

Investigating the impact of artificial intelligent systems on productivity at a mine

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SOLEMN DECLARATION

I B.H. Pretorius declare herewith that the mini-dissertation I submit to the North-West University as partial completion of the requirements set for the MBA degree is my work.

Signature of student  _____ Student number 29956676

It was signed at Rustenburg on the 6th day of December 2021.

DEDICATION

To my Lord and saviour, Jesus Christ, who placed so many great people in my life and made it possible for me to complete this cycle.

My wife Elani has stood by my side and sacrificed a great deal for five years. I cannot thank you enough for the inspiration and support given over the years. Under challenging circumstances, you run the household and always make sure everyone is looked after. And my son and my daughter who had lost a lot of play-time. And last but not least, my mother, who had a lot less family time with her grandchildren during the extent of my studies.

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Wickus, Hein, Anthea, and Zane, I mentioned your names in no specific order for such a fantastic support group; you are the best team. Without the Grace of God and your help, I would not have made it. Doctor Ndlovu, thank you for your guidance and patience. My Employer for having grace when needed to write exams and taking time off to study. Impala Platinum for allowing me to conduct research. The respondents for your participation and quick feedback. Erika Fourie, many thanks for the excellent assistance in the statistical part of the document. The North-West University for a life-changing experience.

ABSTRACT

Production in the mining industry has substantially declined since 2000. Since 2000, the mining industry's productivity has dropped significantly. From roughly 2004 to 2010, the mining industry's productivity dropped by nearly 40%. Between 2010 and 2018, productivity improved somewhat, approximately 15%. Since 2010, it has steadily gained ground, although, between 2010 and 2018, it only increased by about 15%. According to Canart et al., contemporary productivity figures are still 25% lower than those achieved in 2000. New ways of increasing productivity by operating more effective and efficient mines have come to afore using Artificial Intelligence and Machine Learning. This study aimed to investigate the impact of artificial intelligent systems on productivity at a mine. The researcher used a quantitative method employing questionnaires distributed over a representative sample at a specific mine Impala Platinum Rustenburg Concentrator Plant. The respondents completed the fifty-two questionnaires that were handed out. After the questionnaires were collected from the respondents, The questionnaires were submitted to the North-West University's Statistical department for processing. After the information was processed, it was discussed in Chapter 4 of this study. The impact of AI and ML implementation over the past ten (10) years was perceived as positive. The effect was displayed by the data gathered through the questionnaires. The impact of AI and ML on mining productivity is perceived as positive. However, user-friendliness was perceived as positive by users younger than forty (40) and not user-friendly by users 40 and older. It was recommended that users of AI and ML should be trained on how to use AI and ML. But before using AI and ML, it may be a prerequisite, and policies should be implemented to make training compulsory. Ai and ML can be cost-effective by integrating low code into the system. Low-code is relatively inexpensive.

Keywords: Artificial Intelligence, Machine learning, Mining industry, Low Code, Productivity, Impact, User Friendliness.

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LIST OF ABBREVIATIONS AND KEYWORDS:

Abbreviation	Meaning
AI	Artificial Intelligence
ML	Machine Learning
PDS	Proximity Detection System
n.a.	Not applicable
NWU	North-West University
LIE	Low Income Economies
MIE	Middle Income Economies
GDP	Gross Domestic Product
MCI	Mining Contribution Index
MCI-Wr	Mining Contribution Index WIDER
MPI	Mine (Lens) Productivity Index
MHSA	Mine Health and Safety Administration
ILO	International Labour Organization
LTIFR	Lost Time Injury Frequency Rate
WEF	World Economic Forum
ADP	Advanced Digital Production
HMI	Human Machine Interfaces
LC	Low Code

1 CHAPTER ONE: NATURE AND SCOPE OF THE STUDY

1.1 CHAPTER INTRODUCTION

Productivity in the mining industry has declined substantially since 2000. From around 2004 to 2010, productivity in the mining industry has declined by nearly 40 per cent (Canart et al., 2020:86). From 2010 productivity has slightly increased to around 15 percent from 2010 to 2018. Since 2010 it has gradually gained ground but has only raised an estimated 15 percent from 2010 to 2018. The recent productivity figures remain at 25 percent below the figures attained in 2000, Canart et al. (2020:231). As a result of the slight increase in productivity, the mining industry must track the productivity of its assets. They must also address what enables the productivity of their assets to increase. By monitoring their investments, mining companies will guarantee to a greater extent that they will remain sustainable and increase their rate of productivity in the long run (Canart et al., 2020:232).

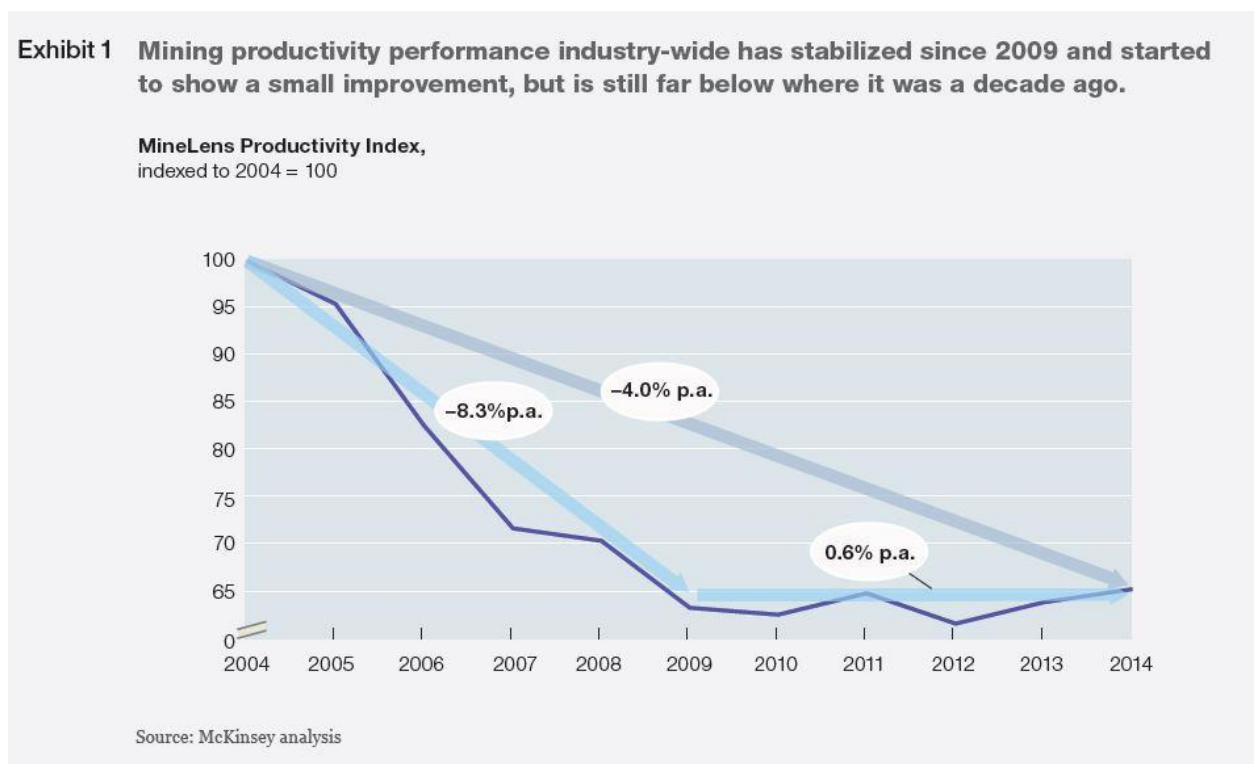


Figure 1-1 Mining Productivity Performance

Source: Mckinsey, Productivity in mining operations: Reversing the downward trend, 2020.

It is a proven fact that productivity in the mining industry has increased substantially since the introduction of AI. According to RockMass Technologies (2017), "Implementing this

technology allowed our team to process day-to-day data 18 times faster than what is typically done in the field" (RockMass Technologies, 2017). Furthermore, recently, scenarios suggested that AI's introduction to the mining industry unlocks an incremental cost saving of between \$ 900 billion to \$ 1.6 trillion by 2035. To put these amounts in perspective, Indonesia's GDP is equivalent to \$ 900 billion and Canada's GDP to S 1.6 trillion (Mckinsey,2017.1). Furthermore, cost savings and efficiency can be attained by technological advances, according to Mckinsey, 2017.1, "*As a result of lower energy intensity and technological advances that improve efficiency*" (Mckinsey,2017.1).

1.2 PROBLEM STATEMENT

Reaching production targets and creating and maintaining an efficient mine is a problem for mine managers (Mkinsey, 2020). Recent data reflects that since 2009 the mining industry as a whole has stabilized its productivity performance compared to its performance in 1999 (Lala, A. *et al.*, 2016). However, turning the focus onto individual mines' performance shows another picture. Many respective mining companies fail to grasp the productivity improvements that AI provides.

Communication and knowledge sharing between departments is critical. A massive contributor to the loss of production is improper maintenance, resulting from no or little communication between departments. A great deal of production is lost through improper maintenance and miscommunication or no communication between departments. Data gained from equipment and machines have to be transformed into useable data that could help operations managers to manage their plants to optimal performance.

Raw and incomplete data that are not processed to meaningful useable data do not help mine managers make better decisions. Information is gathered from equipment or machines in different mining departments. One department is dependent on another department to keep productivity to its optimal best. As the study suggests, the mining industry benefits from investing continuously in technology to increase profit. Technology and the mining industry have evolved in synergy (Canart *et al.*,2020.86). More efficient and effective production methods to extract ore from an open-pit mine or the rockface have been developed and should reflect the same statistic. Production figures should emulate the efficiency by which machines can now extract ore from the rockface. AI and ML have become a core part of daily life compared to ten years ago where it was commonly unknown (Mihajovic, 2019.23).

Mine managers can be significantly assisted by AI and ML (in theory) to run super-efficient mines with the tools and information available from AI and ML (Karatzoglou, 2020). Secure, compliant, and dependable management can be attained by utilizing technology, which improves management effectiveness and efficiency in production/service delivery. Continuous improvement, Enhanced performance and a culture that motivates have been achieved by integrating technical systems and human capabilities (Munir., 2019). This study aimed to determine the impact of AI and ML systems in mining productivity to date.

1.3 RATIONALE AND SIGNIFICANCE OF THE STUDY

Existing studies are loosely focused on a specific department at a mine. For example, case and point, *"This case study, uses a surface mine to investigate multidisciplinary logistics analysis methods for improving refinery operations"* (K.D. Strang, 2011, 207 – 219) where he investigates a refinery. However, from observation, when visiting 38 mines during three years, the same method of operation is conducted. Different departments, for example, ore services, production, projects and more. Furthermore, from experience gained, it seems these departments function on their own and not like one unit working together, and with their vision, excluding other departments in decisions being made on their production planning either intentionally or unintentionally.

Planning and production meetings are held weekly. These weekly meetings are structured to become unproductive as soon as the session is done. For example, a session may consist of a project manager and ten site managers working for different contractors on the mine. When the first Site manager explains his program for the week, he can leave the meeting. However, the site manager's work depends on several other site managers' tasks. By exiting the session, he is not aware of the activities of the other site managers; this may influence his planning and production. In addition, not being present in the discussion of the overall plan, which includes all site managers, causes frustration and delays.

Yes

Maybe

No

More options

All,

I will use the attached SI summary spreadsheet to get a weekly progress update on work allocated / SI issued from Site Managers on Monday mornings, in my office. After the meetings, an updated spread sheet will be distributed again.

The provisional schedule is as follows:

Romni, Hennie:	09:30
BSCFA, Gert:	09:45
IMA, Gary:	10:00
PSW, Kingsley:	10:15
PSW, Another:	10:30
Rhimak, Henk:	10:45
Spilastar, Marius:	11:00
SAC, Pheko:	11:15

These sessions will end 11:30 sharp as I have another meeting starting at 11:30.

Site Managers must please ensure they have updates on deliveries, planned work and progress on existing work ready in order not to spend too much time recording progress.

For the first few weeks, until the RFI documents are up to date, we will also discuss your outstanding RFI documents and progress with punch listing on open RFI documents.

Regards,

Figure 1-2: An actual meeting request from the project manager at a mine.

Such individual sessions ring true to mining. As R.J Hickson *et al.* 2015 state," Mining projects are complex. The path to successful project completion is embedded with situational uncertainties and strewn with obstacles". Although most mining industries can be classified as operations when the mine is established, the operations part is divided into small projects that keep the wheel turning.

Bronwyn Swartz, the founder of Swartz Technical Consulting (STC), is quoted in PM World Library, 2020, stating that "*Project management is useful to the mining industry, as it organises a team of specialists, such as geologists, environmental specialists, mining engineers and processing specialists, who need to collaborate to complete projects*". Arguably, project management manages a wide variety of disciplines in a single mine, for example, but it does not address the overall management of the entire mine. It may be done by a project manager in a department, for instance, the production department, but it does not pull through to the other departments like processing, ore services, or such. The reason might be that complete overall management of the plant might be too intricate to conduct.

The comprehensive management of a mine is where AI comes into play. The data gathered from operating the plant can be obtained and processed into meaningful information that can be used to plan/ manage more efficient operations.

1.4 OBJECTIVES OF THE STUDY

1.4.1 Primary objective

The primary objective of this research was to investigate the impact of artificial intelligent systems on productivity at a mine.

1.4.2 Secondary objectives

- To determine the effects of AI and ML on mining activities.
- To determine how the introduction of new technology has impacted the social environment of a mine.
- From the data gathered and processed, recommendations will be made on advancing efficiency in a particular mine.

1.5 RESEARCH QUESTIONS

1.5.1 Primary research questions

- What is the impact of artificial intelligent systems on productivity at a mine?

1.5.2 Secondary research questions

- What was the impact of artificial intelligence on mining operations in the past ten years at specific mining houses?
- How "user-friendly" is the machinery if some operators may be illiterate?
- What processes or steps need to be taken to run a more efficient mine?

1.6 SCOPE OF THE STUDY

The study will be conducted in Rustenburg and surrounding areas in South Africa in the North-West province. The research will be done at Impala Platinum Mine and other private institutions, where data will be gathered electronically or manually. The reason for this is to ensure that sampling can take place during the current pandemic (Covid-19) and will allow for the researcher to conduct his research within Covid regulations and stipulations.

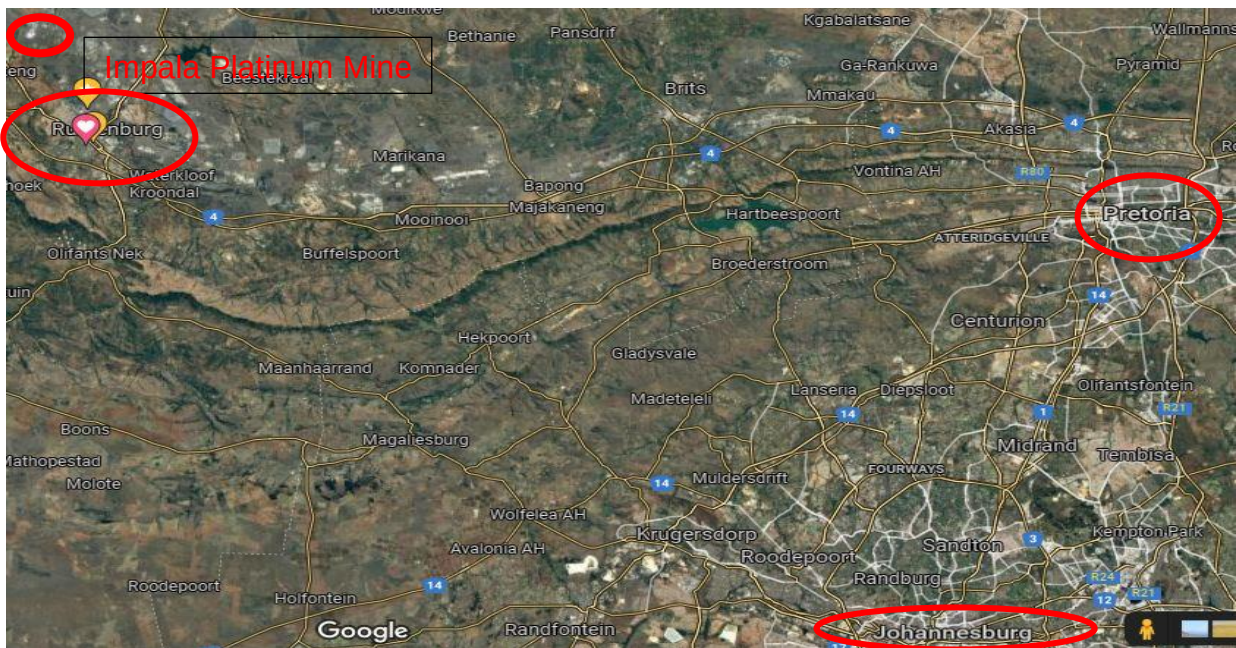


Figure 1-3: The location of the North-West Province and Rustenburg Area within South Africa. Johannesburg, Pretoria, and Rustenburg.

Source: Google Maps

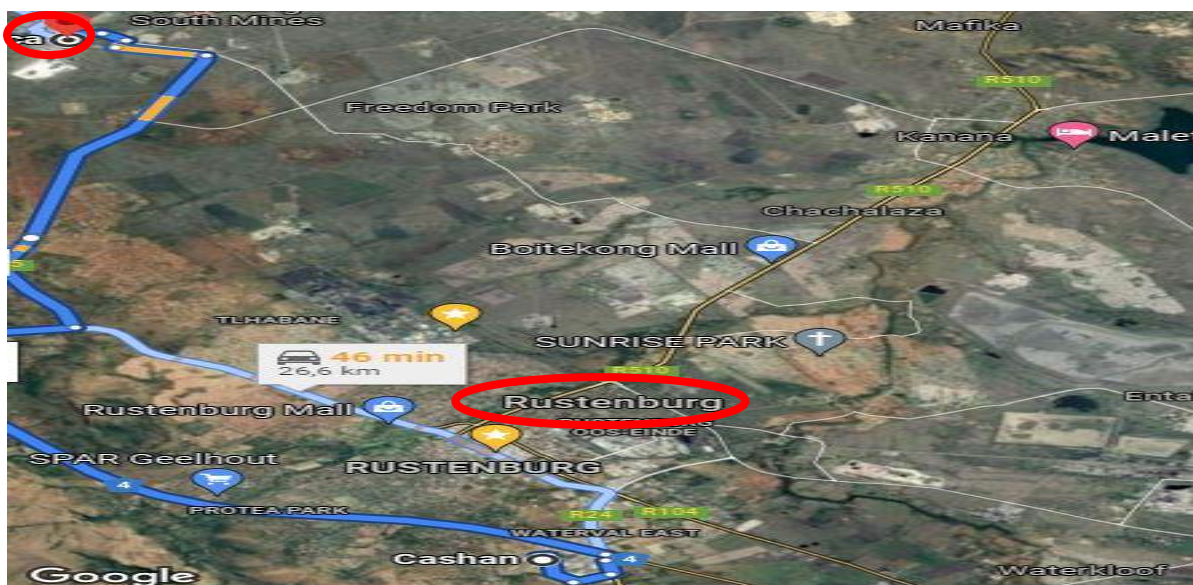


Figure 1-4: Rustenburg to Impala Mine

Source: Google Maps

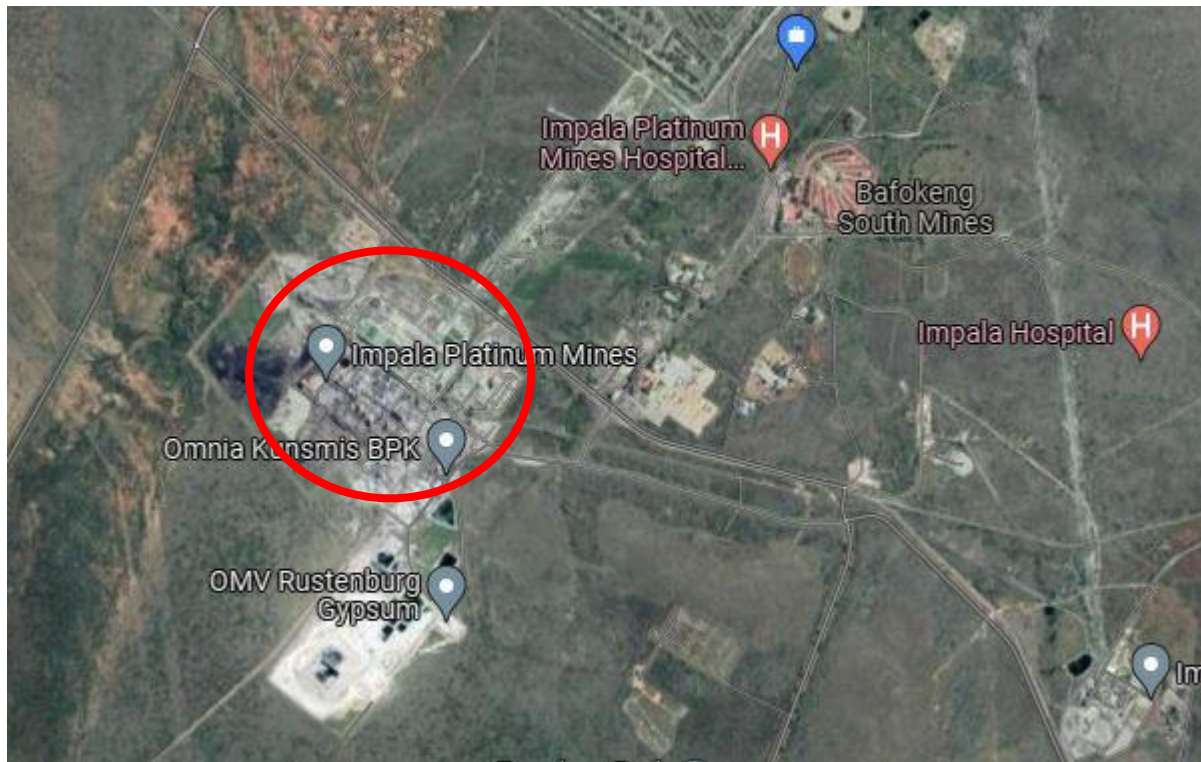


Figure 1-5: Impala Mine's Location

Source: Google Maps

1.7 RESEARCH METHODOLOGY

1.7.1 Empirical study

Research paradigms are defined as a shared understanding of reality. It is viewed as being objective in that everything around us has meaning and an impact on our lives (Chilisa & Kawulich, 2012). A research paradigm is a shared worldview representing convictions and qualities that aid how problems are settled (Bryman & Bell, 2011). A pragmatic research paradigm was used in this study.

The researcher chose a research philosophy that follows a positivist research paradigm/ approach because a positivist approach believes that there is one central truth and that it is measurable. The positivist paradigm of social reality investigation is based on the premise that observation and reason are the best approaches to explain human behaviour. In other words, science can only be based on objective, observable facts (Nel, J.P. 2016).

The researcher has opted to take a deductive approach in this research, whereby he can test ideas and explore what has occurred in the field based on previous data. The deductive research method looks into a well-known idea or phenomenon to see if it holds

up under different circumstances. "The deductive approach most closely follows the route of logic," it has been said. "Starting with a theory, the logic leads to a new hypothesis. This theory is put to the test by having it confronted with observations that either corroborate or refute the hypothesis." (Schneider, *et al.*, 2009:16)

The research quantitatively collected data. The difference between qualitative and quantitative research is that quantitative research is based on amount or quantity measurements, whereas qualitative research is based on behavioural sciences. Quantitative data collection was used to acquire measures needed through questionnaires to prove the argument and the influence that artificial intelligence has had since its entrance into the mining industry.

The collection of numerical data is referred to as quantitative research. Quantitative research has an objectivist view of social reality, prefers a natural science method, and believes that theory and research are inextricably linked. "Research Methodology, Business and Management Contexts Bryman, Bell, Hirschsohn, Dos Santos, Du Toit, Masenge, Van Aardt, Wagner," according to "Research Methodology, Business and Management Contexts Bryman

Quantitative techniques derive knowledge from post-positivist assumptions with an experimental or quasi-experimental inquiry strategy. Closed-ended questions, performance, attitude, observations, and census data are some of the ways to be considered. The study was statistically based. Quantitative approaches are used in the practices of testing or verifying theories or explanations, identifying variables to study, evaluating variables in questions or hypotheses, using validity and reliability standards, numerically observing and measuring information, using unbiased approaches, and employing statistical procedures (Bryman and Bell 2007, Creswell 2009, Saunders, *et al.* 2019:56).

The researcher chose to do cross-sectional research, which means that the researcher did not return to the Impala multiple times to assess it but only did an initial sample at the mine. A cross-sectional survey collects information to establish assumptions about a target population (universe) at a certain period. Cross-sectional surveys are thought of as snapshots at a point in time of the communities they study (P. Lavrakas, 2013).

1.7.2 Questionnaire design

The quantitative data was collected through the use of questionnaires in answering the research questions. The questionnaires derived information from the research questions and were structured so that the data used that was extracted from the questionnaires could answer the research questions. This questionnaire used in this research was modified and based on a template previously used by Shaun Enslin in his 2009 dissertation at NWU. The questionnaire comprises sections A to D. Section A provides eleven questions on demographic variables to gather information on gender, age, ethnicity, marital status, etc.

Section B has eight questions that follow a Likert scale approach. A Likert scale is used in data representation, where one indicates the candidate strongly disagrees, and five indicates the candidate strongly agrees. In this case, the Likert scale tests how the respondents feel that Artificial intelligence impacted their working environment in the past ten years. Section C has seventeen questions on the ease of using Artificial Intelligence and specifically on the less literate individuals. Finally, section D has seventeen questions focussing on how artificial intelligence influenced productivity on the mine. The IBM SPSS Statistics Version 27 (Questionnaire Analysis Software) was used to import the questionnaire findings and then calculate the information.

Consent was given to use the questionnaire template. The template format was used, and the questions were adapted to suit the current research. Information gathered from the questionnaires was sent to the Statistical Consultation Services of the NWU, which assisted with the analysis and interpretation of data.

1.7.3 Study population

The population is employees working at Impala Platinum mine and specifically the Concentrator. Of these, 52 individuals (permanent employees and contract workers) were selected to sample. The sample consists of General Assistants, Artisans, Supervisors, Site Managers, and Foremen that work with equipment managed by Artificial intelligence. The focus was on Impala Platinum in the Rustenburg area.

1.7.4 Data collection

The data collection method was done through a questionnaire compiled by the researcher. The questionnaire focused on addressing the research questions stated by the researcher. The questionnaire was distributed at Impala Platinum Operations near Rustenburg's Concentrator Plant. At the Concentrator at Impala, approval was obtained by approaching top management. Furthermore, all permissions and actions were documented to show what has been done to gain approval. The researcher worked at the Concentrator at Impala and distributed the questionnaires with permission.

A letter of consent was written and sent to both the General Manager and Human Resource Manager of the Impala at the Concentrator Plant. It was done to get approval to distribute the questionnaires and collect data from the relevant employees. Ethical aspects applicable to the study were thoroughly discussed with the respondents. All government regulations and safety procedures of Covid-19 will be observed during issuing and collecting questionnaires.

1.7.5 The process will be as follows

The researcher is employed at Impala Platinum Concentrator. The Concentrator is part of a mining company (Impala Platinum) that currently has Artificial Intelligence and Machine Learning applications on the mine, for example, partly autonomous trucks and remotely operated conveyor belts and Silos. Therefore, managers and relevant authorities were contacted to get permission to issue the questionnaires. As a result, approval was given in written consent by the general manager to authorize the researcher to continue with the research.

After permission was granted, the respondents were approached and asked if they could complete a questionnaire. The respondents must have freedom of choice to reflect an actual sample. Selection and approach of participants: Participants were selected based on their involvement level with the equipment, in other words, how frequently they work with or the extent to which the equipment/ technology impacts their working environment. The respondents/ candidates were fully briefed on the scope and content of the questionnaire and given the option to accept or decline to take part in the study. The option to accept or decline provides the respondent with freedom of choice, they can leave the questionnaire at any time, and their data will be anonymous.

Questions were centred on themes that have been established ahead of time to create a suitable dataset. When the respondents had completed the questionnaires, it was collected by the researcher. Once collected, the questionnaires were sent to the NWU Statistics Department for processing. The statistics department does a scientific analysis not accessible to the researcher. The processed information received from the NWU Statistics Department can now be used as information to complete the dissertation.

1.7.6 Statistical analysis

The statistical analysis discusses the demographic variables. These variables were analysed by calculating the frequencies (Section A) and percentages.

The instruments that were used are:

- Reliability: using Cronbach Alpha (Concise)
- Sum/ Average of Scales/ Instruments: based on Shaun Enslin's template.
- Descriptive statistics: The Mean, minimum, maximum, and Standard Deviations.

1.7.7 The validity of the measuring instrument

Validity relates to a research instrument's ability to measure what it promises to measure, according to Cooper and Schindler (2006:318) and Leedy and Ormrod (2010:92). Three frequently accepted classes can be found in the classifications mentioned above. The classifications are divided into three categories:

- *The content's reliability.*

To what extent does the content of the items accurately represent the universe of all relevant objects under investigation?

- *The adequacy of linked criteria*, as well as

The extent to which the predictor captures the criterion's key properties

- *The material's content constructs validity.*

Answer the question, "What accounts for the measure's variance?" by attempting to identify the underlying construct(s) being measured and determine how well the test represents them in response to the question "What accounts for the variance in the measure?" (them).

It is critical that the information acquired remains accurate. Therefore, this document does not include any corrupt data that cannot be trusted. Before being included in the findings, the data submitted from the respondents was checked for validity.

1.7.8 Reliability of the measurement instrument

The term "reliability" refers to whether a measurement is trustworthy in the sense that it produces consistent results (Diamantopoulos & Schlegelmilch, 2006:34; Leedy & Ormrod, 2010:93). If a measure is not dependable, it cannot be valid, according to Diamantopoulos and Schlegelmilch (2006:34), but it may or may not be valid if it is reliable. A valid measure is trustworthy, while the opposite is not always true. Reliable instruments are resilient and perform well at different times and under varied conditions. This contrast between time and condition is the foundation for commonly used dependability views, such as internal consistency, stability, and equivalence.

Table 1-1: Summary of reliability estimates

Type	Coefficient	What is measured	Methods
Test-retest	Stability	Reliability of a test or instrument inferred from examinee scores.	Correlation
Parallel forms	Equivalence	The degree to which alternative forms of the same measure produce the same or similar results	Correlation
Split half, KR20, Cronbach's Alpha	Internal consistency	The degree to which instrument items are homogeneous and reflect the same underlying construct(s).	Specialized correlation formulas

Source: Cooper and Schindler (2006:322)

The researcher used Cronbach alpha (α) to measure the reliability of a measuring device. Cronbach alpha estimates the average of all feasible split-half dependability coefficients, according to Bryman and Bell (2007:164). The estimated alpha coefficient ranges from 1 (one) to 0 (zero), with 1 denoting excellent internal dependability and 0 denoting no internal reliability (zero). The rule of thumb is that a figure of 0.80 indicates an acceptable level of internal reliability; however, other authors accept a slightly lower figure of approximately 0.75. According to Eiselen and Uys, and Potgieter (2005:114), the closer the alpha value (α) is to 1 (one), the more dependable the scale's internal consistency is.

According to Cooper and Schindler (2001:218), the following procedures can be done to improve reliability:

- Reduce external causes of variance,
- standardize measuring circumstances; and
- expand the sample of measurement questions by including similar questions in the data collection instrument. Values of 0.5 will suffice in the early stages of the study (but interpretation should be made with caution). However, reliability estimates of 0.8 are generally deemed acceptable, whereas values of less than 0.6 are considered unsatisfactory.

1.8 LIMITATIONS OF THE STUDY

The study's sample size was 52 participants, limiting the quantity of valuable data collected if individuals did not complete the questionnaire as intended. The data for the study was collected using a self-assessment, which may be skewed because the participants were answering based on their perceptions. Questionnaires were used to collect data rather than interviews or observations.

1.9 LAYOUT OF THE STUDY

CHAPTER ONE: Introduction, background and problem statement and limitations. This chapter explains what the research is about and the importance of the study. The limitations of the study were expounded on in this chapter. The problem to be solved and the problem as per previous research done is stated in this chapter. Finally, the primary and secondary objectives are discussed and elaborated on in more detail.

CHAPTER TWO: The literature review will portray the significance of Artificial Intelligence and Machine learning when it comes to future mining and Ai and ML being an integral part of future sustainability and the new shift of global environmental awareness.

CHAPTER 3: Research methodology - In this chapter, the focus will be given to the approach to research methodology. A process will be followed on how data is gathered, processed, and analysed and how that data will be transformed into useable data.

CHAPTER FOUR: Discussion of the results obtained; When all information is gathered, assessed and processed into comprehensible and useable data, the results obtained through the research will be discussed.

CHAPTER FIVE: Conclusion and recommendations; after the results have been discussed, this chapter will make recommendations on the findings systematically. This chapter will make a systematic summary that includes the whole research project.

1.10 CHAPTER CONCLUSION

Chapter 1 explained the decline in productivity since the year 2000. The need for operating more efficient and effective mines has been identified, which may lead to the mine's survival in the long run. Since the year 2000, the implementation of AI and ML has increased, but mining production has decreased. However, AI and ML have only been introduced in certain mining sectors and only run those specific sections, and not an overall linked management system. In the South African Mining industry, implementation has been slow due to various contributing factors, such as red tape and the labour coefficient that some say perceive AI and ML as a threat to job security. The labour issue will not be addressed in this study. Chapter 1 also explains the research objectives, the research questions, and the research methodology approach, which in this case was 52 individuals at Impala Concentrator' Rustenburg operations. The research followed a quantitative approach where questionnaires were handed out to a representative sample of the employees at Impala. The aim was to have the returned questionnaires analysed by North-West University's statistical department, interpret the results, and give valuable recommendations when receiving the feedback data.

2 CHAPTER TWO – LITERATURE REVIEW

2.1 CHAPTER INTRODUCTION

This chapter gives an overview of the mining industry and its global worth, including the major mining companies. Furthermore, the decrease in productivity and the reason thereof will be discussed. The contribution and implementation of AI and ML will be examined. The benefits and drawbacks of AI and ML in the mining industry will be explained. Furthermore, a history of the first industrial revolution (industrial revolution) to the fourth industrial revolution (4IR) will be given.

2.1.1 The Mining industry global worth

Several industries throughout the world rely on the subsurface supply of mineral commodities. The reliance of many high-tech industries on rare earth is a relatively new

problem; coal, on the other hand, remains one of the world's most important energy sources. As a result, the mining industry is critical to the global economy. In 2020, the top 40 global mining businesses, which account for the vast majority of the industry's revenue, generated \$656 billion in sales. The mining industry's net profit margin has declined from 25% in 2010 to 11% in 2020 (Statista, 2021)

2.1.2 Leading mining countries

Iron ore, coal, potash, and copper are the most exploited commodities in volume. The top three coal-producing countries are China, Indonesia, and India. China is also the world's third-largest iron ore producer. Indeed, China is fast becoming the world's top mining country for various commodities, particularly rare earths, for which China produced roughly 58 percent of worldwide output in 2020. In addition, China is the world's biggest producer of gold from mines (Statista, 2021).

2.1.3 Major mining companies

Anglo-Australian BHP and Rio Tinto head the mining industry's top five businesses by market capitalization, followed by British corporation Anglo America, Anglo-Swiss company Glencore, and Newmont of the United States. BHP had a market capitalization of 180.5 billion USD in May 2021. Glencore was the most significant mining corporation globally in terms of revenue, with 142 billion dollars in revenue in 2020. However, it must be remembered that commodities trading accounts for a significant portion of Glencore's revenue. In addition, four of the world's top 10 mining corporations by revenue were based in the United Kingdom in 2020, while six were based in China (Statista, 2021).

Top mining companies outshine their competition

The biggest mining companies worldwide by revenue (in billion U.S. dollars)

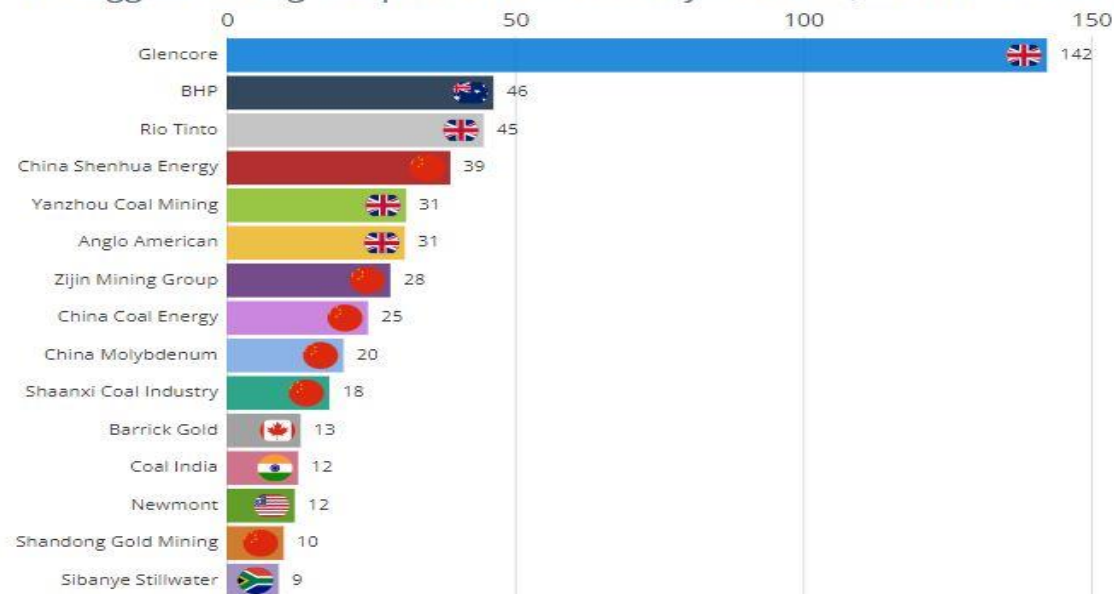


Figure 2-1: Top Mining Companies Revenue

Source: Financial Times, 2021

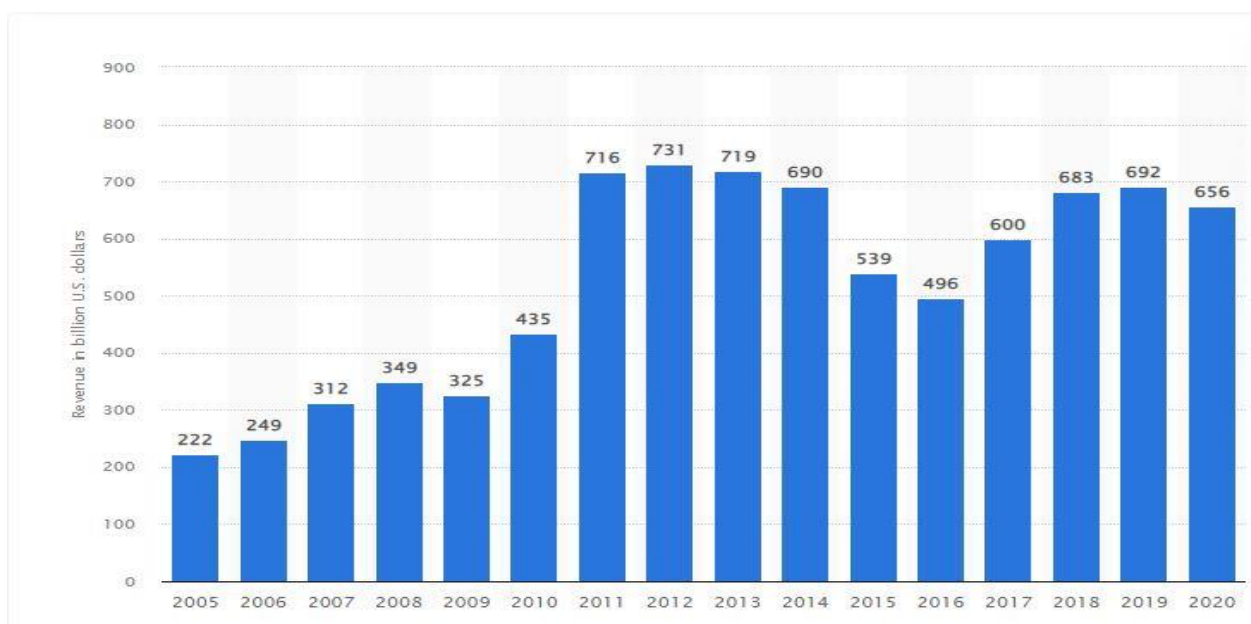


Figure 2-2: Revenue in billion dollars 2005 to 2020

Source: Statista, 2021

2.1.4 Decreases in productivity

Resource depletion can be addressed by increasing productivity and exploration. The mining industry, through innovative ideas, has been growing its productivity substantially over the past hundred to hundred and fifty years. However, in contrast to the phenomenal growth in the past hundred and fifty years since 2000, productivity seemed to slow down (West, 2011).

2.2 MINING INDUSTRY

2.2.1 General facts on profitability and necessity of mining

The production of minerals or the products we obtain from producing minerals touches nearly all of the aspects of our day-to-day modern lives. All different kinds of minerals, for example, coal, precious metals, iron sands limestone, aggregates and industrial minerals, are elements used in manufacturing items such as vehicles, construction, manufacturing of fuel and by-products, electronics, computers, health care, energy transmission and production, and a plethora of other products. Apart from supplying minerals to the world to produce much-needed products and infrastructure, mining provides employment and is directly responsible for a country's economic well-being (Straterra, 2021).

Mining indirectly contributes to the economy through dividends and taxes that help build infrastructure and much-needed services, for example, hospitals, public facilities, schools, police stations, and public services. Mining requires qualified and trained employees for a safer work environment. Because of the need for qualified employees, many related businesses originate from it (Ward, *et al.*, 2002:10)

Mining acts as an incubator for related activities such as environmental and engineering services, manufacturing of goods and equipment for mining, and universities that cater to speciality courses related to mining, such as mining engineering, geology, and metallurgy (Ward, *et al.*, 2002:10). The supply of equipment and goods that can be locally sourced paves the way for local businesses. When goods are unavailable locally, or the products that the mine produces are in demand overseas, the goods or the products need to be imported or exported as required.

Foreign exchange is fuelled by import and export directly and indirectly created by mining activities, and it contributes a great deal to the GDP of a country. Therefore, mining contributes substantially to wealth generation and economic opportunities in many countries (Ward, *et al.*, 2002:11). The contribution of mining in the global economy, especially in the Low - to Middle-Income Countries, had increased significantly from 1996 to 2016 (Ericson, *et al.*, 2019:183). The most significant increase during that period was in Low-Income Economies rather than Middle Income Economies. The contribution that mining provides toward the GDP increased 43% over the period ranging from 1996 to 2016 for LIE's and MIE's. The contribution amount in 2016 was 1.2% toward GDP in 2016, compared to 1996's contribution of 0.8%. The increase in mineral exports in LIE's and MIE's in that period was 50% (Ericson, *et al.*, 2019:176).

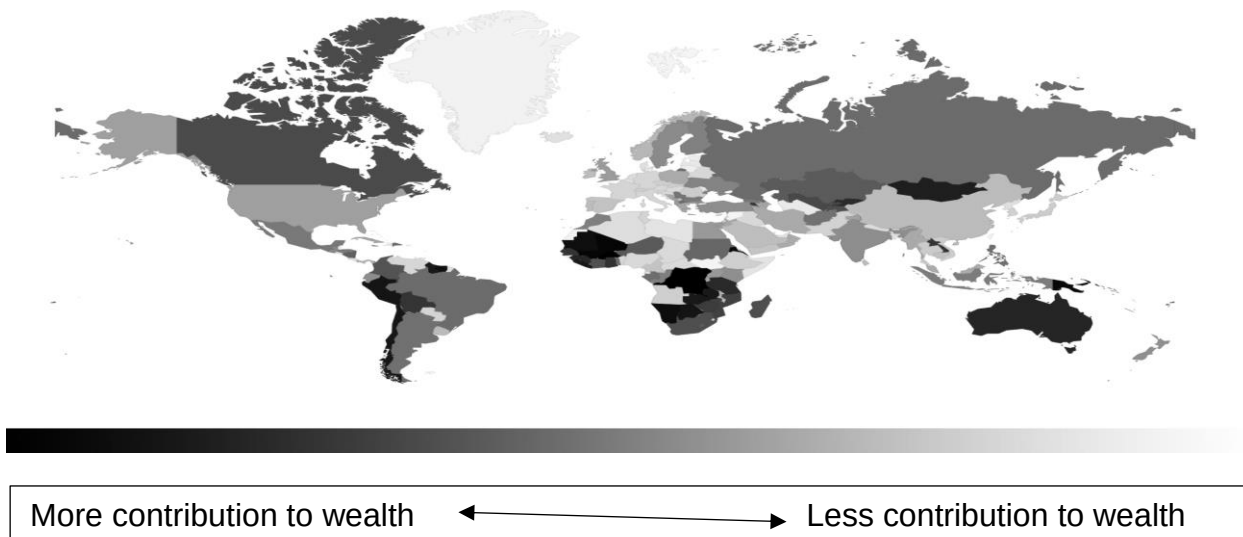


Figure 2-3: Mining Contribution Index (MCI-Wr) score by country 2016

Source: Own calculations

The mining of minerals and metals is crucial to our everyday lives; they are part of an array of economic enablers: healthcare, farming, communications, energy and water supply space technology, transport, and the construction industry. As the minerals and metals become more critical, so will mining of them and will help create a more sustainable ecological responsible future (ICMM, 2021)

By 2040 global energy consumption is forecast to increase by 48 percent. Green energy needs to keep track of the demand in energy consumption whilst assessing the impact of climate change, improving energy efficiency, focusing on renewable resources, and diversifying power supply. A key to making this transition is technological solutions offered by-products created by the mineral and mining sector (Walser, 2005).

Mining is a crucial contributor to the economic growth of many countries. Emerging markets/ economies are significant producers of key commodities. For example, 70% of copper and 40% of bauxite globally are being produced by emerging economies (Walser, 2005). Economic research on mining deals with the industry's macro-economic impact, studying the mining industry's positive and negative contribution to the economy. Mining is an important cause of fiscal receipts and foreign exchange, providing the government is fiscally sound in its dealings. If the mining industry is adequately managed, the industry can drive economic growth and uplift such a country. Examples of such countries are Botswana, Papua New Guinea, Peru, Chile, Ghana and Mali (Walser, 2005).

Income generation and employment are other results of mining. Globally commercial-scale mining yields skills transfer and employs more than 2 million people. The employment rate has an employment multiplier effect of 2 to 5 impact on the community.

Furthermore, poverty-driven mining activities employ 13 million people and dependants globally, such as Brazil, Colombia, Tanzania, Venezuela, and Indonesia (Walser, 2005).

The social and economic aspects of mining and how they impact the community are of utmost importance. The mining department of the World Bank has done an in-depth study in Bolivia, Peru, Chile, Papua New Guinea, and West Africa to determine the economic and social impacts. The assessment showed that there are substantial economic and social benefits. However, these benefits do not come naturally, and the critical issue around them is their sustainability. The contribution of mining to these countries is that small, and micro-enterprises flourish when providing services and supplies to the mining industry (Walser, 2005).

Mining's contribution to economic growth:

- Well-paid and High-quality employment
- Contributes to exports and regional economies
- Mineral production for products essential to society
- Operates world-class workplace health and safety
- Runs world-class environmental, conservation and rehabilitation management.
- Provides training to employees (Straterra, 2020).

2.2.2 Decrease in productivity

Easy to access deposits are being depleted. Resource depletion can be addressed by increasing productivity and exploration. The mining industry, through innovative ideas, has been growing its productivity substantially over the past hundred to hundred and fifty years. However, in contrast to the phenomenal growth in the past hundred and fifty years since around the year, 2000 productivity seemed to slow down (West, 2011).

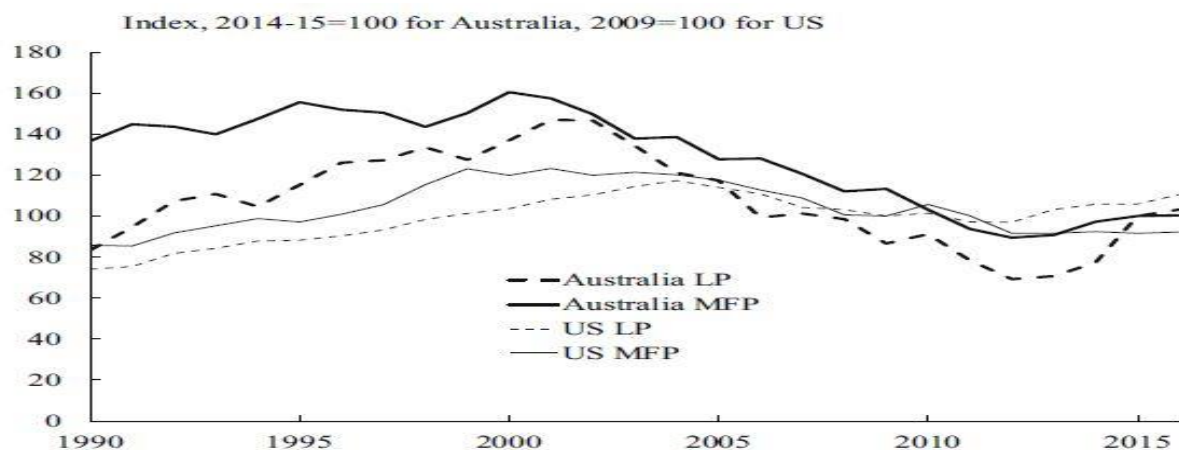


Figure 2-4: Productivity in the United States and Australian mining industries

Source: Australian Bureau of Statistics

As shown in Figure 2.5, the mineral reserves represent a subsection of the potential ore/mineral endowment of an area of ore/minerals. A greater area of resources is visible in figure 10, showing a lesser well-quantified ore deposit present within an individual exploration/ project site. Figure 2.5 shows that, however, ore reserves in an area could be depleted over time by mining resources and converting them to reserves; the more significant area through exploration could yield a far greater return in ore resources. As a result, the exploration of the area of resources can yield a larger ore deposit over time, which can increase production.

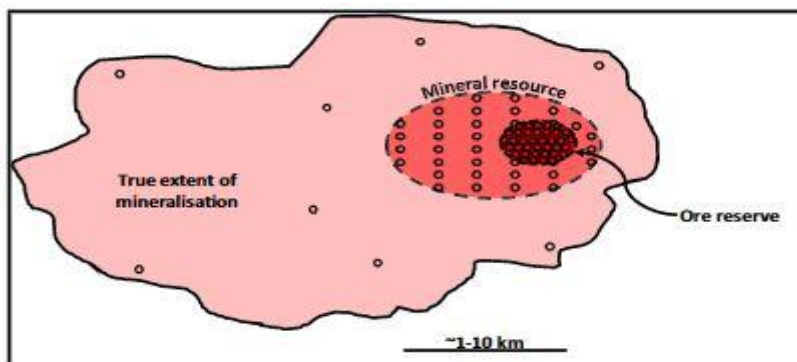


Figure 2-5: A schematic design shows the link between ore reserves, true amount of mineralisation, and mineral resources within a hypothetical mineral deposit system.

Source: Australian Bureau of Statistics

The loss of production since around the year 2000 may be linked to cyclical aspects, but data contradicts this. Long-term production remains lower than before 2000, and factors that previously drove productivity are no longer prevalent. Factors that drove production that stem from the second industrial revolution is larger equipment that made it possible to operate and explore larger mines. The fourth industrial revolution is said to make a difference in productivity through intelligent processes in the mining industry, but up to date, only a few examples that change productivity for the better have been presented. Without the fourth industrial revolution becoming an integral part of mining, the industry faces rising CAPEX and lower ore grade, resulting in more mined volumes (West, 2011).

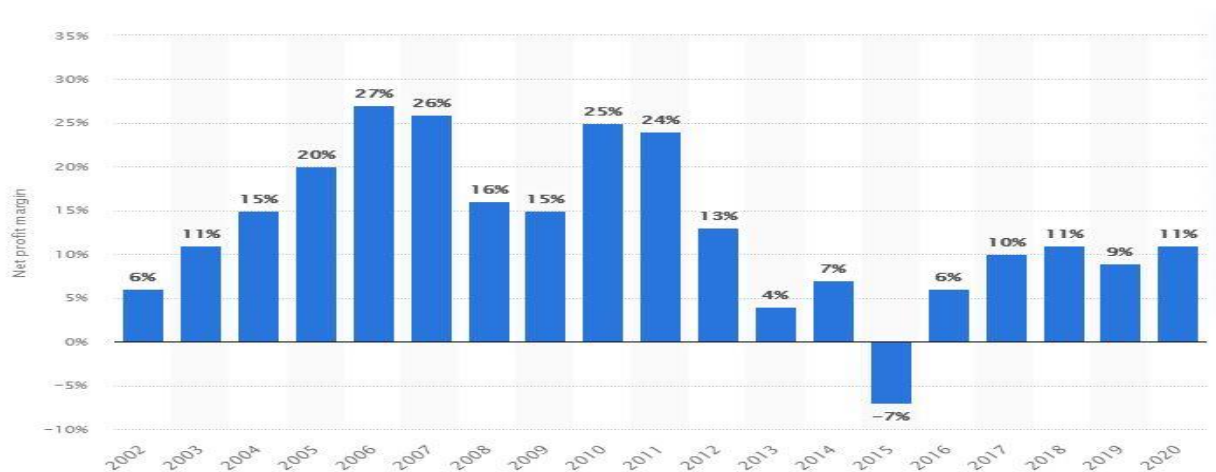


Figure 2-6: Global mining net profit margin from 2002 to 2020

Source: Statista 2021

Mining productivity has increased slightly since 2015 but has not gained pre-2000 figures (McKinsey, 2021). Statistics show that the grade of minerals also declined, resulting in higher operating costs. For example, some statistics show that between 2001 and 2012, the average head grade for Zinc declined by 10 percent, copper by 30 percent and Nickel by 40%; in some cases, gold ore yielded less than one gram per excavated ton. Lower-grade ore equals more tons of ore mined to achieve the same targets, equal higher capital expenditure. Another contributor to high CAPEX is that gold ore is now being mined at deeper levels, requiring cooling equipment and other equipment that raises the cost of extraction. (Deloitte, 2014).

2.2.3 Increasing safety requirements

Increasing productivity does not contribute to a less safe environment; on the contrary, it boosts safety, as statistics show over the last forty years. For example, according to reports by the MHSa, production over the past forty years has increased by 77 percent compared to the mining fatalities, which have decreased by 80 percent. These two statistics may not be linked to one another but shows that an increase in productivity results in an increase in safety. (Ramjack, 2019).

Another safety statistic from the International Labour Organization (ILO) shows that in a safer work environment with lower fatalities, companies that attain these standards are more competitive globally (Deloitte, 2014). Studies on underground coal mining show that in the second year after an accident, productivity decreases by 11 percent. Mines in the near vicinity accident rates decrease between 18 to 80 percent, which may also be

due to an introduction of more managers to oversee the work done. Statistics show that the cost of the accident is 2.51 times more than the cost for increased safety measures. (Gowrisankaran *et al.*, 2015).

2.2.4 Organizational management in mining

The organisational structure is defined as how the work is divided into different tasks, achieving coordination. The organisational model of enterprise management includes the characteristic features of the management of the property complex, the principles of formation, delegation of powers and the vesting of responsibility (Yaschenko *et al.*, 2021).

Organisational structures are the relationship between individual organisational units in a company and how they go by completing administrative and managerial tasks and executive functions. On the other hand, the management of an industrial enterprise entails specialized functional units linked together by substantiating, developing, adopting, and implementing managerial and administrative decisions in a single property unit. The reasoning behind implementing organizational structures is to (and especially in an industrial enterprise) create more effective management and fulfilment of tasks (Yaschenko *et al.*, 2021).

A structure can be defined as business processes by organizational, technological, hierarchal and other bonds, and a combination of organizational units. The structure of mining companies can be seen as being static and dynamic. A dynamic structure comprises technological processes determined by the organization of mining works, a working system, and mining technology. A static structure comprises technological processes infrastructure and includes a group of organizational units connected by their operation's specific standards and procedures. The definition of the type of structure of a mine considers the mine's organizational structure and hierarchy (Kudelko, 2016). Although, the mining industry employs only 1% of the global labour force, it generates 8% of all fatal accidents.

Risk assessment and risk management are becoming more necessary in regulations governing worker health and safety worldwide. Codes of practice have been produced in the European Economic Community and Australia to include risk assessment as part of the process in areas such as plant safety and hazardous chemical storage. The Australian coal mining sector began investigating the application of more systematic

safety engineering fifteen years ago to minimize the industry's highly unacceptable injury and death rates. The regulatory agencies and the coal mining sector both expressed interest simultaneously, with the regulators giving information on safety and risk management and the industry launching a research initiative to study and test the ideas.

Since its early beginnings, risk assessment and management, frequently utilizing system safety principles, has been a fundamental element of coal mining in eastern Australia. Some of the associated measures have aided in reducing the lost time injury frequency rate (LTIFR) in Australian coal mining from pre-1988 site levels of up to 200 LTIFR to current levels of 20 and, in some cases, closer to 5. The current trend is encouraging, prompting all mining companies to feel that single-digit LTIFRs are possible.

2.2.5 The mining environment in the context

Minimising risk and hazards are of great importance to the mining industry globally. The mining industry generates 8 percent of fatal accidents globally, although it only employs 1 percent of the entire global workforce. Risk management and risk assessments have become a means to an end in regulating the health and safety of workers globally. Codes of practice must include management of risks by implementing risk assessments to increase underground mining safety, plant safety, and storage and use of hazardous chemicals safely (ILO.org, 2021).

The Australian Coal mining industry started implementing systematic safety engineering around 20 years ago to decrease the number of accidents and fatalities. As a result, some of the safety initiatives of coal mining in Australia have reduced the LTFIR from 200 in 1988 to less than 20 currently (ILO.org, 2021).

2.2.6 Lower grades deposits of minerals

It is commonly accepted that most of the best ore grades have been mined previously, and now only lower grade ore remains to be mined, and the rate of exploration and new high-quality ore that is found is declining rapidly. The decline may be true in, for example, the case of petroleum. Still, in most minerals, a shift to lower-grade ore mining resulted from improvements in metallurgical technologies that can now convert previously sub-economic ore into economically viable ore. Another fact is that low-cost extraction technologies can now extract higher volumes of low-grade ore. The new technology sorts ore selectively, and older mines life of mine can now be extended, which cuts the cost of exploration of new mines. (Rötzer & Schmidt, 2018).

2.3 HISTORY – MAJOR SHIFTS

2.3.1 Industrial revolution (1st Industrial Revolution)

The first industrial revolution started in England in the late 18th century at around 1760 and continued until 1840. The industrial revolution saw the move from animal and human labour to the use of machinery, iron production and chemical production processes, steam power, improvement of the efficiency of water power, and the development of machine tools. The Industrial Revolution's core driving force was the textile and iron industry (Ashton, 1948).



Figure 2-7: An assembly line, Ford Motor Company

Source: History.com

2.3.2 The Second Industrial Revolution

In the Second Industrial Revolution (1870 to 1914), tremendous leaps and strides were made to advance technology, manufacturing, and industrial production methods. A great deal of these advancements was made in the United States. The production of steel (i.e. the Bessemer process that produced cost-effective steel) and electricity brought about mass production. These advancements brought forth a railroad network spanning the United States, which established cities. The increase in factory output, and the invention of the telegraph and later the telephone, cars, and radio broadcasting would change the face of American history and ultimately the history of the world (Longley, R., 2021)

2.3.3 The Third Industrial Revolution

The development and exploitation Of Digital Technology was the core foundation of the

third industrial revolution. With the creation of the transistor in 1947, the seed was sown for digital technology to start evolving. Computers were already used as early as the 1950s by militaries, governments, and many organizations. Personal computers were introduced into society as early as the 1970s. By the 1950s and 1960s, many governments, military forces, and other organizations had already used computers. Soon after, the personal computer was introduced for household use, and by the 1970s, many families had computers for personal use. The introduction of Digital technology created a new job market; for example, businesses that integrated digital record-keeping needed data entry clerks. The digital integration into businesses grew as far as the film industry in the 1980s, the introduction of Automated Teller Machines (ATM).

The analogue mobile phone made way for the digital mobile phone, introduced in 1991. In 1991 the internet saw the light of day, which connected the world. Mobile phones were commonplace by the start of the 21st century, and high-definition television was the most popular broadcast medium. By 2015, 50 per cent of the world had access to constant internet connectivity. The possession of smartphones and tablets by 2015 has almost exceeded the ownership of personal computers. Storage of data has increased to terabyte volumes and was made easily accessible, which paved the way for the fourth industrial revolution (Pariona, A., 2017)

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2.3.4 The Fourth Industrial Revolution

Klaus Schwab the executive chairman and founder of the world economic forum (WEF) coined the phrase The Fourth Industrial Revolution (4IR). The Fourth Industrial Revolution is characterised by the emergence of technology domains such as biotechnology, nanotechnology, the invention of new materials and advanced digital production technologies (ADP) such as 3D printing, Human Machine Interfaces (HMI's) and artificial intelligence (AI). The introduction of ADPs into the industrial production process gave rise to Industry 4.0, also known as the Smart Factory. The Smart Factory learns as it produces, adapting and optimizing its processes continuously (Pariona, A., 2017).

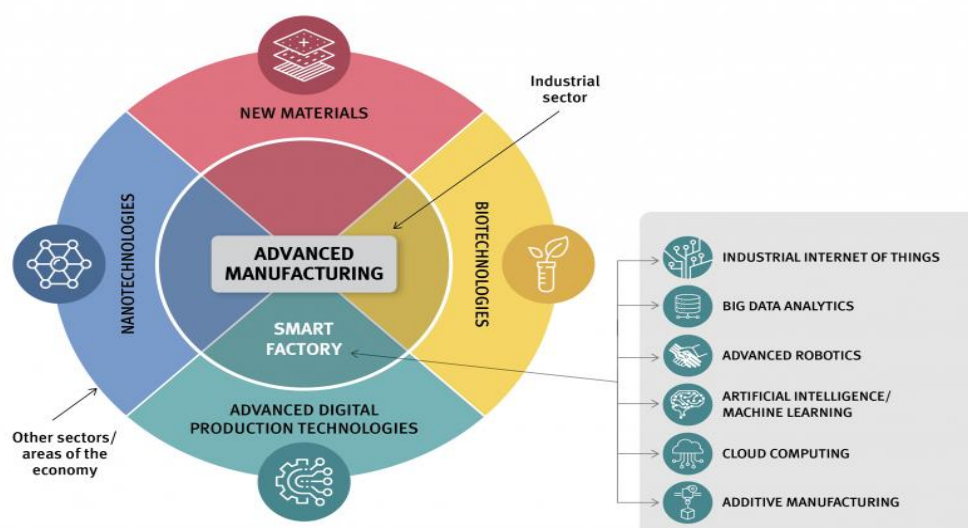


Figure 2-8: Advanced manufacturing

Source: UNIDO Industrial Development Report, 2020.

2.3.5 AI and ML's introduction into mining

AI and ML became more prevalent around ten years ago in the mining industry using autonomous trucks. Autonomous technologies, Machine Learning, and Artificial Intelligence provide many benefits to the mining industry, for example, cost reduction by operating more efficiently and effectively, keeping workers out of harm's way, utilizing machines in hazardous environments, and increasing productivity. However, there are some drawbacks in any scenario, such as the financial expenditure of implementing the AI and ML systems (Hyder *et al.*, 2019).

2.3.6 Machine learning

Learning is the acquisition of new knowledge, enhancing or updating an individual's existing knowledge (Bavakutty, 2006) (Jordan & Mitchell, 2015). The scientific study of statistical models and algorithms performed by computers completing a specific task is called machine learning. Machine learning algorithms build a mathematical model based on sample data, known as training data, to make predictions or decisions without explicitly programming to perform the task (Bishop, 2006) (Jordan & Mitchell, 2015).

Machine learning is an evolving branch of computational algorithms designed to emulate human intelligence by learning from the surrounding environment (el Naqa & Murphy, 2015). In the era of Big Data, Machine learning can be seen as a workhorse. Machine Learning has been applied in various disciplines with great success, for example, in the

engineering of spacecraft, computer vision, biometrical applications, the medical field, and finance. Machine Learning's processes are applied with varying degrees of complexity and, on occasion, involve human-machine interaction, which assists in decision making. As a result, machine learning algorithms can now make a better decision whereby processes can be optimized and automated (el Naqa & Murphy, 2015).

2.3.7 Benefits and costs of Machine Learning

Benefits:

There is an endless number of benefits to Machine Learning. To name a few would be:

- The automation of numerous business processes
- Improvement and continuous learning of business processes
- Efficient handling of data
- Simplifies time-consuming documentation in data entry
- Increases Efficiency of Predictive Maintenance in the Production and Manufacturing Industry

Cost:

For machine learning to be successful, a model must be deployed. Machine learning has to make viable business sense, and for it to make sense, ML has to engage models that change and interact with business processes. The immediate or long-term requirements of the deployment of an ML model may not be evident until you are well into the project (Coop, 2021).

There are different phases by which other companies approach the implementation of ML systems. For example, Discovery & Analysis Phase, Data Collection and Preparation Phase, Prototype Implementation and Evaluation Phase, Minimum Viable Product (MVP), Product Release, Maintenance and Support. All these phases have a cost related to them. For example, to deploy the most basic system for the first five years, as quoted by Robbert Coop, 2021 will cost in the vicinity of R 900,000.00. Implementing such a system when it does not scale over time will lead to performance issues and be redundant soon. Therefore, a scalable framework must be built to support activities in the future, and a fair cost for implementation would be R 1,500,000.00 (Coop, 2021).

2.3.8 Artificial intelligence

Intelligence is the ability to create, to memorize, to think, to understand, to imagine, and recognize patterns, to make choices to adapt to change and to learn from experience

Artificial intelligence (AI) is the integration of physiology and computer science. Intelligence in simple language is the computational part of achieving goals in the world (Poole & Goebel, 1998). Artificial intelligence can also be described as programming computers to have human characteristics and doing the tasks humans do in much less time (Poole & Goebel, 1998).

2.3.9 The Benefits of using AI in mining

Artificial intelligence benefits mining companies by assisting them to overcome challenges that could previously not be achieved, have an exceedingly high price tag to it or would be too time-consuming. For example, ai helps simplify ore extraction by detecting ore deposits and identifying potential promising deposits. Data of these potential areas can be analysed, and the algorithms from ML can be used to focus on these areas. (Allerin.com., 2021). Another example of the beneficial attributes of AI is in the optimization of transport. In modern-day mining, an autonomous truck transports materials from the rock face. Ai can work out the most efficient routes and the optimal speeds by which energy/fuel efficiency can be attained. An example is Rio Tinto, which has reduced its operating cost by 13 percent using autonomous trucks (Allerin.com., 2021).

2.3.10 Employee safety

By analysing data from AI, hazardous working environments can be forecasted. AI sensors can help stop moving Trackless Mobile Machines (TMM) equipment when danger is sensed, for example, the Pedestrian Detection System (PDS) used at Impala and various other mines. Another example is the Belton tripping device; it trips the conveyor belt if it senses irregularities any many more devices, which increases human safety. These raise the safety standard in the mining industry.

2.3.11 Reducing the ecological impact

AI helps reduce the energy demands of mines and decrease mines' ecological and environmental footprints. AI devices can monitor ecological parameters like groundwater and temperature to help evaluate the impact of mining activities (Allerin.com., 2021).

2.3.12 Ethics

For decades, one of the sciences of artificial intelligence goals has been to create artificial agents capable of interacting harmoniously with people and other systems. The computing research community developed artificial agents capable of performing tasks involving cognitive mechanisms such as planning, decision-making, and learning. Nowadays, the application domains of such software agents are apparent. Unmanned cars, intelligent dwellings, and humanoid robots capable of caring for people are examples of artificial agents in the human environment. Therefore, research in machine ethics has become more than a hot topic in this setting. Machine ethics is concerned with developing ethical procedures that will allow artificial agents to engage in moral action. However, there are still significant obstacles to developing genuinely Artificial Moral Agents.

2.3.13 AI and ML adoption into mining

AI and ML complement each other. Even slight increases in yields, speed, and efficiency can significantly impact an industry like mining, where efficiency and productivity are critical to profitability. Mining firms primarily generate interchangeable commodities (Marr, 2021).

2.3.14 Mineral exploration

Mining companies may use artificial intelligence and machine learning to locate minerals to extract, which is an integral part of any intelligent mining operation. Even though this is a relatively new application of AI and machine learning, it has piqued the interest of many mining corporations (Marr, 2021).

2.3.15 Autonomous vehicles and drillers

While many of us have been focused on the advancements made by Uber, Google, and Tesla in the field of autonomous cars, many people are unaware that Rio Tinto has been employing autonomous haul trucks capable of carrying 350 tonnes and operating entirely independently since 2008. These vehicles have helped the company save money by cutting fuel consumption by 13% and are safer to drive (Marr, 2021).

2.3.16 Sorting minerals

To find the valuable commodities being mined for, the bulk of mining operations must remove a substantially more significant volume of material. Separating the unwanted rocks and debris from the valuable minerals is invariably an expensive endeavour. As a result, some businesses have begun to employ smart sorting devices that can sort mined material according to whatever criteria they desire. This effort may result in fuel and energy savings during processing (Marr, 2021).

2.3.17 Digital twinning

Rio Tinto is building an intelligent mine that will deliver its first ore by 2021 as part of its efforts to make pit-to-port operations as intelligent as feasible. The corporation is studying more than 100 ideas, including one program dubbed digital twinning, which was first developed by NASA and adopted by many in the industrial sector. Scenarios can be promptly tested, and operations and production may be optimized, thanks to creating a virtual model that is fed real-time data from the field. Better outcomes and cost savings result from the capacity to test decisions before they are implemented in a replica system (Marr, 2021).

2.4 GLOBAL PERSPECTIVE ON ML AND AI IN THE MINING INDUSTRY

2.4.1 Uses of AI and ML in mining

- **Mineral exploration**

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- **Sorting minerals**

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- **Safety and maintenance**

Mining equipment can be monitored and maintained before faults occur thanks to Internet of Things technologies and sensors. Sensors can track temperature, speed, and vibration on machines, allowing predictive maintenance to take place. Mining operations can be made safer for everyone involved by analysing real-time data and analytics (Marr, 2021).

2.4.2 The Benefits of integrating AI

- **Profitability**

Aside from safety, another concern that emerges with conventional preventative maintenance is expense. Conveyors and slurry pumps, for example, have been engineered with redundancy at an extra expense so that "replacement parts" are accessible in the event of a breakdown. Furthermore, the high cost of downtime might have a significant impact on income for mining businesses; our customers have told us that unforeseen downtime costs three times as much as scheduled downtime.

Companies can reduce unplanned downtime by forecasting and mitigating asset performance issues and enhancing equipment effectiveness utilizing AI software in their operations. The benefits of autonomous and predictive maintenance for this industry are significant right now. With the potential for a double-digit decrease in maintenance costs and a 10% boost in production, it's no surprise that prominent mining firms are focusing on digitalizing maintenance procedures (Stridiron, 2020).

- **Productivity**

Organizations can analyze multiple operations in the current operation and discover critical areas for development by combining AI with mine monitoring technologies. Sensors in mining can provide a wealth of data that AI can use to better analyze mining operations (Analytics India Magazine, 2018). Process Enhancement To increase efficiency and effectiveness, assisting in the optimization of the value chain in the

organization process of extraction, processing, and sales through collaboration and coordination among diverse departments. Implementation of e-procurement by a consortium of 15 mining businesses from around the world that do global internet business to business (B2B) for procurement saves money by 5% to 15% . (Mura, 2019).

- **Safety**

The bulk of mining applications require a massive cluster of sensors to gather data about machines, but only machine learning algorithms can organize and apply the insights in real time. They can use historical equipment data, the environment, weather, and current events to predict when a machine requires maintenance or is about to fail (Analytics India Magazine, 2018). One area where digital technology has lately become a potential to add value to the mining processing industry is the ability to function efficiently with minimal human interaction and forecast errors before they cause downtime or asset degradation (Stridiron, 2020).

According to the Occupational Safety and Health Administration (OSHA), unplanned downtime or machine breakdowns account for more than 20% of all incidents in the industry. Many of the 80% of accidents that occur during routine maintenance are caused by a lack of subject matter expertise, a lack of a preliminary diagnostic before accessing the equipment, and poor work procedures (Stridiron, 2020).

2.5 BARRIERS TO ADOPTION

2.5.1 Knowledge and understanding

The mining industry can use innovation to address some of its most urgent issues. The finite nature of minerals and metals in bedrock, as well as challenges with lower-grade new deposits that are often difficult to access, frequently in geographically inaccessible places (Kurkkio et al., 2014), necessitate the use of innovative technology such as sensors and advanced analytics. In the mining industry, there are areas of highly inventive activity; for example, equipment providers are considered active innovators (Bladier, 2016; Deloitte, 2016). However, the mining industry has a long history of being associated with a conservative culture that is resistant to change, while others focus on structural impediments to innovation, such as high capital intensity (Bartos, 2007).

Because artificial intelligence (AI) is a relatively new idea in the mining business, the industry has yet to properly grasp what it entails and how to apply it. The notion of AI, according to Jean-Jacques Verhaeghe, programme manager for real-time information management systems at Mandela Mining Precinct, is very broad (Ali & Rehman, 2020).

He went on to say that there doesn't appear to be a unified vision throughout the sector. As a result, a board-level digitization journey must be plotted out and drawn up extremely clearly, methodically, and consciously (Ali & Rehman, 2020).

Due to the complicated nature of mining processes and the extraordinarily long lead time involved in creating and altering any type of mining equipment, the mining sector has been reluctant to adopt machine automation technologies in comparison to other industries (Bellamy & Pravica, 2011).

2.5.2 Upfront cost

It is critical to invest in and train the proper workers in order to reach digital maturity. "The secret is policy innovation and adopting technology with minimal disruption to the workplace without increasing the cost of business, and also without increasing the cost of consumer goods at the end of the line," said Jean-Jacques Verhaeghe, programme manager for real-time information management systems at Mandela Mining Precinct. Ali and Rehman (Ali & Rehman, 2020).

2.5.3 Translation of insights from AI are often not clear to managers

The findings show that most organizations still have a long way to go in building the key procedures that will allow them to realize AI's immense promise at scale Figure 2-9. Only 17% of respondents claim their firms have mapped out where all potential AI opportunities are located across the organization. Only 18 percent of respondents said their firms have a clear strategy in place for obtaining the data needed for AI to function. Indeed, roughly a quarter of those polled said their organizations haven't implemented any of the 11 best practices we inquired about (Mckinsey, 2021).

Few organizations have adopted the core practices that would enable them to realize AI's potential value at scale.

Core AI practices in place at organizations,¹ % of respondents

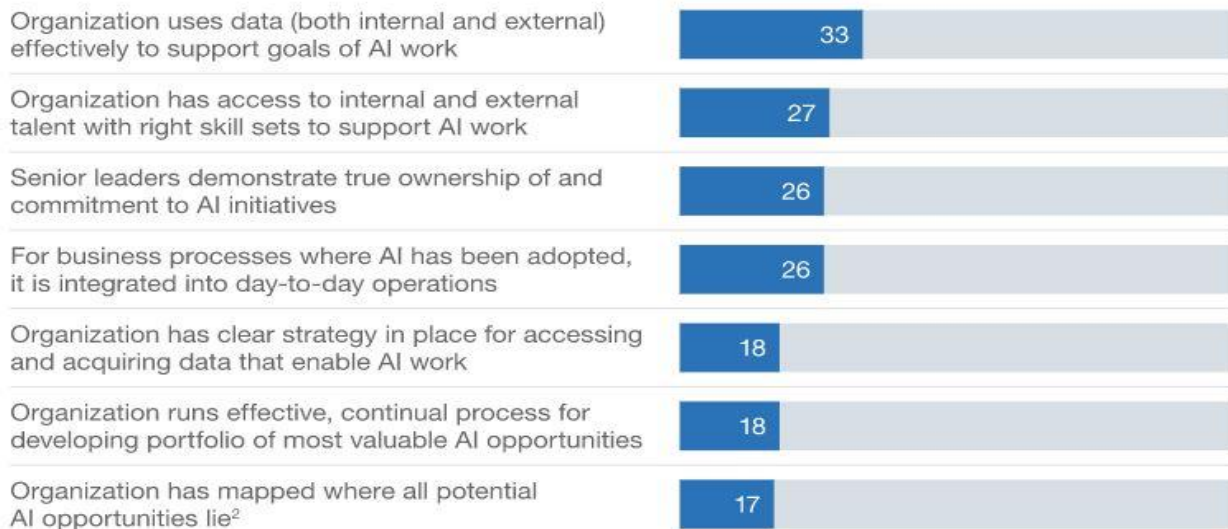
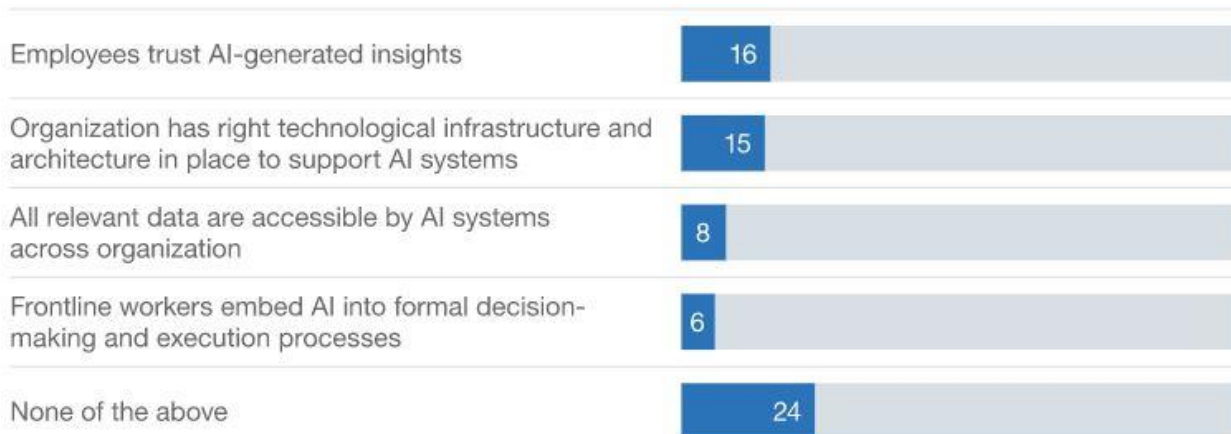


Figure 2-9: Core AI practices in place at organizations

Source: McKinsey 2020



¹This question was asked only of respondents who said their organizations have piloted or embedded AI in 1 or more functions or business units, and they were asked to select all practices that are in place. Respondents who said "don't know" are not shown; n = 1,646.

²Including required level of investment, difficulty of implementation, and potential value at stake.

McKinsey&Company

Figure 2-10: Core AI practices in place at organizations

Source: McKinsey 2020

2.6 ETHICS OF AI

When we speak of ethical issues of AI, there tends to be an implicit assumption that we are speaking of morally bad things. And, of course, most of the AI debate revolves around such morally problematic outcomes that need to be addressed. However, it is worth highlighting that AI promises numerous benefits. As noted earlier, many AI policy documents focus on the economic benefits of AI that are expected to arise from higher levels of efficiency and productivity. These are ethical values insofar as they promise higher levels of wealth and wellbeing that will allow people to live better lives and can thus be conducive to or even necessary for human flourishing. It is worth pointing out that this implies certain levels of distribution of wealth and certain assumptions about the role of society and the state in redistributing wealth in ethically acceptable manners which should be made explicit. The EU's High-Level Expert Group on AI makes this very clear when it states:

"AI is not an end in itself, but rather a promising means to increase human flourishing, thereby enhancing individual and societal well-being and the common good, as well as bringing progress and innovation." (Stahl, 2021).

2.7 USES OF AI AND ML IN MANAGEMENT AND ORGANISATION

The question of how to structure organizational decision-making—that is, where, when, and how to make and integrate decisions involving groups of people—has long been a central problem in organizational theory and microeconomics. The process of picking the alternative that is likely to result in the most favored outcome, as defined by Herbert Simon, is known as rational decision-making. Identifying and cataloguing the options, estimating their implications, and comparing the accuracy and efficiency of each of these outcomes are all part of this process. Organizations can be thought of as "networks of decisions" that must be organized in order to achieve organizational objectives. Delegating choices to specialists or pooling the decisions of a group of individuals—choosing the best effective decision-making framework has significant implications for organizational success (Shrestha et al., 2019).

While the difficulties of creating decision-making frameworks involving human actors are well-known, the recent advent of artificial intelligence (AI) algorithms adds a new set of hurdles to this age-old topic (Shrestha et al., 2019). AI and, in particular, machine learning algorithms, enable the production of new information and predictions from data

by synthesizing robust patterns from vast data sets (provided that the future can be fairly well predicted by existing data). The promise of quick, precise, repeatable, and low-cost judgments with quality approaching human intellect has been a major driving force behind AI's rapid advancement (Shrestha et al., 2019).

Indeed, experts in a variety of fields, such as medicine (e.g., surgery allocation), psychological counseling (e.g., therapeutic conversational agent), human resource management (e.g., hiring decisions), banking (e.g., credit risk predictions), science (e.g., astronomy), transportation (e.g., self-driving vehicles), public administration (e.g., immigration decisions), and legal counseling (e.g., bail decisions), are increasingly relying on AI (Shrestha et al., 2019).

2.8 OVERVIEW OF AI AND ML IN MINING

According to Accenture's research, which was conducted in cooperation with the World Economic Forum (WEF) in 2017, a combination of seven digital initiatives can assist the mining industry in South Africa generate ZAR213 billion (\$14 billion) in value by 2026. Businesses may unlock ZAR153 billion (US\$10.2 billion) of this in the form of cumulative top and bottom-line gains. Meanwhile, society can benefit from ZAR60 billion (US\$4 billion) in cost and time savings for customers, increased productivity, new jobs, and lower carbon emissions. Accenture conducted a separate poll of 30 local mining executives in 2019 to assess how South African mining businesses are handling digital transformation and the impact of their digital investments. South African mining businesses are investing millions of rands in new technologies such as augmented and virtual reality (AR/VR), drones, robots, self-driving vehicles, and artificial intelligence (AI), according to their poll (Accenture.com, 2021).

South African mining companies are investing in AI and machine learning to meet two key objectives:

- unlocking incremental value-creation opportunities by productively and safely extracting the country's mineral resources at the lowest possible cost; and
- building more resilient businesses capable of quickly recouping losses resulting from economic distress or business disruption.

However, when we looked at their technology choices in relation to the value generation opportunity, we discovered some startling results. According to our research, mining businesses in South Africa are likely to miss out on more than a third of the value creation

opportunity (Accenture.com, 2021).

According to Laura Cornish of Microsoft South Africa, the company is collaborating with its partner ecosystem and customers to demonstrate the power of technology, particularly AI (artificial intelligence) and cloud technologies, in assisting the mining industry in accelerating digital transformation and uncovering solutions through the adoption of new technologies (Miningreview.com., 2021). In early September 2020, Microsoft will open its Mining Core - AI Centre of Excellence for Mining facilities in Johannesburg, South Africa (Miningreview.com., 2021). The Mining Core, which is the first of its kind in the country, leverages Microsoft's extensive partner ecosystem to enable customers to immerse themselves in emerging technologies to build and create solutions that not only address specific business challenges but also enable the mining sector to reimagine new and better ways of working, drive sustainable recovery, and transform mining communities (Miningreview.com., 2021).

2.9 SOUTH AFRICAN PERSPECTIVE ON AI AND ML IN MINING

South Africa's mining industry is still the backbone of the country's economy. Traditional underground gold and platinum group metals mines, on the other hand, have been struggling to stay viable due to a number of issues, including rising operating costs, fluctuating commodity prices, increased mining depth, and poor occupational health and safety performance.

Modernization of the South African mining sector has the potential to increase the sector's viability (via increased productivity, mining efficiency, and occupational health and safety), drive economic growth, and create jobs. As a result, the mining industry aspires to anticipate and adopt technological developments, as well as to comprehend the ramifications (especially in terms of skill supply and demand) and develop appropriate countermeasures. The Mining Qualifications Authority hired the CSIR to look at the expected scope of technological innovation and its implications in the mining industry (CSIR.co.za., 2021).

The following priorities were determined for the medium and longer terms:

- Process improvement.
- Mechanization.
- Remote-controlled mining.

- Autonomous mining.
- Local power generation.
- Robotics; and
- Sensor-based real-time information management systems.

2.9.1 Mine modernization

Lack of skills, money, adequate change management, strategic visioning in planning, and the adoption of improved systems thinking methodologies are all key problems. Sustainable modernization necessitates coordination among all key mining stakeholders, as well as government initiatives and incentives, particularly in terms of labor, education, and training policy. The importance of innovation in mining modernization cannot be overstated. It ensures the evolution of safety, health, and environmental stewardship, for example, through the development of new processes and technology. Innovative solutions, if properly implemented and disseminated, can boost operational efficiency and productivity. This includes the creation of strategic and relevant competencies (skills, expertise and infrastructure). It is the mining industry's responsibility to discover ways to improve the socioeconomic standing and conditions of the communities it supports (CSIR.co.za., 2021).

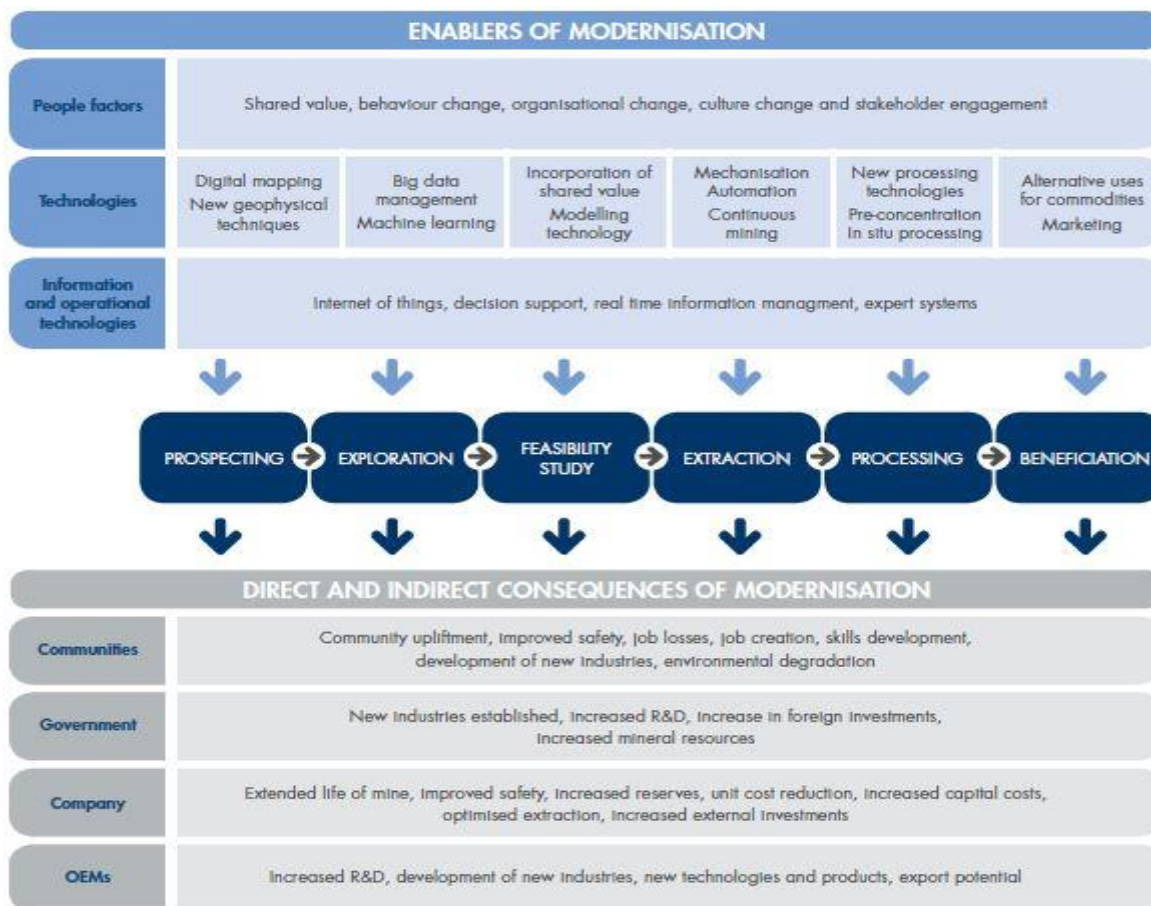


Figure 2-11: Enablers of modernisation

Source: Enabling activities for modernisation components across the mining value chain and potential direct and indirect consequences of modernisation (Ngobese, 2019).

For more than a century, the South African mining industry has been regarded as a labor-intensive business that relies on physically demanding manual drilling operations, as well as stop-start blasting and cleaning, primarily in narrow reef, hard-rock mining for gold, platinum, and chrome. Abrasive rock, high grades, and seismicity are the most common working conditions. The temperature of fresh rock continues to climb as you go deeper. The temperature of virgin rock at depths of 2,000 meters below the surface in the Witwatersrand Basin, which is home to the world's greatest gold deposit, can reach 40°C. Temperatures on the Bushveld Complex, which contains 80 percent of the world's platinum reserves, are much higher, reaching 70°C (Mineralscouncil.org.za., 2021).

Most deep-level underground mines are now old, and transit times to the face can take an hour or more. As a result, as the depth and distance from the shaft have increased, actual drill time at the workplace has decreased, posing more health and safety risks, reducing production, and adding to rising expenses. Increasing costs and lower

productivity have worsened the recent price volatility (Mineralscouncil.org.za., 2021). Modernization will aid in the pursuit of zero harm by improving safety and health. It will also help to boost skill development, employment, exports, and revenue, not to mention the impact on local communities. Without a change in mining methodology, the industry will be unable to profitably extract South Africa's deep-level complex orebodies. This could lead to resource sterilisation, mining closures that are rushed and premature, and job losses. According to Jacobs et al., 200,000 job losses by 2025 might effect 2,000,000 people indirectly (Jacobs *et al*, 2016).

Spiraling labor and energy costs are putting a strain on the financial performance of South African gold mines, but integrating digital technologies could be the answer. The majority of these new technology solutions concentrate around automation, which is made possible by the convergence of several technologies, including artificial intelligence and robots. Operators can remove underground personnel from harm's way by using automation, and this will become an increasingly important requirement if gold miners are to remain (or rather, become) investable by international capital (Mining Indaba, 2019).

The mining automation market is growing as a result of the increased focus on the safety of the employees and mines. Previously, old-style exploration and drilling practices jeopardized the safety of mine workers. Operators have been pushed to design smart resolutions and methods to ensure worker safety as a result of such situations. Rio Tinto's Mine of the Future program, for example, is focused on developing innovative methods for extracting minerals from deep beneath the Earth while decreasing environmental consequences and increasing safety (Mining Indaba, 2019).

Technology is one of the four fundamental pillars for success, according to a new McKinsey research titled "Putting the Shine Back on South African Mining." Employee safety, performance management, and visibility can all benefit from it. "Companies can supply linked gadgets that can communicate real-time data on jobs, work plans, and progress reports," according to the research (Mining Indaba, 2019).

The report cites the example of a worldwide mining business that gave its underground workers linked tablets and saw a ten percent increase in output. Other instances include the use of remote operation centers to monitor and manage the performance of

continuously working automated drills, minimizing downtime and boosting both performance and safety (Mining Indaba, 2019).

The mining value chain has always been the foundation of South Africa's economy. It directly contributes more than 300 billion rand to the country's GDP, employs over 450,000 people, and serves as the economic backbone of many towns. Unfortunately, much of the recent news about mining in South Africa has been negative. In the last ten years, total mining employment has decreased by around a tenth, resulting in a net loss of more than 50,000 jobs. Furthermore, according to a McKinsey report, the productivity of South African mining operations for major commodities has decreased over the last five years, despite substantial productivity advances in other regions (McKinsey, 2021).

Unless the South African mining industry improves its cost effectiveness, the country's fortunes could plummet even further. According to McKinsey's analysis, 47 percent of South African mining jobs, as well as 42 percent of revenue, are in the bottom quartile of global cost competitiveness. Global developments such as the shift to renewable energy and China's economic focus shifting away from infrastructure building and toward new technologies could depress demand for South African mining commodities in the coming years (McKinsey, 2021).

Put the shine back into South African mining

Face up to a challenging context

Global trends

- Clean energy scale-up impacts demand for commodities, e.g., coal and platinum
- Changing investor profile favours new commodity mix
- China's changing economic focus impacts demand for, e.g., iron ore
- Technology advances about to scale – can SA mining keep up?

Mining lags well behind other industries on digital maturity



Local factors

- High volatility exposure – both currency and commodity mix
- Declining productivity – while all other regions are improving
- Risky cost position – 42% of SA mining revenue and 47% of jobs in bottom quartile of global cost-competitiveness



Embrace four paths to competitiveness and growth



Figure 2-12: Putting the shine back into South African Mining

Source: ("Putting the shine back into South African mining: A path to competitiveness and growth | McKinsey," s.a.)

2.10 THE RESEARCH GAP

Artificial Intelligence and Machine Learning might be the key to operating future profitable mining operations in the global and South African arena. The effect on productivity and the ease and acceptance in mining operations have not yet been greatly explored. This study aimed to research the impact that AI and ML have had since being implemented in the mining industry.

2.11 CHAPTER CONCLUSION

South Africa's mining industry is still the backbone of the country's economy. However, due to several issues, such as rising operating costs, shifting commodity prices, increased mining depth, quality of ore deposits, and poor occupational health and safety performance, traditional underground gold and platinum group metals mines have struggled to remain profitable.

Modernization of the South African mining sector has the potential to increase the sector's viability (via increased productivity, mining efficiency, and occupational health and safety), drive economic growth, and create jobs (CSIR.co.za., 2021). Plainly stated the backbone of the South African economy (mining) which is a labour-intensive operation has run into difficulty operating and keeping the mining industry viable. Production has declined during the past twenty years as experienced globally due to a number of facts, whereby operating at optimal effectiveness and efficiency is crucial for survival and advancement of current mining operations.

3 CHAPTER THREE: RESEARCH METHODOLOGY

3.1 CHAPTER INTRODUCTION

This study was done to determine the impact of artificial intelligent systems on productivity at a mine in the Rustenburg area and more specifically at Impala Platinum Mine's Concentrator Plant. The study aims to show the impact that the Integration of AI and ML has had over the past ten years, the ease of use as perceived by the users/ operators, and the impact it has had on productivity.

A quantitative approach was adopted using a questionnaire issued to 52 respondents. The questionnaire is based on a questionnaire previously compiled by Shaun Enslin (2009) and formatted to address the research problem. The respondents form a representative view of the personnel at the Concentrator plant varied between, operators, supervisors, assistants and a broad spectrum of respondents. The levels of education, age, gender, and ethnicity were also broad, improving the sample reliability.

3.2 RESEARCH METHODOLOGY

3.2.1 Empirical study

Research paradigms are defined as a shared understanding of reality. It is viewed as being objective in that everything around us has meaning and an impact on our lives (Chilisa & Kawulich, 2012). A research paradigm is a shared worldview representing convictions and qualities that aid how problems are settled (Bryman & Bell, 2011). A pragmatic research paradigm will be used in this study.

The researcher chose a research philosophy that will follow a positivist research paradigm/ approach for the reason that a positivist approach believes that there is one central truth and that it is measurable. The positivist paradigm of social reality exploration is based on the premise that observation and reason are the best ways to explain human behavior. To put it another way, science can only be founded on objective, observable facts (Nel, 2016).

The researcher has opted to take a deductive approach in this research, whereby he can test ideas and explore what has occurred in the field based on previous data. The deductive research method investigates a well-known theory or phenomena and determines whether it is valid in specific conditions. "The deductive approach most closely follows the route of logic," it has been said. Starting with a theory, the logic leads to a new

hypothesis. This theory is put to the test by having it confronted with observations that either corroborate or refute the hypothesis." (Schneider, *et al* 2009:16)

The study will use a quantitative data collection method. The differentiation between qualitative and quantitative approaches is that quantitative research is based on measurements of amount or quantity, and qualitative research is based on behavioural sciences. To prove the point and the effect that artificial intelligence has made since its introduction into the mining industry, quantitative data gathering, will be used to gather measurements that are needed through questionnaires.

The collection of numerical data is referred to as Quantitative research. Quantitative research has an objectivist view of social reality, prefers a natural science method, and believes that theory and research are inextricably linked. (Bryman & Bell, 2011).

Quantitative techniques derive knowledge from post-positivist assumptions, with an experimental or quasi-experimental inquiry strategy. Closed-ended questions, performance, attitude, observations, and census data are among the planned approaches. The research is based on statistics. In the practices of testing or verifying theories or explanations, identifying variables to study, evaluating variables in questions or hypotheses, using standards of validity and reliability, numerically observing and measuring information, using unbiased approaches, and employing statistical procedures, quantitative approaches are used (Bryman and Bell 2007, Creswell 2009, Saunders et al.).

The researcher chose to do cross-sectional research, and by this it means that the researcher did not return to the Impala multiple times to assess it, but only did an initial sample at the mine. A cross-sectional survey gathers data to make assumptions about a target population (universe) at a specific point in time. Cross-sectional surveys are regarded as snapshots of the populations they collect data about (P. Lavrakas, 2013).

3.2.2 Questionnaire design

The quantitative data was collected through the use of questionnaires in answering the research questions. The questionnaires will derive their information from the research questions and will be so structured so that the data used that was extracted from the questionnaires could answer the research questions. This questionnaire used in this

research is modified and based on a template previously used by Shaun Enslin in his 2009 dissertation at NWU. The questionnaire is comprised of four sections, section A to D. Section A provides multiple eleven questions on demographic variables, to gather information on gender, age, ethnicity, marital status, etc.

Section B has eight questions that follow a Likert scale approach. A Likert scale is used in data representation, where one indicates the candidate strongly disagrees and five indicates the candidate strongly agrees. In this case, the Likert scale tests how the respondents feel that Artificial intelligence impacted their working environment in the past 10 years. Section C has seventeen questions on the ease of use of Artificial Intelligence and in specifically on the less literate individuals. Section D has seventeen questions focussing on how artificial intelligence influenced productivity on the mine.

The questionnaire was imported at the Potchefstroom Campus into the IBM SPSS Statistics Version 27 (Questionnaire Analysis Software SPSS,2020) used to import the findings of the questionnaires and then calculate the given information. Consent was given to use the questionnaire template. The format of the template was used and the questions were adapted to suit the current research. When information is gathered from the questionnaires the Statistical Consultation Services of the NWU was approached to assist with the analysis and interpretation of data.

3.2.3 Study population

The population is employees working at Impala Platinum mine and specifically the Concentrator. Of these, 52 individuals (permanent employees, and contract workers) were selected as the sample size. The sample consists of General Assistants, Artisans, Supervisors, Site Managers, and Foremen that work with equipment managed by Artificial intelligence. The focus will be on Impala Platinum in the Rustenburg area.

3.2.4 Data collection

The data collection method will be done through a questionnaire compiled by the researcher. The questionnaire focused on addressing the research questions stated by the researcher. The questionnaire was distributed at Impala Platinum Operations near Rustenburg at the Concentrator Plant. At the Concentrator at Impala, approval was obtained by approaching top management. All permissions and actions were documented to keep a record of what has been done to gain approval. The researcher

works at the Concentrator at Impala and distributed the questionnaires at the location with permission.

A letter of consent was written and sent to both the General Manager and Human Resource Manager of the Impala at the Concentrator Plant. This was done to get approval to distribute the questionnaires and collect data from the relevant employees. Ethical aspects applicable to the study were thoroughly discussed with the respondents. All government regulations and safety procedures of Covid-19 were observed during issuing and collecting of questionnaires.

3.2.5 The process will be as follows

The Concentrator is part of a mining company (Impala Platinum) that currently has Artificial Intelligence and Machine Learning applications on the mine, for example partly autonomous trucks and remotely operated conveyor belts and Silos. Managers and relevant people in authority will be contacted to get permission to issue the questionnaires. Permission will be given in the form of written consent by the general manager, this is to give authorization to the researcher to continue with research. This also indicates that the researcher has been approved by the upper management to conduct research on-site.

After permission was given, the respondents were approached and asked if they would like to participate in completing a questionnaire. The respondents must have freedom of choice to reflect a true sample. Selection and approach of participants: Participants were selected on the involvement level they have with the equipment, in other words how frequently they work with or the extent to which the equipment/ technology impacts their working environment. The respondents/ candidates were fully briefed on the extent and content of the questionnaire and given the option to accept or decline participating in the study. The option to accept or decline gives the respondent freedom of choice, they can leave the questionnaire at any time, and their data will be anonymous.

To achieve an appropriate dataset, questions were focused on themes identified beforehand. When the respondents have completed the questionnaire, it was collected by the researcher. Once collected the questionnaire was sent to the NWU Statistics Department for processing. The statistics department does a scientific analysis not accessible to the researcher. The processed information received from the NWU

Statistics Department can now be used as information to complete the dissertation. A document was compiled and if requested copies of the questionnaire and findings will be given to the relevant companies/ persons.

3.2.6 Statistical analysis

First and foremost, descriptive statistics were calculated, frequencies for the demographics, reliability assessments were done on three scales, the scales are impact, user-friendliness, and productivity. The descriptive statistics of these three scales were taken namely the sum of the mean value, of all of the questions in each scale and then provided the descriptives. Lastly, a T-Test was done to compare the scores for impact, user-friendliness, and productivity between individuals 39 years and younger and 40 years and older. The researcher is testing that variable calculated for differences between age groups with a T-Test. The statistical analysis discusses the demographic variables. These variables were analysed by calculating the frequencies (Section A) and percentages.

The instruments that were used are:

- Reliability: using Cronbach Alpha (Concise)
- Sum/ Average of Scales/ Instruments: based on Shaun Enslin's template.
- Descriptive statistics: the Mean, minimum, maximum as well as Standard Deviations.

3.2.7 The Validity of the measuring instrument

Validity relates to a research instrument's ability to measure what it promises to measure, according to Cooper and Schindler (2006:318) and Leedy and Ormrod (2010:92). Three frequently accepted classes can be found in the above-mentioned classifications. Classifications are divided into three categories:

- *The content's reliability.*

To what extent does the content of the items accurately represent the universe of all relevant objects under investigation?

- *The adequacy of linked criteria, as well as*

The extent to which the predictor captures the criterion's key properties

- *The material's content construct's validity.*

Answer the question, "What accounts for the measure's variance?" by attempting to identify the underlying construct(s) being measured and determine how well the test represents them in response to the question "What accounts for the variance in the

measure?" (them). It is critical that the information acquired remains accurate. This document will not include any data that is corrupt or cannot be trusted. Before being included in the findings, the data submitted from the respondents will be checked for validity.

3.2.8 Reliability of the measurement instrument

The term "reliability" refers to whether a measurement is trustworthy in the sense that it produces consistent results (Diamantopoulos & Schlegelmilch, 2006:34; Leedy & Ormrod, 2010:93). If a measure is not dependable, it cannot be valid, according to Diamantopoulos and Schlegelmilch (2006:34), but if it is reliable, it may or may not be valid. To put it another way, a valid measure is also trustworthy, while the opposite is not always true. Instruments that are reliable are resilient and perform well at different times and under varied conditions. This contrast between time and condition is the foundation for commonly used dependability views, such as internal consistency, stability, and equivalence.

Table 3-1: Summary of reliability estimates

Type	Coefficient	What is measured	Methods
Test-retest	Stability	Reliability of a test or instrument inferred from examinee scores.	Correlation
Parallel forms	Equivalence	Degree to which alternative forms of the same measure produce the same or similar results	Correlation
Split half, KR20, Cronbach's Alpha	Internal consistency	Degree to which instrument items are homogeneous and reflect the same underlying construct(s).	Specialized correlational formulas

Source: Cooper and Schindler (2006:322)

Cronbach alpha (α) was used by the researcher to measure the reliability of a measuring device. Cronbach alpha estimates the average of all feasible split-half dependability coefficients, according to Bryman and Bell (2007:164). The estimated alpha coefficient ranges from 1 (one) to 0 (zero), with 1 denoting excellent internal dependability and 0

denoting no internal reliability (zero). The rule of thumb is that a figure of 0.80 indicates an acceptable level of internal reliability; however, other authors accept a slightly lower figure of approximately 0.75. According to Eiselen and Uys, and Potgieter (2005:114) the closer the alpha value (α) is to 1 (one), the more dependable the scale's internal consistency is.

According to Cooper and Schindler (2001:218), the following procedures can be done to improve reliability:

- Reduce external causes of variance.
- standardize measuring circumstances; and
- expand the sample of measurement questions by including similar questions in the data collection instrument.

Values of 0.5 will suffice in the early stages of study (but interpretation should be made with caution). However, reliability estimates of 0.8 are generally deemed acceptable, whereas values of less than 0.6 are considered unsatisfactory.

3.3 CHAPTER CONCLUSION

The purpose of this chapter was to explain a method to be followed when doing quantitative research on the given sample (52 respondents). The research method was done to create knowledge and understanding about the social environment of the respondents. Social scientists, including communication scholars, employ quantitative research to examine phenomena or occurrences that affect humans. The study of people is what social scientists are interested in. Quantitative research is a method of learning about a specific group of people, referred to as a sample population. Quantitative research, which is based on scientific inquiry, uses data that is observed or measured to investigate questions about a sample population.

4 CHAPTER FOUR: DISCUSSION OF THE RESULTS

4.1 CHAPTER INTRODUCTION

In this chapter, the results obtained from the NWU statistical department will be discussed. The four sections namely Demographics, Impact of AI and ML over the past ten years on the mining industry, User Friendliness, and Productivity were tested and the results discussed.

The questionnaires were distributed by hand to the supervisors/ managers of the relevant departments, mainly concerning respondents directly affected or dealing with AI and ML in the field. All 52 questionnaires were received back and completed in full. The Descriptives, Cronbach Alpha, and t-Test were done on section A, B, C, and D are discussed in this chapter.

4.2 QUESTIONNAIRE RESPONSES

Table 4-1: Questionnaire statistics

Response type	Frequency	Percentage
Number of questionnaires distributed	52	100.00%
Number of questionnaires returned	52	100.00%
Number of questionnaires discarded	0	0%
Number of questionnaires analysed	52	100%

The following represents the information received from the questionnaires handed out to respondents. Section A determines the demographic orientation of the respondents. Section B relates to the research question “What was the impact of artificial intelligence on mining operations in the past ten years at specific mining houses?”. Section C relates to “How “user friendly” is the machinery if some of the operators may be illiterate?”. Section D’s questions are related to the research question “What processes or steps need to be taken to run a more efficient mine?”.

4.3 DEMOGRAPHICS

Question A01 to Question A11 determines to which demographic sector each respondent belongs to information such as gender, age, ethnicity, marital status, number of

dependants, highest qualification, employment status, management level, years working for the company, and years working in the current position at the company was gathered to determine the different types of respondents. Question A11 tries to indicate that the respondent has a tendency toward technology.

4.3.1 Question A01: Indicate your gender:

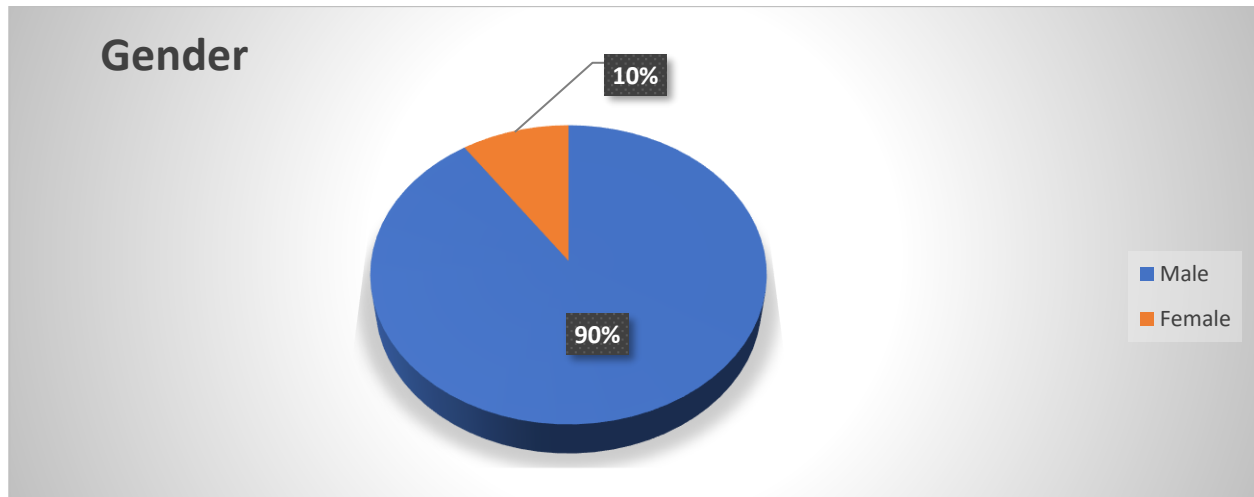


Figure 4-1: Gender

The majority of respondents are Male. To be exact 90.4% of the respondents ($n = 47$) is male, and 9.6% of the respondents ($n = 5$) is female. The representation of males in the operations side of the mining industry in South Africa is common and is reflected in the sample.

4.3.2 Question A02: Indicate your age group:

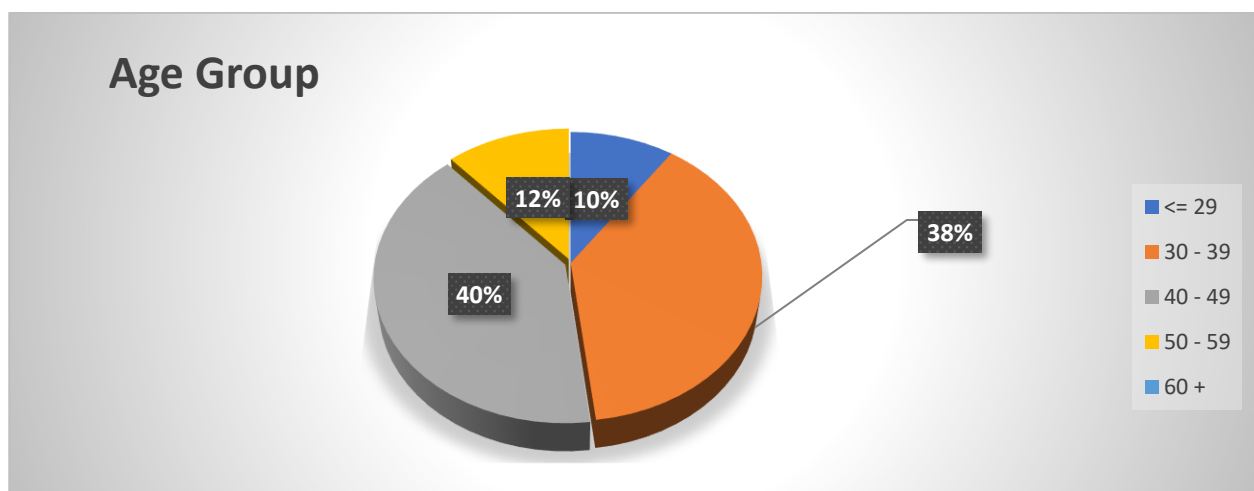


Figure 4-2: Age group

Close to half of the respondents who completed the questionnaire are younger than 40 years of age. Respondents at age ≤ 29 accounts for 9.6% ($n=5$) of the data gathered,

respondents aged 30 to 39 years of age account for 38.5% (n = 20), together these two age groups amount to 48.1 % of the sample. The remaining 51.9% comprises respondents aged 40 years and older. Respondents aged between 40 and 49 years account for the biggest part of the sample at 40.4% (n= 21), and the remaining part of the sample aged at 50 to 59 years of age account for 11.5% (n = 6).

4.3.3 Question A03: Indicate your ethnicity

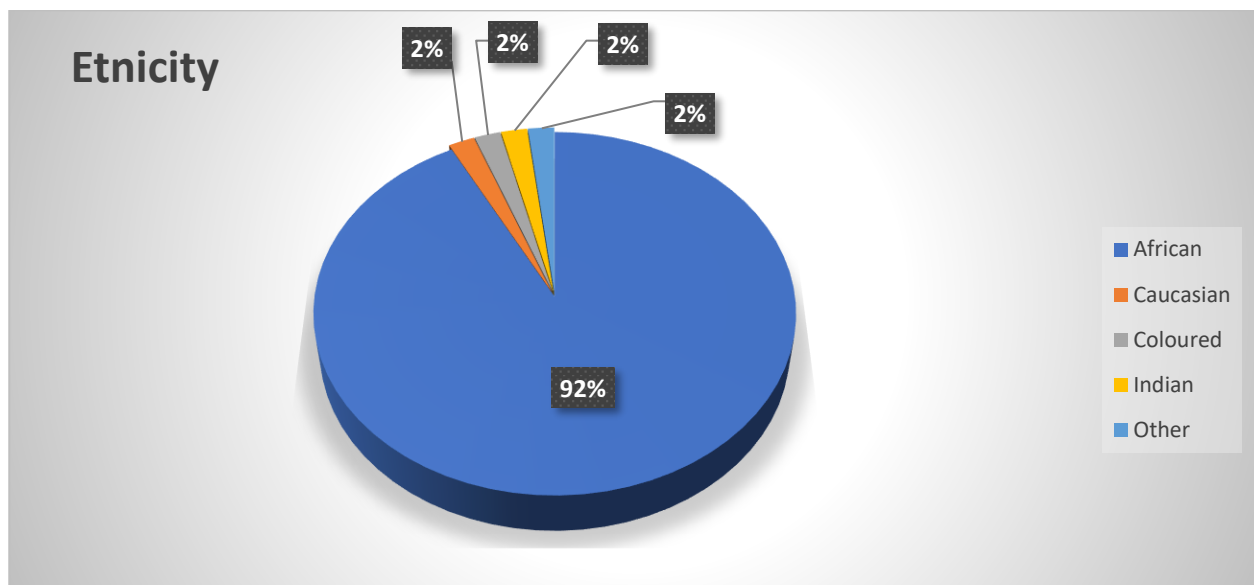


Figure 4-3: Ethnicity

The majority of respondents belong to the African ethnicity group. The sample reflects what is current in the mining industry in South Africa 92.3% (n = 48) of the sample is African. The minority of the sample Caucasian Coloured and Indian each respectively accounted for 1.9% (n = 1) of the sample. Another 1.9% chose the “Other” option of the questionnaire.

4.3.4 Question A04: Marital Status

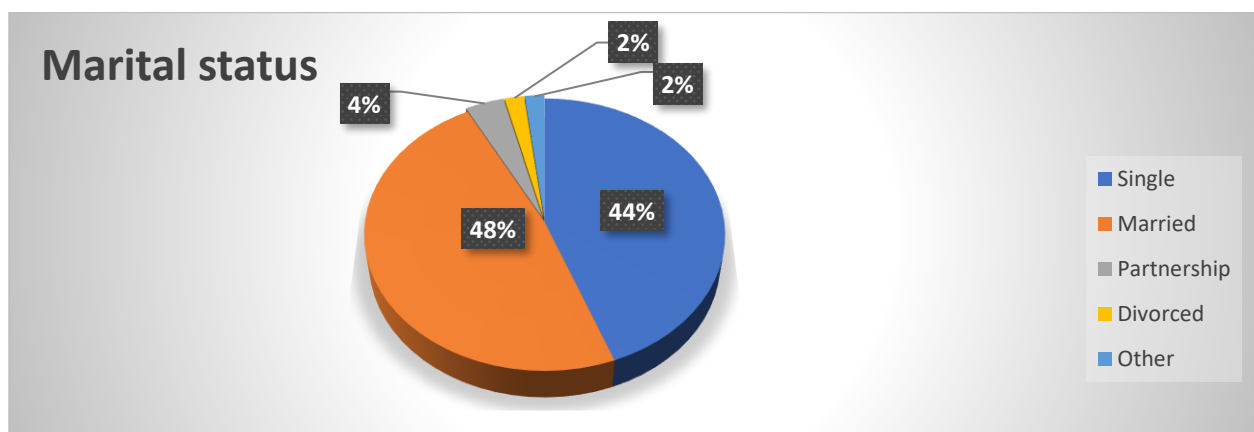


Figure 4-4: Marital status

The respondents are almost split in half by their marital status. Close to half of the respondents 48.1 % (n = 25) are married. Another 44.2% (n = 23) are single. A smaller part of the sample 3.8 % (n = 2) of respondents' form part of a Domestic Partnership / Committed Relationship. The remaining 3.8% (n = 2) comprise of Divorced respondents 1.9% (n = 1) and the "other" option 1.9% (n = 1).

4.3.5 Question A05: How many dependants do you have

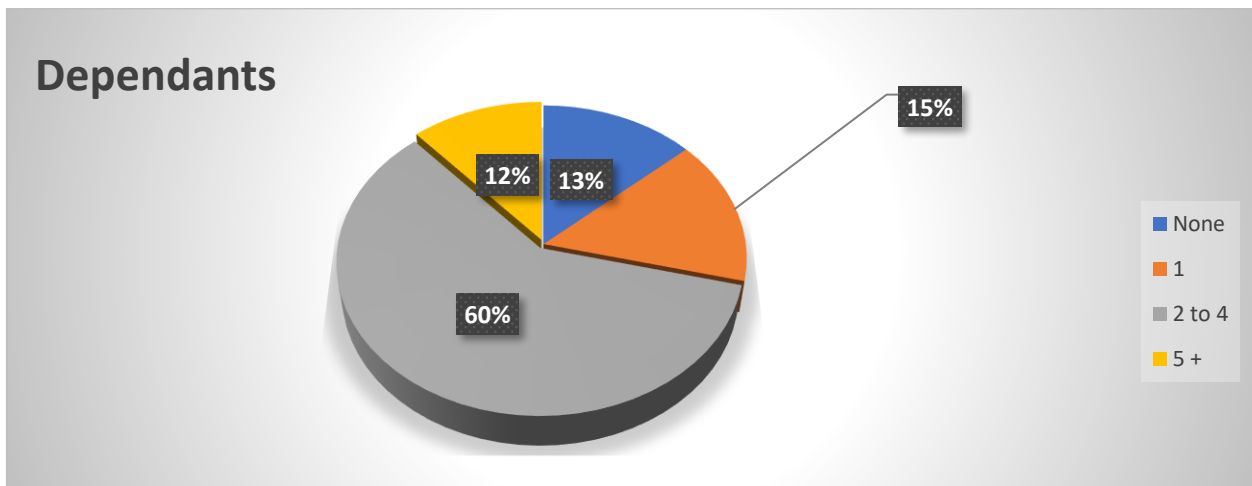


Figure 4-5: Dependents

Most of the respondents have two to four dependents which account for 59.6 % (n = 31) of the sample. Another 15.4% (n = 8) of the respondents only have one dependent. Respondents who have 5 or more dependents are 11.5 % (n = 6) of the sample, and the remaining 13.5 % (n = 7) of respondents have no dependents. In the previous sample (Marital Status) it was noted that 44% of the sample were single, yet in this statistic 87% of the sample has one or more dependents, indicating despite being single the respondents have someone to look after.

4.3.6 Question A06: Indicate your HIGHEST qualification

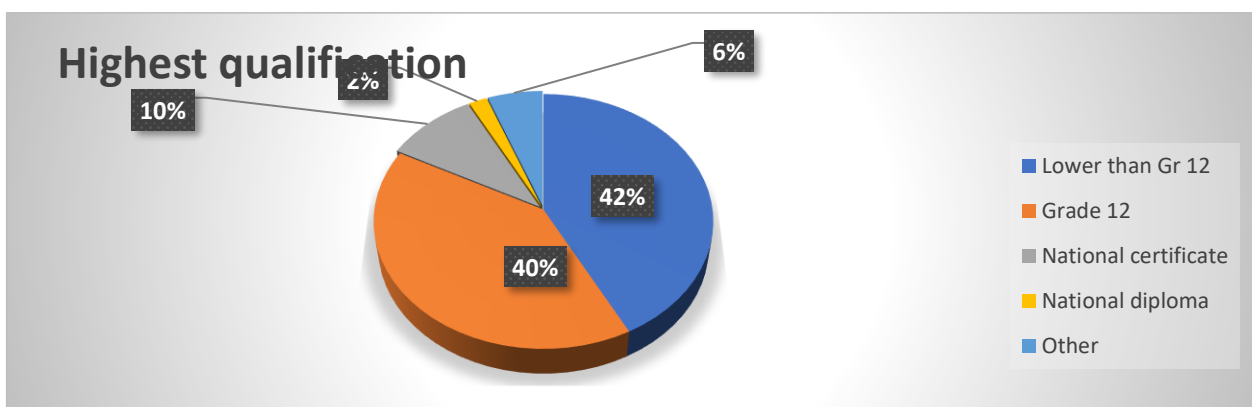


Figure 4-6: Highest qualification

The majority by far 82.7 % (n = 43) of all the respondents' highest qualification is Grade 12. Of that 82.7 %, the majority 42.3 % (n = 22) does not have a Grade 12 certificate. Another 40.4 % (n = 21) has a Grade 12 certificate. The remaining 17.3 % (n = 9) of the respondents are divided into 9.6 % (n = 5) which has a National Certificate, 1.9 % (n = 1) which has a National Diploma and 5.8 (n = 3) % which is classified as “Other”. This is representative of the mining industry that the majority of non-managerial positions have grade 12 or less.

4.3.7 Question A07: Your current employment status

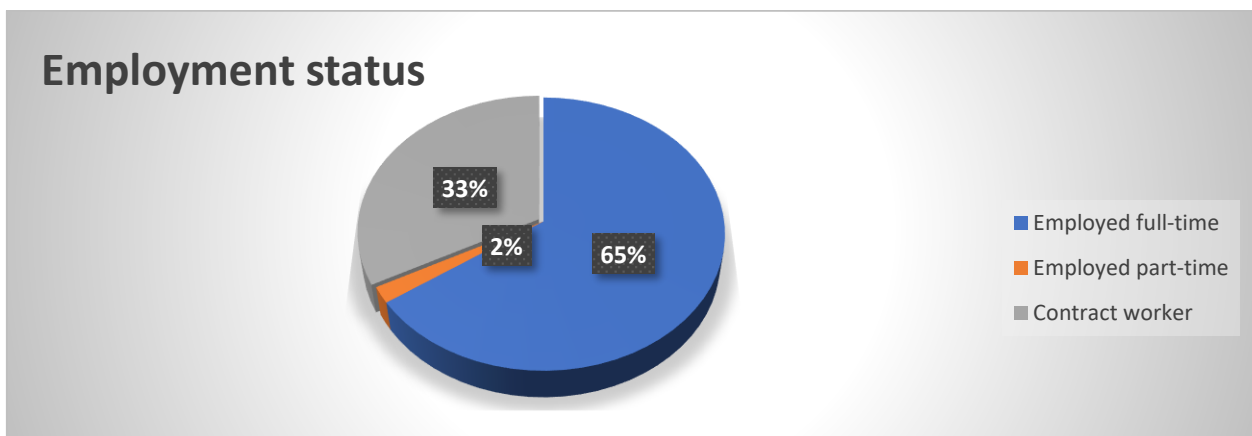


Figure 4-7: Employment status

Most of the respondents 65.4 % (n = 34) are full-time employees. Contract workers account for 32.7 % (n = 17) of respondents, and the remaining 1.9 % of respondents are employed part-time. Impala Platinum Mine at the Rustenburg Concentrator employs 864 people of which 274 are contractor company employees. The 274 contractor company employees are roughly one-third of 864 total employees at Impala Rustenburg Concentrator. In the sample, it is evident that the contractors form roughly a third of the Concentrator employees.

4.3.8 Question A08: Management level

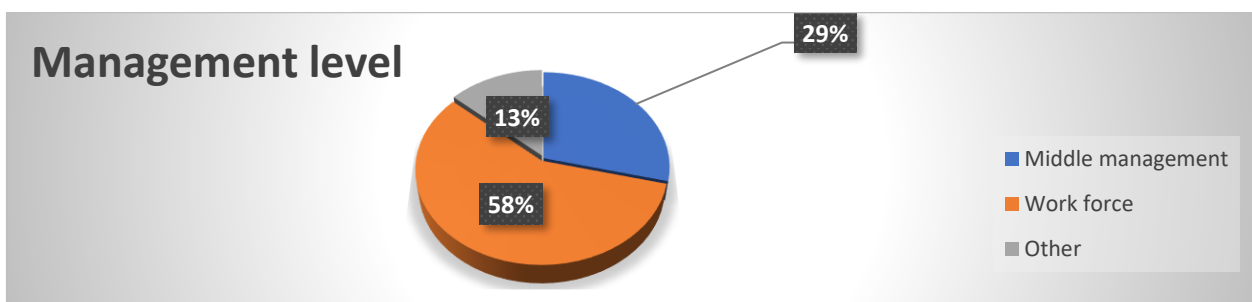


Figure 4-8: Management level

Most of the respondents 57.7 % (n = 30) comprise the workforce (Cleaners, general workers, technical assistance, reception, etc.). Middle management accounts for 28.8 % (n = 15) which consists of Supervisors, Technicians, team leaders, officers, etc.). Another 13.5% (n = 7) identified as “Other” which may be specialists, consultants, or an occupation not listed in the questionnaire.

4.3.9 Question A09: Years working in the company

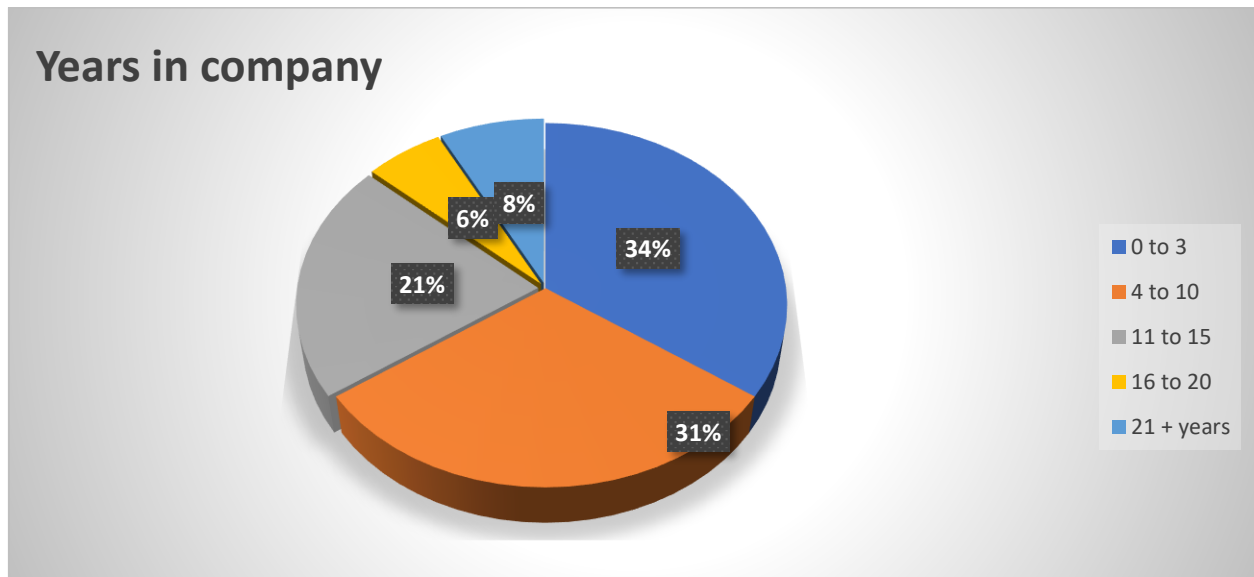


Figure 4-9: Years in the company

Most of the respondents 65.4 % (n = 34) work at their company for at least ten years . Another 34.6 % (n = 18) of the respondents are employed with their company for three years or less. Some 30.8 % (n = 16) of respondents are employed with their company for four to ten years. Another 21.2 % (n = 11) of employees work at their company for 11 to 15 years. Of the sample, 5.7% (n = 3) of respondents worked at their company for 16 to 20 years, and the remaining 7.7 % (n = 4) respondents are employed at their company for more than 21 years. Mineworkers typically move from one employer to another if the remuneration is better. This may account for the majority of the sample working at their company for less than ten years.

4.3.10 Question A10: Years working in the current position

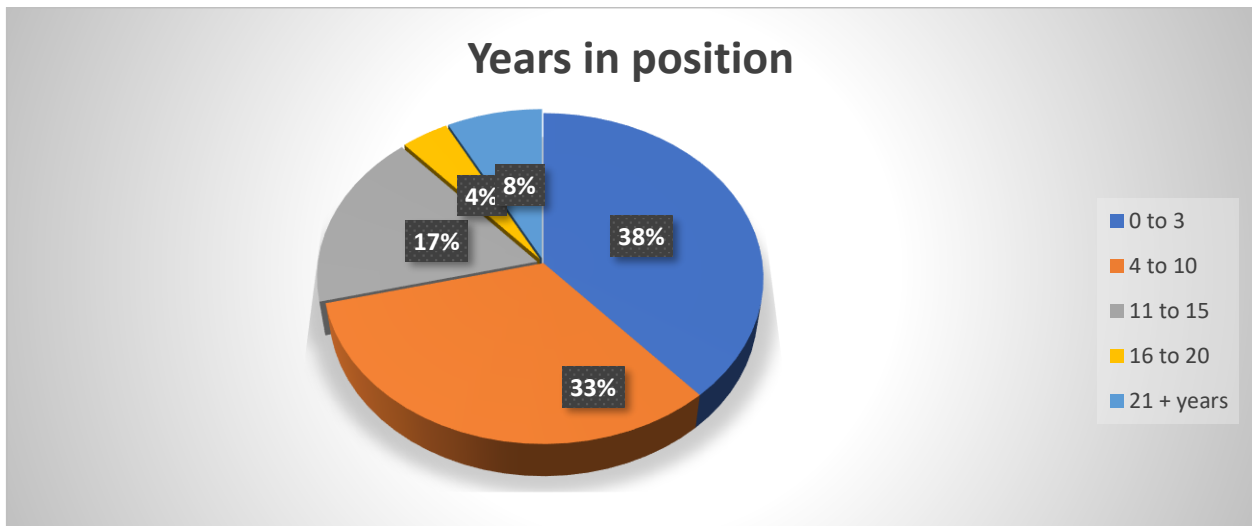


Figure 4-10: Years in the position

Respondents who work in the same position for at least three years in the position account for 38.5 % (n = 20) of respondents, and 32.7 % (n = 17) account for employees working in the same position for four to ten years. Employees in the same position for 11 to 15 years amount to 17.1 % (n = 9) of the respondents, and 3.8 % (n = 2) are employees working in the same position for 16 to 20 years. The remaining 7.7 % (n = 4) are in the same position for 21 and more years.

4.3.11 Question A 11: Do you own a smartphone?

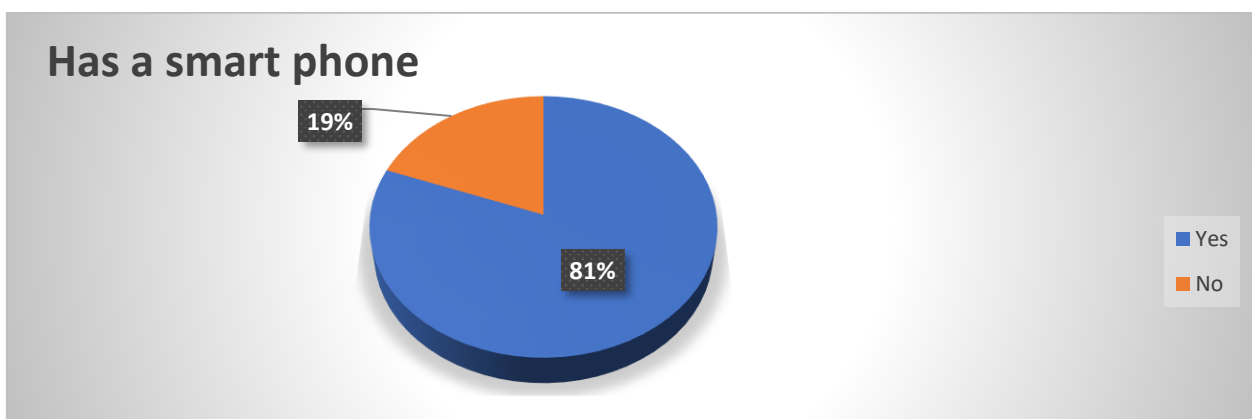


Figure 4-11: Do you own a smartphone

Most of the respondents 80.8 % (n = 42) own a smartphone. The remaining 19.2 % (n = 10) respondents do not own a smartphone. However, 19.2% of the sample remain a significant amount of people not having a smartphone. The reason for this does not seem to be affordability because smartphones nowadays are rather inexpensive. The study

does not delve deep into this finding, but it may show that people do not see technology as user-friendly.

4.4 SECTION B, C, AND D:

4.4.1 Descriptives

In Section B broadly speaking the researcher observed that primarily there was an agreement with the means ranging between 3.79 (SD = 0.78) – 4.10 (SD = 0.69), the minimum scores varying from one (1) to maximum scores of five (5). Overall, the researcher found strong support of agreement in the majority of “Impact over 10 years” questions.

Assessing Section C the researcher observed that broadly speaking the mean leaned more toward agreement, although the means ranged between 2.58 (SD = 1.18) – 4.08 (SD = 0.59) most of them were close to 4. This indicates that the majority of the sample has strong support of agreement toward the User Friendliness of Artificial Intelligence and Machine Learning which indicates that most of the respondents find AI and ML to be user friendly. Again, minimum scores vary from one (1) to maximum scores of five (5).

Section D’s statistic showed that primarily there was agreement. The means ranged between 3.77 (SD = 0.76) – 4.13 (SD = 0.63), with minimum scores varying from one (1) to maximum scores of five (5). Overall, the researcher found strong support of agreement in the majority of “Productivity” questions.

4.4.2 Cronbach Alpha

For items on the Likert scale, the Alpha coefficient approach (Cronbach, 1951) is a suitable option (e.g., 1-3, 1-4, 1-5) to test reliability. As a result, it is not restricted to true-false or correct-incorrect formats (Oncu, 1994). Cronbach's alpha coefficient is the weighted standard variations mean, which is calculated by dividing the total of the scale's k items by the general variance (Thorndike et al., 1991).

$$\alpha = \frac{n}{(n-1)} \left[1 - \frac{\sum_{i=1}^n \sigma_{y_i}^2}{\sigma_x^2} \right]$$

n : Number of the items

σ_{y_i} : i^{th} item's standard deviation

σ_x : General standard deviation

Figure 4-12: Cronbach Alpha calculation

Source: (Ercan et al., 2007)

For standardized items, the coefficient is determined using the correlation means of the items or the variance-covariances mean (Carmines & Zeller, 1982; Ozdamar, 1999a; SPSS, 1991; SPSS, 1999).

Calculation of alpha coefficient due to the correlation mean,

$$\alpha = \frac{n \bar{\rho}}{1 + (n-1) \bar{\rho}}$$

Figure 4-13: The correlation mean

Source: (Ercan et al., 2007)

Calculation of alpha coefficient due to the variance-covariance mean,

$$\alpha = \frac{n \overline{\sigma_{xx}} / \overline{\sigma_x}}{1 + (n-1) \overline{\sigma_{xx}} / \overline{\sigma_x}}$$

Figure 4-14: The variance-covariance mean

Source: (Ercan et al., 2007)

When the formula for calculating Cronbach alpha using correlation means between items is studied, it is clear that the number of items and the mean of the correlation between items is proportionally related (Carmines & Zeller, 1982).

The alpha coefficient will be negative if the correlation between the elements is negative. Because this condition ruins the scale's additive property, the reliability model is ruined, and the scale is no longer additive (Ozdamar, 1999a).

All the reported Cronbach Alpha values are above the guideline value of 0,7 as recommended by Field (2009) which indicates that the resulting factors are reliable and usable. The following questions were reversed scored before calculating the Cronbach Alpha values seeing they were phrased negatively: C04, C05, C06, C08 and C14. It should also be noted that D16 and D17 is highly correlated ($r = 0,842$) and therefore D17 was omitted from the factor.

Table 4-2: Constructs

Construct	Questions	Cronbach's Alpha	Mean	SD
Impact	B01-B08	0.893	3.99	0.57
User Friendly	C01-C17	0.813	3.64	0.48
Productivity	D01-D16	0.940	3.95	0.49

Looking at Section B “Impact” the mean score was almost 4 (3.99) and thus suggests agreement and the standard deviation is fairly small (0.57). Section C “User Friendliness” had a slightly lower score (3.64) still tending towards an agreement but a bit more neutral, also with a fairly small standard deviation (0.48). Section D “Productivity” trends toward agreement (3.95) with a fairly small standard deviation (0.49).

4.4.3 T-Tests:

A t-test is an inferential statistic that is used to determine if two groups differ statistically. It establishes the problem mathematically by assuming that the means of the two distributions are equal ($H_0: 1=2$). If the t-test rejects the null hypothesis ($H_0: 1=2$), the groups are extremely likely to be different (Fernandez.J. , 2020). The t-test never accepts the null hypothesis; it rejects or fails to reject it (Fernandez.J. , 2020).

4.4.4 p- Value:

The p-value or probability value is the probability of obtaining test results at least as extreme as the results observed during the test, assuming that the null hypothesis is correct.

The borders of the test's acceptance zone are defined by the critical values of a statistical test.

The p-value is a variable that allows us to reject the null hypothesis ($H_0: \mu_1 = \mu_2$) and prove that the two groups are distinct. We must compare the p-value to the critical value (α) because it is merely a number.

p value $> \alpha$ (Critical value): Statistical test fails to reject the null hypothesis.

p value $\leq \alpha$ (Critical value): Reject the statistical test's null hypothesis.

Most statisticians choose the value $\alpha = 0.05$ as their critical value. This means that If we repeat the experiment 100 times, we will be able to reject the null hypothesis 5% of the time and not 95% of the time. The following table is an example of the table used in this section to describe the information gained from the questionnaires done with a t-Test:

Table 4-3: Example of t-Test

1. Construct	2. Age group	3. n	4. $\bar{x}$	5. s	6. p	7. d
Impact	≤ 39	25	4.01	0.62	0.772	0.08
	≥ 40	27	3.96	0.53		

Column number:

1. Indicates the Construct used, in this case, "Impact".
2. The question is used for comparison.
3. The number of respondents per group.
4. The mean value of the specific group.
5. The standard deviation of the specific group.
6. Indicates practical significance of the differences between the means of the two groups being compared as well as the effect size: (p-value)
 - ≈ 0.2 Small, No practically significant difference
 - ≈ 0.5 Medium, Practically visible difference
 - ≈ 0.8 Large, Practically significant difference

Indicates if there is a statistically significant difference between the means (reported for completeness's sake but will not be interpreted since a convenience sample instead of a random sample was used).

4.4.5 The d-Values:

The d-values, also known as effect sizes, will be interpreted using Cohan's d-measurements as guidelines. These guidelines are lower than (d-value = 0.2) are not significant, results between (d-value = 0.29 - 0.49) are small, results between (d-value =

0.50 – 0.79) are medium and results higher than d-value = 0,80 are large (Gravetter & Wallnau ,2009:264).

Table 4-4: Age groups

Construct	Age group	n	$\bar{x}$	s	p	d
Impact	≤39	25	4.01	0.62	0.772	0.08
	≥40	27	3.96	0.53		
User Friendliness	≤39	25	3.83	0.52	0.007	0.68
	≥40	27	3.47	0.37		
Productivity	≤39	25	3.96	0.56	0.926	0.02
	≥40	27	3.94	0.44		

When the researcher looked at the t-Test he noticed non-significant differences for the “Impact” and “Productivity” factors between the two age groups. However, for the “User Friendliness” factor there is a significant difference between the age groups “39 and younger”, and “40 and older”.

The younger group (mean = 3.83, SD = 0.52) on average Agreed with the statements within this factor and the older group (mean = 3.47, SD = 0.37) on average leaned somewhat towards Neither agree nor disagree. This reflects that the younger age group found AI and ML implementation more user-friendly than the older age group.

Table 4-5: Qualification grouped

Construct	Qualification Level	n	$\bar{x}$	s	p	d
Impact	<Gr. 12	22	4.07	0.53	0.336	0.25
	≥Gr. 12	30	3.92	0.60		
User Friendliness	<Gr. 12	22	3.50	0.44	0.068	0.49
	≥Gr. 12	30	3.75	0.49		
Productivity	<Gr. 12	22	3.98	0.38	0.674	0.10
	≥Gr. 12	30	3.93	0.57		

When the researcher looked at the t-Test he noticed that between groups “Lower than Grade 12” and “Grade 12 and above” there are non-significant differences for the Constructs “Impact”, and “Productivity” factors. There is a practically visible difference when considering the “User Friendliness” factor. The “Lower than Grade 12” group (mean

= 3.50, SD = 0.44) on average leaned somewhat towards Neither agree nor disagree and the “Grade 12 and above” group (mean = 3.75, SD = 0.49) on average Agreed with the statements within this factor. This reflects that the groups with “Grade 12 and above” found AI and ML implementation more user-friendly than the other group.

Table 4-6: Employment Status grouped

Construct	Employment Status	n	$\bar{x}$	s	p	d
Impact	Full-time	34	3.90	0.63	0.116	0.37
	Part-time and Contract	18	4.14	0.42		
User Friendliness	Full-time	34	3.57	0.45	0.184	0.38
	Part-time and Contract	18	3.77	0.52		
Productivity	Full-time	34	3.88	0.54	0.132	0.37
	Part-time and Contract	18	4.08	0.38		

When the researcher looked at the t-Test he noticed that between groups “Full-time employment”, and “Part-time and Contract employment” there are small differences for the Constructs “Impact”, “User Friendliness”, and “Productivity” factors. There is a small practically visible difference when considering all the factors. The “Full-time” group, “Part-time”, and “Contract workers group on average leaned more towards Agreeing with the statement within this factor. This reflects that all the groups agreed that the “Impact”, “User Friendliness”, and “Productivity” had a positive effect on them.

Table 4-7: Years working in the company grouped

Construct	Years in Company	n	$\bar{x}$	s	p	d
Impact	≤3	18	4.08	0.62	0.429	0.23
	≥4	34	3.94	0.55		
User Friendliness	≤3	18	3.75	0.47	0.222	0.36
	≥4	34	3.58	0.48		
Productivity	≤3	18	3.99	0.48	0.679	0.12
	≥4	34	3.93	0.51		

When the researcher looked at the t-Test he noticed that between groups “Working in the company for at least 3 years” and “Working in the company for more than 4 years” there are non-significant differences for the Constructs “Impact”, and “Productivity” factors. When the researcher looked at the t-Test he noticed that between groups “Lower than Grade 12” and “Grade 12 and above” there are non-significant differences for the Constructs “Impact”, and “Productivity” factors. There is a small practically visible difference when considering the “User Friendliness” factor. The “Working in the company for at least 3 years” group (mean = 3.75, SD = 0.47) and “Working in the company for more than 4 years” group (mean = 3.58, SD = 0.48) on average leaned toward Agreeing with the statements within this factor. This reflects that both groups found AI and ML implementation slightly more user-friendly than the “Impact” and “Productivity” factors.

Table 4-8: Years working in the same position grouped

Construct	Years in Position	n	$\bar{x}$	s	p	d
Impact	≤3	20	4.08	0.59	0.351	0.27
	≥4	32	3.93	0.56		
User Friendliness	≤3	20	3.71	0.46	0.430	0.22
	≥4	32	3.60	0.50		
Productivity	≤3	20	3.98	0.46	0.777	0.08
	≥4	32	3.94	0.52		

When the researcher looked at the t-Test he noticed that between groups “Working in the same position for at least 3 years” and “Working in the same position for more than 4

years” there are non-significant differences for the Constructs “Productivity” factor. However, there were small differences for the groups “Working in the same position for at least 3 years” group (mean = 3.71, SD = 0.46) and “Working in the same position for more than 4 years” group (mean = 3.60, SD = 0.50) regarding “Impact”, and “User Friendliness”, and on average leaned toward Agreeing with the statements within this factor

4.5 THE SUMMARY OF THE MAIN FINDINGS

In section A of the questionnaire, the demographic representation of the respondents was determined. The following questions were asked, and their result noted:

Indicate your gender,

- The results regarding “indicate your gender” indicated that the majority of the respondents are male 90.4% (n=47), 9.6% were female (n=5).

Indicate your age group,

- The results regarding “Indicate your age group” showed that the majority of respondents were 40 years and older (n = 27) and the rest were 39 years and younger (n = 25).

Indicate your ethnicity,

- The results regarding “Indicate your ethnicity” showed that the majority of respondents belong to the African ethnicity group 92.3% (n = 48). The rest with each 1.9% belonged to the Asian, Caucasian, and Indian ethnic groups. Another 1.9% chose the “Other” option.

Marital status,

- The results regarding Marital status indicated that almost half 48% (n = 25) of the sample are married. Another 44.2% (n = 23) of the sample is single. The remaining 7.6% (n = 4) is divided by Domestic partnership respondents 3.8% (n = 2), a Divorced respondent 1.9% (n = 1), and a respondent who chose the option “Other” 1.9% (n = 1).

How many dependents do you have?

- The results regarding “How many dependents do you have” indicated that 59.6% (n = 31) have two (2) to four (4) dependents. Respondents who have one dependent account for 15.4% (n = 8) of the sample, respondents who have no dependents account for 13.5% (n = 7) of the sample, and the remaining respondents 11.5% (n = 6) have five (5) or more dependants.

Indicate your HIGHEST academic qualification,

- The results regarding “Indicate your HIGHEST academic qualification:” indicated that the majority 82.7% (n = 43) of respondents have at least grade 12 and lower. The remaining 16.3% of respondents are divided into 9.6% (n = 5) who have a National Certificate, 1.9% (n = 1) who has a National Diploma, and another 1.9% (n = 1) who chose the option “Other”.

Your current employment status,

- The results regarding “Your current employment status” indicated that the majority of respondents 65.4% (n = 34) are full-time employees, another 32.7% (n = 17) of respondents are contract workers, and the remaining 1.9% (n = 1) of respondents are employed as a part-time worker.

Management level,

- The results regarding “Management level” indicate that the majority of employees 57.7% (n = 30) are part of the workforce (Assistants, general workers, etc.), another 28.8% (n = 15) are middle management (Supervisors, team leaders, etc.). The rest of the sample comprises 13.5% (n = 7) which chose the option “Other”.

Years working in the company,

- The results regarding “Years working in the company” indicate that 65.4% (n = 34) work at their company for at least ten years and less. Another 21.2% (n = 11) employees work at their company for eleven (11) to fifteen (15) years, 7.7% (n = 4) work at their company for more than twenty-one (21) years, and 5.7% (n = 3) work for their company for sixteen (16) to twenty (20) years.

Years working in the current position,

- The results regarding “Years working in the current position” indicates that 71.2% (n = 37) are employed in the same position they were employed as for at least 10 years or less. Another 17.1% (n = 9) worked in the same position for eleven (11) to fifteen (15) years, 7.6% (n = 4) are working in the same position for twenty-one (21) or more years, and 3.8% (n = 2) works in the same position for sixteen (16) to twenty (20) years.

Do you own a smartphone?

- The results regarding “Do you own a smartphone” indicate that the majority of the respondents 80.8% (n = 42) own a smartphone, and 19.2% (n = 10) does not own a smartphone.

There were 52 respondents in total.

Reliability

Construct	Questions	Cronbach's Alpha	Mean	SD
Impact	B01-B08	0.893	3.99	0.57
User Friendly	C01-C17	0.813	3.64	0.48
Productivity	D01-D16	0.940	3.95	0.49

All the reported Cronbach Alpha values are above the guideline value of 0,7 as recommended by Field (2009) which indicates that the resulting factors are reliable and usable. The following questions were reversed scored before calculating the Cronbach Alpha values seeing they were phrased negatively: C04, C05, C06, C08 and C14. It should also be noted that D16 and D17 are highly correlated ($r = 0,842$) and therefore D17 was omitted from the factor.

4.6 CHAPTER CONCLUSION:

Demographical information was gathered from a broad spectrum of respondents that was a fair representation of the personnel working at the Rustenburg Impala Concentrator. The questionnaire also addressed questions pertaining to the Impact AI and ML have had on the mining industry over the past 10 years, the User Friendliness of AI and ML with respondents and more so respondents that are not that conversant with technology, and lastly the effect on Productivity at the mine.

Descriptives, Cronbach Alpha, and t-Test results were displayed via graphs and tables to create a better understanding of what was being discussed.

5 CHAPTER FIVE: CONCLUSION AND RECOMMENDATIONS

5.1 CHAPTER INTRODUCTION:

Mining productivity in general declined globally since the year 2000. It has increased slightly from the year 2009 to 2014 but has not regained the production levels before 2000. The need to run mines optimally and not just in certain departments can be of great value to marginally profitable mines. Another reason for the decrease in mining productivity is the depletion of high-grade ore. New mining technology has made it possible to mine these lower grade ore economically. That being said optimization is still necessary and especially in the detection of new ore reserves which can now be done with the aid of Ai and ML.

The primary objective of this study was to investigate the impact of artificial intelligent systems on productivity at a mine. The secondary objectives are to determine the effects of AI and ML on mining activities and to determine how the introduction of new technology has impacted the social environment of a mine. From the data gathered and processed, recommendations will be made on advancing efficiency in a particular mine.

The study followed a quantitative approach where questionnaires were handed out to 52 employees at the Impala Concentrator Operations at the Rustenburg plant. The Primary Research Question is, do AI and ML have an impact on mining productivity? The questionnaires also aimed to answer the secondary research questions namely:

- What was the impact of artificial intelligence on mining operations in the past ten years at specific mining houses?
- How "user-friendly" is the machinery if some of the operators may be illiterate?
- What processes or steps need to be taken to run a more efficient mine?

5.2 RESEARCH QUESTIONS RESOLUTIONS

5.2.1 Question 1: What was the impact of artificial intelligence on mining operations in the past ten years at specific mining houses?

Looking at chapter two there are several positive impacts on integrating AI into mining operations. Profitability is one of the aspects where for example AI can predict maintenance schedules so that a machine does not break down when production is critical. By not having machines break down regularly, mines can now have constant production schedules. In chapter four the feedback showed that question B07 and B08 in

the questionnaire regarding profitability is being positively received with the majority of respondents leaning toward the Agree option. This means that the respondents find AI helpful in managing systems to create a profitable mine. Productivity is another positive aspect that was noticed with the introduction of AI in the past 10 years in chapter two. Sensors used in machinery can give feedback to optimize processes and operations. AI can help in the managing of administrative systems, to ensure accountability for inflow and outflows of operational capital. In chapter four respondents had a positive response to productivity and can be seen in questions B01, B02, B04, and B06 leaning more toward the option Agree to Strongly Agree. Safety is an important factor that covers both profitability and production. If an employee/s gets injured, production may come to a halt. If no production, then profits decline. In chapter two's research can be seen that most accidents occur during unplanned downtime or machine failures. AI monitors machines and decreases downtime which in turn minimizes the accident rate/ probability. Fewer accidents equal more production equals more profit. In chapter four can be seen that respondents opted for Agreeing to lean toward Strongly Agree, which indicates that respondents feel that AI contributed to safety over the past 10 years.

5.2.2 Question 2: How "user-friendly" is the machinery if some of the operators may be illiterate?

In this research question, the most significant differences were noticed in the t-tests conducted. It clearly showed that the age group 39 years and younger experienced AI as being user friendly and the age group 40 years and older found AI as less user friendly. The p-value (0.007) indicated a significant difference between the age groups. This may be because the older group did not "grow up" and were not submerged into technology from a young age. As stated in chapter two regarding the third industrial revolution and the discovery of the transistor "The analog mobile phone made way for the digital mobile phone which was introduced in 1991. In 1991 the internet saw the light of day which connected the world. By the start of the 21st-century mobile phones were commonplace and high-definition television was the most popular broadcast medium. By 2015, 50 percent of the world had access to constant internet connectivity. The possession of smartphones and tablets by 2015 has almost exceeded the ownership of personal computers. the mobile phone only became an attainable asset to the greater public in 1991 and smartphones more recently flooding the market in 2015. This might explain the fact that older employees did not find AI very user-friendly, seeing that they did not grow up in a saturated technological environment.

5.2.3 Question 3: What processes or steps need to be taken to run a more efficient mine?

Chapter two clearly states that integrating AI with mine monitoring algorithms, organisations can analyse various activities in the current operation and identify key areas of improvement. Using sensors in mining can also provide plenty of data which aids AI for better interpretation of mining operations and by using AI software in the operations, companies avoid unplanned downtime by predicting and mitigating asset performance issues and increasing equipment effectiveness through machine learning and AI. The benefit available today for this industry, through autonomous and predictive maintenance, is enormous. With the double-digit potential reduction in maintenance costs and up to 10 percent increase in production, it is no doubt that leading mining companies are turning their focus to the digital transformation of maintenance processes. This indicates that mining can by structuring its processes, administration and operations achieve greater productivity and profits. In chapter 4 the majority of respondents Agree that AI contributes to productivity.

5.3 FUTURE RESEARCH

- This study was done on one mine and only on one plant of the specific mine. The comments given and feedback received is only limited to the specific mine and their personnel. A broader research design can be taken in researching more mines in South Africa to get a broader sample of what is happening in South African Mining.
- Mine management was not approached to participate in the studies. The researcher feels that valuable input in the form of one-on-one interviews with management can be gained in terms of gaps where AI and ML can give contributions, where ai and ML is currently applied in the applicable mine, and what are the costs of implementing such a system/s.
- What would be the demand for AI and ML in the current and future mining industry? Where can it deliver value in the value chain?
- At what cost can AI and ML be implemented and at what scale? Low code/ no code might be an option to start implementing AI and ML at a reasonable cost.

- Does mine management find it necessary to implement AI and ML as a total turn-key project in mining and what would the social barrier to entry be?

5.4 RECOMMENDATIONS

- A practical recommendation would be that as it is a requirement in most mines that employees should be trained in every task they do, for example when grinding metal, they should have grinder/ portable electrical tool training. In the same way, the suggests training companies or mining training departments should have training on AI and ML on their training matrix. Training employees enhance their effectiveness and efficiency in the workplace. It also makes them more confident at doing their tasks and in turn reduces accidents.
- Using Low Code is an easy, user-friendly, and very cost-effective way to implement AI and ML into mining. Employees can be easily trained, and literacy is not a deal-breaker. Using LC is as if you are playing a game, drag and drop, and you do not need to be literate to do that. However, most mines require that you must be able to read and write to be able to be employed with them. That being said training on low code should be cost-effective and a time saver.
- Seeing that AI and ML are the future of mining, as stated before mining companies should invest in training employees to make for a more safe, effective and efficient mining environment. Policies should be implemented to make AI and ML training a part of the mining modus operandi opening up career opportunities for employees conversant in disciplines such as programming, automation, and machine learning.
- By implementing AI and ML mining plants can now be run remotely. However, this is limited to autonomous vehicles in some mines, stopping and starting conveyor belts, silo chutes, feeders, and crushers. The whole operation cannot run remotely but part of it can be done from an office environment. As implementation progresses in light of the covid pandemic fewer people have to be on the plant and can run the plant remotely from an office.

5.5 LIMITATIONS

No top management was sampled in this study. What would be a great contribution is interviews with top management to find out what their view is on and plans to implement AI and ML. For example, the budget allocated to implement AI and ML if any.

Only one company (Impala Rustenburg Concentrator) was assessed, and this is what the sample represents on implementing AI and ML. The information gathered does not account for the mining industry in South Africa as a whole and more so the global mining environment. Only a small sample (52) was taken from the potential 864 employees at Impala concentrator. A more comprehensive sample might display another outcome.

5.6 CHAPTER CONCLUSION

The aim of this study was to investigate the impact of artificial intelligent systems on productivity at a mine. The findings of this study showed that the implementation of AI and ML is well received and the impact over the past ten (10) years was seen as positive. However, the user-friendliness of AI and ML can be improved. According to the findings, AI and ML help improve productivity.

Demographic variables used are gender, age, dependents, ethnicity, marital status, highest qualifications, current employment status, management level, years working at the company, years working in the same position, and do you own a smartphone. It can be concluded that overall the implementation of AI and ML is received positively among the selected sample. The respondents did not show any animosity toward AI and ML and received it as a positive contribution to their working environment.

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7. APPENDICES

7.1 APPENDIX A: QUESTIONNAIRE

Document Code number:

AI001

ARTIFICIAL INTELLIGENCE IMPACT QUESTIONNAIRE

CONFIDENTIAL

Note: All the information provided by the participants are confidential and no employee or employer would be identified during or after the study.

ARTIFICIAL INTELLIGENCE IMPACT QUESTIONNAIRE

Dear Respondent:

By participating, you will contribute toward **“Investigating the impact of artificial intelligent systems on productivity at a mine”**. This will help the organisation to determine the impact of artificial intelligence systems might have on productivity at a mine.

This study will focus on the impact that artificial intelligence has had over the years in specifically the mining industry and how it has benefitted production and cost saving on the mine. Mines invests substantial capital in maintenance and production costs to increase profit. This study will investigate the effect of artificial intelligence systems, cost saving and the increase or decline of productivity since artificial intelligence and machine learning has been introduced into the mining industry.

Participation is completely voluntary, and you may opt-out at any time. The procedure to be followed is a quantitative research design, which entails a questionnaire. Confidentiality of the data is guaranteed and only the combined results will be used for research and publication purposes. The data gathered from the questionnaires will only be used for research purposes. You may also select the option not to answer the specific question should you feel like it. The study does not have a correct or incorrect answer to any of the questions. This questionnaire will take approximately fifteen (15) minutes to complete.

This **Informed Consent Statement** serves to confirm the following information as it relates to the officially approved research project at the North-West University on **“Investigating the impact of artificial intelligent systems on productivity at a mine”** in the Rustenburg area.

Please indicate your consent:

I hereby give my consent after having read the above information that my data may be used as stated above.	YES	NO
I hereby give my consent that my demographic data may be used to develop a profile for the research.	YES	NO

GENERAL INSTRUCTIONS

All questions may be answered by marking a (X).

The following scale indicates your preference:

SCALE	TERM USED
5	Strongly agree
4	Agree
3	Neither agree nor disagree
2	Disagree
1	Strongly disagree

The following example shows how to complete the questionnaire. In the example below the respondent “Strongly Agrees”.

		Strongly Disagree	Disagree	Neither agree nor	Agree	Strongly Agree
A03	My manager helps me to get my work done by removing obstacles in my way.	1	2	3	4	~~5~~

SECTION A: DEMOGRAPHICS

This section consists of 11 demographical questions. Please mark the applicable block with a cross (X).

A01	Indicate your gender	Male	Female		Prefer not to answer	
A02	Indicate your age group	≤ 29	30 - 39	40 - 49	50 - 59	60+
A03	Indicate your ethnicity					
	African					
	Asian					
	Caucasian					
	Coloured					
	Indian					
	Other					
A04	Marital status					
	Single					
	Married					
	Domestic Partnership / Committed Relationship					
	Widowed					
	Separated					
	Divorced					
	Other					
A05	How many dependants do you have					
	None					
	1					
	2-4					
	5+					
A06	Indicate your HIGHEST academic qualification					
	Lower than Grade 12					
	Grade 12					
	National certificate					
	National diploma					
	3-year degree					
	Post graduate qualification					
	Other					
A07	Your current employment status					
	Employed Full-Time					
	Employed Part-Time					
	Contract worker					
	Other					

A08	Management level	
	Senior management (Top management in finance, marketing, operations, HR, Sales, etc)	
	Middle management (Technicians, team leaders, officers, etc)	
	Work force (Cleaners, general workers, technical assistance, reception, etc.).	
	Other	
A09	Years working for this company.	
	0-3	
	4-10	
	11-15	
	16-20	
	21+ Years	
A10	Years working in current position.	
	0-3	
	4-10	
	11-15	
	16-20	
	21+ Years +	
A11	Do you own a smart phone	
	Yes	
	No	

INTRODUCTION:

Please respond to every statement to ensure the validity and reliability of the study.

The following questions relate to artificial intelligence and machine learning. This is technological advanced systems put in place to assist in daily tasks, productivity and reduce expenses.

Artificial Intelligence (AI) according to John McCarthy 2004 is " It is the science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable."

Machine Learning (ML) according to T Zia, 2021 is "is a sub-topic of artificial intelligence (AI) that focuses on building algorithmic models that can identify patterns and relationships in data. In this context, the word machine is a synonym for computer program and the word learning describes how ML algorithms will automatically become more accurate as they receive additional data".

SECTION B: THE IMPACT OF AI AND ML OVER THE PAST 10 YEARS

This section consists of 8 statements. Please indicate to what extent you agree or disagree with each statement. Please mark the applicable block with a cross (X).

		Strongly Disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree
B01	My workload has decreased since the introduction of AI and ML	1	2	3	4	5
B02	Because of AI the pace at which I work increased over the past 10 years	1	2	3	4	5
B03	The introduction of AI and ML made the work environment safer over the past 10 years	1	2	3	4	5
B04	AI took over repetitive work and gave me more time to focus on more important work over the past 10 years	1	2	3	4	5
B05	The amount of AI and ML applications increased in my work environment over the past 10 years	1	2	3	4	5
B06	With AI and ML production has increased over the past 10 years	1	2	3	4	5
B07	AI and ML brought a positive change to the working environment in the past 10 years	1	2	3	4	5
B08	Systems are better managed with the introduction of AI and ML	1	2	3	4	5

SECTION C: USER FRIENDLY

This section consists of 17 statements. Please indicate to what extent you agree or disagree with each statement. Please mark the applicable block with a cross (X).

		Strongly Disagree	Disagree	Neither agree nor	Agree	Strongly Agree
C01	AI has made my job easier.	1	2	3	4	5
C02	It was easy to learn to use AI	1	2	3	4	5
C03	My current job encourages me to use AI and ML	1	2	3	4	5
C04	I would rather choose not to use AI and ML	1	2	3	4	5
C05	I am afraid to learn about AI and ML	1	2	3	4	5
C06	I am afraid I will be discriminated against if I cannot learn how to use AI and ML systems	1	2	3	4	5
C07	I know what AI and ML is	1	2	3	4	5
C08	I need help adapting to AI and ML	1	2	3	4	5
C09	Implementation of AI and ML can be managed better	1	2	3	4	5
C10	I use computers daily	1	2	3	4	5
C11	It was easy to learn how to use AI	1	2	3	4	5
C12	I have been told about the implementation of AI and ML before it was introduced	1	2	3	4	5
C13	The current AI system is user friendly	1	2	3	4	5
C14	AI and ML is dangerous to the working environment	1	2	3	4	5
C15	The AI System helps me to perform my daily tasks better	1	2	3	4	5
C16	AI and ML has improved my business environment	1	2	3	4	5
C17	I see AI and ML as an opportunity	1	2	3	4	5

SECTION D: PRODUCTIVITY

This section consists of 17 statements. Please indicate to what extent you agree or disagree with each statement. Please mark the applicable block with a cross (X).

		Strongly Disagree	Disagree	Neither agree nor	Agree	Strongly Agree
D01	AI and ML is useful in my current position	1	2	3	4	5
D02	When using AI and ML production has increased	1	2	3	4	5
D03	I prefer using AI to completing tasks manually	1	2	3	4	5
D04	AI and ML contributes to productivity	1	2	3	4	5
D05	Systems and equipment have run more efficiently since the introduction of AI and ML	1	2	3	4	5
D06	AI and ML has shortened the completion time of tasks	1	2	3	4	5
D07	The current AI and ML system enhances business performance	1	2	3	4	5
D08	I know how to improve production using AI and ML data	1	2	3	4	5
D09	Using AI and ML alerts me to areas of production that needs improvement	1	2	3	4	5
D10	I have been able to reach targets more easily with the introduction of AI and ML	1	2	3	4	5
D11	AI and ML have increased production targets since its introduction	1	2	3	4	5
D12	The data from AI and ML helps me make better informed decisions	1	2	3	4	5
D13	The data from AI received is of value to my daily tasks	1	2	3	4	5
D14	I can see that AI and ML is a benefit in the long run	1	2	3	4	5
D15	More systems managed by AI and ML will increase production	1	2	3	4	5
D16	The introduction of AI and ML gave me more time to focus on more important tasks	1	2	3	4	5
D17	AI and ML gave me tools to better manage my job	1	2	3	4	5

THANK YOU VERY MUCH FOR YOUR VALUED INPUT.