cumulative risk indication*

3 Shaft compressors

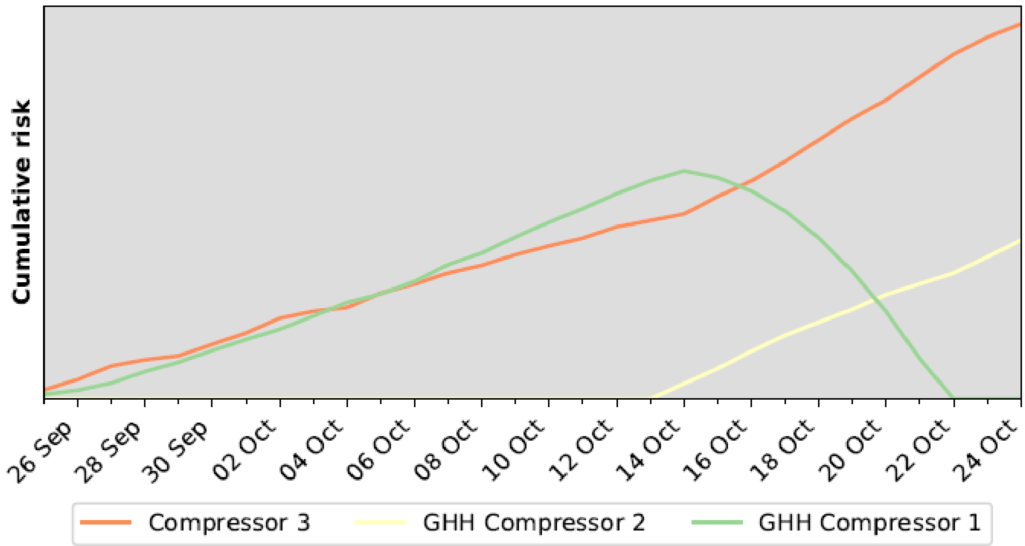


Figure 3.1: *Compressor cumulative risk indication*

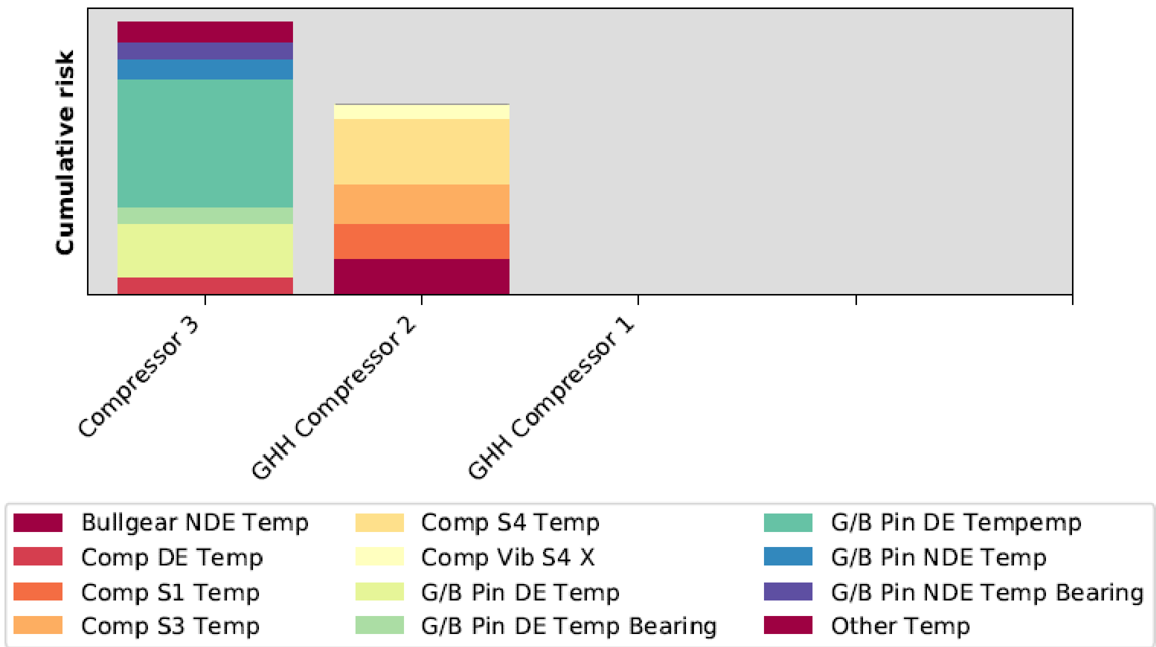


Figure 3.2: *Compressor distribution of cumulative risk indication*

4 Shaft fans

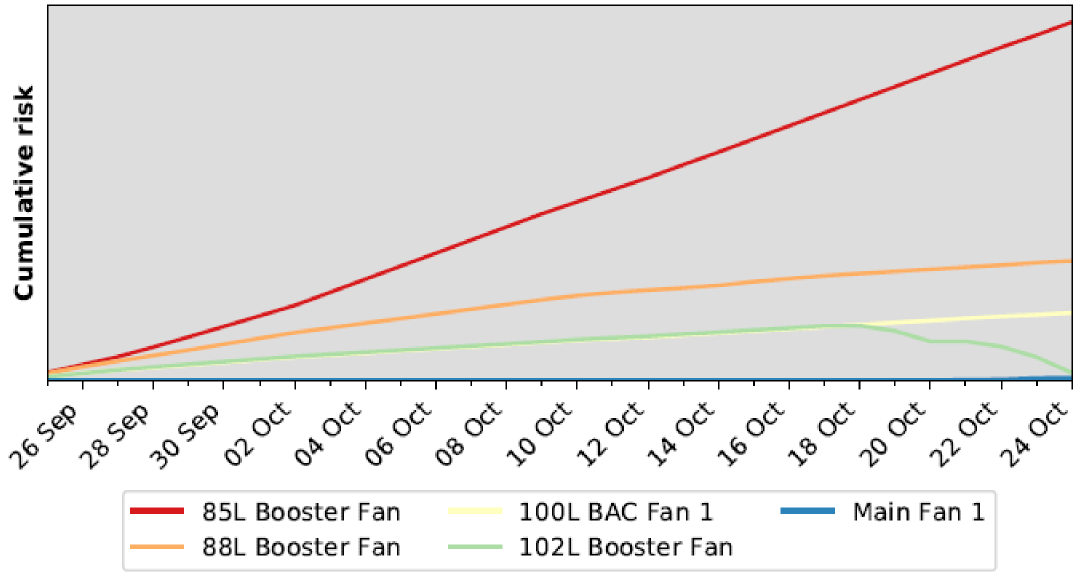


Figure 4.1: *Fan cumulative risk indication*

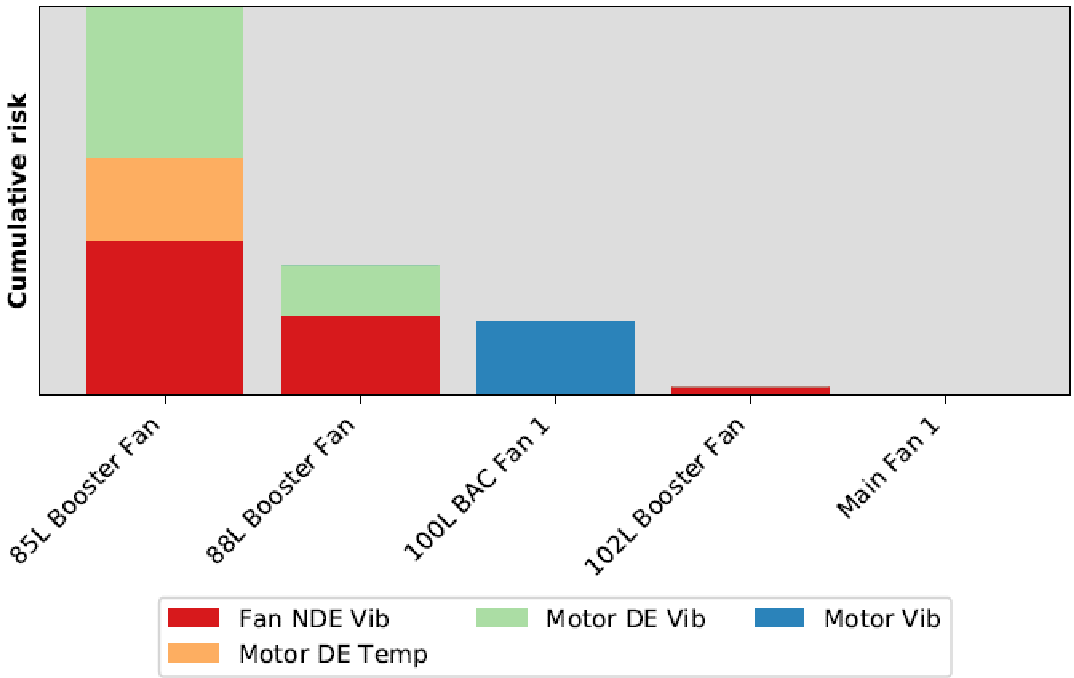


Figure 4.2: *Fan distribution of cumulative risk indication*

5 Shaft fridge plants

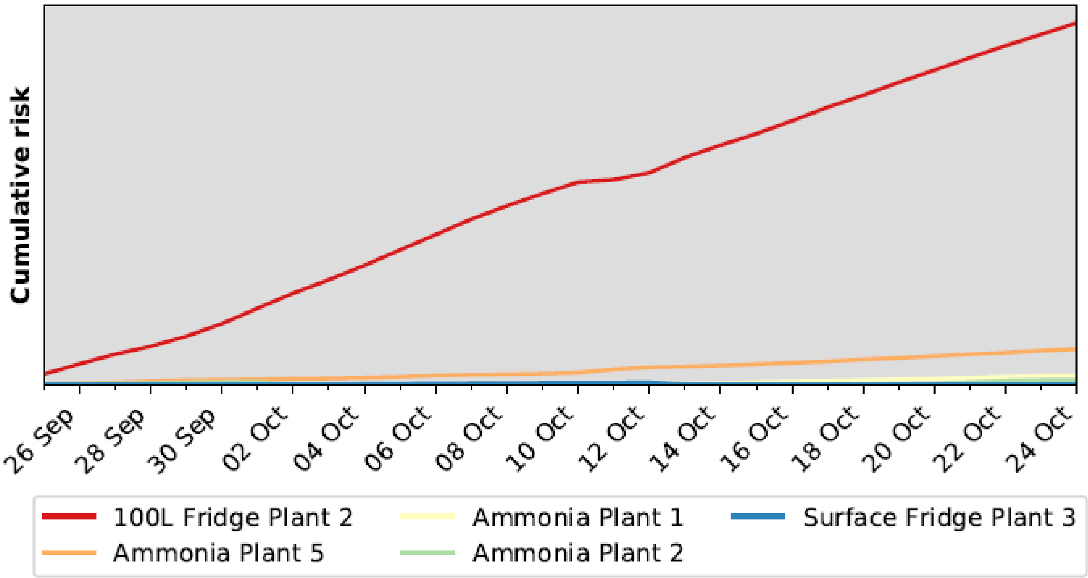


Figure 5.1: *Fridge plant cumulative risk indication*

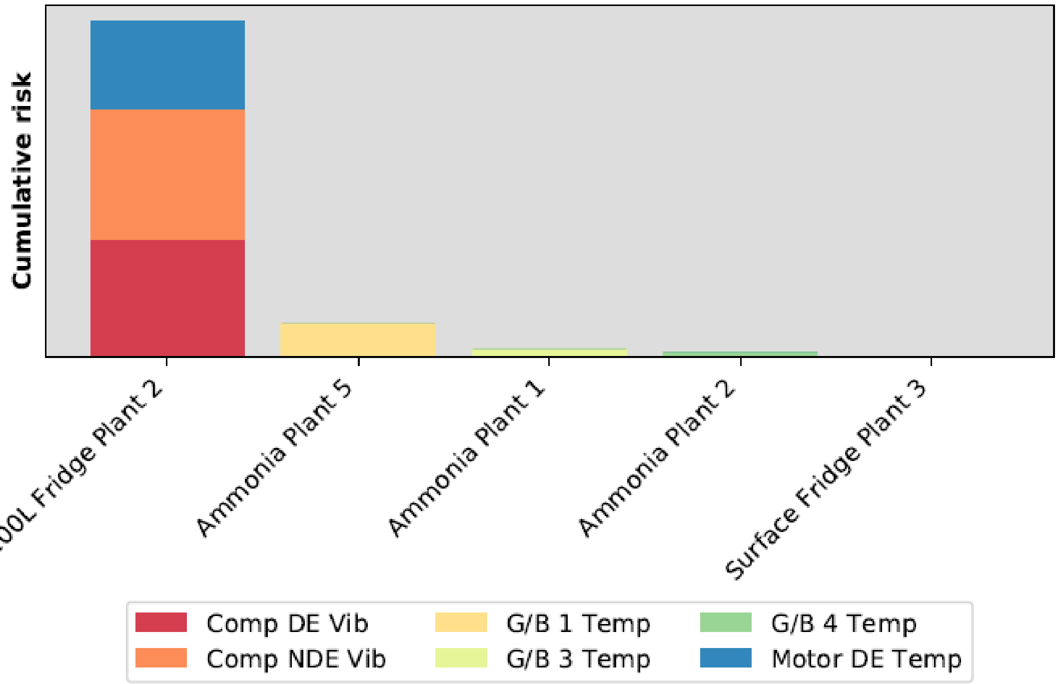


Figure 5.2: *Fridge plant distribution of cumulative risk indication*

6 Shaft pumps

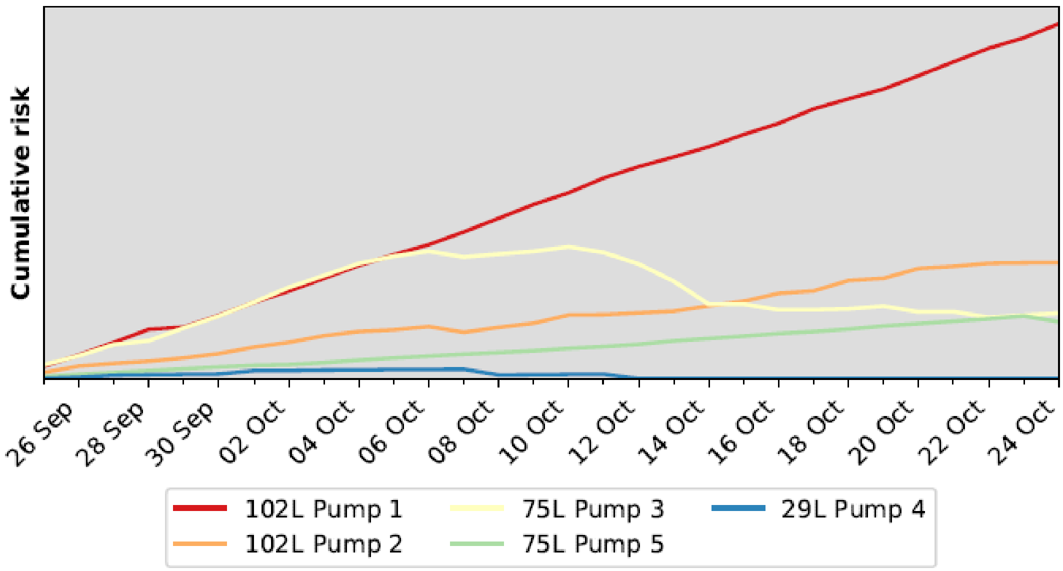


Figure 6.1: *Pump cumulative risk indication*

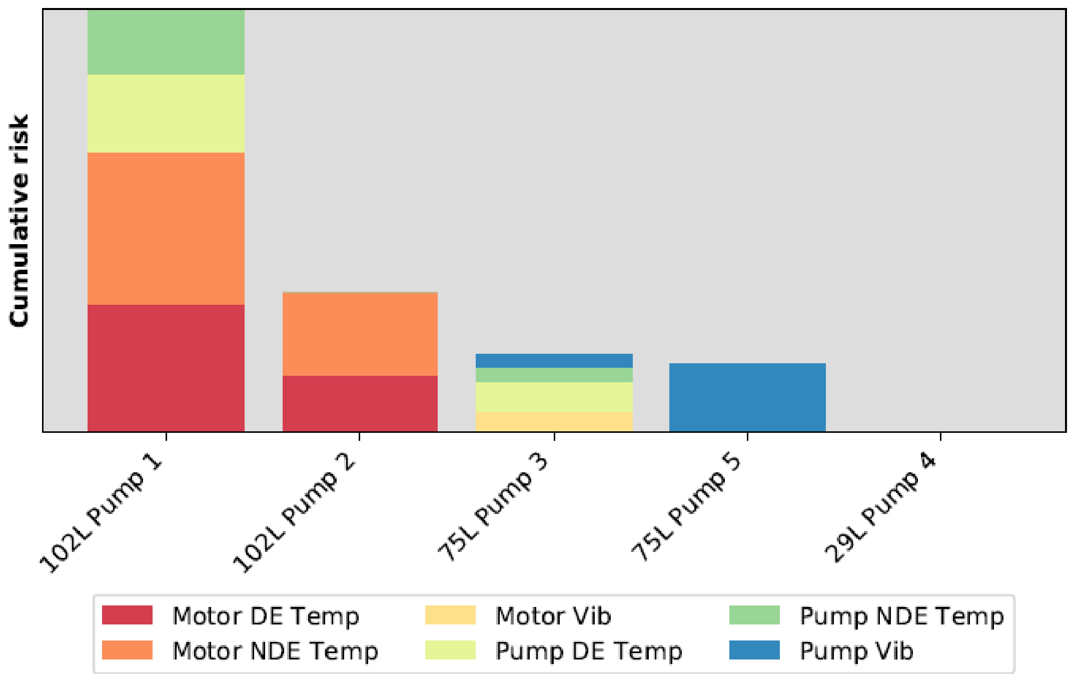
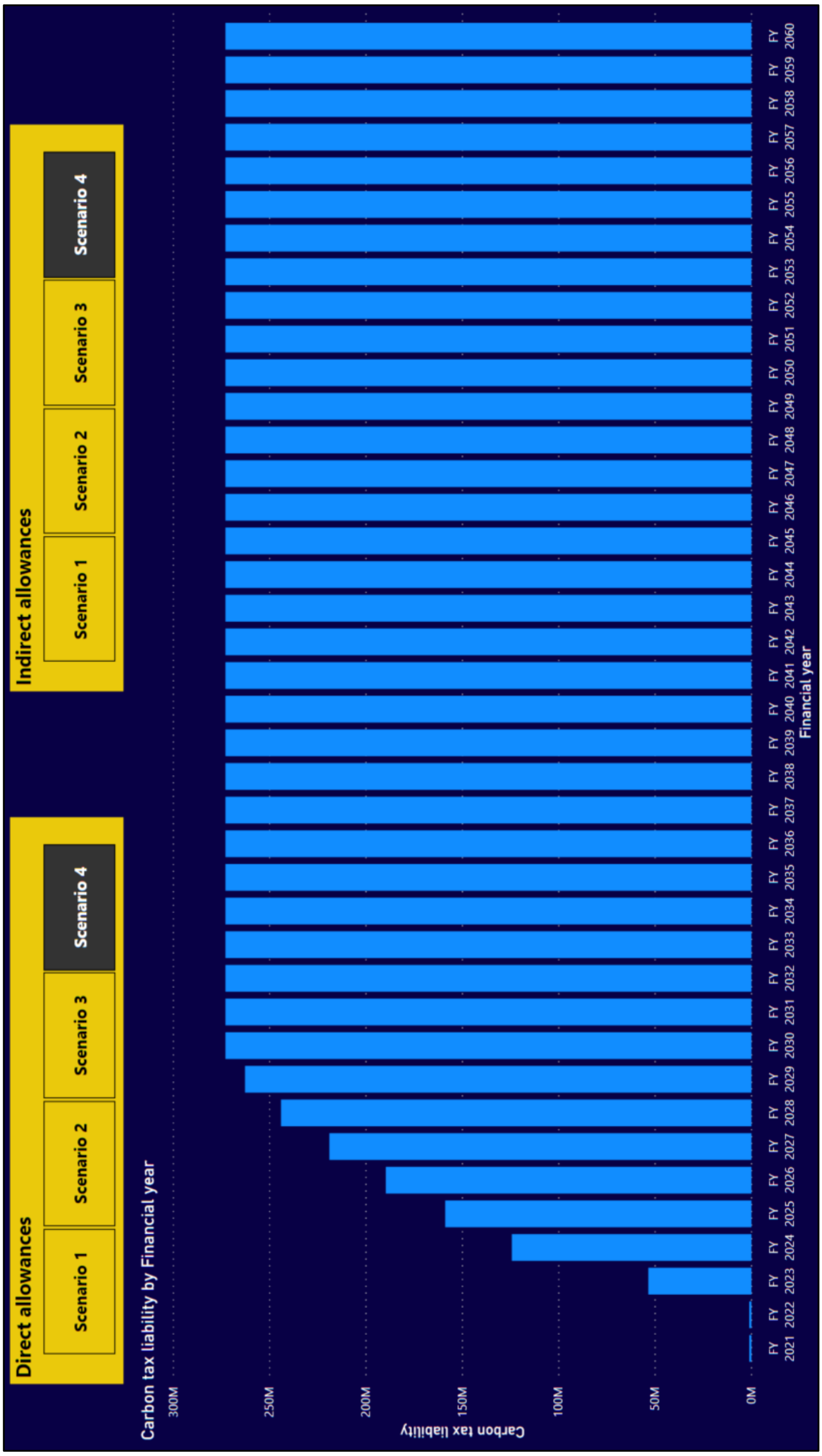


Figure 6.2: *Pump distribution of cumulative risk indication*

Case Study C



Direct allowances
Scenario 1
Scenario 2
Scenario 3
Scenario 4
Indirect allowances
Scenario 1
Scenario 2
Scenario 3
Scenario 4
Carbon tax liability by Financial year
Carbon tax liability
0M
50M
100M
150M
200M
250M
300M
FY 2021
FY 2022
FY 2023
FY 2024
FY 2025
FY 2026
FY 2027
FY 2028
FY 2029
FY 2030
FY 2031
FY 2032
FY 2033
FY 2034
FY 2035
FY 2036
FY 2037
FY 2038
FY 2039
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FY 2048
FY 2049
FY 2050
FY 2051
FY 2052
FY 2053
FY 2054
FY 2055
FY 2056
FY 2057
FY 2058
FY 2059
FY 2060
Financial year