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UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

The Fourth Industrial Revolution: Assessing the potential socio-economic effects of automation in a South African coal mine – case study

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MSc (50/50)	MSc By Research only	PhD
X		

A research report submitted to the Faculty of Engineering and the Built Environment, University of the Witwatersrand, in fulfilment of the requirements for the degree of Master of Science in Engineering.

Johannesburg, July 2022

DECLARATION

I declare that this Research Report is my own, unaided work. Where use has been made of the work of others, it has been duly acknowledged. It is submitted to fulfill the requirements of the degree of Master of Science at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in any other University.



Signed

Varaidzo Esther Dhege

This_____30th____day of_____July_____2022

ABSTRACT

Industrial revolutions have been in existence since the end of the 18th century. The revolutions were adopted to improve productivity and efficiency in all industries worldwide. Before 2010, three industrial revolutions occurred, and now we are in the advanced technologies industrial revolution called the Fourth Industrial Revolution. Technological advancement is integral to the Fourth Industrial Revolution in various industries, including mining. The digital, physical, and biological aspects are three technological drivers of the Fourth Industrial Revolution. For everyone adopting innovation, the fusion of these technologies creates new markets and growth opportunities and influences the socio-economic status. All the previous industrial revolutions have been associated with socio-economic disruptions, and the Fourth Industrial Revolution will not be different.

In the Fourth Industrial Revolution era, automation in the mining industry's production process has increased. Low, middle, and full automation have been applied in the mining industry, with full automation being the latest adoption. The mining value chain from exploration, mining, processing, marketing, and trade has been using the latest technologies related to Fourth Industrial Revolution, such as drones, driverless trucks, and trains.

Mining giants in developed countries have adopted automation to reduce operating costs, improve safety, access low-grade ore, and improve productivity and efficiency. Companies that have embraced automation have remained competitive. Loss of employment and skills shortage are some of the challenges of automation adoption. Developed countries are in the lead of automation adoption and research of the potential socio-economic effects compared to developing countries such as South Africa. As a result, there is minimal information on the potential socio-economic effects of automation adoption in developing countries.

The explanatory mixed-method was used to investigate the potential socio-economic effects of automation adoption in an opencast coal mine in South Africa. The study assessed the level of understanding of automation and the perception of the potential socio-economic effects of automation adoption. Factors that may impede a successful

automation adoption and possible mitigation measures were investigated. The information was gathered through an online questionnaire completed by 102 respondents and qualitative interviews completed by 8 respondents.

The identified socio-economic effects by participants were closely related and were not significantly different from the literature findings. The differences in responses were noted in the depth and scope of the benefits and challenges. There is a general view by participants that automation is inevitable. The misalignment in the education system, skills shortage, high unemployment rate, a strongly unionised labour force, and high socio-economic inequality are some challenges to mitigate for automation adoption to succeed.

DEDICATION

The research report is dedicated to my late parents, Mr. and Mrs. Makore, who have taught me to be courageous and resilient no matter the situation. Always in my heart and thoughts.

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LIST OF SYMBOLS

≠	Not Equal or Not Equal To
α	alpha
e	precision
p	Statistical *p*-value

LIST OF ABBREVIATIONS

1IR	First Industrial Revolutions
2IR	Second Industrial Revolution
3IR	Third Industrial Revolution
4IR	Fourth Industrial Revolution
AHS	Auto Haul System
AI	Artificial Intelligence
AT	Autonomous Technology
CMC	Computer Mediated Communication
CPS	Cyber-Physical Systems
GDP	Gross Domestic Product
GPS	Global Positioning Satellite
FDI	Foreign Direct Investment
LHD	Load Haul Dump
LOM	Life of Mine
IRs	Industrial Revolutions
IoT	Internet of Things
IoS	Internet of Systems
IORC	Integrated Remote Operations Centre
PGM	Platinum Group Metals
R&D	Research and Development
SA	South Africa
STEM	Science,Technology,Engineering and Mathematics
SLO	Social Licence to Operate

SLP	Social and Labour Plan
WEF	World Economic Forum

1. INTRODUCTION

1.1 Introduction and Background of the Research Problem

The application of automation in the mining industry has advanced with time. In recent years there has been an increase in its use. The Fourth Industrial Revolution (4IR) has enabled the adoption of different technologies by mining companies. The need for automating machinery was driven by technical problems with machines and production problems, which were proving costly and less efficient for mining companies (Black Livingston et al., 2018). The other contributing factors are the scarcity/high costs of operators, aging workforce, low grade of the ore remaining, areas not easily accessible, and safety challenges for current mining progressing into the future. Automation adoption has transformed the mining value chain from prospecting, exploration, and exploitation (construction and operation) to closure and remediation (Korinek, 2020). Jacobs and Webber-Youngman (2017) argued that resources would sterilise if automation is not adopted.

Although most mining activities are automated worldwide, the mines in full automation are mainly in developed countries. Full automation is streamlined for cyclical mining activities such as drilling, excavation, and hauling (Rogers et al., 2019). Economic benefits such as increased productivity, safety, efficiency, reliability, access to difficult orebodies, and improved Life of Mine (LOM) have been achieved through automation, promoting mining companies' competitiveness (Matysek and Fisher, 2016).

There are promising opportunities for automation adoption and unique physical and socio-economic challenges (World Economic Forum (WEF), 2016). Research has shown that automation has had negative and positive socio-economic effects on companies, employees, communities, and countries. There have been disruptions in jobs and local economies, changes in employees' demographic constitution, skills, and economic growth. Although jobs are threatened, the outlook points to new roles (Mckinsey Global Institute, 2018).

The challenges to the adoption of automation are associated with people and culture. Economic and social changes will impact the potential to implement the technology. A significant investment in people capabilities has to be made for automation adoption to succeed. According to McNab et al. (2013), most people in the mining industry will

no longer be working in Australia's remote operations but will be positioned in bigger cities. There will be a reduction in certain conventional types of jobs while new roles are being created. For example, truck drivers' requirements will decrease from 5% to approximately 2%, while mining engineers will increase from 2% to 4% (Ernst and Young (EY), 2019a).

The new tasks require highly skilled workers and upskilling to fill positions with the latest technology. Professions such as information technologists, artisans, and communication engineers have increased in demand since automation's adoption (International Labour Organisation, 2020). Responsible mining companies have to turn to socio-economic changes brought about by automation adoption, as mining companies have always paid much commitment to issues of shared value (Porter and Kramer, 2011; MacNab et al., 2013; Holcombe and Kemp, 2019). Most mining companies' key shared value was the employment of the local workforce (Rogers et al., 2019). In the automation era, this is more than likely to change.

In the South African (SA) context, mining has contributed to the economic growth and development of the country. Despite SA having over 50 different minerals, there are four most significant contributors to minerals exports: Platinum Group Metals, iron ore, diamonds, and coal (Baxter, 2015; Minerals Council South Africa (MCSA), 2021). SA's primary energy source is coal, with Eskom generating over 70% of the power needed in the country (International Trade Administration, 2021). Coal accounts for over 75% of domestic needs, with the remainder exported (Department of Mineral Resources and Energy: Republic of South Africa, no date). An estimated 53% of coal production is from open cast mines, while the rest is from underground mines. The coal mining industry is heavily mechanised for opencast and underground mines and has more skilled employees than hard rock mines (Coal Mining Matters (CMM), 2020).

Statistics show that in 2020 the coal mining sector employed 91 649, representing 19% of the total workforce in the mining industry (MCSA, 2020). The coal mining sector has indirectly created and sustained over 170 000 jobs (Mining Review Africa, 2018). In 2017 the mining industry contributed 2% to the Gross Domestic Product (GDP), with coal value for domestic sales and export reaching R134.4bn in 2018 (Research and

Markets, 2019). The coal mining industry has contributed tremendously to the economic and social status of SA.

According to Baxter (2015), the current conventional way of mining is deemed uncompetitive due to low efficiency, reliability, productivity, relatively poor occupational safety and health, high labour costs, and fluctuating commodity prices. Global pressures in terms of environmental issues have become a concern as the carbon footprint in the mining industry has to be reduced (Harvey, 2019).

In addition, the SA mining industry is unique as a highly unionised workforce characterises it with low-skill employees. Production has been paralysed each time these unions went on strike. Mining companies worldwide are adopting the latest technologies to remain internationally competitive (Black Livingston et al., 2018). Adopting the latest technologies has resulted in socio-economic changes for workers and surrounding communities (Holcombe and Kemp, 2019).

Factors such as a well-developed infrastructure, sound education systems, readily available capital resources, and employment levels influence automation adoption and consequences after that. The SA mining industry relies heavily on Foreign Direct Investment (FDI). For the past few years, this has declined in the African continent (United Nations Conference on Trade and Development, 2017a). Low FDI inflows do not favor automation adoption for SA Mining Industry. In addition, the unemployment rate for SA is high and was at 32.6% in the first quarter of 2021, with the high unemployment being among the youth (those aged between 15-34 years) irrespective of their education level (Department: Statistics South Africa: Republic of South Africa, 2021).

The levels of education in SA are still considered low (National Economic Development and Labour Council (NEDLAC), 2019). SA's education systems still need to align with 4IR (Kayembe and Nel, 2019; Tyatya, 2019). The challenges that the SA education system faces include skills to prepare graduates for participation in 4IR, insufficient funds, and infrastructure (Kayembe and Nel, 2019). A report of the Ministerial Task Team indicated the need to start planning and implementing skills development strategies, digital jobs, open learning programs in line with 4IR and short courses in Technical and Vocational Education in preparation for the adoption of 4IR

technologies (Department of Higher Education and Training: Republic of South Africa, 2020). In a framework to test SA ‘s readiness for 4IR, some findings were a scarcity of skilled workforce, technological infrastructure, and a rapid decrease in economic complexity (Butler –Adam, 2018).

How developed countries have handled socio-economic issues currently and in the future will not be the same for developing nations. The prevailing conditions in SA, such as labour market structure, education and skills levels, and existing government policies, are likely to result in worse socio-economic effects than in developed nations. There is a need to assess the potential socio-economic effects of automation adoption in a SA coal mine. Stakeholders' engagement with their perception, ideas, knowledge, and experience concerning the potential socio-economic effects of adopting full automation will be crucial to improving the positive impacts, identifying problems that may arise, and suggesting mitigation measures to be implemented.

1.2 Problem Statement

Most open cast mines in SA use conventional mining machines for excavating, loading, and hauling, proving costly and not competitive. Although literature reveals that the coal mining industry is better automated than the hard rock mines, full automation adoption in SA open cast coal mines is soon inevitable. Modernising the mines is already being discussed at the Minerals Council of SA (MCSA, 2019). Other coal operations, such as Belfast, owned by Exxaro, have already started adopting automation technologies (Kotze, 2021). Detailed research on automation's socio-economic effects has been carried out primarily in developed countries. Research to date indicates that it is essential to have stakeholder engagement and participation from the initial stages of automation adoption to identify, understand and examine levels of expectation, priorities, and influence. The process will help find ways of enhancing the positives and mitigating possible hurdles ahead of automation adoption.

Stakeholders need to understand the scale of change and new technologies' implications (Lynas and Horberry, 2011; MacNab and Garcia Vasquez, 2011; Rogers et al., 2019). Transitioning from conventional operating methods requires proper change management and an understanding of change (McCathy, 2016). Technological changes affect social and behavioural changes (Koul and Eydgahi,

2018). It is also clear that each scenario has unique features and findings on the socio-economic effects of adopting automation (Holcombe and Kemp, 2019).

One research is not "a one size fits all" for different communities. The risks, social impacts, effects on work, welfare, education needs, and Social and Labour Plan (SLP) before, during, and after automation, adoption has to be understood. Researchers continuously assess socio-economic risks, changes, and implications of automation to ensure automation adoption is a success. The socio-economic issues need to be integrated into the whole automation adoption process.

1.3 Research Aim and Objectives

This research aims to assess the potential socio-economic effects associated with automation as perceived by the coal mine employees at an opencast Coal Mine “X” in SA. An assessment of the opinions on factors that impede automation adoption and suggested ways of mitigating the problems are also covered.

The primary objectives include:

- Assessing the level of understanding of automation for mine employees;
- Establishing the potential socio-economic effects of automation adoption at the coal mine;
- Determining how various stakeholders at the mine perceive the potential socio-economic impacts of automation adoption.

The secondary objective includes:

- Assessing critical socio-economic factors that may impede the adoption of automation and possible mitigation measures to better prepare for automation.

1.4 Research Questions

Main Questions

- What is the level of understanding of automation for coal mine employees in relation to education qualifications;
- How does the opinion on the potential socio-economic effects of automation adoption vary among stakeholders at various levels of the coal mine;

- What are the potential socio-economic effects of automation adoption identified by participants?

  Minor Question
- What are the factors that may act as barriers to automation adoption;
- What mitigation measures can be implemented to cover potential socio-economic effects on automation adoption at the coal mine?

1.5 Significance of the Research

The SA coal mines are at different stages of automation. Where there is advancement in technology worldwide, most mining companies, including SA mines, are slow to embrace socio-economic issues. Since SA has a unique history and has a strong labour union, a high unemployment rate, and less skilled employees, the socio-economic effects may be worse than the developed world. The socio-economic effects of automation have been reasonably researched in developed countries compared to developing countries. Some researchers in developed countries still call for more work (Holcombe and Kemp, 2019). For a developing country such as SA, automation adoption's potential socio-economic effects have been researched for hard rock mines (Gumede, 2018). The socio-economic effects of automation adoption in hard rock mines is the first research done in SA. As scenarios may differ per mining commodity, there is a need to research the potential socio-economic effects of automation adoption in a mining commodity such as coal.

The outcome of this research can be used to identify ways of enhancing the positives and mitigating possible hurdles ahead of automation adoption. Valuable learnings from this research work provide information on areas of need for training institutions, government departments, and other opencast coal mining companies. The results of this research will interest government departments, for example, the Department of Mineral Resources and Energy, in realigning the SLP to accommodate socio-economic changes associated with automation in coal mines. An insight into stakeholders' perceptions, such as coal mine employees, will help other coal mining companies better plan for the workforce and spread awareness of the socio-economic effects of automation. Training institutions such as schools, universities, and colleges will also benefit as levels of education, curriculum, and

training needs will be identified. These institutions would be exposed to areas they can target for further development. The changes in employer labour union interaction will require unions to seek new roles. The positive findings may be used to enhance what is already existing.

Most coal mine employees have higher educational qualifications, have been trained, and are more skilled than hard rock mines in the SA setup (MCSA, 2018). Perceptions of automation from coal mines might differ from that of hard rock mines. For the mining industry, the literature reveals that automation has focused more on the benefits of engineering, productivity, and efficiency of new technology with minimal emphasis on the downside socio-economic effects on employees and surrounding communities (Holcombe and Kemp, 2019).

Although the coal mining industry in SA has been in the lead in adopting new technologies, especially for underground mines, not much has been published regarding how they dealt with the socio-economic issues. Literature on how the coal mines have dealt with the socio-economic effects of adopting new technology is scarce. According to Gumede (2018), the information on socio-economic issues in the coal mines might have been dealt with through internal change management, making it impossible to be made public. Furthermore, due to 4IR exponential growth in technologies, the rate of change of the technology is high and socio-economic issues will need constant and persistent research work. Socio-economic issues associated with automation adoption require proper management to achieve successful results.

1.6 Definition of Terms

1.6.1 Fourth industrial revolution

The 4IR era is characterised by advanced technologies that rely on information and communication (Min *et al.*, 2019). The 4IR "is the fusion of these technologies and their interaction across the physical, digital and biological domains that make the fourth industrial revolution fundamentally different from previous revolutions" (Schwab, 2016, pg.12). The 4IR takes emphasis on digital technology through the interconnectivity of the Internet of Things (IoT), Internet of Systems (IoS), access to real-time data, and the introduction of Cyber-Physical Systems (CPS) (Marr,

2018). CPS is a computer system in which computer-based algorithms control mechanisms. The 4IR production is mainly driven by CPS (WEF, 2016). The CPS is dominated by smart machines, storage systems, and production facilities capable of operating autonomously, exchanging information, and enabling production (Kagermann et al., 2013). Advances in technological development are integral to the 4IR in various industries, including mining. The use of automation in the mining industry's production process has increased. The fusion of technologies creates new markets and growth opportunities for everyone adopting innovation and threatens employment (Xu et al. 2018). The 4IR is a technological revolution that will change the way people live, work, and associate with one another as the digital domains with technology will assist and manage life (Xu et al. 2018).

1.6.2 Automation

Automation has evolved for almost five decades in the mining industry (Rogers et al., 2019; Viewpoint, no date). Only teleoperated machines were considered automated decades back (Rogers et al., 2019). Automation is defined as the "intelligent management of a system using appropriate technology so that its operation can occur without direct human involvement" (Lynas and Horberry, 2011, p. 74). Automation is classified into three levels: low-level automation, mid-level automation, and full automation. Low-level automation is whereby operators in a remote location take control of mining machinery using cameras, sensors, and positioning software (Cosbey et al., 2016). Mid-level automation is whereby part of the functions are automated, and there is a need to engage the operator using remote control technology. Using robotics components without involving an operator is considered full automation (Black Livingston et al., 2018). Full automation in the mining industry is ideal for cyclical activities, such as drilling, loading, and hauling (Rogers et al., 2019).

1.6.3 Socio-economic effects

The socio-economic concept has a much different meaning to academics and development practitioners and is considered an evolving concept that does not have an agreed definition. In general, the socio-economic phrase represents positive and negative development that affects communities' economic and social

well-being (Cuartero-Enteria, 2018). Socio-economic status is measured by considering the interaction of social and economic elements. The socio-economic status is measured using combined aspects of education, income, and occupation or a varied combination of these elements (Baker, 2014). Socio-economic factors have been found to influence health. Any developmental activity is expected to directly or indirectly contribute to economic and social status (Morris and Baartjes, 2010). Socio-economic effects should be assessed and understood throughout the lifecycle of a mine. The changes in or advances in technology, efficiency and productivity, improved access to education, employment, health, the general well-being of people, and safety improvements all contribute to socio-economic development (Ericsson and Löf, 2019). In this study, socio-economic effects will cover shared value concepts in employment and procurement, productivity, efficiency, and the general well-being of people.

1.7 Research Methodology

A (mixed method) sequential explanatory was the design for this research. It is a two-stage process in which quantitative data is utilised to build and explain qualitative data (Almalki, 2016). This study conducted quantitative research (phase 1), followed by qualitative research (phase 2). Both methods were integrated into the interpretation of the results.

There are two approaches to the research instruments that the researcher used for the study. During the quantitative data collection (phase 1), the researcher used questionnaires for data collection. The outliers and significant factors from the quantitative data (phase 1) were further utilised to generate semi-structured open-ended questions for phase 2 for the qualitative research. The researcher conducted semi-structured interviews to explore the meaning people attach to the potential socio-economic effects of adopting automation.

A single-stage stratified random sampling was the method used to gather quantitative data (phase 1) of the research (Fowler, 2009; Creswell, 2014). A total of 120 participants was the target for quantitative surveys. For the qualitative survey, a total of 8 participants were selected. The purposive sampling method, a non-probability method, was used for the study's qualitative data (phase 2) (Etikan

et al., 2015). The sampling method selection, target number of participants for both quantitative surveys and qualitative interviews, and the pros and cons of each method are further explained in Chapter 6.

During the data analysis phase, the researcher used statistical software in Microsoft Excel to give descriptive statistics and compare and establish the nature of relationships between variables for quantitative surveys. Creswell (2012) outlined the six steps for qualitative data analysis, which the researcher followed as explained in Chapter 6.

1.8 Limitation of the Study

The study aims to assess the potential socio-economic effects of automation adoption on a single opencast Coal Mine "X." Therefore, the findings of this research cannot be generalised for evaluating the socio-economic effects in all the opencast coal mines in SA. Automation is a new concept that most people do not fully understand. Time of study and virtual interviewing was a limitation. The virtual interviewing approach was new to most participants, and unreliable internet connections were occasionally experienced.

1.9 Outline of the Chapters

Chapter 1: The chapter presented the introduction with background, problem statement, research aims and objectives, research questions, the significance of the research, research methodology, and study limitations.

Chapter 2: The chapter is mainly the literature review. The chapter focuses on analyzing the four industrial revolutions, the technological changes, and the socio-economic changes encountered. Although the different industrial revolutions covered all the sectors, there was more emphasis on the mining sector. The chapter culminates by looking at the 4IR and the various aspects, especially automation.

Chapter 3: This chapter focused on the definition and application of automation in the mining industry. The history of automation, processes, and levels of

automation was also considered. The chapter concludes by taking a closer look at the current automation application in the mining industry.

Chapter 4: The chapter looked into why mining companies adopt automation. The trends in automation adoption worldwide and the implications of automation adoption have also been covered. Changes in productivity, employment, skills requirements, research and development, shared value concept, labour unions, and human rights are covered. The chapter concludes by looking at the challenges of automation adoption, how the developed world has dealt with employment issues, trade unions, and educational requirements, and how SA differs from the developed world.

Chapter 5: This chapter focused on automation adoption in the SA mining industry. The chapter looks into mining in SA, the challenges the mining industry faces, the enablers of automation, trends in automation adoption, and the implications of automation adoption on economic development and mining linkages.

Chapter 6: The chapter covered the research methodology and design. The research approach, the research design, the population of the study, the sample and sampling procedure for qualitative and quantitative methods, the data collection instruments and method, pilot testing, data analysis and interpretation, and data validation for mixed-method were considered. The limitations of the research method were also covered.

Chapter 7: The chapter mainly analysed, interpreted, and discussed the research's quantitative and qualitative findings from phases 1 and 2. The quantitative online survey results from phase 1 were presented first, followed by the results from computer-mediated communication (CMC) interviews in phase 2. The interpretation of joint summarised integration of quantitative and qualitative components of the survey. The findings and discussion were linked to the literature review in chapters 2,3,4, and 5 to elaborate and answer the question set up in the aims and objectives of chapter 1.

Chapter 8: This chapter covered the main findings from the research and provided a link between the research aim and objectives and the results. Recommendations and further research work suggested were also included in this chapter.

2. INDUSTRIAL REVOLUTIONS

2.1 Introduction

The chapter focuses on the previous Industrial Revolutions (IRs) to the 4IR. The development of the different technologies and the associated opportunities, challenges, and socio-economic effects have also been considered. In this chapter, the 4IR is discussed in the context of mining. An understanding of what 4IR entails, possible benefits, and limitations of 4IR are covered. The chapter concludes by briefly describing automation.

2.2 History of the Industrial Revolution

Historically there have been three IRs, namely the first, second, and third, before the most recent 4IR. Since the past two and a half centuries from the start of the IRs, there has been a transformation (Lars et al., 2015; Schwab, 2016; Schäfer, 2018). The first industrial revolution (1IR), which began in the early eighteenth century in Britain and later extended to other parts of the world, used hydraulic and steam power to mechanise production in factories transitioning from human and animal labour technology to machinery (Mohajan, 2019). The use of newly developed raw materials such as iron and steel and the commercial use of coal to generate steam made the 1IR possible (Bouchirika, 2021). Lars et al. (2015) allude that 1IR was made possible due to changes in power sources. During 1IR, there was an increase in production and a notable difference in global economic and population growth. Transportation and communication also improved. The 1IR led to the creation of specialised jobs (Stearns, 2012).

During the 1IR, coal mining was critical as there was a massive demand for coal to power the machines. In industries, steam power was used to transport coal in wagons. The same steam power was used in machinery to bring coal to the surface and pump water. In addition, horses were used to haul coal from the deepest mines (Clark and Jacks, 2007). As the demand for coal increased, mining went deeper with challenges of high cost in shaft sinking, hauling of coal, and pumping water out (Encyclopedia.com, 2018). The miners working underground were cutting coal using a pickaxe, and for more complex ore, a pick and a hammer or heat were used to break

the rock. Conditions were not favourable as it was dark, not well ventilated, the roof support was of wood, and dangerous gases could not easily be detected as there were no instruments to do so (Davy and Stephenson, 2020). According to Trueman (2015), to overcome the challenges of deeper coal mining, such as ventilation, gas accumulation, and draughting, young children called "trappers" would be employed to open and shut doors that went across the mine. This would generate ventilated systems and the power to move some machinery. Haulage was in trucks and wheelbarrows, while windlass was for hoisting shafts and inclines (Mero et al., 2017). As time progressed, air pumps and safety lamps were invented.

In 1811 a group of protestants known as the "Luddites" protested the introduction of machinery in the textile factory (Archer, 2000). The machines were to replace people as less skilled labour, and low-wage workers were displaced from their workplaces (O'Rourke et al., 2013). During the 1IR, the gap between the poor and the rich increased (Britannica, The Editors of Encyclopaedia, 2020). Many factory owners became rich, while those who migrated from villages to work in factories were in crowded, dirty, and unhealthy places (Fultz, 2020). There was an increase in women and child labour in unsafe and unhygienic work conditions, and people had to work more than 16 hours a day (Mohajan, 2019).

The second industrial revolution (2IR), also referred to as the American IR, started almost a hundred years after 1IR. It used electric power to create mass production (Hull, 2009; Schäfer, 2018). It is also referred to as the age of science. 2IR was linked to a switch from coal fuel to oil in terms of energy (Mero et al., 2017). In the 2IR, electrification, the invention of internal combustion for the automobile, the adoption of telegraph systems, and railroad networks were some of the significant inventions. Mechanisation was first in agriculture and manufacturing, followed by mining (Brune, 2019). Other notable inventions were internal combustion engines, chemical industries, petroleum, running water, indoor plumbing, and steel. Communication technologies such as the telephone and radio facilitated information sharing (Richard, 2010).

Lighter metals, new alloys, plastics, and oil energy sources were introduced during this period. Deeper mining was enabled due to powerful steam, electrical hoists, ventilation fans, and dewatering pumps. Hand loading with shovels was replaced with

a variety of mechanical loaders. Haulage improved mine cars driven by electric locomotives, conveyors, and large capacity rubber-tired vehicles (Mero et al., 2017). Production competitiveness, efficiency, energy consumption, cost reduction, and optimization in production were the key challenges during this era. Data from the United States shows that the technologies adopted in the 2IR resulted in a surge in productivity and a cost reduction, further stimulating worldwide growth (Humphreys, 2019). According to Prinsloo et al. (2019), it is argued that the second industrial revolution led to the globalization of manufacturing.

According to Mohajan (2020), the socio-economic effects involved increased life expectancy and food production during the 2IR. In Britain, daily lifestyles changed due to transportation and communication technologies. Safety improvements were achieved during this period. There was an increase in migration, with people looking for better opportunities. Working conditions were marked by long hours, child labour, low wages, and wage discrimination. There was a displacement of skilled labour as new technologies were introduced (Rinaldi, 2014). The challenges experienced in 2IR led to the concept of industrial automation.

The third industrial revolution (3IR), also known as the digital revolution, followed 70 years later in the 1960s or 1970s with electronics and information technology to automate production during the manufacturing process (Schwab, 2016; Li et al., 2017; Schäfer, 2018). This period started shifting from mechanical and analog technology to digital electronics (Bouchirika, 2021). This phase has been considered the information and communication technologies revolution. Computer technology was used to automate processes (Mokyr et al., 2015). The use of computers, cell phones, and the internet increased, significantly changing communication and trade (Roberts, 2015; Taalib, 2018). Two critical inventions, for example, Programmable Logic Controllers, were made at this time. There were advancements in research, space expeditions, and biotechnology. It marked the start of the shift from fossil fuel energy, which was affecting the environment, to renewable energy.

According to Humphrey (2019), although there were no transformational changes during this period, improvements in computing have played a significant role in mining. Activities such as mine planning, scheduling of trucks, maintenance, process control monitoring, and cost monitoring have been accomplished through computers.

Communication development has enabled management to improve safety and assisted in procurement. Humphrey (2019) argues that the 3IR was more inclined to optimize existing technologies rather than a technological breakthrough.

According to Brune (2019), mass mining occurred during this stage using fully mechanised loading, hauling, and conveying. There was a notable increase in production and productivity. The introduction of 3IR technologies resulted in a two-thirds decrease in factory workers in the USA (Establishment Survey, 1960-2019). Many tasks were reserved for automation (Prinsloo et al., 2019). A coal loading machine, "Joy Loader," was developed in the early 20th century, replacing miners doing manual hand loading. Blasting was replaced by the continuous miner. Bucket chain and bucket wheel excavators were utilized, allowing the loosening, loading, and hauling of ore at least once for soft rocks. Significant developments in drilling transformed the blasting process, and blasting was made more effective with high explosives. During the 3IR, productivity and efficiency were boosted, translating into economic gains in manufacturing and mining. Since advances in new technologies are capital intensive, require less labour, and are skills biased, the main risk the technologies bring would result in job losses (Roubini, 2021). There were no noticeable changes in the measured living standards. The 3IR is considered as the stepping move to 4IR.

The German government first introduced the term "Industry 4” during the Hanover Trade fair in 2011 (Kargeman et al., 2013). In 2016, Klaus Schwab, the Founder and Executive Chairman of the World Economic Forum predicted a new IR that would begin soon in the world economy forum Global Challenge Insight Report (Schwab, 2016). A new IR known as the 4IR is building on the 3IR. Economist (2012) argued that the 41R is only an evolution of 3IR. The 4IR is becoming known as the digital revolution because it unprecedentedly combines technological and human capacities through self-learning algorithms, self-driving cars, human-machine interconnection, and big-data analytics (Schwab, 2016; Schäfer, 2018). The 4IR is distinct from the first three IRs and is characterized by the widespread application of CPS in the manufacturing environment (Li et al., 2019). It is an advanced technology age based on information and communication. 4IR has a more powerful impact on the economy than in the past (Xu et al., 2018). Companies globally are working to understand and

use these emerging technologies. Many plan to invest significantly in the 4IR (Union Bank of Switzerland Chief Investment Officer, 2020). The mining industry is not excluded from these developments, and companies in this sector have been proactively exploring 4IR-related solutions for several years (Geschwindt, 2021).

Many changes in the production paradigm have taken place since the start of industrialization end of the 18th century. The application of novel technologies at different stages of technological development has increased production and changed the socio-economic landscape. Historically the world has witnessed three industrial revolutions with technological advancement, which were not as fast as the current 4IR (Kayembe and Nel. 2019). The timeline for the industrial revolution is depicted in Figure 2.1

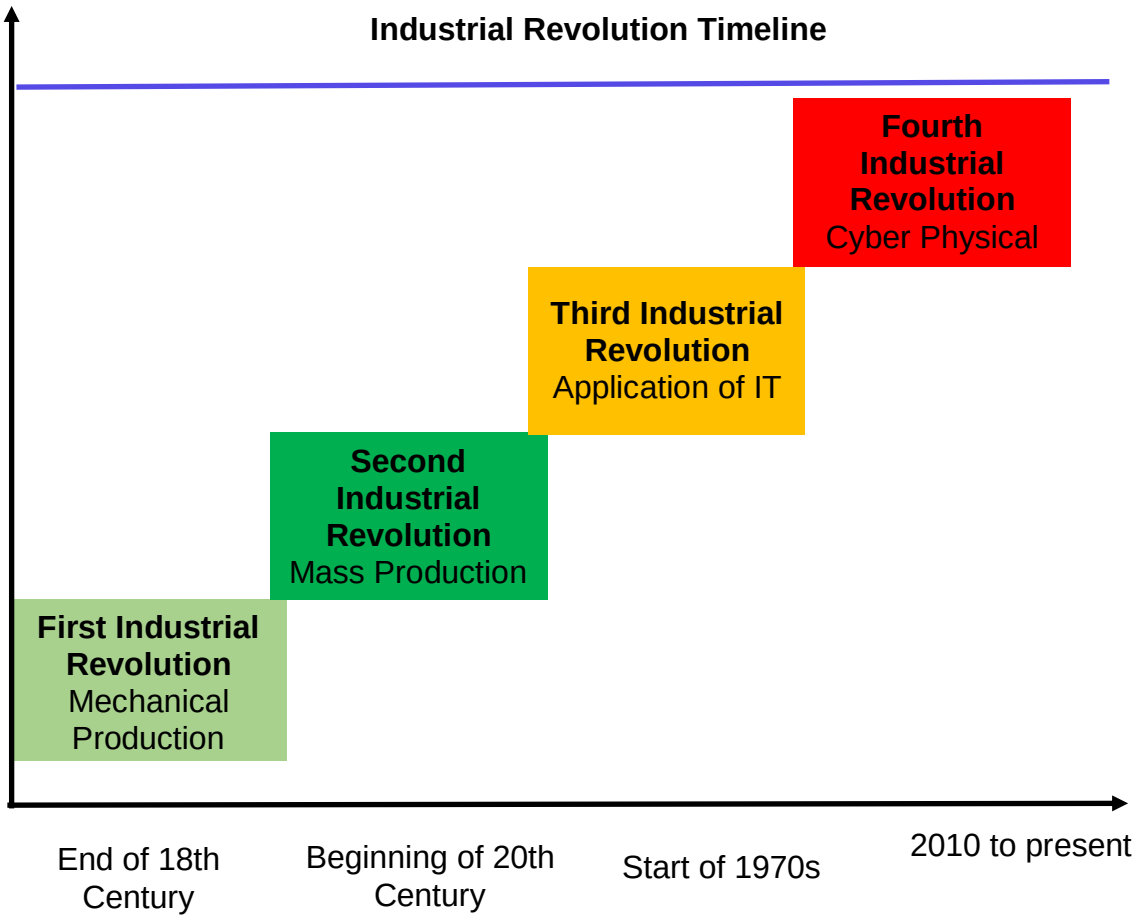


Figure 2.1 Industrial revolutions timeline (Koloszár and Németh, 2020)

The 1IR started towards the end of the 18th century, with the most remarkable change in the industries coming from mechanisation (Institute of Entrepreneurship Development, 2022). According to Agarwal and Agarwal (2017), almost a century

later, end of the 19th century, the 2IR started. Technological advancements during this stage were in the development of a new source of energy, electricity, gas, and oil. Steel demand and chemical synthesis, communication improvements, and the inventions of the automobile and the plane were noticeable achievements during this period (Institute of Entrepreneurship Development, 2022). The 3IR was witnessed towards the second half of the 20th century. There was a rise in electronics and telecommunication use at this stage (Roberts, 2015). The 4IR started in the third millennium and is currently about the digital revolution (Kayembe and Nel, 2019).

2.2.1 Technological Drivers for 4IR

The developments of digital, physical, and biological technologies are the main technological drivers for 4IR. Breakthroughs in these three different areas drive the 4IR, and at the same time, there is a fusion of them with each other (Li *et al.*, 2017). The three technological drivers are summarised in Table 2.1.

Table 2.1 Technological Drivers for the 4IR (Li et al., 2017)

Technology drivers	**Fields**
	The Internet of Things (IoT)
Digital	Artificial intelligence (AI) and machine learning
	Big data and cloud computing
Physical	Autonomous cars
	Three-dimensional (3D) printing
Biological	Genetic engineering
	Neurotechnology

2.2.2 Digital

A significant driving force for 4IR is digital technology. Schwab (2016) argues that digital power enables and enhances almost all the innovations and advances made through the 4IR. This technology cluster is making the whole world a digitally connected one. The four aspects where digital technology is commonly displayed are IoT, AI and machine learning, big data and cloud computing, and digital platforms (Li *et al.*, 2017).

IoT is a connection via the internet that enables various devices to send and receive information. Gartner.com (2022, para. 3) defines IoT as “the network of physical objects that contain embedded technology to communicate or interact with their internal states or the external environment.” This digital interaction between and within machines and systems forms an integral part of the 4IR (Karabegović and Husak, 2018)**.**

AI and big machine learning are computers' ability to perform complex functions associated with human intelligence; however, AI has superior intelligence and capacity (Li et al., 2017; Kayembe and Nel, 2019). According to Kayembe and Nel (2019), AI machines can learn and respond to certain behaviours like humans. This is conducted by computer algorithms and commands, which are given instructions to carry out tasks in the same manner as human beings. AI aims to provide machines with the capacity to perform functions such as logic, reasoning, planning, learning, and perception.

Big data refers to large complex data that may or may not follow a structured pattern and that traditional processing methods cannot operate. The volume, variety of information assets, and speed are high for big data, resulting in the need for cost-effectiveness and new information processing ideas that allow enhanced insight, decision-making, and process automation (Taylor-Sakyi, 2016); Kayembe and Nel, 2019). Big data platforms could help organisations analyse and make meaningful decisions based on the available data. As the world becomes more connected, large amounts of data are collected from different devices. The analysis of this data is needed to reveal information for future use.

2.2.3 Physical

The best-known technology drivers of 4IR, where achievements that have tangible results have rapid application and wider prospects, is the physical technology that directly impacts daily lives. There are two primary physical manifestations: autonomous vehicles and 3D printing (Li *et al.*, 2017). Autonomous vehicles, also called self-driving, driverless, or robotic vehicles, allow cars to operate without manual manipulations. They use traditional vehicle production techniques and advanced sensors, adaptive cruise control, active steering, brake by wire, Global Positioning, Satellite navigation (GPS), lasers, and radar (Fagnant and Kockelman, 2015).

3D printing is a form of rapid prototyping that uses additive manufacturing technology where a 3D object of any kind or shape is created by successive build-up laying of materials. It generally uses a Computer-Aided or 3D scanned file to generate physical models (Bishwal, 2019). It is distinct from traditional techniques, primarily relying on removing material by drilling and cutting (Bishwal, 2019).

2.2.4 Biological

The technology developed for 4IR has biotechnological development applications that advance biological technology and are centered around genetic technology and neurotechnology. One of the branches of biological research which have always been important is genetic study (Li *et al.*, 2017). Genetic sequencing, activating, and editing at a lower cost with ease and efficiency have been achieved with advancements in computing power (Li *et al.*, 2017).

2.3 New Competencies in 4IR

The main objectives of 4IR are to increase and maintain operational efficiency and advance the new automation methods to new heights (Thames and Schaefer, 2016). Verwey (2021) is of the opinion that the massive increase in sensors and processing makes it easy to make the world programmable. The increased connectivity in the world calls for changes, greater adaptability, and diversity by humans. The rise of

smart machines at workplaces will result in workplace automation that will result in repetitive jobs being eliminated, as shown in Figure 2.2.

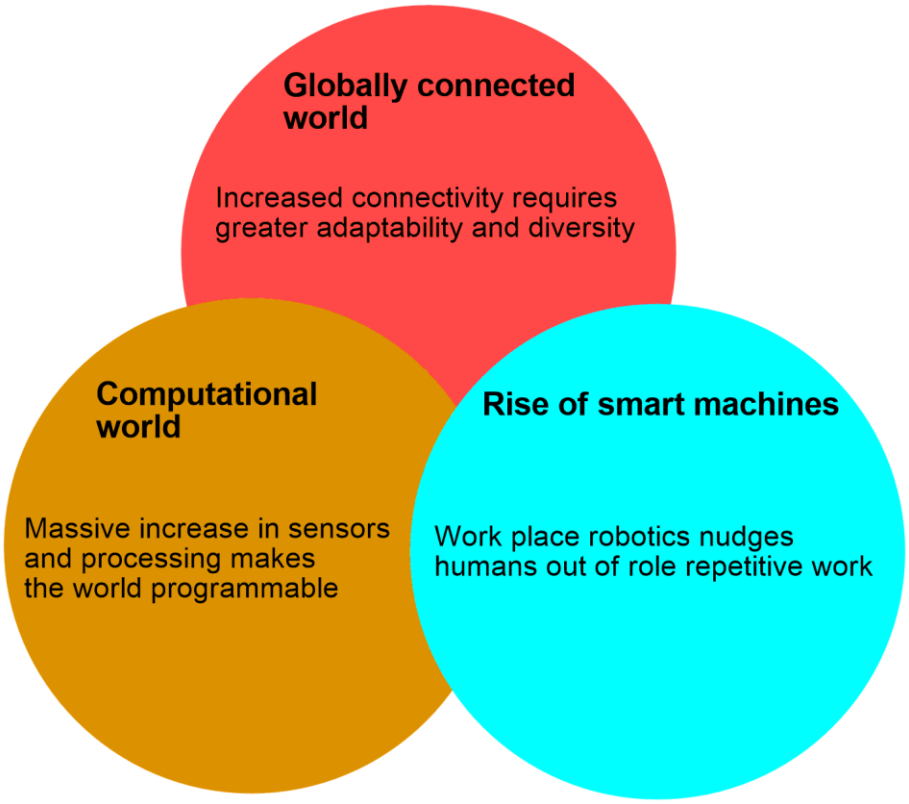


Figure 2.2 New Competencies in 41R (Verwey, 2019)

2.4 Current Status of 4IR Adoption

A survey carried out by the trade journal Mining Magazine (2016) covering 120 companies on specific technologies that will impact mining profitability, productivity, and safety in 5 to 10 years had the following results, as shown in Figure 2.3

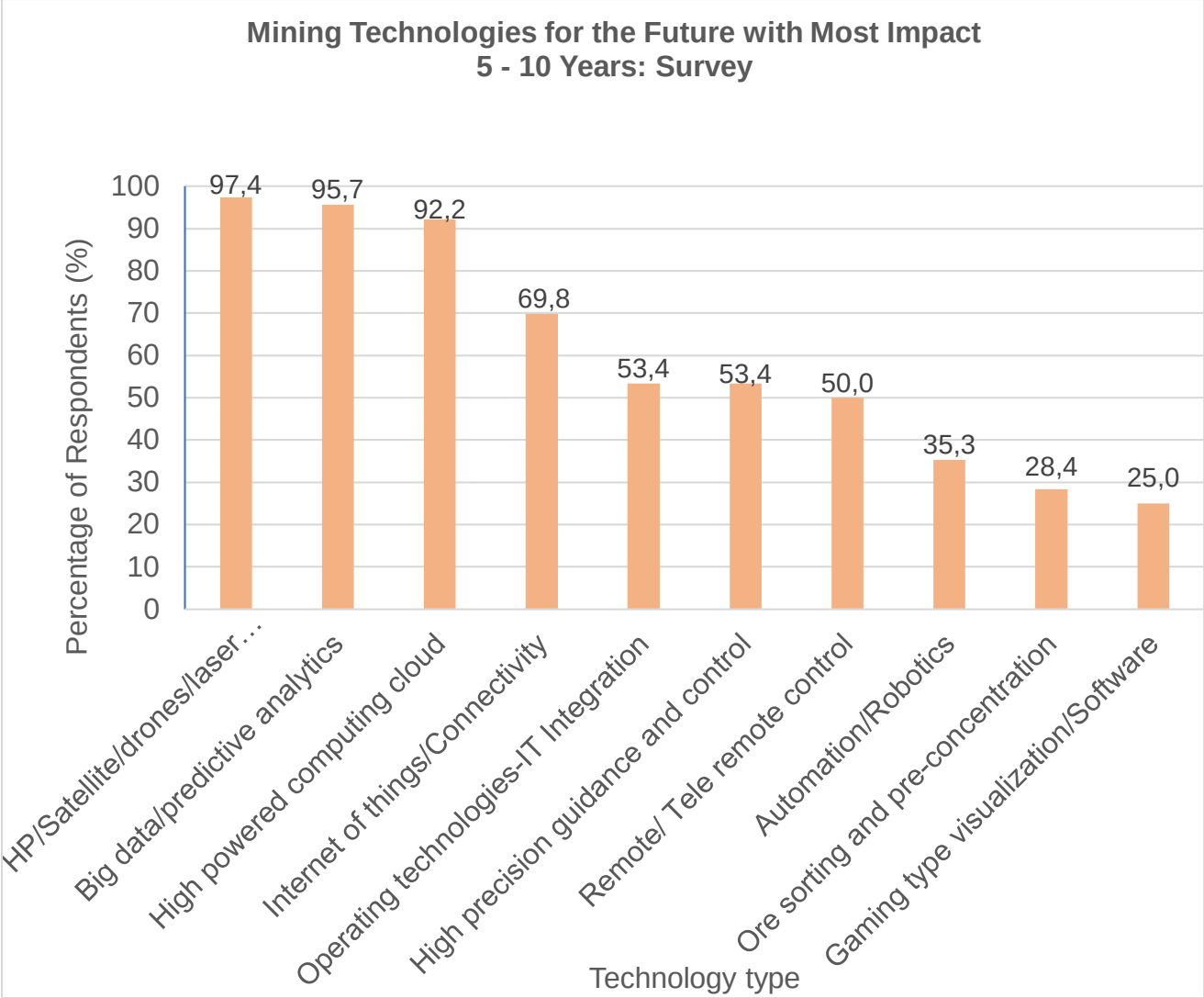


Figure 2.3 Responses: Future mining technologies (Mining Magazine, 2016)

According to this research by Mining Magazine (2016), looking at the 5-10 years mining horizon, technologies with the most significant impacts were improvements in the satellites, drones, imaging, and laser survey, mainly used for exploration and surveying. Big data and predictive analytics have the most enormous contribution to the high performance of the mining business. The ability to generate real-time data using lean means, reduce downtime, save energy, increase safety, and increase output makes this technology preferable in the mining industry. The IoT and operating technology information technology were in position 3. Mining conditions are constantly changing and are shaped by nature. Information and management systems must be continually modified to suit the existing conditions. Better amalgamated, real-time systems unlock significant productivity by improving mine planning, maintenance, and asset utilization. Visible and physical technologies such as automation, remote mining

pre-concentration, in-pit crushing, conveying systems, and blasting techniques are closer to the bottom of the list (Mining Magazine, 2016).

The use of technologies related to 4IR has already begun in Europe, the United States of America (USA), Canada, and Australia. A transformation due to the adoption of 4IR has been observed in these countries. According to Humphrey (2019), autonomous trucks and driverless trains are already operational and reality in the mining industry. On the contrary, research in Korea shows that most industries have not used the 4IR technology (Chung, 2021). Literature also reveals that most African countries are still lagging in adopting 4IR. China and India were preparing to adopt strategies for 4IR (Petrillo et al., 2018).

2.4.1 Adopted technologies in mining

Most mining companies have implemented communication technology to use robotics and automation for mining companies' integrated operations (Sanchez and Hartlieb., 2020). Trends in technologies to be adopted, as revealed in the Mining Magazine (2016), are similar to the trends found in the research (WEF, 2020). The recent technologies anticipated to be adopted by 2025 by global mining companies across the mining value chain, from exploration, mining, trade, and marketing, are shown in Table 2.2.

Table 2.2 Technologies Likely to be Adopted by 2025: (WEF, 2020)

	Technology Adoption in the Mining and Metals Industry	**% Share of Companies Likely to Adopt the Stated Technology by 2025**
1	Robots, non-humanoid (e.g., industrial automation, drones, etc.)	90%
2	IoT and connected devices	90%
3	Big data analysis	90%
4	Cloud computing	87%
5	Encryption and cybersecurity	83%
6	Text, image, and voice processing	76%
7	Artificial intelligence (e.g., machine learning, neural networks	76%
8	E commerce and digital trade	62%
9	Power storage and generation	57%
10	Augmented and virtual reality	57%
11	Distributed ledger technology), e.g., blockchain	50%
12	3D and 4D printing and modelling	48%
13	New materials (e.g., nanotubes, graphene	37%
14	Quantum computing	21%
15	Biotechnologies	16%
16	Robots, humanoid	15%

2.5 Challenges of 41R Technologies and Socio-economic Effects

The adoption of 4IR technologies is not without challenges. Some of the identified challenges in Europe were skills mismatches, the need to consider investing in these technologies, and changing business and organisational models and standards. Research by Lee et al. (2018) shows that technologies will allow the government to decentralize and distribute node power.

There are going to be human and social changes associated with 4IR. Societal changes such as job disruptions and increased social security have stood out in countries ahead with automation, such as Germany (Dredger et al., 2016). The inequality gap will increase, especially in developing countries (Cosbey et al., 2016). According to Davis (2016), an increase in unemployment may result in economic inequality and worsening poverty. Zervoudi (2019) indicated that in 2019, the wealthiest 8% of the world's population earned half of the world's total income, while the remaining 92% shared the other half. An increase in inequality is a cause of concern regarding security for citizens in segregation and social unrest. The innovators and intellectual and physical capital providers will benefit more from the 4IR.

2.5.1 Potential job loses

With the increase in automation and adoption of AI in the workplace, the demand for highly skilled workers has been set to increase while the demand for lowly skilled workers is decreasing. Naude (2017) alludes that advanced technologies complement higher-skilled workers while lower-skilled workers are displaced. Many fear that there will be massive job losses due to automation (Dredger et al., 2016). In the European Union, the number of low and medium-skilled workers has significantly reduced (Zervoudi, 2019). These technologies significantly impact jobs, displacing specific jobs while creating others. The jobs of the future will have titles such as "Driverless car Engineer," "Big data Analyst," "Robot Coordinator," and "Drone Instructor" (Van Dam, 2017). To fully realise the opportunities of the 4IR and mitigate negatives, there is a need to prepare and anticipate future skills requirements.

2.5.2 Skills challenges

Technological advances will result in skills mismatch and redundancy (WEF, 2016). The development and implementation of smart technologies require communities to be educated, have skills, and be knowledgeable. There is a need to reskill and upskill people who are already employed. At the same time, the education system needs to introduce subjects that directly link with the labour market, such as science,

technology, engineering, and mathematics (STEM) (Zervoudi, 2019). In the 4IR, investing in research and development (R&D) is necessary as it has become increasingly important. The WEF (2016) researched the future strategies for successfully adopting automation, and the findings are shown in Figure 2.4.

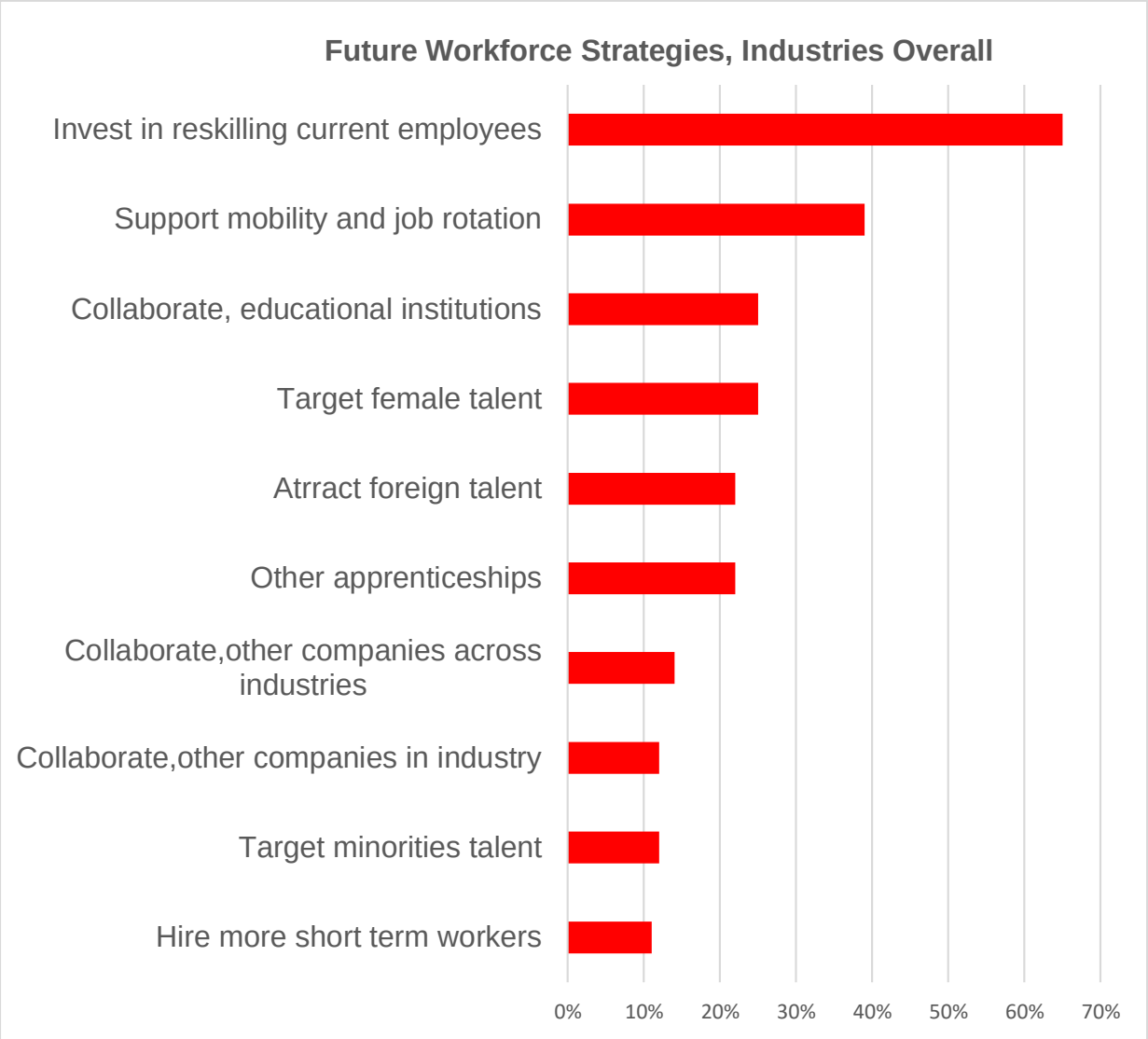


Figure 2.4 Future workforce strategies (WEF, 2016)

2.5.3 Infrastructure

The introduction of 4IR technologies requires a well-developed infrastructure in terms of networks. Developed countries have a well-developed and advanced infrastructure systems while developing countries have unreliable electricity supplies and lack decent network connectivity (United Nations Industrial Development Organisation

2016). For the previous IRs, African states mainly relied on developed countries, and as such, there is a lack of infrastructure to support 4IR technologies (Mamphiswana and Bekele, 2016).

2.5.4 Security and privacy challenges

Data privacy and protection issues are a concern in the 4IR era, which has become a genuine concern regarding trust issues (Manda and Backhouse, 2016). When implementing AI algorithms, training and testing them through sharing data is necessary. Companies are not comfortable with sharing such information with solution developers. The expansion of new security and protection is needed for faster and more flexible application of production systems (Waidner and Kasper, 2016).

2.6 Justification of 4IR

Petrillo et al. (2018) indicate that the main objective of 4IR is to drive manufacturing faster, improve efficiency, and productivity, reduce waste, promote sustainability, and promote circular economy and safety. Real-time data is accessed, enabling management to immediately decide about the cases at hand. More excellent business continuity is enabled by advanced maintenance and monitoring possibilities by advanced technology. Better working conditions and superior sustainability are achieved. According to Schwab (2016), in the 4IR era, global income levels are anticipated to improve the world population's quality of life.

New markets will open as the cost of trade will become less. The means of transportation and communication will drop. The nature of work for many people will change due to the setup and growth of remote control centres and virtual work. All these will contribute to economic growth. According to Carter (2019), IoT and blockchain are new tools to reduce corruption and improve accountability. 4IR addresses the planet's environmental concerns as most of these technologies do not negatively affect the atmosphere through Greenhouse Gas Emissions.

2.7 Other Revolutions After (4IR)

According to Ritchter (2020), Japan has already indicated that there will be a fifth industrial revolution (5IR) based on the cooperation between human beings and machines. Human beings in the production process will now control the best practices. There are two visions for 5IR that are being suggested. The first vision is anticipated that machines will perform the most repetitive work while humans are more on strategic planning, while the second vision is Bioeconomy (Demir and Halil., 2018).

2.8 Automation

The development of autonomous systems has evolved through mechanisation, where there was a replacement of human or animal labour through machines. According to Groover (2020 pg. 75), automation is “the technology by which a process or procedure is accomplished without human assistance. It is implemented using a program of instructions combined with a control system that executes the instructions”. Automation depends on the use of computers and computer-related technologies, and the system can operate without human involvement. Mechanisation is often referred to simple replacement of human labour by machines. Automation has affected almost all aspects of modern life. Besides applying automation in manufacturing, there have been improvements in automation in communication, transportation, service industries, and mining.

3. AUTOMATION

3.1 Introduction

The chapter will focus on the definition of automation and understanding of what automation in the mining industry entails, its possible benefits, and its limitations. A brief history of automation and its effects on employment are covered. The chapter concludes with automation applications in the mining industry.

3.2 Automation

The concepts of automation and mechanisation have been around for decades (Janssen et al., 2019). Automation is “applying machines to tasks once performed by human beings or, increasingly, to tasks that would otherwise be impossible.” Lynas and Horberry (2011, pg. 74) define automation as the “intelligent management of a system using appropriate technology so that its operation can occur without direct human involvement.” According to Parreira (2013, pg. 8), the main objective of automation is “to control the behaviour of dynamic systems and emulate the maximum physical a human intellectual capacity to improve productivity through increased accuracy.” Although the term mechanisation is often used to refer to the simple replacement of human labour by machines, automation “refers to the use of mechanised equipment that performs the physical tasks without the need for oversight by a human worker” (Groover, 2020, pg. 75). This definition seems to mean automation is the loss of jobs (Hornby, 2005).

Many current forms of Automated Technology (AT) or autonomous machines, such as power plants, monitoring devices, automated cars, drones, robots, and chatbots, involve the use of computers (Janssen et al., 2019). Humans use these computer-automated systems, and humans are expected to remain essential contributors to artificial systems and automated systems in the future (Janssen et al., 2019). According to the World Trade Organisation (2017, pg. 76), there are two broad categories of technology, which are either “labour saving technologies that can complete cognitive or manual tasks without human involvement (e.g., autonomous trucks) or labour augmenting technology that complements the work performed by a human (e.g., autopilot).”

Automation is carried out with the help of software robots or AI workers that can perform repetitive tasks accurately (Ribeiro et al., 2021). The developer sets the task instructions using a configuration of screen recording and defining variables. Tasks such as logging into applications, copying and pasting data, opening emails, and filling forms are set up by the developer. With the 4IR period in effect, automation has paved the course of action for new ways to perform mundane rules-based processes in industries, utilising automation tools on information acquired from smart devices. This intends to replace people with automation in an outside-in manner (Ribeiro et al., 2021). Automation extends a human worker's repetitive tasks using an automated system whereby those tasks are done faster with reliable results with reduced variability, resulting in profitability (Rogers et al., 2019; Ribeiro et al., 2021).

According to Schwabe and Castellacci (2020), industrial robotics and AI have increased production activities in the last few years. This has led to the automation of many tasks previously carried out by workers, which smart machines can now perform. The use of AI by machines that can function and complete complex tasks reduces costs and improves the quality of goods and services is the core principle of smart factories and 4IR (Kamarul et al., 2016). AI technologies are permitting the manufacturing industry and merging the physical and virtual worlds with the help of CPS (Zheng et al., 2018). AI makes industries smart and able to address present day challenges like customisable requirements, reduced time to reach the market, and an increasing number of sensors used in equipment (Zheng et al., 2018).

Automation has extended beyond its roots in manufacturing to include its use in healthcare, security, transportation, agriculture, construction, energy, mining, and many other fields (Goldberg, 2012; Mamodiya and Sharma, 2014; Rogers et al., 2019). Both robotics and automation prospect the frontiers of automated and semi-automated machines. The fields of robotics and automation are increasingly concerned with the role of humans and human interfaces (Goldberg, 2012). The continuation of digital industrialisation and higher levels of automation will change the role of human resources in the industrial workplace (Rogers et al., 2019). Dickmanns (2002) argues that profits, safety, comfort, and reliability have to a greater extent, improved due to the use of intelligent, autonomous machines. However, it is essential to note that human input in terms of reasoning and forward planning remains crucial as it is relied on in any complex system, especially the mining environment. There are many

unforeseeable, unknown, and unpredictable situations in today's industrial and mining operations that humans still have to oversee (Dickmanns, 2002; Rogers et al., 2019). The involvement of humans is still integral in the complex system design, establishment, installation, and use of any partially automated or fully autonomous system. The automated system is unable to replace humans' roles completely. The benefit of using an automated system is the reduction of operator workload, which improves working efficiency. There is a need for a gradual change to autonomous systems to ensure that users are part of the design input process and only trained workforce to interact with, oversee, and, most importantly, override and manipulate an automated control system (Rogers et al., 2019).

3.3 History of Automation in Mining

Compared to other industries, such as manufacturing and computing, there is a general perception that the mining sector has been lagging in applying technology. According to Bellamy and Pravica (2011), this is attributed to the lead time between 7 -10 years needed to develop and commercialise new equipment in the mining industry. The literature indicates an increase in mining companies' uptake of the latest technologies.

According to Konyuk (2002), the development of mining automation is divided into three stages chronologically. Automation in the mining industry started in the late 1960s when unmanned underground carriages were used in Germany. The same systems were developed for ore mines in Russia, Sweden, the United States of America, and Poland. At the same time, re-programmable positioning for drills was designed for France, Japan, and Norway (Konyuk 1995 as cited in Konyuk, 2002). The second stage was when remote control autonomous underground machines were introduced. The operators were positioned on the surface while controlling the machines underground with the aid of cameras (Thring 1976, as cited in Konyuk, 2002). Towards the end of 1990, the third stage of automation was introduced. The remote control was applied from the surface load and haul machines, with automatic machines also being used (Konyuk, 2002). At this time, the hard rock mines adopted some ATs in the coal industry. The timeline showing the evolution of automated systems in the coal mining industry is depicted in Figure 3.1.

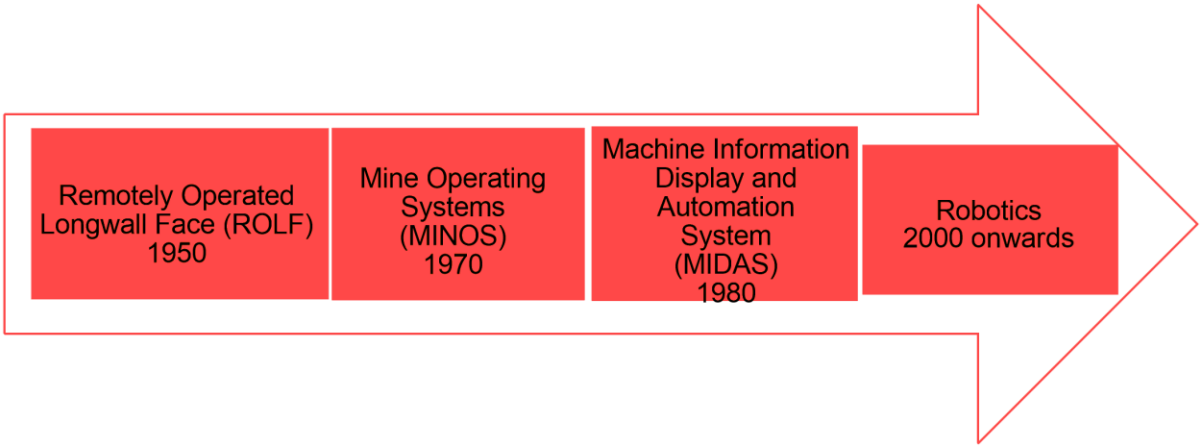


Figure 3.1 Mining automation developmental history of Longwall faces (Rogers et al, 2019)

The mining industry is slowly progressing to full automation. In early 1900, the average working hours per week were 70, but with automation, this has reduced to 40-45 hrs (Rogers et al., 2019). Underground coal mines have successfully adopted automation (Mavroudis and Pierburg, 2017). It is estimated that by 2025 the rate of implementation of new automated equipment such as robotic trucks, trains, and diggers in the mining sector will be 25% compared to 0,1% in 2017 (Mining Industry Human Resources Council (MiHR), 2020).

The advances in information and communication technology determine the development of AT. McNab and Garcia-Vasquez (2011) have identified four technologies that promote automation: communication, sensing system process, navigation, and imaging. Large amounts of data, with minimal time delay, over long distances have been enabled due to the advances in communication technology. In the mines, advanced sensing technologies are used for monitoring equipment, health, operations, and location, promoting automation development. System processes also have advanced and become complicated. With the aid of improved computer processing power, the processing and control capacity of the system process has enabled the management and analysis of mine wide information. Navigation and imaging technology is also being used at the mines, allowing the location of machines in an open pit with a high-precision GPS.

It is essential to integrate three key components for effective mining automation: sensing, processing, and control. These are essential for a system architecture perspective in the mining industry (Ralston et al., 2014). The mining automation cycle is depicted in Figure 3.2, and it shows the three components of sense, decide, and act.''

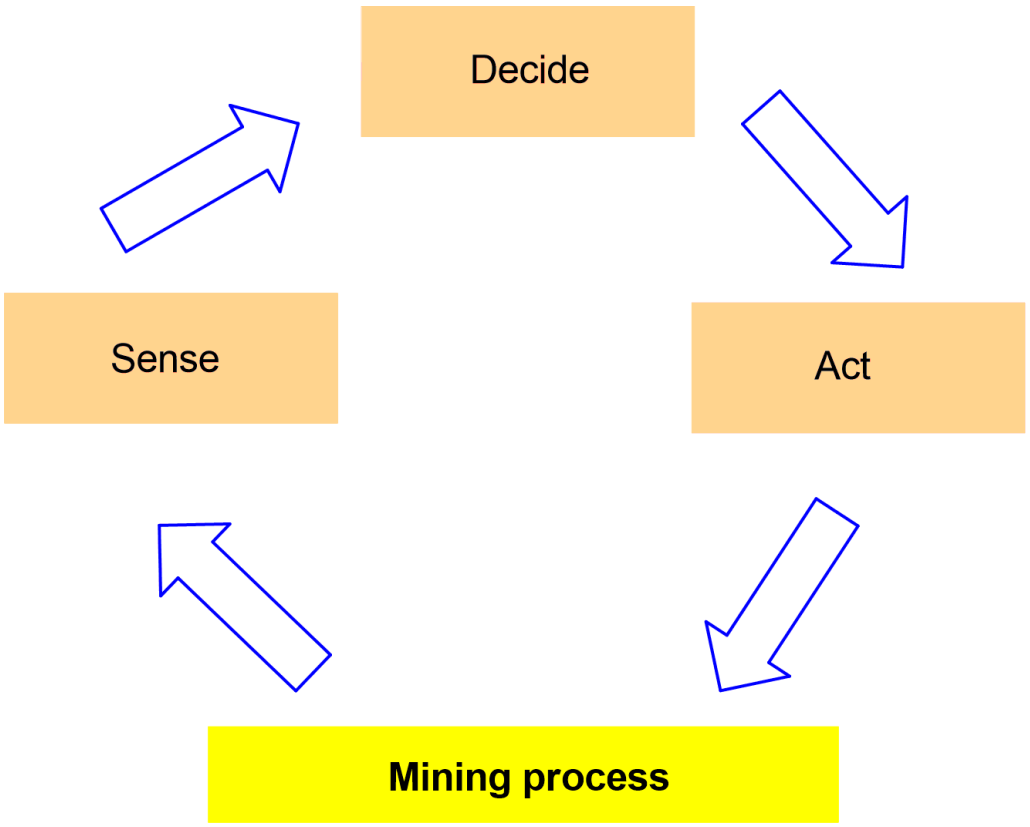


Figure 3.2 Mining automation cycle (Ralston et al., 2014).

According to Ralston et al. (2014 pg 306), the " sense, decide and act" represent the underlying mechanisms that give awareness, decision support, and process management to achieve a complete mining cycle. The integration of these three components makes it possible for mining automation. The main focus of mining automation is to improve safety and improve efficiency.

3.4 Levels of Automation

The Royal Academy of Engineering (2009) has further subdivided automation into categories that can mean a controlled, supervised, teleoperated, semi-automated, or fully automated machine, with each higher level requiring less human intervention. According to Cosbey et al. (2016), automation in the mining industry is divided into

system control levels. These are lower, mid, and full automation levels. The lower-level automation is characterised by warning systems such as proximity detector systems (Swanson et al., 2019). The operator will be in complete control all the time, taking control of mining machinery using cameras, sensors, and positioning software while the machine provides a warning or assistance (Lynas and Horberry, 2011; Cosbey et al., 2016). Mid-level automation or semi automated is whereby part of the functions are automated. At this level, the operator controls the machine most of the time, although some processes are automated and overseen by the operator (Cosbey et al., 2016). The operator is positioned in proximity to the machines. At the full automation level, the operator will be in a remote location from the equipment. The equipment is controlled using computer screens, joysticks, and other controls without involving an operator (Lynas and Horberry, 2011).

Ralston et al. (2014) identified continuum levels associated with automation as local manual control, remote manual control, teleoperation, tele supervision, and full automation. As the contiuum levels of automation increase from local manual control to full automation, the distance of the operator line of site with the equipment increases, while the direct machine control interface decreases to the level of mining processes functioning autonomously at full automation.

According to Rogers et al. (2019), automation tasks range from simple to complex, but full automation is best suited to perform repetitive or cyclical tasks such as drilling, loading, and hauling. Human involvement is an integral part of systems design in automation (Janssen *et al.*, 2019). It is not entirely possible to remove the human element from automated machines. Rogers et al. (2019) made a comparison between humans and machines. One of the conclusions was that human beings' reason, analyse, and rational thinking is practised, whereas, in automation, the reasoning is deductive and computational.

3.5 Effect on Employment and Control Levels of Automation

Before advancements in technology, only teleoperated machines were deemed automated. Teleoperation is still utilised as a stepping stone to full automation in mining difficult terrains (Rogers et al., 2019). Regarding employment disruptions, teleoperations are unlikely to affect the job compliment, but the skill set will change. At

the same time, semi-automation and full automation will require a different skill set, and there is a reduction in the number of people operating the mine (Cosbey et al., 2016).

3.6 Automation in the Mining Industry

Initially, automation was adopted in the mining industry to improve the health and safety of mineworkers, but there have been extra benefits in the whole value chain of mining. The AT is a transverse change process through the complete mine value chain from exploration, planning, mineral exploitation, processing, marketing, and trading. Novel technologies are not used in isolation for a specific activity, bringing changes to the mine value chain (Sánchez and Hartlieb, 2020). The effective use of real-time information has enabled the mining process to be precise and predictable**.**

3.6.1 Exploration and planning

The network of physical objects such as sensors, equipment, machinery, and other data sources uses IoT, smart sensors/ real data capture to create big data. Using big data has drastically reduced the cost of exploration (Tauber et al., 2018). Companies can discover minerals easily by using high-performance AI technology. The 3 Dimensional (3D) modeling, AI, and drones have increased in use for prospecting and exploration. Technologies such as hyperspectral imaging and drones are used to monitor ground subsidence, perform *in situ* scanning, and conduct survey and security functions on the mines (Jacobs and Webber-Young, 2017). It has been established that drone work can now carry out aerial survey work previously done by a helicopter crew (McKenzie, 2020). The use of smart sensors has allowed real time data capture. Singh (2005 pg. 7) defined smart sensors as “chip with sensors and digital interface.” According to Gartner (2018), smart sensors collect large amounts of digital data on varying aspects of operations and relay this to central controllers or operating machines in real time. Advanced sensing technology assists in precisely targeting ore deposits, and by so doing, there is a reduction in wasted drilling time, and outputs are maximized (Ranjith et al., 2017).

Data generation is the base for integrated planning and control of the various units. Data generation enables the use of virtual reality “digital twin.” According to Tauber et al. (2018), digital twin simulations are performed to determine potential failures, efficiency, and productivity from the comfort of offices. Mining activities are complex, have uncertainties, and are expensive to carry out. As a result, estimation of production levels must be carefully and accurately predicted to establish the viability of mining (Brzychczy, 2019). Probability modeling becomes essential as it saves time and costs.

3.6.2 Mining and processing

Automation robotics and remote operation technologies hold the highest level of implementation in the mining industry. Real-time data makes it possible for companies to manage operations remotely. Autonomous vehicles, drillers, and haulage systems are rising (Mckenzie, 2020). Automated drilling removes people from dangerous locations such as high temperatures, rockfalls, and outbursts. In Sweden at Garpenbeg, mine sensors feed data to operators in a control room away from the active mining face. The GPS indicates the machine's location at any given time. It communicates with the operator if there are mechanical issues and when the machine is due for service (Steenkamp, 2020). In terms of maintenance, 3D and 4D printing will remove the need to procure spare parts from far (Tauber et al., 2018). 3D or 4D printing could transform the mining sector by condensing or eliminating supply chains (Bliss, 2018). In rock crushing, semi-autonomous crushers, rock breakers, and swings” are utilised to break large rocks and scoop up the ore from the extraction location. Haul trucks are eliminated as mobile crushers crush and transfer the ore directly onto conveyors instead of the trucks carrying the ore (Cosbey et al., 2016).

Autonomous equipment such as haul trucks, Load Haul Dumps (LHD), and drills have been used on the production line. The “self-driving trucks” can easily navigate the mine with AI (Rogers et al., 2019). In coal mines, automated longwall plows and shearers are operated remotely, keeping workers away from active faces (Cosbey et al., 2016). Caterpillar started research in the autonomy program in 1985 (Viewpoint, no date). Caterpillar first deployed six commercial trucks in 2013 (Mining 2020). In 2020,

Caterpillar provided over 239 autonomous trucks to major mining corporates in Australia, Brazil, Canada, and the USA (Sánchez and Hartlieb, 2020). In underground and surface mines, automation to many units of the mining operation is applied to excavation, drilling, and hauling (Rogers et al., 2019).

3.6.3 Supply chain and logistics

Mines are often located far from the ports, industries, and cities, and ore transportation is costly to mining companies. Auto Haul Systems (AHS) can safely move and transport higher volumes of materials safely and far than the human workforce could not do, resulting in productivity gains and safety (Mckenzie, 2020). Productivity gains of 20% have been realised since the implementation of the AHS (Rio Tinto, 2021a). The world's first automated heavy-haul long-distance rail network covered a distance of 280km. It was deployed in 2018 by Rio Tinto from its operations in the Pilbara region to the port (Rio Tinto, 2021b). This rail system saves almost 1,5 million kilometers of road travel every year.

3.6.4 Marketing and trading

There has been an increase in the application of blockchain technologies since 2017 (Steenkamp, 2020). Blockchain can promote trackability, transparency, and security through -to-peer sharing (Hussein, 2018). This is often referred to as a “tamper-proof digitized ledger and can document the provenance and characteristics of the original product peer, making information accessible to buyers at every stage” (Tauber et al., 2018). Market Intelligent captured through digital channels helps mining companies capitalise on buying and selling opportunities in the commodity market. Transparency in the supply chain, as well as downstream integration, enhances customer experience and engagement. The examples of new and emerging technologies in the mining value chain are depicted in Figure 3.3.

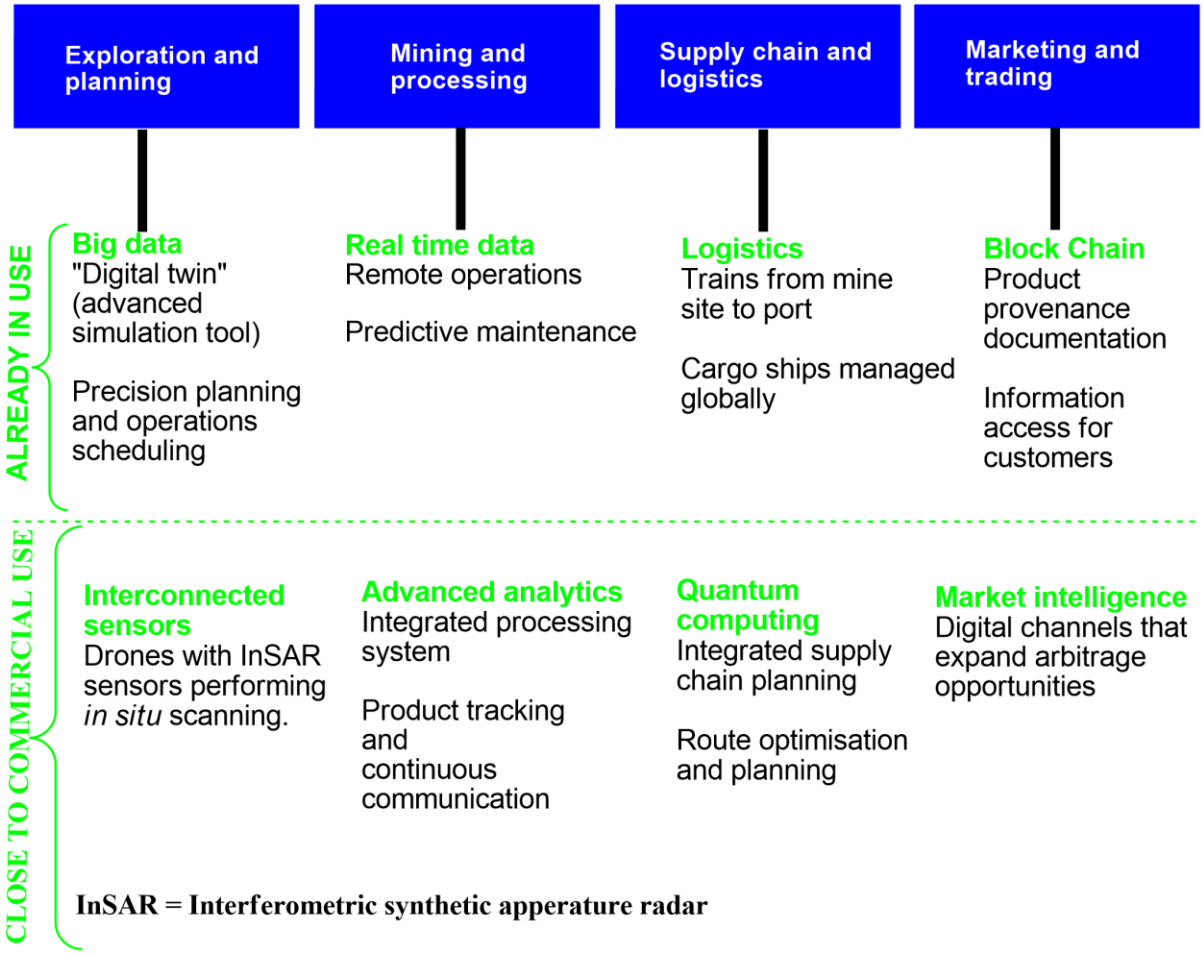


Figure 3.3 Examples of new and emerging technologies (Tauber et al., 2018)

3.7 Challenges of Automation in Mining

Although there are benefits to adopting autonomous technologies, there are some limitations. According to Groover (2020), high capital investment is required to set up autonomous systems, which decreases the plan's flexibility. Automation systems have an increased dependency on maintenance and repair, resulting in high maintenance costs. Retrofitting autonomous systems on existing equipment is almost impossible due to costs. The assumption that an automation system performs at a lesser price than operators is not always valid. There are instances where the system designer malfunctions and an operator needs to be engaged (Lynas and Horberry 2011). According to Rogers et al. (2019), mining work sometimes involves “navigating difficult terrains,” which requires human creativity compared to the factory set up with a

controlled environment. Automated machines are also less flexible, and failure of automation systems can result in catastrophic events.

The lead time to develop and commercialise new equipment, ranging from 7 to 10 years, may not apply to some mines as some operate for less than 10 years (Bellamy and Pravica, 2011). The new technology brings in new forms of risk, which need to be managed differently from the already known risks. More comprehensive data connectivity exists between equipment, remote centres, and different operational units. Companies are at high risk of security breaches (High, 2020). There is a need to focus on cybersecurity in an advancing digital environment.

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4. AUTOMATION IN THE MINING INDUSTRY

4.1 Introduction

The chapter covers the reasons mining companies opt to adopt automation and the application of automation worldwide. The chapter further looks into the implications to date of automating the mines and the lessons that can be drawn. It briefly covers the lessons SA can draw from these findings.

4.2 Reasons for Automation in the Mining Industry

The mining industry has been facing varied challenges in ore production. AT has been gradually expanding in the mining industry due to automation benefits for the past 50 years (Rogers et al., 2019). In 2014, Accenture surveyed executives of 151 mining companies worldwide. Survey results had 85% strongly supporting of adoption of digital technology because of the benefits such as the reduction in operating costs, improved safety, ability to extract low-grade ore, and improvement in productivity and efficiency associated with automation (Sganzerla et al., 2016). When a mine is automated, it functions around the clock, allowing maximum input utilisation (Natural Resources Canada, 2016). The forces driving automation seem to have originated from four different perspectives: the corporate world, the Original Equipment Manufacturer (OEM), the site workforce, and the technology researchers and developers (Lynas and Horberry, 2011). The corporate world has focused on optimising mining efficiency by considering safety and competitiveness through automating mining activities (Deloitte, 2014; Cosbey et al., 2016; Tauber et al., 2018; Rogers et al., 2019). The OEM supports automation by increasing market share by providing products to mining industries and increasing product differentiation. To further support this view of OEM, a survey carried out in 2019; in Chile by mining supplier companies on 105 mining companies revealed that not all mining companies are willing to adopt the new technologies. Only 9% showed a great interest, with 32% showing low interest and 59% showing medium interest (Sánchez and Hartlieb, 2020). Besides these findings, the suppliers are going ahead with manufacturing new technologies.

From the workforce point of view, the reason for automating the mines is that there is a need to lessen the production problems such as reduced throughput on the mine; thereby, research work aimed at improving on efficiency and reliability of the mines becomes necessary. Technology researchers and developers are interested in discovering more about technology as it advances (Lynas and Horberry, 2011). Environmental concerns have recently been the driver of automation (Harvey, 2019).

The mining environment's safety standards have decreased due to mines getting deeper, human error, and the remaining ore not being easily accessible (Sánchez and Hartlieb, 2020). Continuing conventional mining methods will not reduce safety incidents and sustain the industry. Mining companies' standards are continually refined, although the safety statistics remain unsatisfactory (Jacobs and Webber–Youngman, 2017). Automation allows automated equipment to be deployed to unsafe and complex areas with fewer miners, thereby allowing for more output at a lower risk. The vision for large corporate major mining companies is to improve safety in mining (Tauber et al., 2018). According to MiHR (2020), researched Canadian Mines, about 32% of the research respondents indicated that safety is one reason mining companies are adopting new technologies.

The ore grades are diminishing, and the remaining reserves are at deeper levels. Companies are constructing mines in increasingly remote areas with a low or non-existent population (Nebot, no date). The current mining methods are not supporting accessing this ore as it becomes too expensive, costly, and unsafe to mine. Besides the fact that mining operations are becoming deeper, geology is also becoming complex and challenging. Approximately 75% of new base metal deposits from the 21st century have been discovered at depths greater than 300m (Deloitte, 2014). The LOM for most mines has been shortened. Automation has allowed access to the ore at a reduced cost and improved safety (Tauber et al., 2018; Sánchez and Hartlieb, 2020).

Other reasons for mining companies to automate are labour shortages. There is a high annual rate of turnover in the mining workforce and increased employment costs due to retraining needs for new employees, especially in Canada and Australia (Meech and Parreira, 2011; Cosbey et al., 2016). This has been mainly due to the scarcity of

operators and an aging workforce (Bellamy and Pravica, 2011; WEF, 2016). Adopting full automation allows machines to control production, saving time and efficiency (Rogers et al., 2019). Humans are relieved from labour-intensive tasks that can also be time-consuming. This allows for extra time to be available to people for long-term planning and decision-making. Mining companies adopt AT to improve competitiveness and limit environmental impacts (Bliss,2018; Harvey, 2019).

4.3 Trends of Automation Adoption in the Mining Industry

Mining companies adopt the latest AT to modernise their operations (Black Livingston et al., 2018). According to Sánchez and Hartlieb (2020), not all technologies have the same level of adoption. Autonomous and semi-autonomous equipment such as trucks, drills, and trains have been tested for over a decade. Some have been successfully operating and are now expanding to other regions. Autonomous machines have gained prominence in Australia, the USA, Canada, China, and Chile. Global mining companies like Rio Tinto, BHP, Glencore, and Anglo American utilise autonomous machines. For the past few decades, automation has been gradually reducing the role of people in the mining face (Rogers et al., 2019). There has been a transformation in the whole mine value chain.

In 2012, one of the multinational companies BHP Billiton in Australia opened an Integrated Remote Operations Centre (IROC) in Perth (Jang and Topal, 2020). The IROC provides BHP with a Real-Time View of the entire Western Australia iron ore supply chain. The system uses mine fleet management systems for train control and plant control operations at the mine and the port. The Closed-Circuit Television and radio systems are the technologies used to communicate with the worksite personnel.

Rio Tinto has become the most automated mining operation globally and is widely recognised as a leading innovator and one of the least-cost iron ore producers. Major mining activities include drilling, excavation, hauling, crushing, and milling operations at a centralised location with minimal human involvement (Parreira, 2013; Sahu et al., 2015). Rio Tinto's" 'Mine of the future" program, created in 2008, has made strides in automation. The novel technologies are used throughout the mine value chain. "Smart mining" involves a program with a single centralised system located in Perth, where

operations at the mines, ports, and railway are controlled. The company utilises AHS, also known as “self-driving trucks.” For the AHS to operate, according to Redwood (2018), the following components are needed: (a) haul trucks fitted with electronic devices to allow continuous communication and control; (b) software that commands, controls, and tracks vehicle movements in real-time; (c) a reliable and all-encompassing wireless communications network; (d) a team of control room operators and support staff managing the vehicles, equipment, software, and network.

Across Rio Tinto’s Pilbara iron ore operations, over 130 autonomous trucks are operated by a supervisory system and a central controller in Perth (Rio Tinto, 2021a). An automated drilling system where a single operator can manage four drills at any single time is also being utilised at the mine (Mining Technology, 2018). Autonomous machines have allowed Rio Tinto to reduce costs and increase productivity, thereby remaining resilient to the volatility of commodity prices, and operating costs have fallen by 13% (Bliss, 2018). Enhanced mine safety has also been realised at the mine through autonomous trucks, auto drills, and driverless trains, reducing the number of people working in dangerous areas (Global Mining Guidelines Group, 2021).

Although autonomous truck adoption in the iron ore mines in Western Australia is faster than that of the coal mines, it is anticipated that adoption of the same trucks in the coal mines will be high after 2025 (International Mining, 2018). This is when new projects in coal come on board in eastern Australia, as new large coal projects are anticipated to go online after 2025 (International Mining, 2018). The open-pit coal mines on Australia's east coast operated by BHP use automated equipment like the open pits in iron ore mines (Wixted and Shoyama, 2018). In Russia, autonomous trucks are already used in the Siberian coal and energy company (Potapov, 2019).

Randgold Resources and Anglo Gold Ashanti use robotic loaders 800m below the surface to improve output and worker safety at the Kibali mine in the Democratic Republic of Congo. According to Creamer (2019), by implementing AT, Randgold has seen an improvement of a 29% quarter-on-quarter injury rate. Randgold runs the gold mining business out of the country. It only has six people in its corporate office who engage with the host country's government officials and service providers (Creamer, 2019).

Syama Gold mine, owned by Resolute Mining Company, currently operates two mines, an open-pit mine operational since 1984 and a full purpose-built automated mine which became operational in 2018 (Intergovernmental Forum on Mining Minerals, Metals and Sustainable Development (IGF), 2019; Mining Review Africa, 2021). The mine is located in Mali, where drilling, loading, and dumping are mechanical. The operations are run from the surfaces by the local mine employees. OEM, Sandvik, has supplied the mine fleet with “Automine and OptiMine” to control the vehicles and optimise the mine. One of the main benefits of automation in the mine is that production is maintained for extended periods where operations could have stopped in a convectional mine, for example, during shift change. The drivers for automating the mine were the need to remain competitive by increasing machine productivity and performance and reducing cost per tonne. Some factors considered were reduced risk, safety outcomes, reduced equipment wear and tear, and reduced number of people working underground. The new greenfield mine did not create many jobs, and the Mali government did not have a problem (Mining Review Africa, 2021).

In conjunction with Ericson cell phone company, Swedish Mine Operator Boliden’s Kankberg gold mine has constructed an autonomous gold mine through a 5G network (Mining Technology, 2017). High-performance communication is needed for remotely controlled equipment to be a success. Through automation of the mine, 18 Mega Watts energy requirements for ventilation were saved (Mining Technology, 2017).

Drones are being used at Freeport- McMoran mine in Peru to inspect high walls, tailings, power lines, traffic flows, and aerial safety checks before blasting. The areas where scanning by drones is carried out are dangerous and inaccessible to humans. The main advantage of drones is that information is instantly relayed, enabling a more rapid, detailed analysis of the slopes without deploying a skilled geologist or geotechnical engineer to the area (Hussein, 2018).

In Canada, Goldcorp and International Business Machines (IBM) have launched a new technology that applies AI to predict the potential for gold mineralisation. The technology uses search and query capabilities to identify critical information, allowing the exploration team to develop geological extrapolations and quickly propose new

targets for drilling. Goldcorp uses remotely operated drill technology to access very complex ore deposits (International Business Machines, 2018).

4.4. Impacts of Automating Mines

4.4.1 Socio-economic

In general, where mining activities are established, they contribute to the socio-economic development of that area. The socio-economic effects should be assessed and understood throughout the lifecycle of a mine. The “socio-economic” phrase represents positive and negative development that affects communities’ economic and social well-being (Cuartero-Enteria, 2018). Any developmental activity is expected to directly or indirectly contribute to economic and social status (Morris and Baartjes, 2010). Socio-economic is a concept with a much different meaning to academics and development practitioners and is considered an evolving concept that does not have an agreed definition. The socio-economic status is measured using combined elements of economic improvements such as productivity, education, income, occupation, or a varied combination of these elements (Baker, 2014). The changes in, or advances in technology, improve access to education, employment, health, and people's general well-being (Baker, 2014).

4.4.2 Productivity

According to EY (2019b), adopting novel technologies in the mines improved productivity by between 9%-23%. Productivity in mining increases through increased availability and utilisation of equipment and tyre life (Parreira, 2013). Autonomous machines allow convenience and consistency, promoting efficiency and reliability and decreasing expenditure. The mineral commodities are volatile, and there is an assumption that AT performs tasks at a lower cost than people (Lynas and Horberry, 2011). According to research work done by MiHR (2020), for Canadian mines, 57% of the respondents indicated that reducing costs and increasing productivity was the reason for implementing automation. Adopting AT allows the mining industry to alter itself and be attractive.

Boudreau-Trudel et al. (2014) assessed the impact of new equipment on productivity in 10 underground gold mines in North America from 2005 to 2011. The mining methods were the same throughout the research, but the machines varied. The results indicated that productivity does not increase with technological innovation by applying the cost per metre drilled indicators, cost per hour of use, and equipment availability over a year. The results were attributed to different machine functions, standards, and skills shortages. For automation to succeed, operator acceptance, skilling, trust in technology, and use of technology interface design must be considered (Lynas and Horberry, 2011; Rogers et al., 2019). In addition, Lynas and Horberry (2011) argued that, although automation improves productivity and efficiency, there are also human-related issues associated with automation, such as greater flexibility in shift roasters, boredom, complacency, and deskilling. These other effects can easily reverse the potential gains of adopting automation. Eichengreen (2015) argues that productivity is slow at the initial stages of using new technologies as there is a need for new infrastructure, skills, and business models.

4.4.3 Employment

Although technological development is positive for the economy, stakeholders have a growing consensus that technological change brings job displacement, skills need changes, disruption in local economies, and a rising inequality gap (Hermanus, 2017; Holcombe and Kemp, 2019). The increasing use of automation and IROC requires less direct employment. Automation will alter the workforce's size, roles, and location, although it is suggested that the net effect is insignificant as new jobs will be created (McNab et al., 2013; Cosbey et al., 2016). It is accepted that skilled people will always need to oversee autonomous systems. Rio Tinto allows people and computers to augment each other without viewing humans and machine as exclusive sources of knowledge (WEF, 2016; Rio Tinto, 2021a).

Burns and Church (2019) allude that the impact of automation depends on the type of roles represented on the mine. There will be a reduction of unskilled workers in the short term, but skilled and technology-enabled employees will be more in the long run. According to Cosbey et al. (2016), haul truck automation impacts mine employment

directly. The unskilled labour needs will change and result in relocation to other roles, e.g., truck drivers shifting to autonomous truck supervision roles (EY, 2019a).

In Australia, it has been established that automation impacts jobs and employment, and mining companies must consider an interplay between automation and local content policies. Research carried out in Australia's opencast mines showed that when mines are fully automated, the workforce is reduced by 30-40% (McNab et al., 2013). Accenture (2010) research focusing on the economics of trucks, dozers, and drills revealed that unemployment in an automated mine could be as high as 75%. According to MiHR (2020), research findings in the Canadian mines showed that automation would disrupt jobs for low-skilled mining workers who perform manual labour and are in repetitive jobs such as truck driving, drilling, and blasting. Currently, these constitute over 70% of mining employment. A report by the International Institute of Sustainable Development (IISD) authored by Cosbey et al. (2016) has indicated that in the next 10 years, approximately 50% of the mining jobs will be lost due to automation.

In Canada and Australia, the indigenous people are at a disadvantage with the shift to remote operations and increasing demand for higher skills. Most Indigenous people are in low-skill jobs, likely to be affected by automation (Burns and Church, 2019). New jobs are created in information technology, processing data analysis, and servicing and maintaining remotely controlled autonomous equipment (McNab et al., 2013; Holcombe and Kemp, 2019; MiHR, 2020). EY (2019a) report, at the Australian Government's request, has indicated the likely changes in the skills landscape for miners in future work due to technological changes, as depicted in Table 4.1.

Table 4. 1 The Future of Work: The Changing Skills Landscape for Miners (EY, 2019a).

Occupation Group	**Current Proportion of workforce**	**Future Proportion of the workforce**
Drillers Miners and Shot Firers	22%	17%
Metal Fitters and Machinists	11%	15%
Other Building and Engineering Technicians	6%	13%
Truck Drivers	5%	2%
Electricians	4%	8%
Production Managers	3%	6%
Structural Steel and Welding Trade Workers	2%	1%
Other stationery Plant Operators	2%	1%
Geologists, Geophysicist	2%	3%
Mining Engineers	2%	4%
Earthmoving Plant Operators	2%	<1%
Industrial, Mechanical, and Production Engineers	1%	2%
Human Resources Manager	1%	2%
Occupational and Environmental Health Professionals	1%	2%

Cosbey et al. (2016) indicated that employment conditions such as less physical work and reduced operator salaries would be experienced. Employment opportunities for women, people with disabilities, and those over 65 are promoted through automation. According to Mutanga et al. (2021), a study on the implications of 4IR in the SA and Zambian mines revealed that in one of the SA coal mines owned by Sasol, only 13% of the employees are female. One of the primary goals of Sasol mining company is to employ more females soon.

4.4.4 Skills requirements

In response to rapid changes by new technologies, education and training systems must prepare people to be flexible and develop new skills. Literacy is a foundation on which workers can develop higher skills (MiHR, 2020). In the dictionary, literacy means the ability to read and write or knowledge or competence in a specified area. For this

research. literacy refers to competence or knowledge in a specified area. Automation requires a unique skill set for mine employees (Parker, 2021). Research has found that, in both developing and developed countries, employees with low or medium-level education are at a high risk of job automation (Chang and Huynh, 2016; Berriman and Hawksworth, 2017). In the era of automation, one becomes vulnerable by not qualifying for vocational training or post-secondary education in job employment. Higher qualifications ensure access to jobs that demand higher skills. Bruckner et al. (2017) state that skills development programs require changes to enable workers to align with the technological shift. The general education system considers more scientific subjects such as science, technology, engineering, and mathematics (STEM) from elementary, high school, and college levels (Hafni et al., 2020). Policies promoting early education and lifelong learning skills such as mechatronics, systems approaches, and data management becomes crucial (IGF, 2019)

Mining companies in Australia have made firm public commitments to promoting indigenous training, employment, and business development. Lifelong training is the key to continuously upskilling and empowering workers (IGF, 2019). BHP Australia has set up training and upskilling opportunities for its employees at the IORC facility in Perth. Loow et al. (2019) argue that while automation has cost benefits to the company, this also allows for the loss of knowledge and experience. The aging workforce needs to be considered for retraining as there is much potential.

Collaboration between companies, government, and educational institutions are essential in supporting the local communities to participate and align with the changing economy (Burns and Church, 2019). Research in the Canadian mine environment has shown that the automation era's skills requirements will continue to change. Technical skills such as computer programming, systems analysis, leadership collaboration, and communication skills will be highly demanded (MiHR, 2020). In Rio Tinto’s operations in Western Australia, the government realised the need to embrace the move towards automation by taking a collaborative approach to retraining, reskilling, and redeploying. In Western Australia, the government, Rio Tinto, and South Metropolitan have partnered to develop a nationally recognised Certificate IV in Autonomous control and automation (Rio Tinto, 2019).

4.4.5 Research and development

Historically the mining industry has proven to have low levels of expenditure in R&D compared to other sectors such as pharmaceuticals, information, and communication technology (Sanchez and Hartlieb, 2020). Expenditure on R&D, on average, is estimated to be 0.5% of the total revenues (Filippou and King, 2011). Numerous Australian research centres, universities, and industries invest millions of Australian dollars in automation technology research. Australia's great mining universities, such as Curtin, University of Western Australia, University of New South Wales, University of Queensland, and Monash, offer courses directly associated with the industry. There is significant research funding, primarily sponsored or partnered by the industry. The universities carry out industry-driven research, and most times, they teach the latest knowledge and technology. Some universities have an industry advisory committee that ensures the university keeps up with the changes in the mining sector (Evans, 2020; Mining Technology, 2018). Rio Tinto collaborates with the government, industry, and educators to create nationally accredited qualifications in automation. Rio Tinto Australia welcomed the first nationally recognised qualification in automation in July 2019 (Rio Tinto, 2019).

The Centre for Social Responsibility in Mining (CSRM) was founded at the University of Queensland to assist communities and governments in effectively responding to socio-economic and political challenges associated with mining. The Minerals Futures Collaboration Cluster is a collaborative program between the Australian Commonwealth Scientific Industrial Research Organisation (CSIRO) and researchers from the University of Queensland, the University of Technology, Sydney, Curtin University of Technology, Central Queensland University, and the Australian National University was established as early as 2010 specifically for this purpose (McNab et al., 2013).

4.4.6 Shared value concept

According to Cosbey et al. (2016), the relationship between mining firms and states is based on an exchange of shared value. Porter and Kramer (2011, p. 6) define shared

value as “policies and operating practices that enhance the competitiveness of a company while simultaneously advancing the economic and social conditions in the communities in which it operates. Shared value creation focuses on identifying and expanding the connections between societal and economic progress.” The shared value contributions give the mining firms the Social License to Operate (SLO). Shared value can be created through economic development linkages. There are at least three prominent types of local content opportunities that most governments have sought from mining companies. These are direct employment of locals, acquisition of local goods and services by mining companies, and beneficiation (Cosbey et al., 2016; IGF, 2019). For most local communities, the primary benefits of mining are local jobs and the acquisition of goods by mining companies.

According to Burns and Church (2019), automation will change how local communities benefit from mining companies. In Canada and Australia, for the past 20 years, the number of indigenous people employed at the mines has increased significantly compared to other sectors due to the implementation of policies such as local-level agreements, state regulatory requirements, and mining company policies and commitment (Holcombe and Kemp, 2019). In Western Australia, the aboriginal population comprises about 55% of people employed as drivers and machine operators while 24% as technicians, 6% as labourers, and 5% as professionals. This positive trend will be disrupted by automation as the target group consists of people who are into repetitive jobs. Automation will impact these policies, and there is a need to revisit and find new ways to create value in mining and the communities (IGF, 2019).

With automation adoption, it is anticipated that foreign mining companies will spend less in the host country where they are operating. Cosbey et al. (2016) argue that there will be lower spending on local procurement for items such as fuel or other resources. Goods that mining companies used to procure locally, results in a decreased GDP in host countries while royalties and other taxes increase due to improved efficiencies and revenue. At the Kibali gold mine, Randgold has employed only six people in its corporate office. The gold mining business is run out of country offices that engage with the government and services provided in the host countries (Creamer, 2017). As jobs and procurement opportunities decrease, the future requires re-imaging traditional relationships between host countries and mining companies, such as

communities receiving direct royalties and supporting economic development (Cosbey et al., 2016).

Mining companies need to support community economic development in affected communities. Introducing autonomous machines and setting up IROC has a negative microeconomic developmental effect on the local communities. There is a reduction in government funding for social services and infrastructure when there is a reduction in the skilled population with more disposable income, as these would have moved to urban centres (McNab et al., 2013; Cosbey et al., 2016). A reduction in mine-related jobs locally, economic activity, and population-driven social services such as transportation, food services, accommodation, and recreation stemming from local population growth are likely to occur (McNab et al., 2013; Burns and Church, 2019). Opportunities for local activities such as the maintenance of autonomous trucks may emerge, but this depends on whether local business people will have the capital. There is a lack of capacity for training the locals for new jobs in regions with weak links between mining companies and educational systems (Cosbey et al., 2016).

4.4.7 Labour unions

Powerful interest groups such as trade unions fight to protect workers and industries against the adverse effects of automation. Automation causes a reduction in traditional labour. Workforce reduction needs to be transparent with trade unions (Lööw and Johansson, 2019). Workforce acceptance of automation technology is dependent on the trade union's decision. Developed countries such as Australia and Canada have labour unions that support automation as they have perceived other opportunities associated with automation.

4.4.8 Human rights

According to Holcombe and Kemp (2019), global civil society groups and worker organisations are concerned about data-driven technologies, social, ethical, and human rights implications. In Australia, a significant project referred to as "Human

Rights and Technology” has been set up to protect the rights and freedom of people during the automation era.

4.9 Challenges to Automation Adoption

People and culture have been cited as barriers to the effective adoption of automation and the political, social, and business landscape (EY, 2019a). According to Barnewold and Lottermoser (2020), innovations with high initial costs and the possibility of impacting cash flows or SLO, most companies are cautious so much that take-up of technologies may be slow. Companies with large-scale production adopt these technologies more than those with low production. Digital technologies are associated with broader connectivity for equipment, sensors, and between different business units. Companies are exposed to a high risk of security breaches (Sánchez and Hartlieb, 2020). Companies do not share a lot of intellectual property.

Automation adoption is associated with some barriers. Various people have different perceptions about what can impede the adoption of automation. A study by WEF (2016) on the significance of barriers to change indicated various factors influencing change, as shown in Figure 4.1.

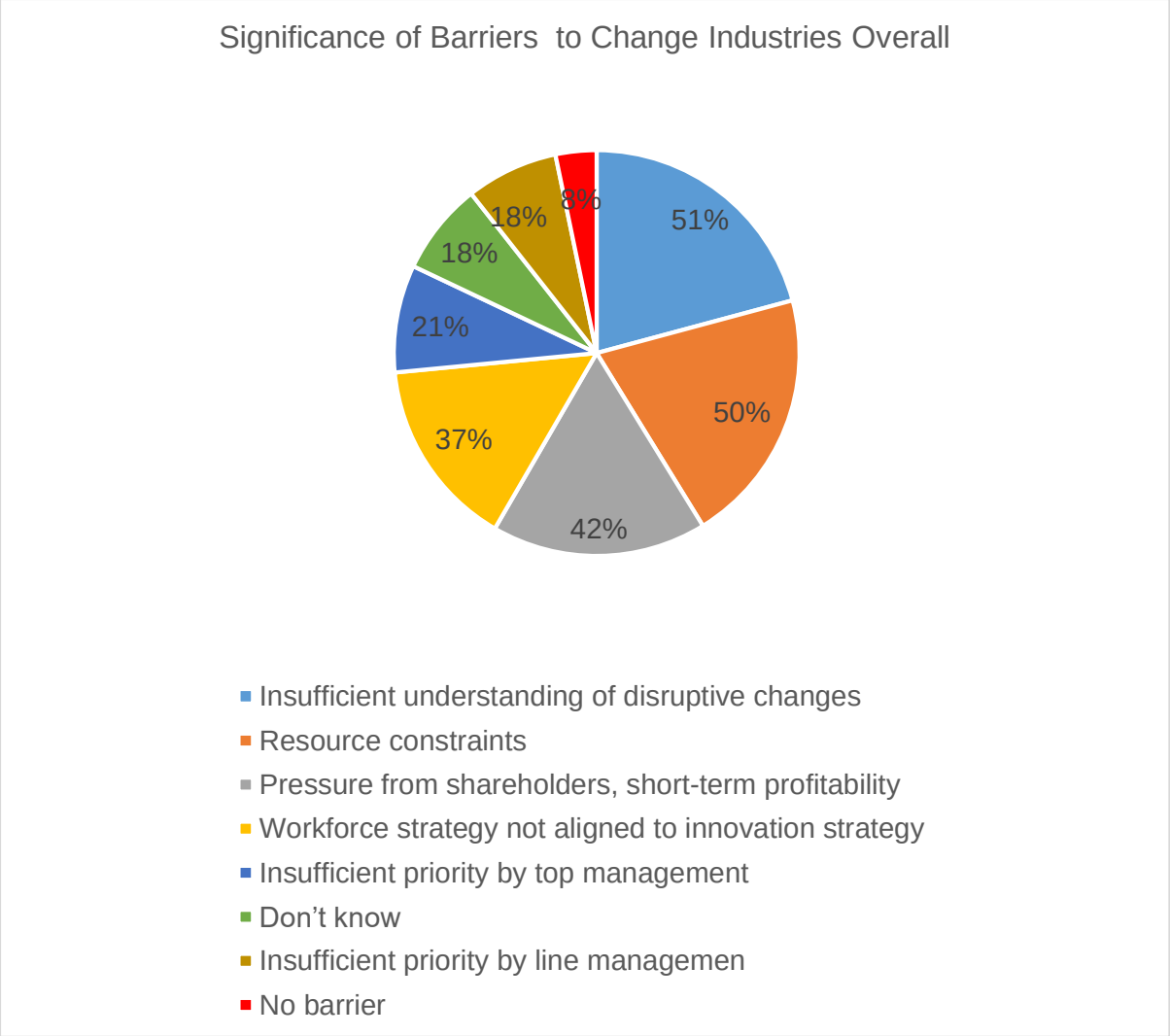


Figure 4.1 Significance of barriers to change (WEF, 2016)

WEF (2016) findings from respondents indicate that businesses are aware of looming challenges and limitations ahead of automation adoption. Insufficient understanding of disruptive changes ahead and resource constraints are the main barriers to automation adoption, with approximately 50% of the survey highlighting this issue. Pressure from shareholders and short term profitability, workforce strategy not aligned to innovation, a low priority by top management, and low priority by line management are some of the challenges identified. There is also a minority group who believe there will not be barriers.

4.10 Key Learnings from Australia and Canada

Economic benefits are realised in the mining industry due to the adoption of automation. Developed countries such as Australia and Canada are in the lead of automation adoption and have carried out most of the research on the socio-economic effects of automation. According to Holcombe and Kemp (2019), more research on the socio-economic challenges associated with automation is still being called for, although some lessons can be drawn from the developed world.

4.10.1 Employment

Mining companies such as Rio Tinto Australia are engaging globally with unions about the impacts of automation and IROC on its workforce. According to Australian Mining (2019), the workforce being made redundant because of automation is being transferred into new roles through upskilling and reskilling. As for the unskilled labour force, the roles have changed to more technical operators and supervision. For example, truck drivers have been moving into autonomous truck supervision and relocating (McNab et al., 2013; Burns and Church, 2019). According to MiHR (2020), in Canada, there has been an increased demand for technical miners, especially those with expertise in wireless technologies, fibre optics, and data analytics.

4.10.2 Trade unions

Trade union membership has declined in developed countries (International Labour Organisation, 2021). The current view by unions is that it could be a chance for Trade Unions to win new victories for workers and demonstrate the value of unions to the next generations. The unions are lobbying for shorter work hours for union members and setting up job security councils that retrain and upskill people (O'Connor, 2020). The Miners Union in Australia had indicated that with automation adoption, there shouldn't be any forced redundancies for workers. There is a need for additional jobs and apprenticeships in other business sectors to accommodate those who may lose employment. Companies that sack their workers should pay more royalties to the government to offset the loss of jobs in regional communities. IROC should not be

established in big cities but at or near affected mines (Mining Energy Union, 2019). The Australian Unions are lobbying for an Organisation to be created that solely oversees the impact of these novel technologies on society (Australian Council of Trade Unions, 2019).

4.10.3 Education and skills development

A strong collaboration between government, industries, and universities has been established for research purposes and assessing and predicting the future automation trends in the mining industry (McNab et al., 2013). The CSIRO Flagship collaboration funded over A$3 million to the Minerals Futures Collaboration cluster for three years. Researchers from the University of Queensland, Curtin University of Technology, University of Technology Australian National University, CQ University, Monash University, and CSIRO were brought together to explore sustainability issues in the mining sector across regional, national and global scales in 2010 (Franks et al., 2013). Universities are working with industries to tailor make subjects relevant to the mining industry with the current changes in technology and funding research work at universities (Mining Technology, 2020). Mining companies such as Rio Tinto have collaborated with universities and are sponsoring qualifications in automation (Rio Tinto, 2019).

4.11 Fundamental Differences between Australia, Canada, and SA

There is no “one size fits all approach” to the socio-economic effects of automation. Developed countries such as Australia and Canada may be less affected by socio-economic effects due to the more diversified economic base, higher skills base, advanced infrastructure with good connectivity, aging population, and lower unemployment rates (IGF, 2019). Automating reasons also differ; for example, in Australia, one of the reasons to automate is the scarcity of operators and an aging workforce (Cosbey et al., 2016). In SA, this is the opposite, as there is high unemployment and the demography consists mainly of young population.

Australia's mining workforce is almost half of the entire workforce in SA. Australia’s large-scale mines are primarily open-pit mines located in remote regions with minority

Aborigines. In Australia and Canada, the mining activities are located on or adjacent to the lands of indigenous people. The mining companies' primary and secondary employment is the only way these indigenous people got involved in the market economy. Automation requires highly skilled employees, which could exclude the already marginalized communities such as the Aborigines (Holcombe and Kemp, 2019). For Australia, the labour sending communities are from big cities flying in and out to the mines. The bulk of the mines in SA are deep underground mines with poorly developed infrastructure. The SA mines are found in the cities; for example, the Gold mines are in or around Johannesburg, and most coal mines are in the Witbank area. Unlike Australia and Canada, there is no flying in an out for mine workers in SA. In the SA history of mining, most mines relied on migrant workers (Gumede, 2018) While the trade unions in the developed countries are decreasing, the trade union of SA is highly unionized, and on some occasions, its members have left the mining industry paralysed due to strikes (Hlatswayo, 2017).

The collaboration between the government, industry, and universities is relatively high in developed countries. In SA, the current mining industry is not funding research work that much. In the SA context, funding for R&D from the government significantly dropped when mining companies started working in silos for research work (Porter, 2014). In R&D, there is a need for collaborative work among stakeholders. According to Singh (2017), mining-related collaboration in SA has the Centre for Sustainable Mining Industries (CSMI), Centre for Mechanized Mining Systems (CMMS), Wits Mining Institute (WMI), Mining Resilience Research Centre (MRRC), Centre of Excellence on Occupational Health and Safety (CEOHS), Mine Health and Safety Research Council (MHSRC) and Mining Research Impact Area (MRIA). Having so many collaborative units presents a problem in finance, which has resulted in researchers competing for inadequate resources, research capabilities, and capacities deteriorating. Mzekandaba (2022) indicated that SA R&D has generally been on a downward trend of approximately 12% in terms of expenditure in the 2019/20 period compared to the 2017/2018 period. The much-needed collaborative work between government, academia, unions, and industries is weak. Australia and Canada have reviewed the education system with an emphasis on STEM**.** SA is still at the conceptual stages.

5. AUTOMATION IN THE SA MINING INDUSTRY

5.1 Introduction

This chapter will focus on mining in SA with some particular emphasis on coal mining. The chapter also provides the reasons for adopting automation in the SA context and the possible socio-economic implications. Suggested ways of minimising the socio-economic negatives and enhancing the positives are included in the conclusion of the chapter.

5.2 Mining in South Africa

Historically, the SA mining sector has been the leading supplier of minerals and mineral products worldwide. The SA mining sector has existed for over a century and is in the top 10 global producers of Platinum Group Metals, gold, chromium, and coal (Baxter, 2015). The economic growth of SA is strongly linked to the development of the mining industry (Sturm and Schimpf, 2016). The mining industry plays a crucial role in the economy, with coal being the backbone of the energy source in all the industrial sectors in the country. The hard rock mines in SA are considered to be labour intensive with less-skilled workers. The hard rock mines use mostly manual conventional methods, which are time-consuming and unsafe (Musingwini and Minnit, 2008). Contrary to the hard rock mines, the coal mines are considered less labour intensive, have more skilled workers, and are technologically better (CMM), 2020).

According to MCSA (2018), the SA coal mining industry has existed since the start of gold mining and has contributed to the economic growth and development of the country. There are 19 coal fields in the Karoo supergroup in SA, with the most significant remaining coal reserves being in the Waterberg, Highveld, Witbank, Freestate, and Ermelo fields. SA coal production has been dominated by mining companies such as Anglo American, currently renamed (Thungela), Exxarro Resources, Sasol Mining, South 32, and Seriti. The bulk of SA coal is derived from opencast mines, which contribute approximately 53%, underground bord, and pillar about 40%, while stoping is 4%, and longwall mining is 3% (Jeffrey et al., 2015).

According to Eberhard (2011), the coal mines in SA had low levels of mechanisation and extraction, and the bord and pillar method was the primary extraction method before 1970. As employees were given low wages and no technological advances, there was no incentive to mechanise. In the 1970s, an increase in labour costs, workers forming unions, and changes in government policies resulted in the coal mines mechanising. In the SA coal mining industry, surface operations became automated in 1971 when the first Dragline was introduced at Optimum colliery (Falconer, 1990). Continuous miners for coal surface operations and long walling for underground mines were introduced, resulting in coal output doubling between 1970 and 1980. Improvements in mechanisation increased productivity. Koul and Eydgahi (2018) have concluded that changes in technology influence social and behavioural aspects. The end of apartheid in 1994 led to more markets for the coal commodity overseas (Eberhard, 2011).

Literature regarding how the coal mines in SA dealt with the socio-economic effects of new technologies is not readily available. Information on how socio-economic issues were dealt with might not have been taken seriously as the focus was more on productivity. There is a view that companies that have implemented internal management change in the coal mining sector have managed to handle issues of technological changes well (Gumede, 2018).

There is a total workforce of 451 427 people in the SA mining industry, with coal mining being the third-largest group after gold and Platinum Group Metals (MCSA, 2018; MCSA, 2020). It is estimated that two or three jobs are created in backward or forward linkages through coal mining (CMM,2020). The coal mining industry has made and sustained about 170 000 indirect jobs in manufacturing, agriculture, forestry and fisheries, petroleum, chemical, and rubber plastics industries (Mining Review Africa, 2018). According to (MCSA, 2018), approximately 70% of coal volume is consumed domestically, and over 80% of electricity demand is generated from coal power. Coal contributes about 30% of liquid fuels in the country. In 2016, the coal mining industry earned over R50 billion export earnings.

5.3 SA Mining Industry Challenges

According to Lane et al. (2015), worldwide, the mining industry has been under pressure due to weak economic conditions, high volatility in commodity markets, environmental pressures, and reduced resource demand due to China's growth. The commodity prices have remained under pressure as there was a decline in resource demand following China's growth decline. Baxter (2015) indicated that hard rock and coal mining in SA faced various challenges. Although low-level automation and middle-level automation have been operational in the mining industry, especially in the coal mining industry, most mining companies want to advance to full automation to improve safety. According to (MCSA, 2019), the mining industry is working with the SA government to drive a technology innovation program entitled "Modernisation: Towards the Mine of Tomorrow." The program aims to accelerate modernisation/automation in the mining industry to ensure that "zero harm" is achieved and that mining remains competitive and contributes significantly to the economy. The SA mining industry has not been doing well in the safety issues, especially for deep hard rock mines.

The existing mining challenges have reduced LOM, higher production costs, and job losses. The ore grade of most resources has declined with the need to mine deeper, which has prompted the need to improve the safety and health conditions (Delloite, 2014, Sanchez and Hartlieb, 2020). Consequently, higher production costs have been experienced, lower revenues generated with low-profit margins, and minimal investment return for shareholders. The declining productivity and escalating cost of production have been a challenge in the mining sector resulting in most mining companies looking for cheaper ways of production (Lane et al., 2015)

In general, there has been a decrease in FDI for most African countries (UNCTAD, 2021). In addition to global pressures, the local challenges faced in the SA mining industry have aggravated the situation compared to the international counterparts (Lane et al., 2015). The challenges faced in the SA mining industry include viability, instability in the labour market, regulatory policy uncertainty, and infrastructure constraints, as shown in Figure 5.1.

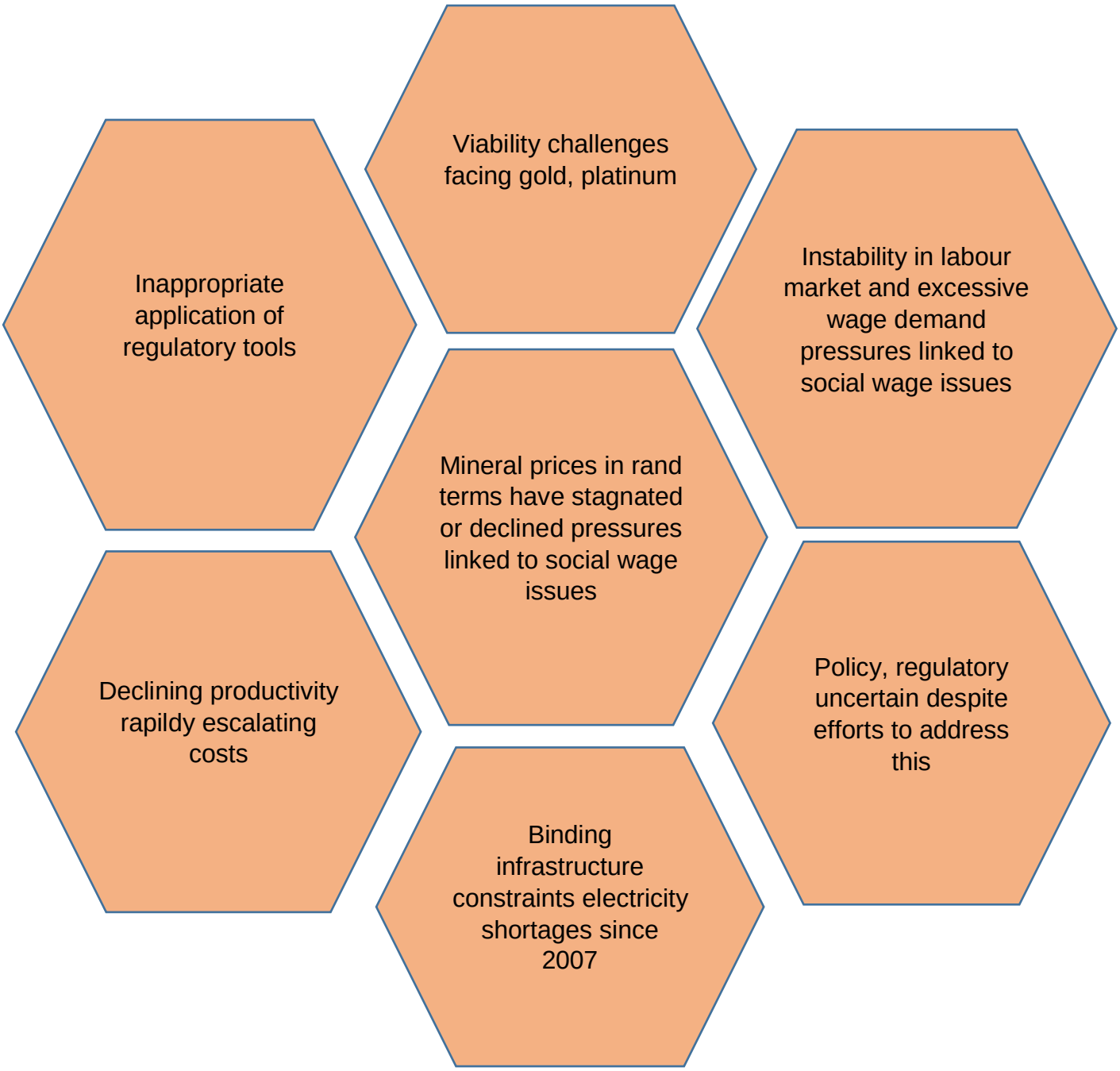


Figure 5.1 South African mining sector: the challenges (Baxter, 2015)

The SA labour market is characterised by a highly unionized workforce, especially low-level employees. According to Hlatswayo (2017)), the labour union has ample bargaining power. There are annual wage negotiations between the employer and these labour unions. The annual wage negotiations sometimes are typically characterised by strikes that paralyse production in the mining sector. Baxter (2015)

argues that the mining industry in SA needs to shift from conventional mining to modernised/ automated technologies to remain competitive. According to Murray (2021), throughput increase, efficiency increase, lower costs, and improvement in safety and health are the main reasons for investing in digital technologies.

The literature considers the coal mines worldwide always to have been in the lead in technological adoption and use, especially for underground mines (Sanchez and Hartlieb, 2020). The SA underground coal sector was successfully mechanised/automated from the 1970s to the 1990s. The technological improvements in the coal mines were mainly from drill and blast operations to continuous miners and longwall. Surface coal mines have always followed international best practise and are mechanised to some extent (Vogt and Hattingh, 2016). It has not been easy for mining companies to adopt new technologies historically. Factors such as lack of investment, lack of innovation from OEM, and failure of the leadership to understand the benefits of modern technologies have played a part (Bryant, 2015).

5.3.1 SA Coal mining industry challenges

Several challenges affect the SA coal mining sector. The hindering factors include depleting ore reserves, a decrease in the quality of coal resources, environmental threats, inadequate infrastructure, access to capital, policy and regulatory factors and export demand risk, low local demand growth, and transportation challenges (Kilian, 2013; MCSA, 2022). According to Van Zyl (2015), the coal mining sector in SA is facing the challenge of coal reserves that are becoming deeper and harder to mine due to a reduction in seam thickness. The mining height and the high frequency of structural features such as faults and dolerite inclusions have been some of the challenges. This has brought about increases in production costs and a reduction in profitability. The proposed carbon tax in SA will significantly affect the competitiveness of SA coal (MCSA,2022). Due to the effects of Greenhouse Gas Emissions from coal, most developed countries, such as the United Kingdom and Germany, have abandoned coal use (Carbon Brief, 2021). World Bank and International Monetary fund are no longer keen to lend money to construct coal power plants due to environmental laws. Indirectly the coal mining companies in SA are affected (MCSA, 2022).

5.4 Enablers for Automation Adoption in SA

Efforts to achieve “zero harm” to improve safety and reduce cost and productivity have resulted in global mining companies considering automating mining activities (Bryant, 2015). According to MCSA (2019), modernising the SA mines will transform mining companies from manual operations to more automated mining. Baxter (2015) argues that government, trade unions, employers, investors, and employees need to create a constructive partnership built on trust to make the transformation possible. The SA mining industry can drive change and create decent jobs by developing skills, being a leader in exports, key taxpayer, thereby significantly contributing to the economy. The vision for a competitive, vibrant, and transforming SA mining industry, as Baxter (2015) shares, is depicted in Figure 5.2.

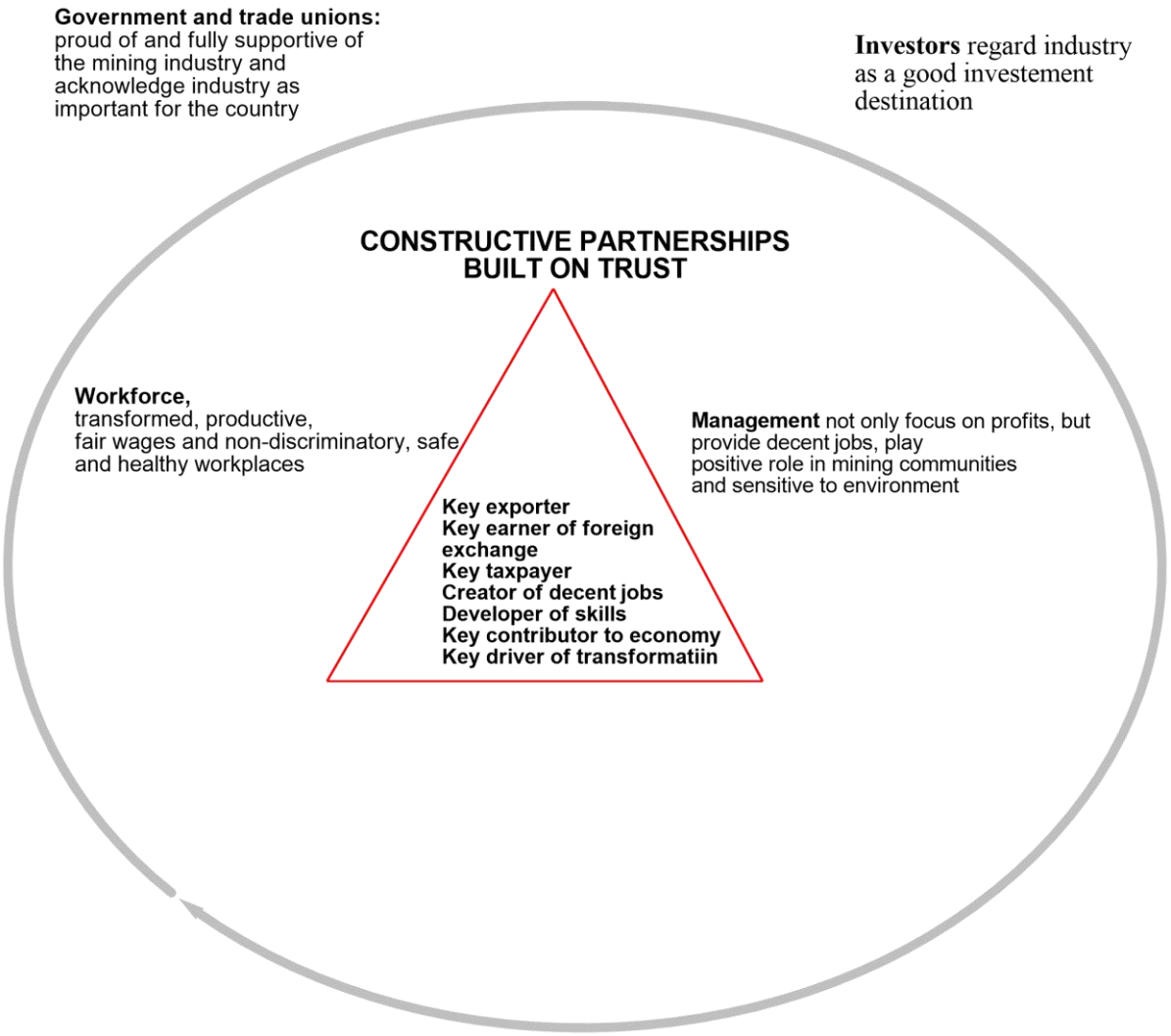


Figure 5.2 Vision for competitive, vibrant, and transforming South African Mining Industry (Baxter, 2015).

Mazzucato (2013) argues that governments are facilitators and "catalysts" of technological innovation. Governments for both developed and developing countries need to provide a conducive environment for adopting new technologies to enable development through infrastructure, institutions for R&D, and proper policy measures.

5.5 Trends for Automation in the SA Mining Industry

SA mines are slowly adopting digital technologies. Several automation technologies are being applied in the SA mining industry. Drone applications, proximity sensors, autonomous trucks, and loaders are implemented at different mines. In addition, modular information management systems that provide real-time data about underground operations have been rolled out in local mines. These technologies have improved safety as people moved far away from dangerous zones, especially in opencast mines, and enabled real-time data available to the mining personnel.

Finsch Diamond Mine has been using fully automated remote-controlled trucks in its underground mine since 2005, and De Beers implemented driverless vehicles at Venetia Mine in 2014 (Bliss, 2018). In addition, motivated by the benefits of automation, SA's other mining companies, such as Exxaro, Anglo American's Kumba Iron Ore, and Anglo Platinum, have adopted automation (Anglo American, 2013; Kotze, 2021).

In 2018, a Proof of Concept for autonomous trucks at an opencast coal mine was successfully completed between a network system provider Cisco and global truck manufacture in SA. The provision of a connected system by Cisco and one of their eco partners permitted the retrofitting of equipment on the manufacturer’s two different trucks enabling communication between trucks and mining equipment as well as demonstrating autonomous hauling. The trucks were remotely controlled through the network. There was a 100% increase in productivity during this PoC as 120 loads were achieved per day compared to 60 loads a day in normal trucks. Mines are adopting autonomous systems due to the need to improve safety and productivity (Moolman, 2018). According to Accenture (2019), Exxaro has digitised its mining value chain, and a productivity shift of 5% has been realised. The changes in productivity have all been made possible by creating a virtual integrated intelligence centre capable of predicting bottlenecks and advising the department involved on the interventions needed.

In another SA colliery, New Vaal in the Vaal basin in the Free State Province, geotechnical data was manually processed by the Rock Engineering department. In 2019, the Rock Engineering department introduced a cloud-based mobile application to collect and display geotechnical risks and improve communication concerning slope issues where strip mining is applied. The technology combines visual, drone, satellite, and radar monitoring (Strydom, 2019). Real-time data obtained allows for a quicker reaction to slope failures, and there has been an improvement in safety issues

Anglo American uses drones to inform where mining has taken place and measure stockpiles (Mutanga et al., 2021). The drones have enabled the mine to access areas of the problematic site and real-time access data, thereby reducing the time in data analysis. A collision avoidance system was implemented on over 100 trucks at Sishen in 2009. Since the implementation, no collision has been recorded on the mine (Test, 2009). Anglo American have also introduced automated drills at Kolomela, and there has not been a net reduction in people; instead, the nature of the jobs changed as most people worked in control rooms. The company ensured that most people were reskilled or upskilled to do the job (Mutanga et al., 2021).

Exxaro is modernising its Belfast coal mine in Mpumalanga, guided by the "Mine of the Future Concept." SA Belfast, a brand new coal mine, was the first to have a digital twin that enabled management to connect, manage and have real-time decision making on aspects of the mine value chain (Kotze, 2021). Increased production, throughput, and better management between mining and processing have been raised. The use of virtual reality has triggered the training of operators, which has improved personnel competency. The success of digital technology adoption at this mine relies on proper change management (Kotze, 2021).

5.6 Implications of Automating Mines

In many countries, the mining sector remains the key to economic and social development growth. There is a need to put in place measurements to create and strengthen development linkages between extractive sectors and the rest of the economy for national development (UNCTAD, 2016). The vertical integration processes in production chains also referred to as linkages, have impacted economic reforms in different nations. The development linkages that are associated with the

mining industry are fiscal, production linkages that consist of forward linkages, backward linkages, side stream linkages that are associated with spatial linkages, horizontal linkages that are associated with technology, and knowledge and consumption linkages that refers to the effect on spending (Beare 2017, UNCTAD, 2017b)

Fiscal linkages are made up of laws and regulations that are used to capture resource rents and subsequent strategic use of the accrued resource revenue, such as taxes, royalties, and production share agreements to boost the broader economy (UNCTAD, 2017b). There is a need to balance between government maximising revenue and investors getting a worthwhile return in a risky mining environment (Beare 2017).

According to Beare (2017), backward linkages involve inputs to the extractive industry from the national economy. This involves employing local communities and buying goods and services from local businesses. Local economic development is promoted as salaries and taxes are spent in the community, boosting local growth. Incentives for mining companies to provide on-the-job training and create government-funded training institutions are examples of creating local content policies.

Forward linkages are also known as promoting downstream manufacturing, completing supply chains, beneficiation, and increasing value-addition to commodities. Some policies encourage companies to minimise exporting raw materials and instead focus on processing them (UNCTAD, 2017b). Governments can provide fiscal instruments to promote investors to support beneficiation.

Spatial linkages involve the development of critical infrastructure such as railways, roads, pipelines, and power generation plants to enable the extraction of natural resources (UNCTAD, 2017b). Infrastructure linkages can help open up opportunities in different sectors of the economy as the local industry can promote the shared use of infrastructure for development (Beare, 2017). Local economic development incentives can be used to promote spatial linkages.

Horizontal or Knowledge linkages involve applying skills and capabilities gained from the extractive sector to develop other industrial activities such as the development of

small and medium sizes enterprises (SME'S) to contribute to job creation and industrialization (UNCTAD, 2017b). Beare (2017) alludes to the fact that skills development in the extractive sector can also be transferred to other sectors.

Consumption linkages entail the spending of income generated from the extractive sector on goods and services provided by other sectors within the national economy. The higher the income of workers in the extractive sector combined with the spending by companies involved in the sector on goods produced locally, the more the contribution to developing new industries and employment. There is less spending by workers in the Extractive sector, resulting in no to less development UNCTAD, 2017b).

5.6.1 Productivity

SA can be considered to be in the early stages of adopting novel technologies of 4IR. The global trends have indicated that several societal changes are influenced by automation adoption. These impact productivity, employment, skills development research and development, and the concept of shared value. According to International Mining (2021), in 2020, Rosond Midrand SA dispatched the last 28 state of the art drill rigs to Anglo American, which invested over two billion Rands in adopting new technology at their mines in the Northern Cape in efforts to mine safer, improve productivity and make mining more environmentally friendly. This move enhanced the operating hours of drilling machines by 20%, enhanced drill holes, and fewer drill machines were required. Rosond Midrand's manufacturing of autonomous drills and supply to Anglo- American indicated a strong backward linkage.

5.6.2 Employment

An analysis by MCSA (2018) revealed that, at the current rate of decline in profit margins for mining companies, in SA, approximately 200 000 mining job losses may occur by 2030, ultimately impacting two million people indirectly if automation is not adopted. Adopting ATwill affect backward linkages as well as consumption linkages. According to the Department of Statistics: Statistics South Africa Republic of South

Africa (2021), the unemployment rate was over 30% in the first quarter of 2021, with the majority of youth unemployed, no matter the levels of education.

There is a general perception that automation will lead to job reduction. A study carried out by Magwentshu et al. (2019) showed that, though not restricted to mining only but to the SA labour force, by 2030, there would be a net gain in jobs if jobs were automated. A separate study by Cosbey et al. (2016) concluded that automation will not always result in job losses but rather a shift to the highly skilled labour force. The only difference is that the new jobs will have a different skill set as a more skilled workforce will be needed.

At the Anglo American Sishen mine, when the new technology was introduced in 2014, most of the drill operators were now operating the fleet of automated drilling machines from safe, air-conditioned control rooms (Southern African Institute of Mining and Metallurgy, 2018). However, in a study on the insights on 4IR in SA and Zambia, part of the findings was that a significant number of people lost jobs due to automation in Zambia (Mutanga et al., 2021). Automation may result in the need to source foreign workers therby impacting backward linkages in the host country. Although the labour costs will be high due to more skilled employees, productivity increases will offset this (Organisation for Economic Co-operation and Development, 2017). In a study carried out by NEDLAC (2019), for the types of jobs to be affected by automation in the SA Energy (oil and coal) mining industry, it was established that specific roles would decrease while other positions would increase. Automation/modernisation will create new jobs contributing to safety and profitability to the economic development of the communities in the mining operations (MCSA, 2018), as shown in Figure 5.3.

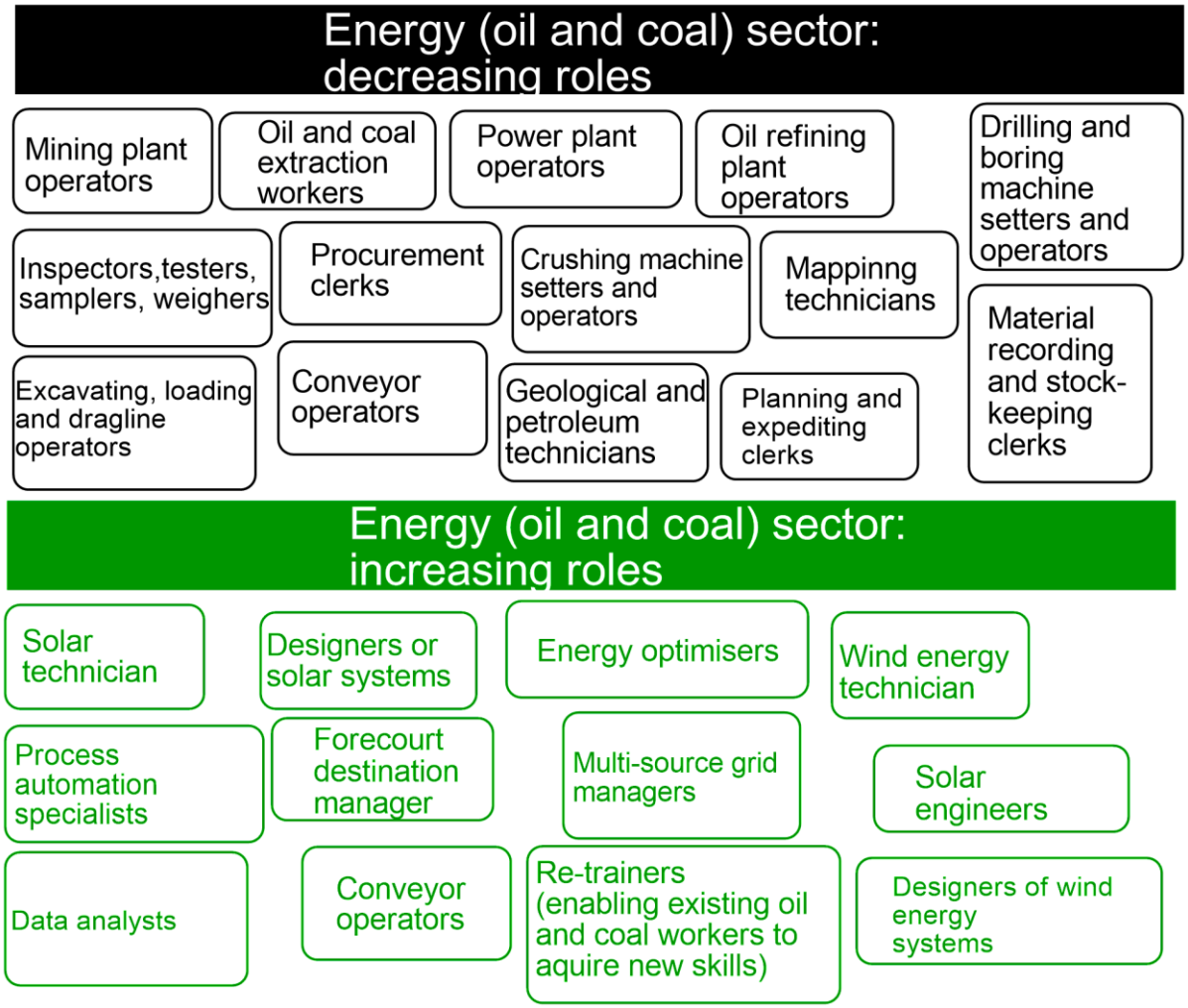


Figure 5.3 Mining Industry: decreasing and increasing roles (NEDLAC, 2019).

The critical driver of change in today and tomorrow's world is climate change and natural resource scarcity (NEDLAC, 2019). The CO_2 emission significantly impacts environmental issues, hence the need to change to other technologies. Some roles will be made redundant such as mapping technicians in the Energy sector, while new roles are adopted to cater to new technologies, such as process automation specialists

5.6.3 Skills development

According to NEDLAC (2019), commendable progress has been made in providing basic education to everyone in SA; however, the levels of education in SA are still considered low. The study showed that most people working in SA had spent less than 12 years at school. Sutherland (2020) argues that SA has significant skills shortages due to the education system's lack of current technologies, limiting managers,

researchers, and workers' generation. There is a need to reskill and strengthen the education system by generating the technology-related need to invest more in human capital to unlock the benefits of digital transformation. Mutanga et al. (2021) allude that the new curriculum with both general knowledge and specific mining knowledge with the assistance of modern teaching methods is nonexistent in the tertiary institutions in the Northern Cape of SA. Vocational Educational Training continues to offer traditional qualifications. The focus on reskilling people has been on agricultural and community-based activities (Stacey et al., 2010). Leeuw and Mtegha (2016) allude that with automation technology adoption, there is a need to reskill people that would have been made redundant in the mining sector by adopting AT. The research carried out by Accenture (2019) indicates that for successful implementation of digital technologies, the top five skills critical in successfully building and scaling digital technologies are depicted in Table 5.1.

Table 5.1 Skill Choices For Digital Technologies (Accenture, 2019)

RANK	TOP 5 SKILL CHOICES FOR GLOBAL MINING COMPANIES
1	Data Analysis/ Visualisation
2	Digital Production Management
3	Automation Expertise
4	Quality analysis
5	Artificial Intelligence/Machine Learning Training

The skills choices from the global mining companies indicate data analysis as the most wanted skill. Digital production management ranks second, automation expertise stands at position three, while quality analysis and machine learning training rank at positions four and five.

5.6.4 Research and development.

As a way of modernisation/ automation drive, MCSA rejuvenated the Mandela Mining Precinct Centre (MMPC), previously the Centre for Scientific and Industrial Research (CSIR) premises, in 2016. The centre continues with research work in innovation, manufacturing, and sustainable development across many geographical boundaries. Additional partners include the Mine Ventilation Society, Geological Society, the CSIR, the MHSR, Coal Tech, Witwatersrand, Pretoria, and Johannesburg based universities (MCSA, 2019). Sibanye Stillwater has established a Digimine, a 21st-century state-of-the-art mine at the University of Witwatersrand Johannesburg, school of mining engineering, intending to make mining safer and sustainable using digital technologies (Braham, 2018).

5.6.5 Concept of shared values

Most developing countries heavily depend on the extractive sector (Cosbey et al., 2016). The SA Mineral and Petroleum Resources Development Act (MPRDA) requires that any mining company that wants to be granted mining or production rights have an SLP. The SLP indicates how a mining company will share the benefits of mining with locals. These include education, health care, initiatives for developing skills, and the locals' employment (Lane et al., 2015; Centre for Applied Legal Studies, 2020). Most mining companies have been adhering to the needs of the SLP, but with automation adoption, there is a need to revise policies. Automation and setting up of remote control centers as in the developed world will affect the microeconomic development of communities, as shown in Figure 5.4.

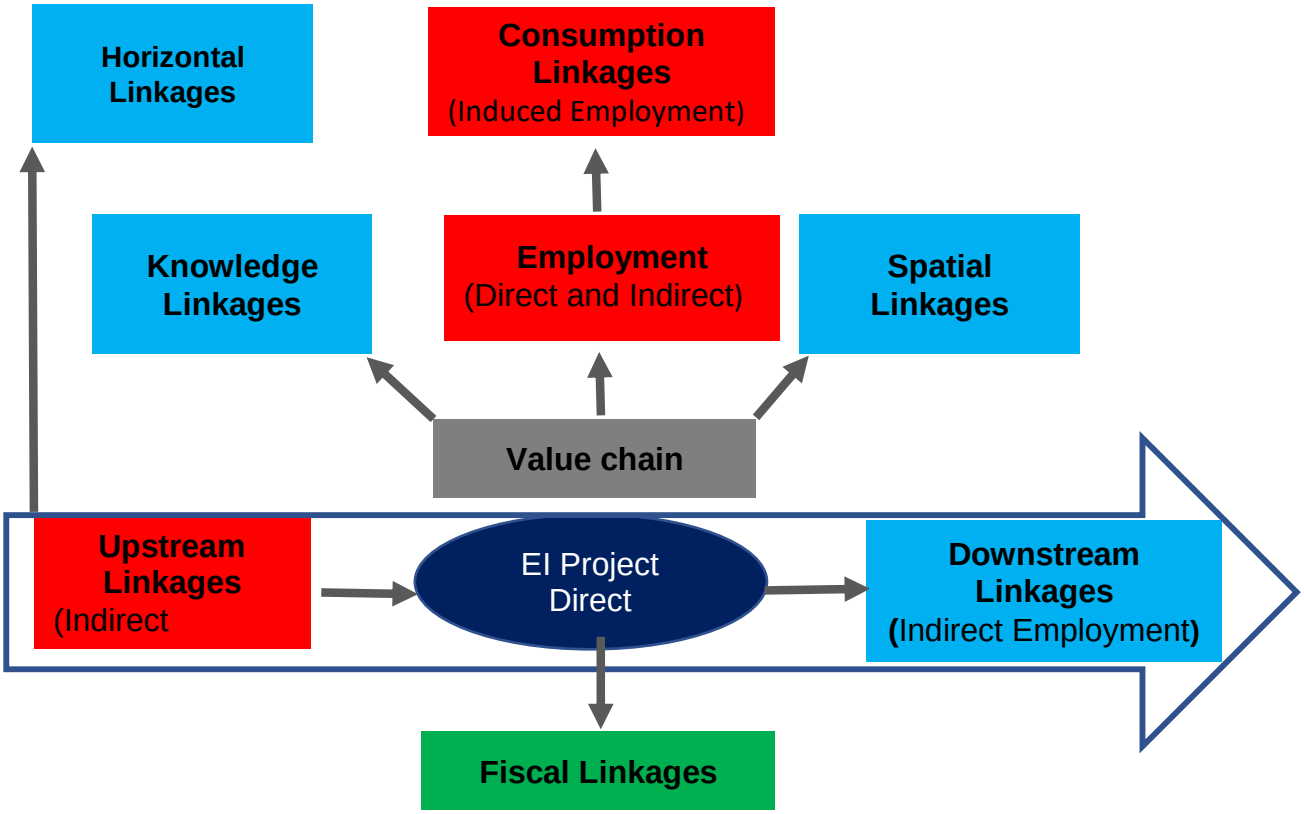


Figure 5. 4 Potential Avenues of Sharing Value of Mining Projects (Source CCSI and GIZ, 2016)

Figure 5.4 illustrates the various avenues to realizing domestic benefits by presenting the linkages to the mining sector that could lead to increased shared value. According to Cosbey et al. (2016), the mining project located at the circle labelled EI Project with automation adoption, and direct employment opportunities are reduced. This, in turn, will reduce expenditure in the local economy by mine employees (consumption linkages), and the amount of personal income tax revenues to be collected by the government from employees (fiscal linkages) is also affected. Cosbey et al. (2016) further suggest that automation is likely to reduce the opportunities for local procurement, particularly in developing countries (backward linkages). As a result, the indirect job opportunities of suppliers are compromised. The red rectangles in Figure 5.4 indicate the reduced opportunities for shared value through the consumption and backward linkage channel. The fiscal linkage channel does not have a definitive conclusion as, on the negative side, it will reduce the opportunities for collecting personal income tax payments. Yet, on the positive side, it will provide an opportunity to collect additional value by reconfiguring the fiscal regime through generating high profits for mining companies (Cosbey et al., 2016).

Although the consumption, fiscal, and backward linkages will be adversely affected by automation, there are four other avenues through which shared value can be created. The blue rectangles representing downstream linkages (forward linkages), spatial linkages, knowledge linkage, and fiscal linkage will positively impact automation (Cosbey et al., 2016. Forward linkages create indirect employment downstream. Knowledge linkages by state-owned companies acquires managing and technological expertise through a joint venture agreement with international investors. When mining companies develop infrastructure such as railway and pipelines (spatial infrastructure) linkages, other surrounding sectors tend to benefit from such development.

5.7 Challenges to Overcome: Automation Adoption

According to Prinsloo et al. (2019), the challenges to overcome in the SA mining industry are grouped into two major categories, physical and psychological difficulties. Examples of physical challenges include communication and network infrastructure, integrating various endpoint devices, and security and privacy issues. The psychological factors cover R&D, communication, and collaboration between industries and academic institutions.

SA is still in the conceptual stages of adopting automation so much that there is still a need for more research on automation and its socio-economic effects. According to the research carried out by Accenture (2019), mining companies identified that the data management systems in SA are not yet mature. The workforce does not have the necessary skills to implement novel technologies, and the risk of cybersecurity issues is a concern. Sutherland (2020) also identified poor quality infrastructure in communication and network and a poor policy formulation and implementation record as challenges for the performance of automation in SA. Willis et al. (2004) allude that poor technology implementation is one of the challenges in the mining sector. Cosbey et al. (2016) indicate that most strategies for adopting automation successfully are fiscally and technically demanding, especially for developing countries.

Research work done by most universities has concluded that automation/mechanisation will negatively impact trade unions. The labour unions in SA, the National Union of Mine Workers (NUM), the Association of Mine Workers and Construction Union (AMCU), and the National Union of Metalworkers of South Africa

(NUMSA), are strong and have a significant influence on union members. Hlatswayo (2017) argues that trade unions are aware that automating the mines can undermine their bargaining power. To remain relevant, the unions should defend the interest of workers and respond accordingly to technological changes by accepting technological changes as a subject that requires education and research (Mutanga et al., 2021). Previous labour unrest has been experienced in SA, and stiff resistance to adopting automation might arise from the labour unions.

The SA history of apartheid makes it one of the countries with unequal economies. According to the International Monetary Fund (2021), when measured by the commonly used Gini Index, SA suffers among the highest levels of inequality which is often manifested through a skewed income distribution, access to opportunities not equal, and regional disparities. The persistence of inequality is sustained by low growth and unemployment. Automation adoption will aggravate the situation as this has a socio-economic disadvantage.

5.8 Ways of Minimising the Negatives

The successful adoption of new technologies requires changes in current social and economic structures. In SA, reskilling and upskilling mining people, such as operators at the Department of Higher Education, such as the CMMS, will reduce the negatives associated with automation (Parker, 2021). This will result in the expansion and availability of technical training to increase the number of artisans in mechanical and electrical fields. There is also the need to introduce STEM subjects to the foundational roots of education to align with industrial needs (Bruckner et al., 2017). The mining industry needs to collaborate with the universities to have tailor-made products for the new mining environment (IGF, 2019). R&D also needs to be well funded and focus more on automation's socio-economic impacts than on machinery and productivity (Holcombe and Kemp, 2019). Understanding people and communities' perceptions of the "concepts of shared values" should be revisited to implement better policies. It is important to draw lessons from the developed world already ahead of automation for successful adoption.

6. RESEARCH METHODOLOGY AND DESIGN

6.1 Introduction

This chapter discusses the research approach to explore the potential socio-economic effects of adopting automation in the SA open cast Coal Mine “X” in the Sasolburg - Vereeniging coalfields. The chapter explains the explanatory sequential mixed research method for data collection, analysis, and interpretation (Creswell, 2009).

A single case study was chosen to explore and describe the views/ perceptions of coal mine employees on the potential socio-economic effects of adopting automation. The study was composed of a cross-sectional survey (Creswell, 2012). The research's quantitative data collection (phase 1) was composed of closed questionnaires. The closed questionnaires used the Likert scale type (Jamieson, 2017). Qualitative data collection (phase 2) was mainly interviews conducted using semi-structured questions. Both methods of research were conducted online.

The study covered a description of the population, selection of participants, and sample size for the study. Procedures applied in data collection and analysis, including methods to assure the study's validity, were considered. The research data collection commenced in July and ended in mid-September 2021. The chapter also covered the limitations of the chosen methods. Ethical considerations and procedures followed while conducting the study are discussed.

6.2 Research Approach

The 4IR and the socio-economic effects of automation are relatively new in the SA coal mining industry and are still under-researched. A sequential explanatory mixed-method design was the approach for the research. The method is a two-stage process in which quantitative data is utilised to build and explain qualitative data (Almalki, 2016). Quantitative research work is considered an inference approach to research (Morse, 2006). Human beings have emotions and feelings, and it is inadequate to focus on the quantitative study without including the qualitative component, especially when seeking people's perceptions. The qualitative approach emphasises exploring and understanding the *"meaning individuals or groups ascribe to a human social problem" (*Creswell, 2014, p.4). Ivankova et al. (2006) have indicated that neither

quantitative nor qualitative methods can fully capture a situation's tendency and details. The quantitative results helped the researcher determine the types of participants to be purposefully selected for the qualitative phase 2 of the research and the types of questions to ask. According to Creswell (2014), there are different types of the mixed-method research approach. Figure 6.1 shows the different types of the mixed research approach.

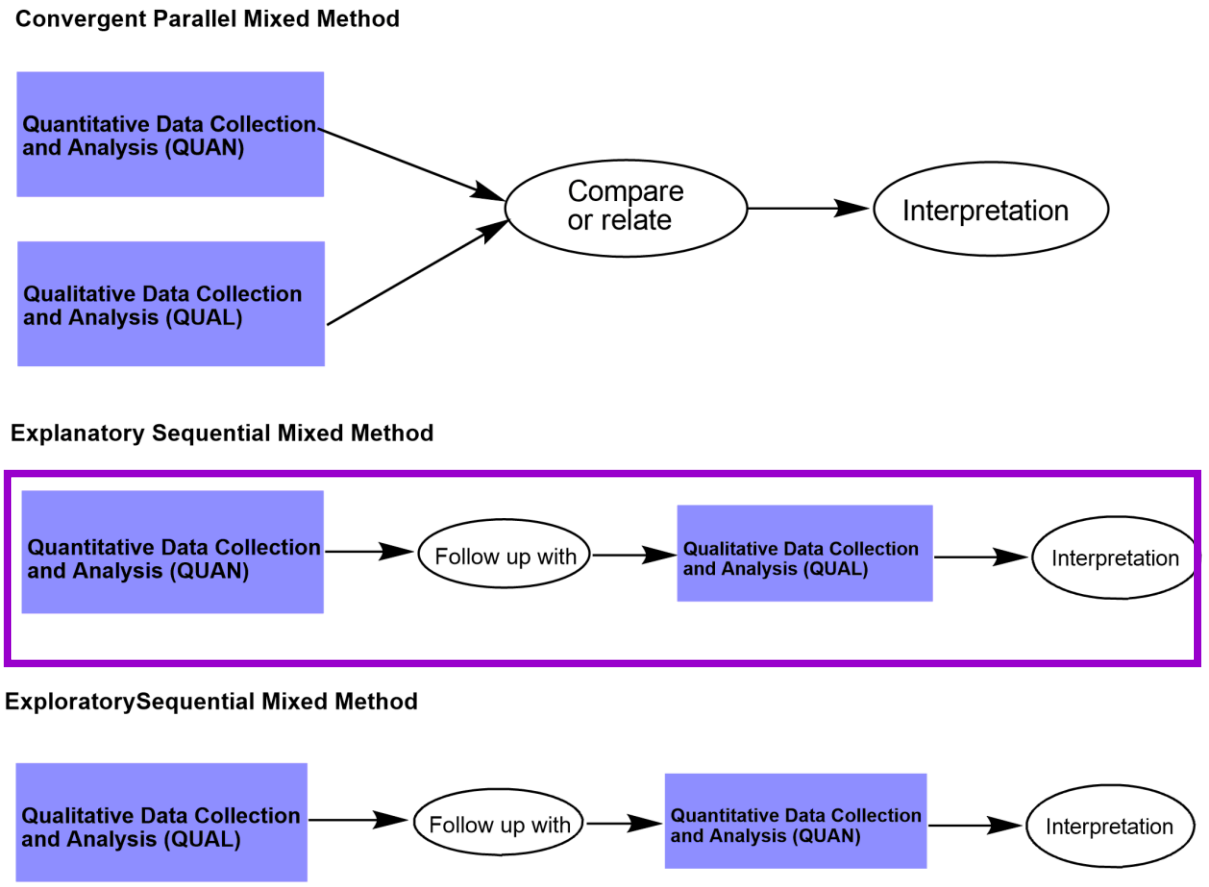


Figure 6.1 The different types of mixed-method research approaches (Creswell, 2014)

According to Bryman (2016), mixed-method has gained acceptance in social science studies for the past 15 years. The mixed-method research is further classified into three broad categories. The categories can be qualitative dominant, equal status, and quantitative dominant. This research study is quantitative dominant (Johnson and Onwuegbuzie, 2013). In this research study, quantitative research (phase 1) was conducted, followed by the study's qualitative research (phase 2). The qualitative

phase gained insights and explanations for quantitative findings. Integration of quantitative and qualitative methods was done to interpret the results.

The advantage of the mixed-method research method is that it is easy to implement and allows for the focus of the research maintenance as one set of data builds on the other. The method can answer an extensive and more complete range of research questions, providing a more comprehensive answer to the research question (Creswell and Clark, 2011).

The limitation of this method is that it is time-consuming, and the selection of participants to provide relevant information can be difficult. Participants may not respond to surveys at the anticipated time by the researcher. The researcher sent out reminders to the selected participants to overcome the problem.

6.3 Research Design

For this study, a single case study design was adopted. A case study design involves investigating a single unit or system bounded by space and time to analyse phenomena, generate a hypothesis and validate a method (Teegavarapu et al., 2008; Hancock and Algozzine, 2017). The mine employees and management at a SA Coal Mine “X” were the participants. A single case study design was suitable as it allowed the researcher to get data directly from the case and analyse it, and the results obtained were more practical than ideal. The limitation of a single case study was that it narrowed the research area, which was limited to a specific group of people; therefore, the findings could not be generalised to other areas (Zaidah, 2007).

6.4 Population of the Study

The study focused on an opencast Coal Mine “X” in SA, where different automation levels have been adopted to improve safety, productivity, and efficiency. A population is a group of individuals with the same characteristics (Creswell, 2012). When carrying out quantitative surveys, population and sample cannot be separated. In this study, the target population constituted adult employees aged 18 to 60 with a composition of operators, supervisors, artisans, mechanical engineers, mining engineers, technical services staff, processing engineers, administration staff, supply chain, labour union

representatives, and management. The employee composition was a good representation of mine employees at the mine.

To date, the research on the socio-economic effects of automation on an opencast coal mine is minimal, if any. The study is helpful for the fulfillment of the research objectives.

6.5 Sample and Sampling Procedure

6.5.1 Quantitative data

A single-stage, random sampling was used to gather the research's quantitative data (phase 1) (Singh and Masuku, 2014). The single-stage random sampling was regarded as the appropriate sampling method as the researcher had access to the email list of employees (Creswell, 2014; Wu and Thompson, 2020). The participants were randomly selected from the mine employee register, thereby establishing an equal chance of selection. A cross-sectional survey was applied for this research. The advantage of the random sampling method in quantitative data collection is that it is the simplest form for data analysis, and there is less risk of carrying an error (Creswell, 2012).

According to Masuku and Singh (2014), quantitative research methods require that the correct sample size is determined to reduce the margin of error and bias in the sampled data. The sample size should be adequate to draw reasonable and generalized conclusions. Too small a sample will introduce a high error magnitude, while too large a sample does not guarantee that the error size is small. Saunders et al. (2012) have indicated that a sample size of at least 30 will be needed to allow accurate statistics tests in a quantitative survey. The researcher used a published table for this study to determine the sample size required for the quantitative research work, as shown in Table 6.1.

Table 6.1 Sample Size for ±5% and ±10% Precision Levels where Confidence Level is 95% and P=0.5 (Singh and Masuku, 2014)

Size of Population	Sample Size (n) for precision (e)	
	±5%	±10%
500	222	83
1 000	286	91
2 000	333	95
3 000	353	95
4 000	364	97
5 000	370	98
7 000	378	98
9 000	383	99
10 000	385	99
15 000	390	99
20 000	392	100
25 000	394	100
50 000	397	100
100 000	398	100
>100 000	400	100

The approximate number of employees at Coal Mine “X” is 1 200. The sample size of 91 is the correct number of responses from questionnaires to fulfill a precision of 10%. The quantitative survey questionnaire received 107 responses. Still, those that were incomplete were not considered, and in the end, only one hundred and two (102) fully completed were considered for computation in this research study.

The advantage of the quantitative method is that comparisons can easily be made, and the effect size can be measured. The quantitative approach is limited in explaining

similarities and unexpected differences hence the need to complement the research with qualitative data.

6.5.2 Qualitative data

The five types of non-probability sampling techniques are quota sampling, purposive sampling, snowball sampling, convenience sampling, and self-selection sampling (Wilson, 2014). The purposive sampling method was applied for the qualitative data phase 2. A purposive voluntary approach ensured the correct selection of participants. The study was conducted in the same area, with participants from different people selected for qualitative interviews. In purposive sampling, the selection of the participants was largely dependent on the researchers' judgment and preferences (Sharma, 2017).

When conducting qualitative research, there are no rules for the correct sample size. Marshal (1996) determined that the appropriate sample size for qualitative analysis is one that adequately answers the question, while Trotter (2012) argues that the correct number of people to be interviewed depends on redundancy or the saturation point. Redundancy is defined by Trotter (2012) as a point where no new concepts or themes will emerge from interviews. Instead, the concepts will be repeated multiple times. In this research, after interviewing 4 people, the analysis of the responses did not bring new themes; as a result, a total of 8 participants were chosen to elaborate more on quantitative results through the semi-structured interviews. The profile of the participants for interviews is shown in Table 6.2.

Table 6.2 Profile of Participants

Description of Respondent	Role of Respondent	Total Number Interviewed
Employee	Trade union Representative	1
Employee	Mining Company official	1
Employee	Mine Overseer	1
Employee	Activity Engineer	1
Employee	Operator	2
Employee	Geologist	1
Employee	Metallurgist	1

The advantage of purposive sampling is that it saves the researcher's time during the collection and analysis of data. Purposive sampling allows the researcher to make a generalisation from the sample and identify the extreme perspectives present in the research. The information collected is essential in real-time (Sharma, 2017).

The disadvantage of this method is that it is solely dependent on the researcher's judgment in selecting participants, and bias can easily be introduced. Selected participants can also manipulate the collected data by providing what they believe the researcher wants to collect (Sharma, 2017). It is not easy to defend the representative nature of the sample, and it is also a method that is not recognised statistically (Singh and Masuku, 2014).

6.6 Data Collection Instruments and Method

For the research's quantitative data collection (phase 1), the researcher set up Likert scale questionnaires **in Google** forms: (https://docs.google.com/forms/u/0/). The Likert scale rating was chosen for the survey as this measures people's opinions or perceptions through responses of strongly agree, agree, neutral, disagree, and strongly disagree. (Jamieson, 2017). This was a perfect fit for this research as it sought participants' opinions. Google forms were also the choice for quantitative surveys for this research as the web page is free, unlimited surveys, unlimited respondents, and data is automatically collected in Google spread sheets. In a survey done at a school

south of Portugal using Google forms, over 1 200 responses were captured in a spreadsheet (Raju and Harinarayan, 2016).

The questionnaire was divided into three different categories. The first category was for agreeing on the consent, and the second category required the provision of the respondent's profile. The requested information on the respondent's profile covered the gender, age, qualification, and position at the mine. The third category was purely quantitative, with various questions seeking the respondents' opinions on the potential socio-economic effects of adopting automation. The researcher emailed the questionnaire link to the participants as shown in Appendix A.

Online surveys are cost-saving, need less time, reach more participants, and ensure data safety (Siva Durga et al., 2019). Online surveys are also quick to analyse and easy to use for participants and researchers. With the prevalence of COVID 19, this was the safest way for both the researcher and participant to collect data.

The limitation of online surveys is that it is not accessible to people without internet access. The other limitation of this method is that the question set may be ambiguous, leading to the possibility of misanswering the question. A pilot survey with the set questions was conducted with a small group of people to avoid ambiguity in the questions. Later, the group of people for piloting was not part of the survey to prevent contamination of the results (Merriam, 2016).

Questionnaire validation was also carried out. According to Yusoff et al. (2021), six steps were followed for data validation of the questionnaires as listed below:

1. Conduct content validation;
2. Conduct cognitive interview and/or response process validation;
3. Conduct field pre-testing (pilot study);
4. Conduct psychometric evaluation of the internal structure;
5. Check for internal consistency; and
6. Revise the survey.

For qualitative research data collection phase 2, the researcher conducted semi-structured interviews to explore the meaning people attach to the potential socio-economic effects of adopting automation as guided in the quantitative survey. CMC

such as Microsoft Teams, was used (Merriam, 2016). The interview was planned to take between 20-25 minutes. Most of the interviews, on average, took approximately 20 minutes, with the longest being 30 minutes.

The data obtained from quantitative data guided the researcher on the questions to ask. The semi-structured interviews were divided into three sections, and each section had a specific issue to address, as shown in Table 6.3.

Table 6.3 Specific Issues on Questionnaires

Section	**Specific Issue**	**Purpose of Issue**	**Participants**
1	Demographics	Determination of the demographics of participants	All
2	Understanding	To establish the knowledge levels of automation at Coal Mine “X.”	All
3	Implications of adopting automation	Perception of participants on the potential socio-economic effects of adopting automation	All

The advantage of semi-structured CMC interviews is that it allows flexibility for the researcher and probing to get more clarity on the issue to be investigated (Merriam, 2016). Semi-structured interviews allowed participants to discuss the research topic more openly and express their opinions and understanding in their own words. The researcher captured the participants' own words. The interviews allowed the participants to share their real-life experiences more than general beliefs (Creswell, 2012). Having open-ended structured questions assisted the researcher in remaining guided and focused. The researcher could provide clarity on questions where needed.

Due to the prevalence of COVID,19, face-to-face interviews could not be carried out, resulting in missing out on the much-needed rapport with the participants. The other limitation was that not all the participants had access to a computer or the internet. Connectivity problems were also a challenge in this research. Participants were aware that they were being studied and may have contributed to biased data. To minimise this challenge, the researcher pretested the research instrument with a small group of people to determine if the set questions were clear and understandable. The other

limitation is that more time was spent on interviews, transcription, and data analysis. The time problem was overcome by generating a proper plan to execute the research work.

Data collection for both quantitative and qualitative methods was conducted among the selected members of the operators, labour unions, and middle and senior management. Participants' consent regarding the recording of data during qualitative interviews was sought. English was the primary language used for data collection. Interviews were audio-recorded on Microsoft Teams and transcribed using the program Otter.ai. After each interview, a record of the researcher's thoughts, reflections, and feelings was captured. The researcher used the information to minimise bias in the final report as much as possible.

6.6.1 Pilot testing

A good practise is to "dry run" all the stages involved in surveys through pilot testing. Pilot testing helps to fine-tune research questions before significant research is done. Each quantitative survey and qualitative interview research was conducted with a small group before considerable research. The pilot study carried out the validation of research questions for both quantitative and qualitative research. The pilot testing was also carried out to test the research instruments such as the google forms used on computers and Microsoft Teams to record the interviews. A program for transcribing data Otter.ai was also trialed.

6.7 Data Analysis and Interpretation

After collecting data, there is a need to give order, structure, and meaning to the collected data (Uys, 2011). The quantitative and qualitative data were analysed separately. The quantitative data guided the researcher on open-ended questions and the participants to choose for qualitative research.

6.7.1 Quantitative analysis

In the quantitative survey, missing data were not considered in the final analysis. There were 107 respondents, but two did not provide demography data, while three did not respond to the question "SA opencast Coal Mine “X” will implement automation in less than 5 years". Incomplete answers (5) were not considered in the final report as they could give false results from the analysis. Only 102 respondents who fully completed the questionnaire were considered in the final report.

The raw data for quantitative questionnaires were imported from a google forms spreadsheet into Microsoft Excel. The participant identification on the spreadsheet was numbered from number 1 to number 102. A column with the date and time of the response to the question was deleted before data analysis. The terms used in the Likert scales needed to be allocated a score and recorded. The "Strongly Agree" was allocated a score of 5, "Agree" was allocated a score of 4, "Neutral" was allocated a score of 3, "Disagree" was allocated a score of 2, and Strongly Disagree" was allocated a score of 1. The weighting of the scores was necessary for later use in the bivariate analysis carrying out Spearman correlation.

The researcher used Microsoft Excel statistical function to provide univariate and bivariate analysis. The univariate analysis was used for descriptive statistics, while bivariate analysis was used to identify relationships between variables. The mean of the ordinal data was not used as it would not provide any meaning to the data. Instead, the mode was used for data description Appendix B. The participants’ responses of each individual were summed to find the highest frequency occurrence. The responses to the questions were summed and then presented in percentage forms. The calculated percentages in tables are shown in Appendix B, together with cross sectional analysis results from some questionnaires. As for cross section analysis, responses were narrowed to three categories Agree (a combination of agree and strongly agree), neutral, and disagree (a combination of disagree and strongly disagree). The graphical presentation of the results is shown in Figures 7.1 to 7.19.

This research needed to establish correlations between responses on chosen questionnaires. Due to the data being nonparametric, the Spearman correlation coefficient was used for the bivariate analysis using the statistical functions in Excel.

The Spearman correlation coefficient, rs, can take values from +1 to -1. An rs of +1 indicates a perfect association of ranks, an rs of zero indicates no association between ranks, and an rs of -1 indicates a perfect negative association of ranks. The closer rs is to zero, the weaker the association between the ranks (Laerd Statistics, 2018; Bradburn, 2021).

It is important to note that the correlation coefficient only measures the strength of the relationship, and not all correlations are what they seem. There is a need not to have wrong interpretations and conclusions. A statistical significance test tells whether or not what is observed in the sample is expected to be true in the population through a hypothesis test (Jaadi, 2019). The hypothesis test allows the inference of whether the value of the population correlation coefficient *p* is close to 0 or significantly different from 0 based on correlation coefficient *r* and sample size *n*. When *p* = 0, there is no significant linear correlation between X and Y, and when p significantly differs from 0, there is a significant correlation between X and Y (Jaadi, 2019). The null hypothesis (*p* = 0) provides evidence that there is no relationship between X and Y, while the alternative hypothesis (p ≠ 0) is the opposite. This research's statistically significant threshold is a *p*-value of 0.05 (Jaadi, 2019; Bradburn,2021). A step-by-step process of performing Spearman correlation in Microsoft Excel and significance is shown in Appendix C. The Spearman correlation results of this research are shown in Table 7.2.

6.7.2 Qualitative analysis

Creswell (2012, p261-p262) outlined the six steps of data analysis which the researcher utilised as:

1. Prepare and organise the data for analysis;
2. Explore and code the data;
3. Coding to build descriptions and themes;
4. Represent and report qualitative findings;
5. Interpret the findings; and
6. Validate the accuracy of the findings.

The recorded data was obtained from the participants with their consent. The interviews were recorded in Microsoft Teams. Audio files were downloaded onto the computer for analysis. Notes were taken to serve as a backup and provided the context of the views. Verbatim and transcription of the responses from the interviews started as soon as possible in order not to lose the data from the interviews. The audio files were transcribed using the Otter.ai program. At the end of the interviews, transcriptions needed to be as authentic as possible to the interview. The transcribed data was given back to 3 of the interviewees to confirm the interview detail. All the transcribed data was filed, and a Microsoft Excel spreadsheet was generated to capture the summarised information from the interviews.

Data coding was later carried out, and themes were generated from the coded information. The findings of quantitative and qualitative data were integrated at the interpretation stage. The qualitative results helped explain and interpret significant and non-significant outliers in the quantitative research.

6.8 Data Validation Mixed Methods

The validity criteria for quantitative and qualitative research methods differ. Quantitative methods consider reliability, replication, internal consistency, and external validity issues. In contrast, qualitative methods are concerned with trustworthiness, credibility, dependability, transferability, reflexibility, and confirmability as the components to check for when carrying out validation (Guba and Lincoln, 1989).

For this study, validation was carried out throughout the data collection, analysis, and interpretation phases. The statistical table guided the determination of the sample size to distribute the online Likert scale questionnaires. During quantitative phase 1 of data collection, to lessen the threat of inappropriate sample size and fulfill the need for 91 responses, a large sample (120) of questionnaires was sent out to cover the effects of non-respondents.

A smaller sample of participants (8) was purposively chosen for qualitative interviews to explain the quantitative results further. A different subset of people

was chosen for the qualitative research to broaden the number of participants from quantitative to qualitative interviews. The advantage of this selected subgroup was that they did not have prior knowledge of the subject at hand and were to add more to the already known facts in the quantitative interview.

During the data analysis phase of the quantitative survey, a measure of validity was essential to determine the reliability of the data due to the inclusion of scale-type questions. Cronbach's alpha was used for reliability testing, as shown in Table 6.4.

Table 6.4 Cronbach's Alpha (Hair et al., 2016)

Cronbach's alpha	**Internal Consistency**
$\alpha \geq 0.9$	Excellent
$0.7 > \alpha \geq 0.9$	Very Good
$0.7 > \alpha \geq 0.9$	Good
$0.6 > \alpha \geq 0.7$	Moderate
$\alpha < 0.6$	Poor

According to Tavakol and Dennick (2011), the alpha value is influenced by the number of test items and item inter-relatedness. Low alpha scores do not mean the instrument is not valid but relatively poor correlation of items or a low number of questions. For this research, Cronbach's Alpha was in the moderate range ($0.6 > \alpha \geq 0.7$).

As a follow-up to qualitative interviews, open-ended questionnaires were carefully generated from the quantitative results, as shown in Appendix D. A deductive approach was used during the qualitative data analysis phase 2 as the literature provided the existing theme categories. The data was grouped manually in an excel spreadsheet and according to the researcher's judgment of categories. In the interpretation phase, to minimize the possibility of merging rather than building, both sets of results were used to answer the questions in the research.

6.8.1 Credibility

Credibility is the extent to which data quality is appropriate and accurate. It is concerned with the truth value (Guba and Lincolin, 1989). The researcher established the credibility of quantitative data as outlined in the six steps (Yusoff et al., 2021).

For qualitative data, the researcher applied interview skills such as probing, clarification, summarising, and ensuring that the data was correctly captured and credibility. Those participating in the interview remained anonymous. As a preliminary validity check, 3 participants were asked to check the transcribed word document from the interview for accuracy. Further, the 5 participants were asked to confirm the interview quotations. According to Bazeley (2012), scanning for agreement from interviewees about conclusions drawn from the research is a practical way to ensure the genuineness of the researcher's quality of findings.

6.8.2 Dependability

Dependability is an art of reproducibility consistent with the same data. Similar results must be produced if the same techniques were repeated in the same context, method, and participants (Guba and Lincolin, 1989). For qualitative data collection, dependability may be challenging to prove, but the methods and procedures can be followed for others who need to conduct similar research. For this report, an "audit trail" outlining the methodological steps was kept and later used for the analysis of results**.**

6.8.3 Transferability

Transferability covers the extent to which the findings of one study apply to a similar context in theory, practice, and future research. Data transferability will be checked through the potential to extrapolate the information to other scenarios in the same setup. Policy and management can rely on this data, so it becomes crucial for researchers to clarify the extent to which the research data can be extended (Moon et al., 2016). In this research, the researcher ensured maximum variation among participants regarding age, qualification, and position on the mine.

6.8.4 Confirmability

Confirmability in research covers the degree to which the findings of the research study could be confirmed by other researchers. Confirmability may be assured if data are continuously checked from the data collection stage and analysis to assess repeatability. There is a need to demonstrate that results can be linked to conclusions in a way that can be followed and the process replicated (Moon et al., 2016; Korstjens and Moser, 2018). Confirmability of the research was guaranteed by recording data and finding similarities between two or more people concerning relevance, accuracy, and meaning for this research study.

6.8.5 Reflexibility

Reflexivity is when a researcher carries out self-reflection on actions and values perceptions in the whole research process from data collection and analysis. On aspects of flexibility, the researcher will self-reflect on preferences, biases, preconceptions, and relationships with the selected population for interviews (Korstjens and Moser, 2018). Capturing notes and reflecting on the outcome for the day assisted the researcher in eliminating some biases that might arise.

6.9 Ethical Considerations

As in all social sciences research, ethical considerations must be followed. The integrity of the research is guaranteed through obtaining ethical clearance from relevant authorities, for example, at the workplace and universities. A general ethical checklist to be considered includes but is not limited to informed consent, data access, ownership, privacy, and confidentiality (Kaiser, 2009). Permission to carry out interviews was sought from the ethics committee school of Mining Engineering at Witwatersrand University to fulfill the requirements stipulated by the university, as shown in Appendix E. Formal official consultations were made to obtain approvals from the mining company and participants. The research was conducted adhering to the guidelines stipulated by the University of Witwatersrand Non-Medical Ethics Committee. The purpose of the study was explained, and the assurance of confidentiality and anonymity was guaranteed to the participants.

Permission was also sought from the mining company to carry out the research at the mine, for which permission was granted. The researcher later used the email addresses of company employees to send a combined covering letter of consent and questionnaires in google forms, as shown in Appendix F and A, respectively, for quantitative data collection. As for qualitative interviews, the online interview invitation was done using the participants' email addresses. The guidelines for the questions are as in Appendix D. Interviews were done formally through Microsoft Teams and recorded.

6.9.1 Privacy and confidentiality

When conducting research, it is crucial to observe and respect the participants' privacy (Merriam, 2016). The participants were assured that the information provided would be treated with confidentiality and that everything would remain anonymous. This was stated in the Participation Information Sheet (PIS) for quantitative and qualitative interview participants, as shown in Appendix G.

6.9.2 Voluntary participation

Participation in this research was voluntary, and at any point, the participant had the right to withdraw with no negative repercussions. The researcher did not force anyone to do the study. Participants were informed that the data collected would be securely stored and destroyed after two years of the study.

6.9.3 Informed consent

The University of Witwatersrand Non-Medical Ethics Committee and the mining company granted consent to conduct the study for the researcher. The Protocol Number is H21/05/06 is shown in Appendix E. The researcher ensured that participants' consent to participate in the study for the questionnaire survey was completed online, as shown in Appendix F. Before the online interviews, formal consent was sought from interviewees. Agreeing to be interviewed after being asked if the interview could continue was a way of approving consent.

6.9.4 Protection of company name

As per the company's request, the name of the mining company remained anonymous. The mine name was replaced with a fictitious name, Coal Mine “X," which is used in this research study.

6.10 Limitations of the Study

A single case study brings rich information about a situation that cannot be generalised. Full automation in the mining industry of a developing country is a relatively new concept. It was challenging to get some of the participants to interview on time. A new way of interviewing through CMC had to be adopted due to COVID 19 pandemic, which was prevalent at the time, and COVID protocols had to be observed to ensure the researcher's and the participants' safety.

7. RESULTS, ANALYSIS, AND DISCUSSION

7.1 Introduction

This study investigated the 4IR: The potential socio-economic of automation in a SA opencast coal mine. The chapter presents the analysis and possible interpretation of the research's quantitative and qualitative findings from Phases 1 and 2. The quantitative online survey results from Phase 1 are presented first, followed by CMC interviews in Phase 2. The possible interpretation of the quantitative results is also covered.

7.2 Quantitative Results

This section represents the findings of the online quantitative survey conducted in Phase 1. The researcher used descriptive statistics, followed by inferential statistics, in the study. Inferential statistics comprised a bivariate analysis of the potential socio-economic effects of adopting automation in SA Coal Mine “X.” The first section of the questionnaire sought to identify the demography of the participants. Gender, age, qualification, and position at the mine were the primary considerations.

At Coal Mine “X,” the majority of respondents were males (71%), followed by females 8 (27%) and those that preferred not to say (2%), as shown in Figure 7.1. It is a known fact that the mining environment is male dominated. From these results, it can be confirmed that the mining environment is still male-dominated, and females are under-represented. The majority of the respondents (56%) are aged between 31-40 years, while those aged between 41 and 50 and 51 to 60 being 15% each, as shown in Figure 7.2. The researcher inferred that this is an advantage for automation adoption as the young age group at the mine can further be empowered through education, upskilling, and reskilling. The skills obtained can be retained for more years as this group is not near retirement.

A minority group did not have matric (4%). A third (33.3%) of the respondents had Matric qualifications, with the remainder having qualifications ranging from diploma level to postgraduate, as shown in Figure 7.3. From the gathered information about qualifications, the researcher inferred that the educational qualification is high and

possible that the literacy level at Coal Mine “X” is relatively high too. Further, an analysis of the position at the mine for participants was also considered, as shown in Figure 7.4. The majority of respondents were operators representing (27,4%) occurrences. This was followed by technical services, contractors, foremen, management, artisan, mine overseer, human resources, labour union representative, and engineer. The deduction made by the researcher from these results is that operators have the mode representation and are likely to be directly impacted negatively by automation adoption. The second highest group, technical services (surveyors, geologists, and mine activity engineers), ranks second, and this group will require training/upskilling on the new technologies. The percentage representation of engineers is minimal at the opencast Coal mine “X,” which may imply reconsideration at the national level of educating, reskilling and upskilling people. Figures 7.1 to 7.4 and Appendix B summarise the respondent's demographics.

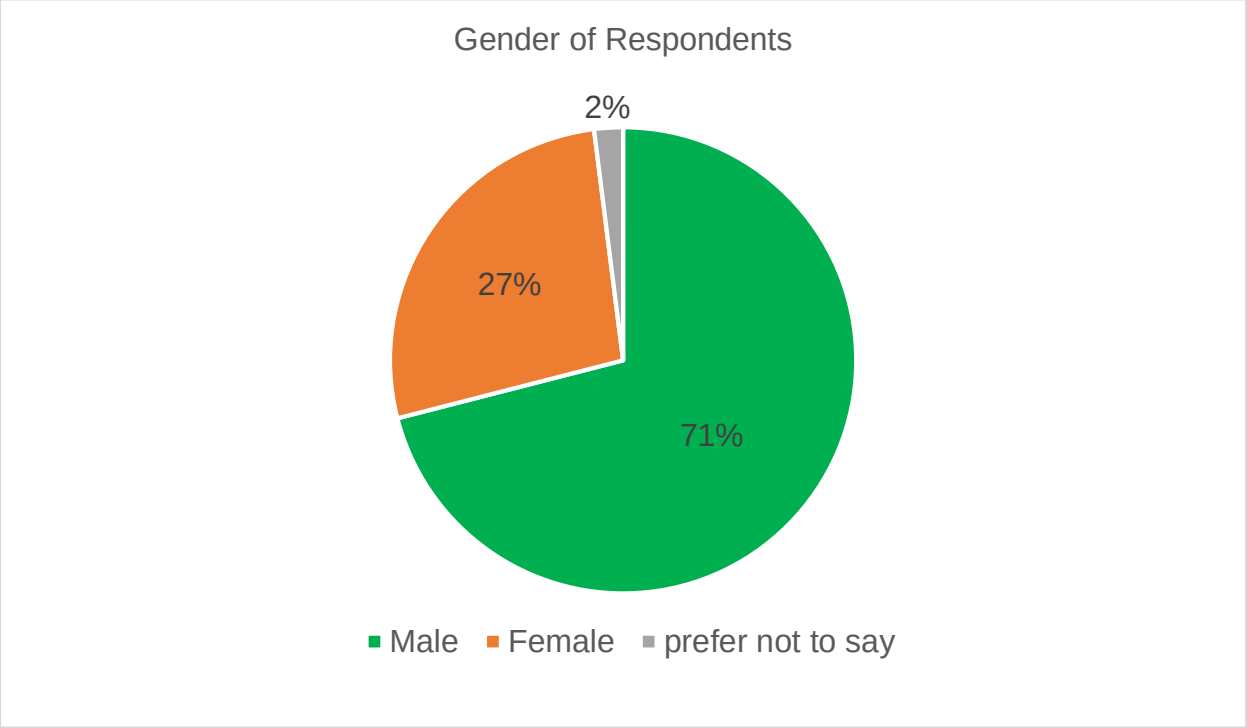


Figure 7.1 Gender of respondents

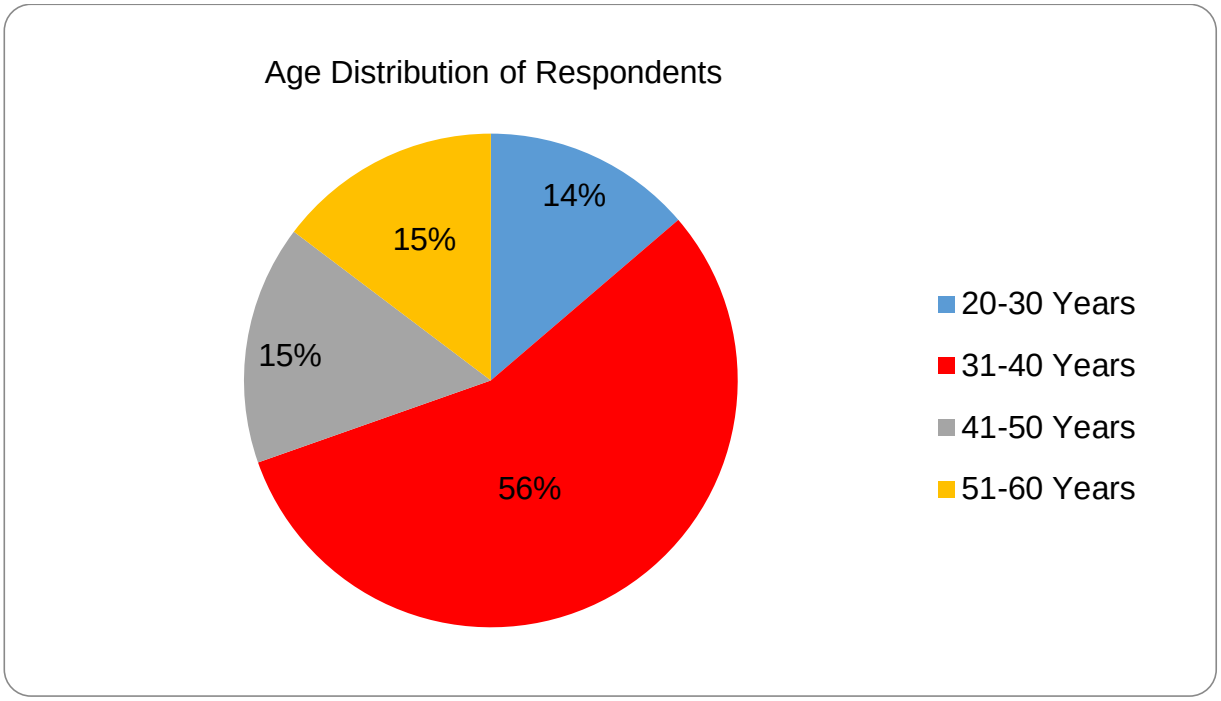


Figure 7.2 Respondents age distribution

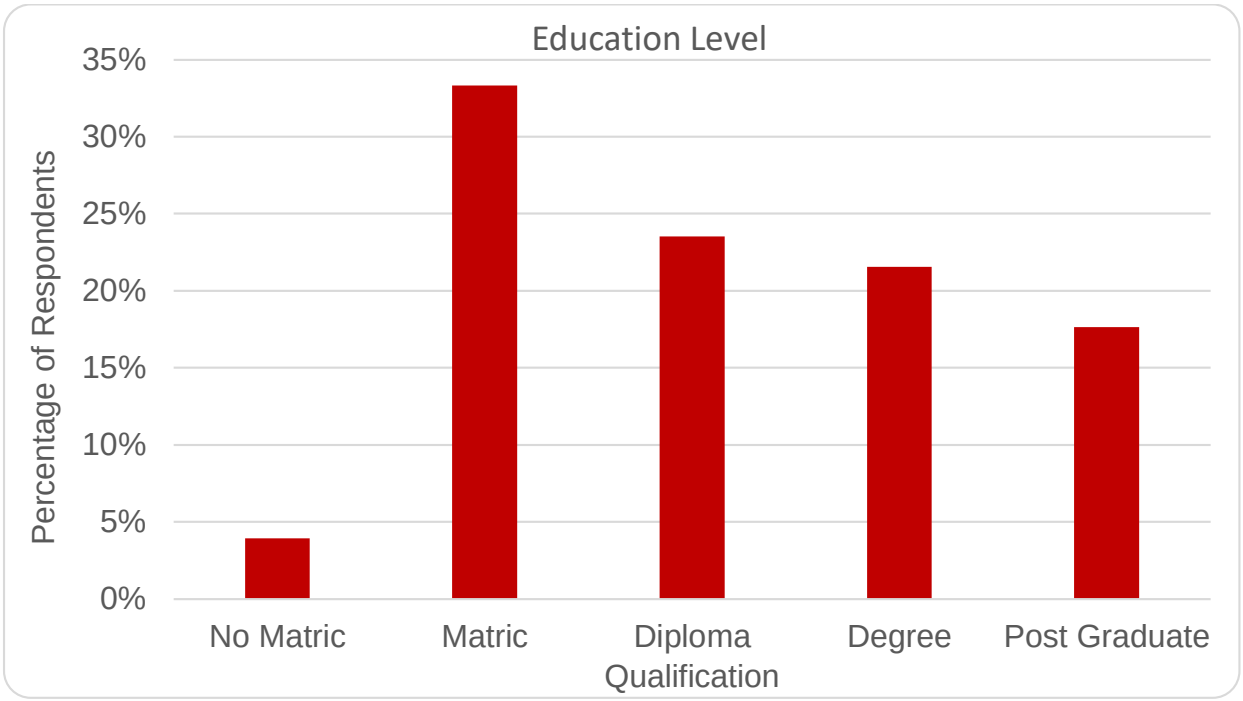


Figure 7.3 Educational qualification of respondents

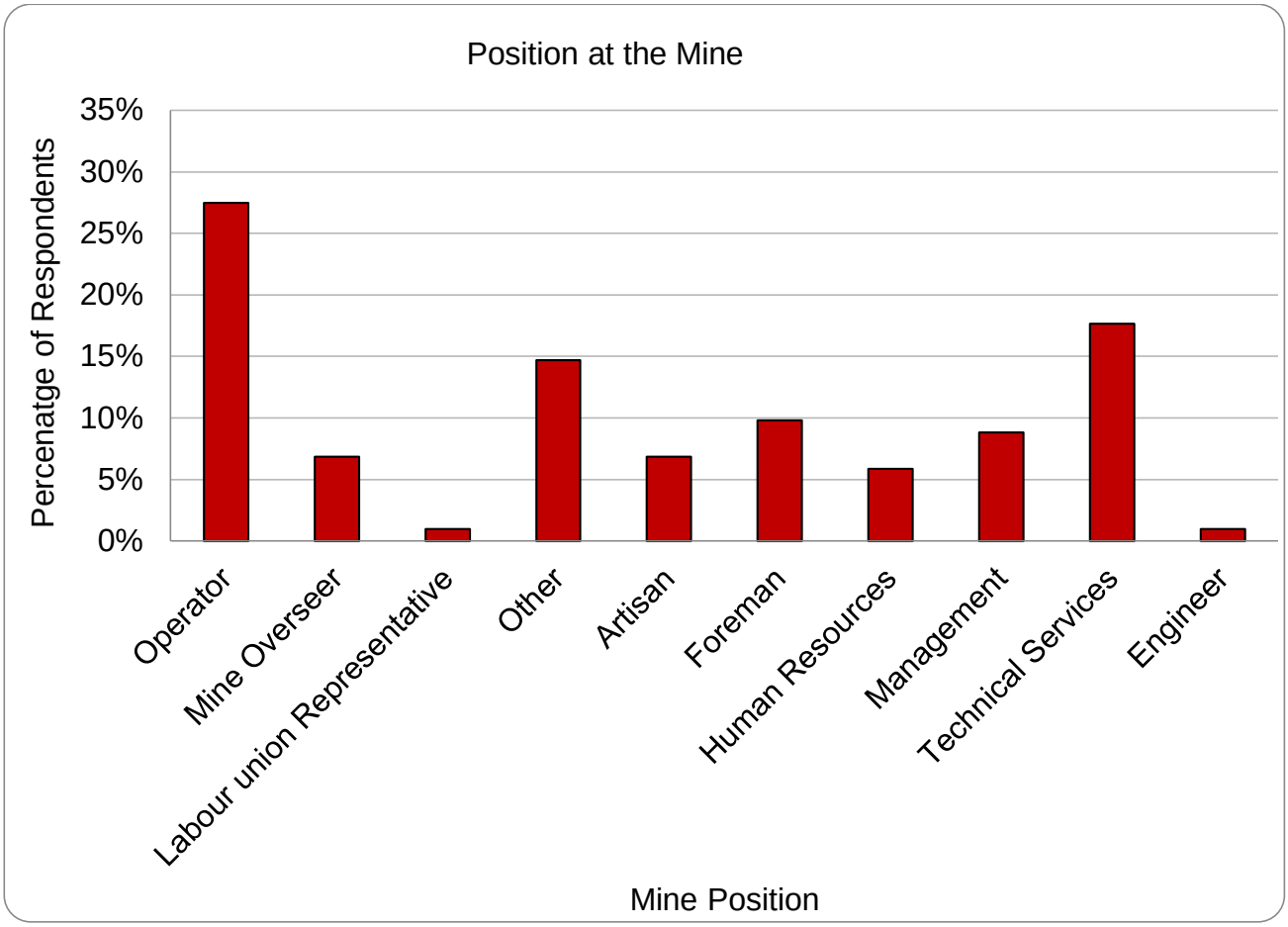


Figure 7.4 Position at the Mine

7.3 Participants' Understanding of Automation

Scale-type questionnaires were generated to seek participants' opinions on the level of understanding of automation. The respondents were presented with questionnaires with response options of strongly agree, agree, neutral, disagree, and strongly disagree. The summarised results are shown in Figures 7.5 to 7.10 and Appendix B.

The responses to automation meaning show the total number of participants in the agree category with the given definition was over (80%). The trend of the category of responses is similar for males, females, and those that prefer not to say, as shown in Figure 7.5. To further probe the understanding of automation, the respondents were provided with one example of a machine that can be utilised on the mine as an automated machine and asked their opinion. The results show that educational qualification does not play a role in the knowledge of an automation machine example

as the majority of participants over (75%) were in the agree category with the given example, as shown in Figure 7.6. It was also essential to establish the source of information of automation technology to assess information flow through technologies such as social media. From these results, as shown in Figure 7.7, it can be inferred that social media and the workplace have played a role in the awareness of automation machinery and its application, as over 60% of the respondents were in the agree category.

Most respondents were young aged 31-40, who had recently completed matric or undergraduate studies. The researcher found it necessary to find the participants' perception of whether the education system is aligned with automation. A total of (59%) of the participants were in the agree category that the education system in SA is offering courses related to automation, a relatively high proportion of participants (34%) are not sure as they remain in the neutral category as shown in Figure 7.8. This is possible as a result of the participants not being at institutions. There was no response in the strongly disagree category. This may imply that the participants are aware that changes are being made in the education system.

It was also essential to establish the prediction from participants on automation adoption at Coal Mine “X” and the time frame of automation adoption, as shown in Figure 7.9 and Figure 7.10. The majority of participants (55%) were in the agree and strongly agree category that Coal Mine “X” will adopt automation. From the results, it can be deduced that the participants are aware that automation in the SA opencast coal mines is inevitable. However, there are also uncertainties as a relatively high proportion of participants (27%) were in the neutral category regarding whether Coal Mine “X” will adopt automation. Furthermore, the researcher also established the time frame of SA Coal Mine “X” to adopt automation. Most respondents (57%) believed it impossible to adopt automation at Coal Mine “X” in the given time frame. A relatively high number of respondents (25%) were in the neutral category. This may imply that the participants are aware of possible challenges that may not allow automation adoption in five years.

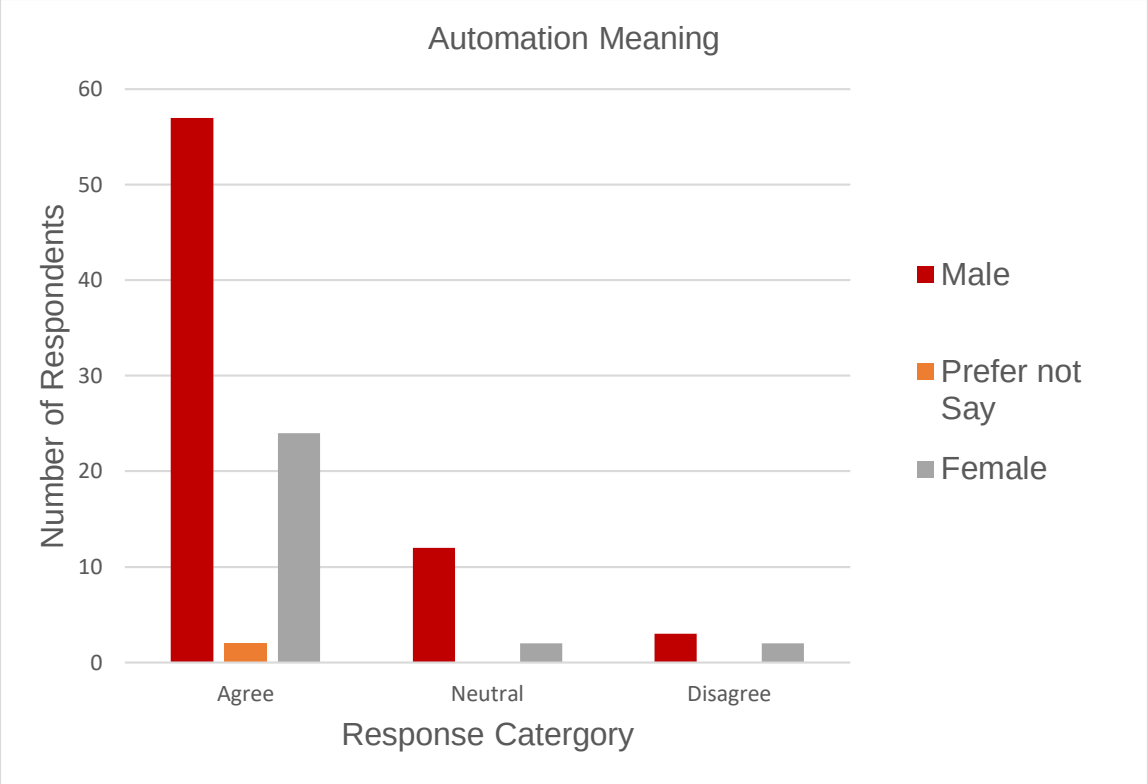


Figure 7.5 Automation meaning

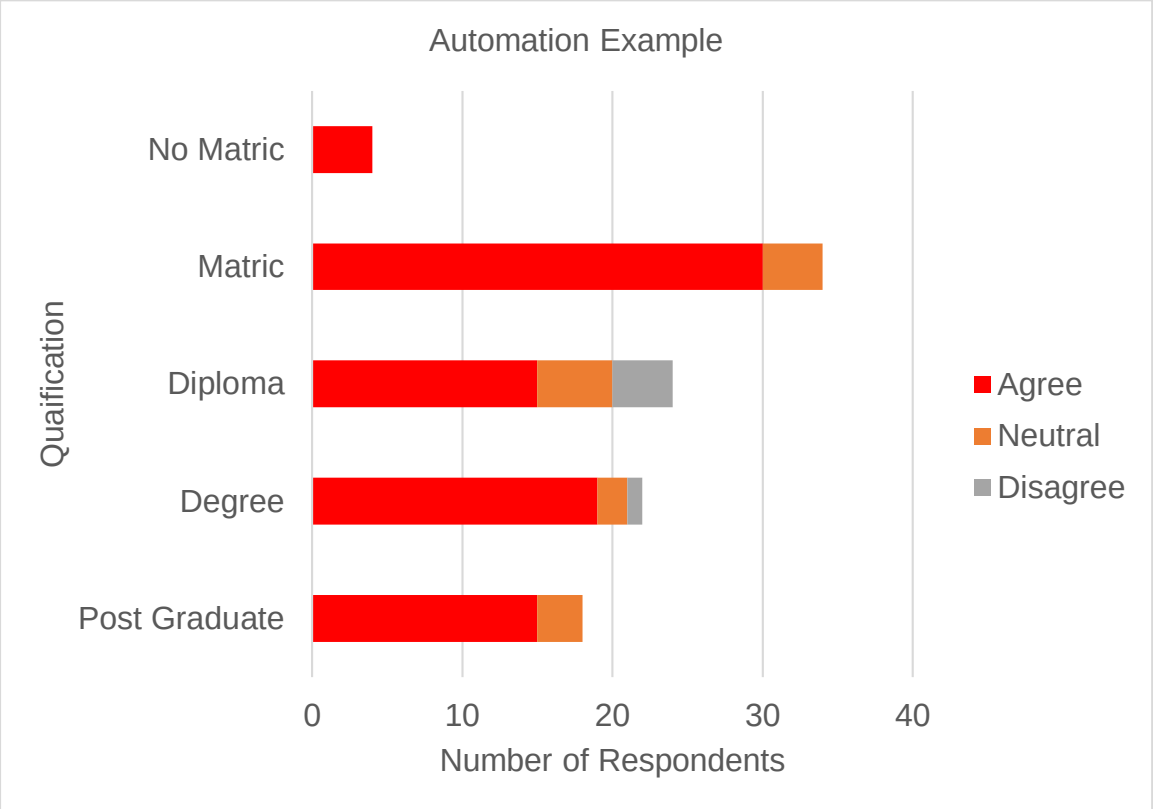


Figure 7.6 Automation Example

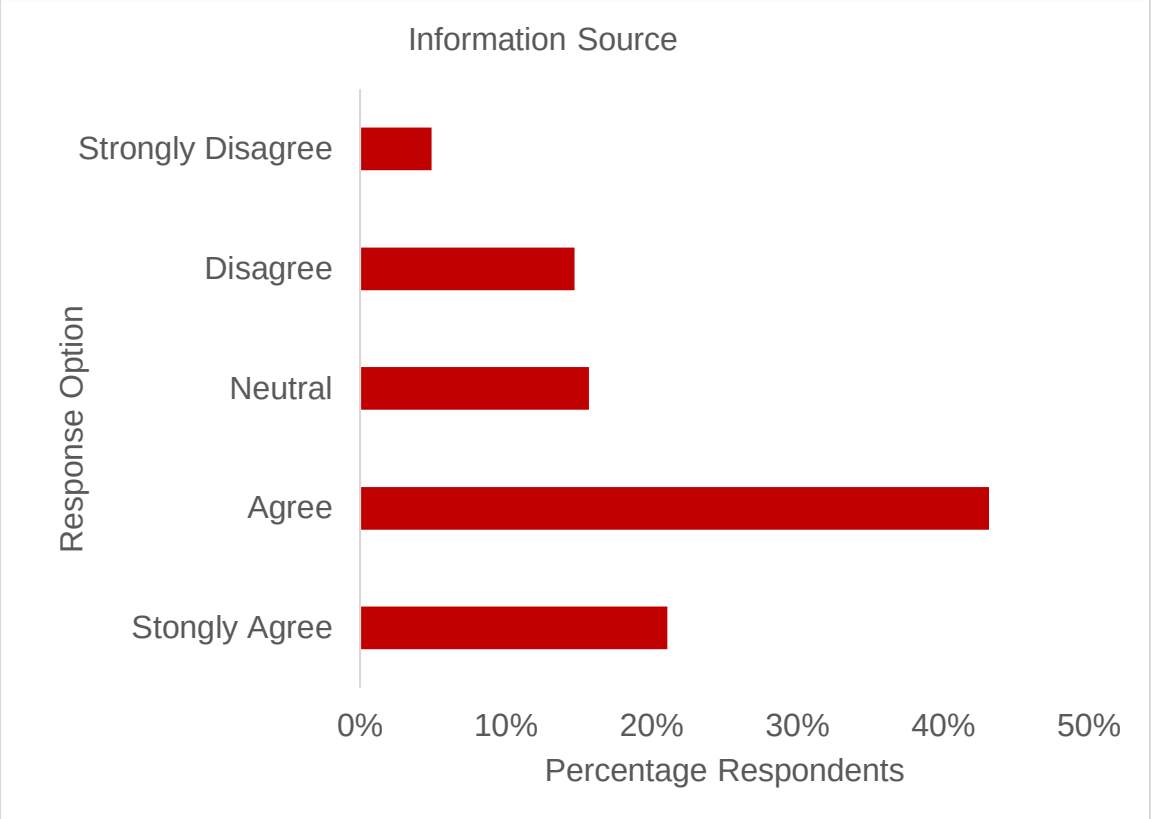


Figure 7.7 Automation Information Source

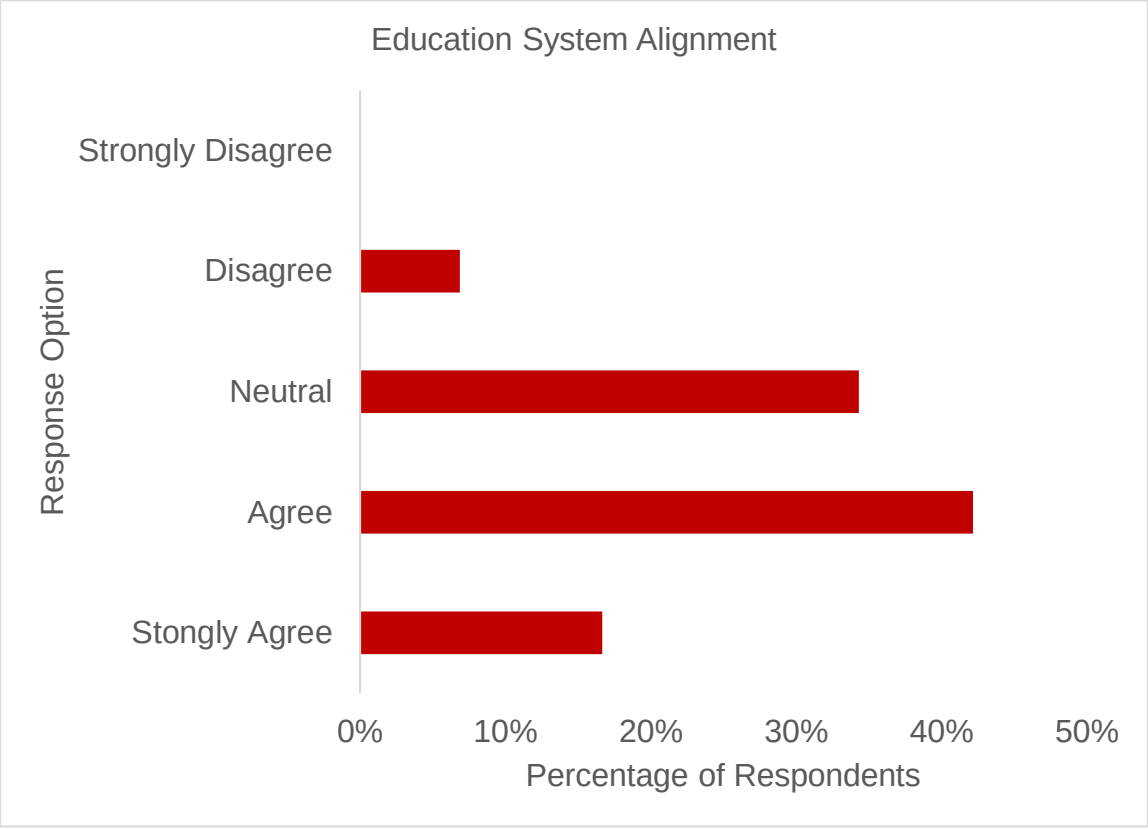


Figure 7.8 Education System Alignment

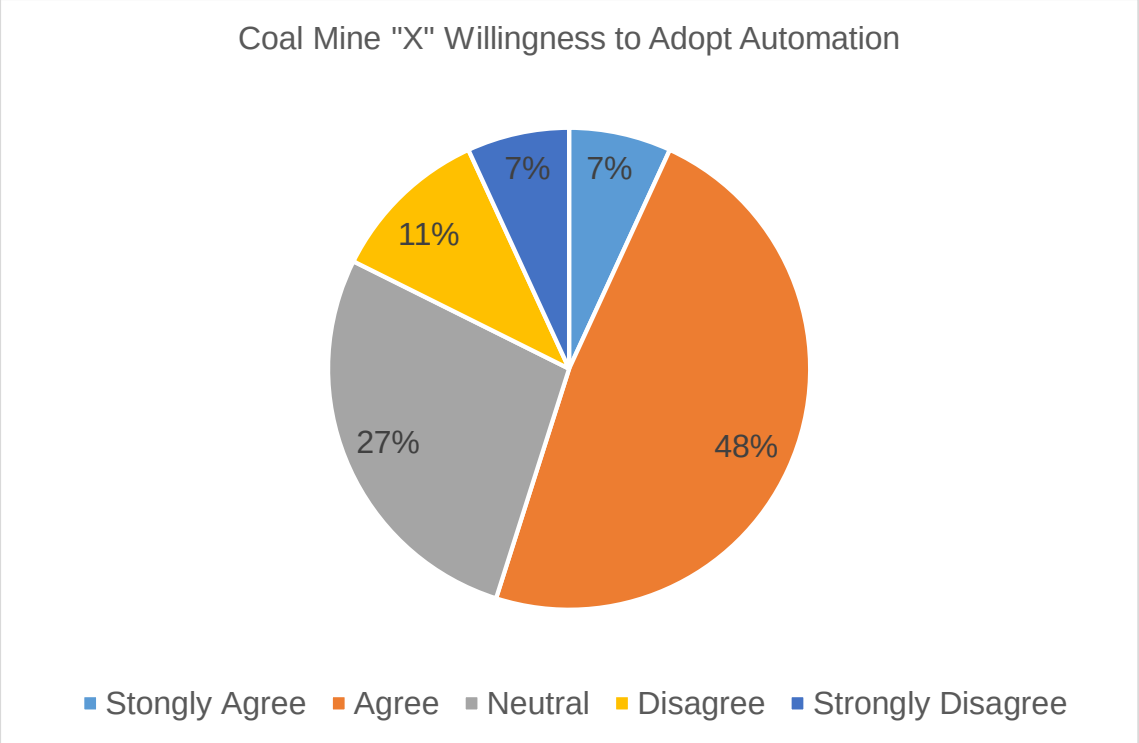


Figure 7.9 Coal Mine “X” Willingness to Adopt Automation

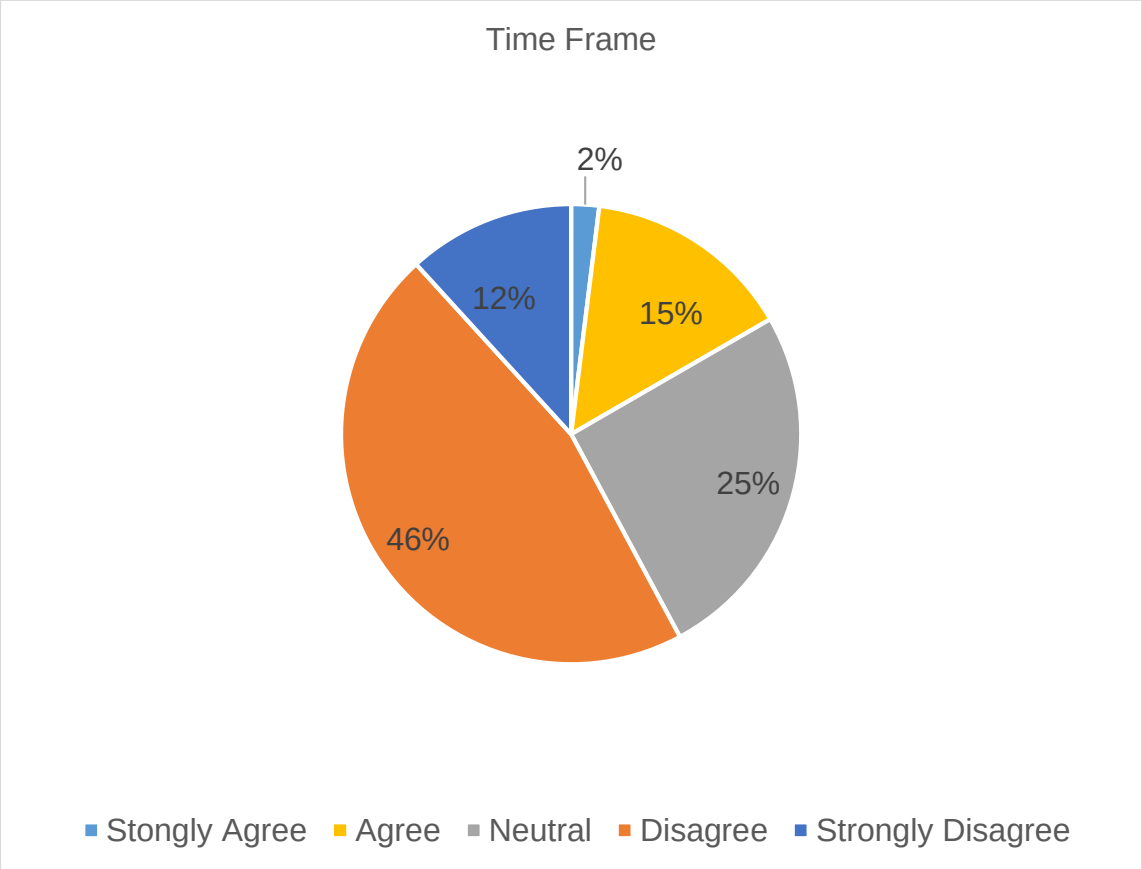


Figure 7.10 Time Frame

7.4 Potential Socio-Economic Effects of Adopting Automation

The questionnaire sought participants' opinions on the potential socio-economic effects of automation adoption in SA Coal Mine “X.” The majority of the participants (82%) were in the agree category option on the improvements in productivity and competitiveness as the benefits associated with automation, as shown in Figure 7.11. On the major adverse of automation, the majority (80%) were of the opinion that employment would be greatly impacted, as shown in Figure 7.12. There was 0% response in the strongly disagree category on the adverse effects of automation. The cross sectional analysis was carried out on those agreeing that automation has a major impact on employment loss; the results had 62 participants in the agree category for those aged between 20-40 years and 19 in the agree category for those aged between 41 to 60 years leading to the inference that automation is highly associated with job loss by all age groups.

To remain gainfully employed, the majority (80%) alluded to the fact that there is a need to reskill and upskill after automation adoption, as shown in Figure 7.13. As shown in Figure 7.14, the researcher inferred that there is a consensus among the participants that there is a skills shortage for automation adoption currently, as two-thirds of the respondents were in the agree category that there are not enough skills for autonomous machinery. A questionnaire on change management was generated to establish some of the steps to better prepare for automation adoption. It can be inferred from Coal Mine “X” participants’ operators, Middle Management, and Management appreciates the need and the importance of change management in the form of awareness whenever new ideas and technology are adopted, as shown in Figure 7.15.

The participants' opinion on the response of the labour unions to automation was necessary as part of the questionnaire for this survey. Labour unions can be potential barriers to automation adoption. The SA labour unions are strong and known for not accepting their members' employment loss. As shown in Figure 7.16, the findings show that operators and Middle Management and Management at Coal Mine “X” are of the opinion that the Labour unions will not support automation. The researcher deduced that there is also no conclusive answer on how the labour unions will react

to automation adoption from the participants, as 23 of the participants remained neutral.

The researcher sought participants, opinions concerning the benefits to surrounding communities after automation. Considering the requirements of the SLP, communities were benefiting from mining companies. When automation technology is adopted, the respondents believe there are minimal benefits to the community as the majority were in the agree category (59%), as shown in Figure 7.17. Regarding the participant's responses on the government support for automation, the majority (43%) were in the neutral category, as shown in Figure 7.18. The researcher inferred that the participants did not yet have much information about the government's position on automation adoption. On changes in mining policies when automation is adopted, the researcher inferred that this would change, as the majority of the participants (79%) were in the agree category, as shown in Figure 7.19. The results are shown in Figures 7.11 to Figure 7.19 and Appendix B.

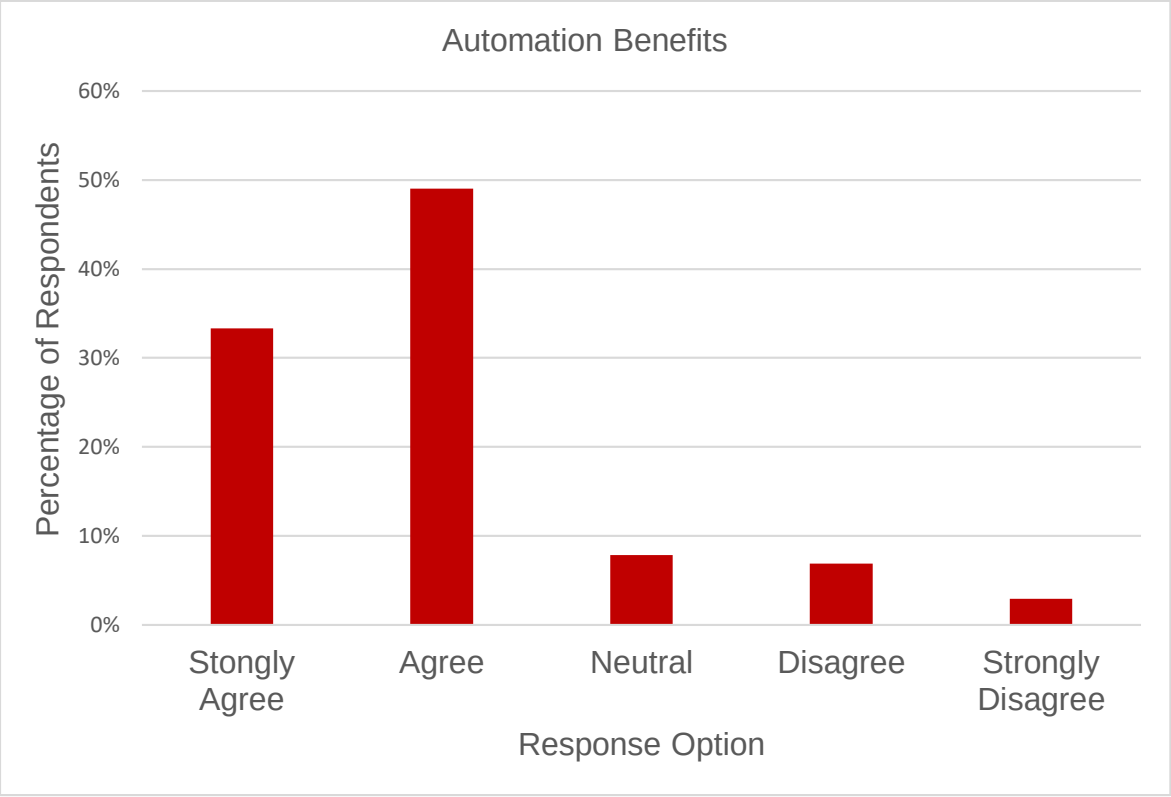


Figure 7.11 Automation Benefits

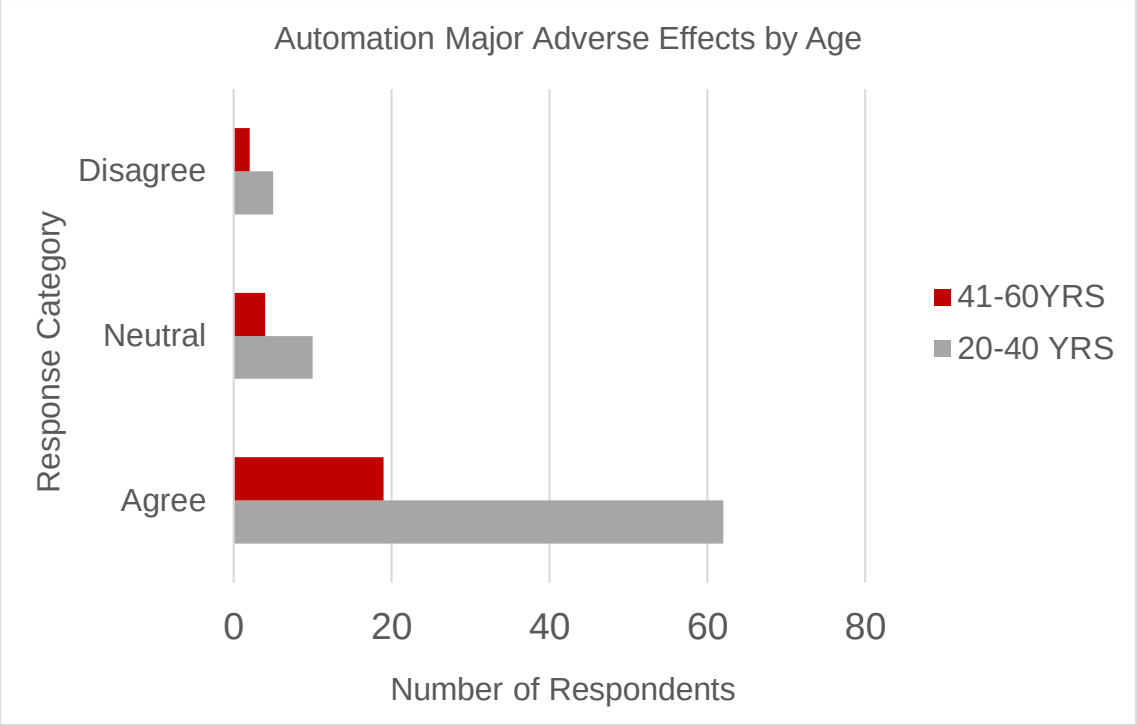


Figure 7.12 Automation Major Adverse Effects

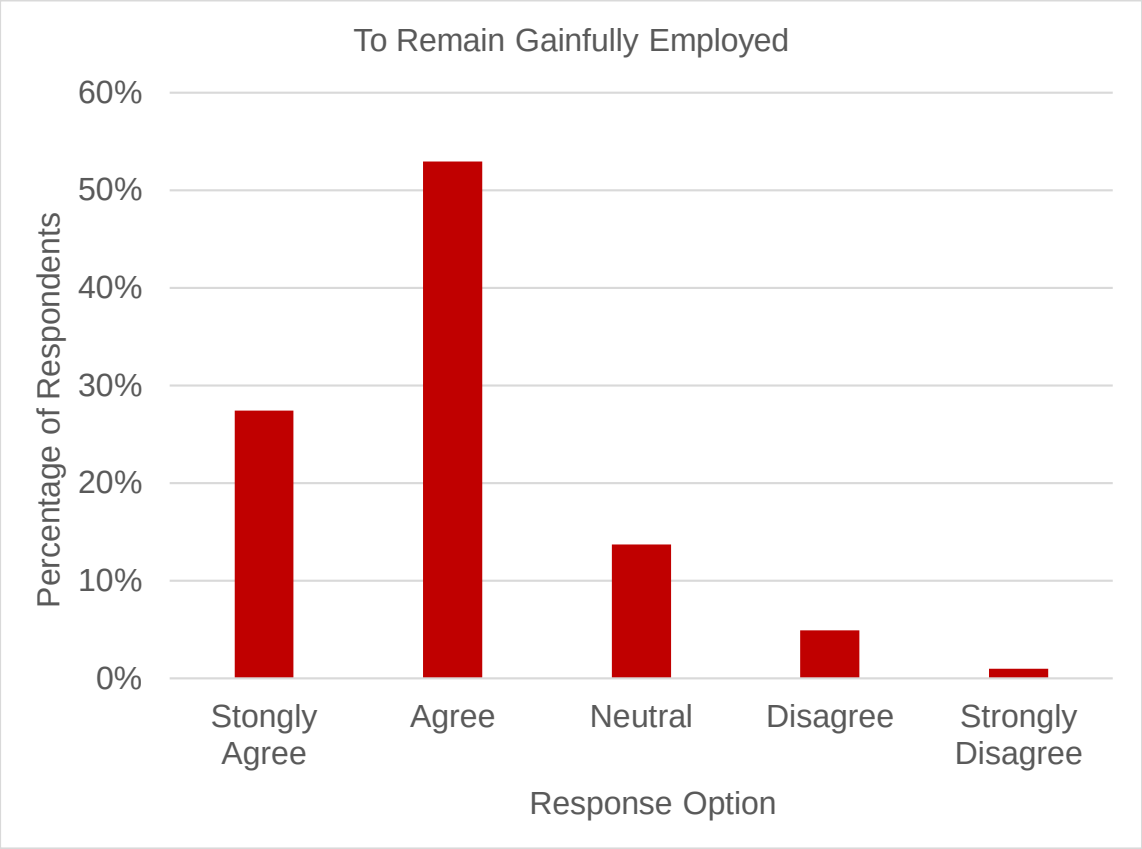


Figure 7.13 To Remain Gainfully Employed

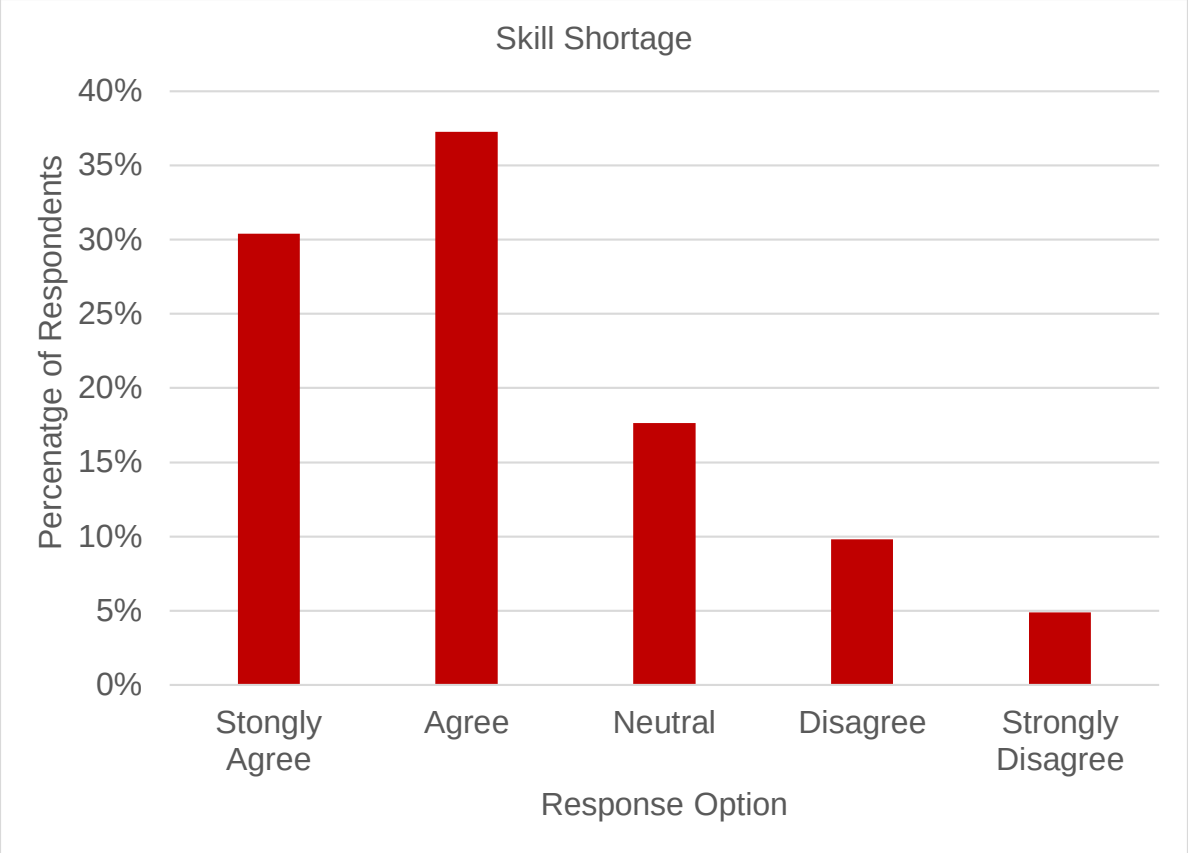


Figure 7.14 Skills Shortage

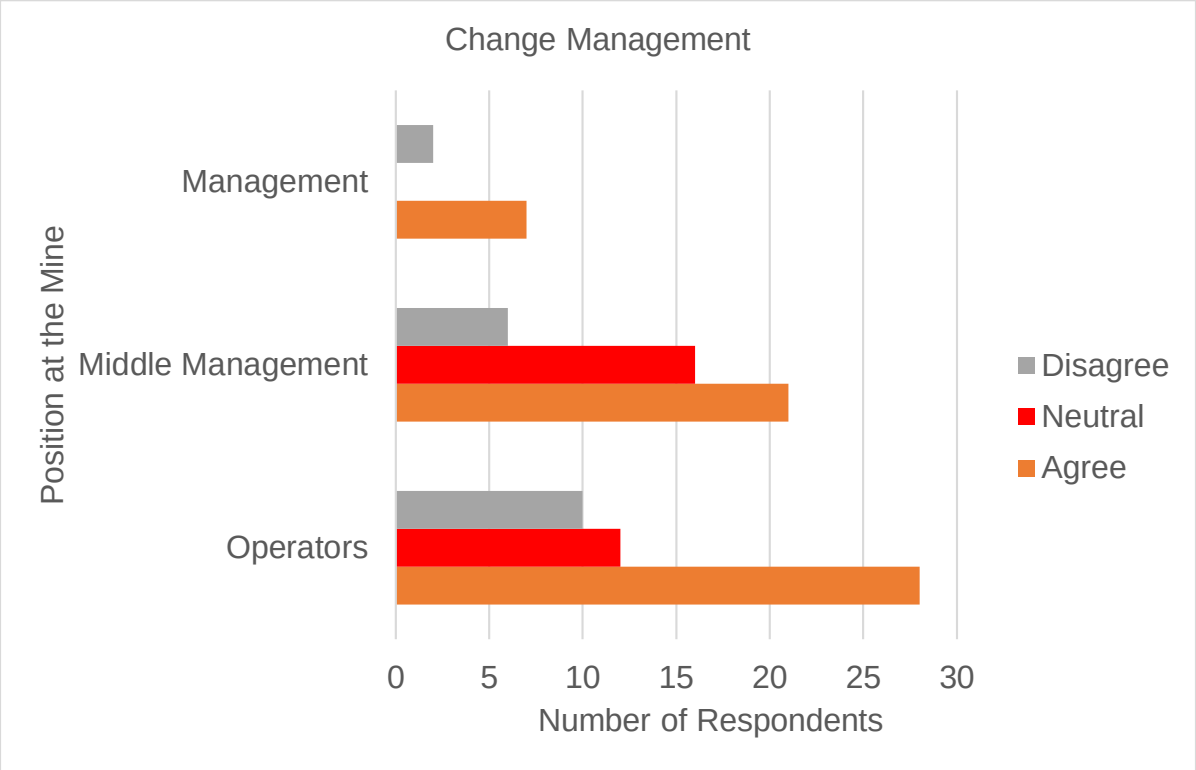


Figure 7.15 Change Management

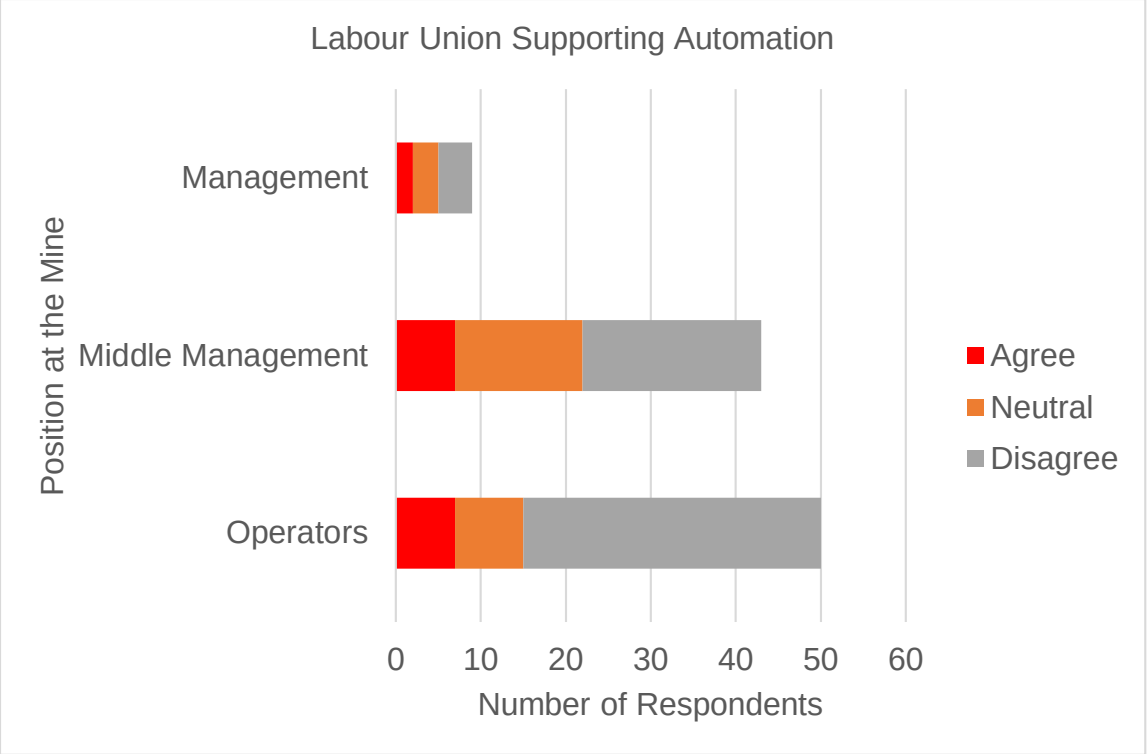


Figure 7.16 Labour Unions

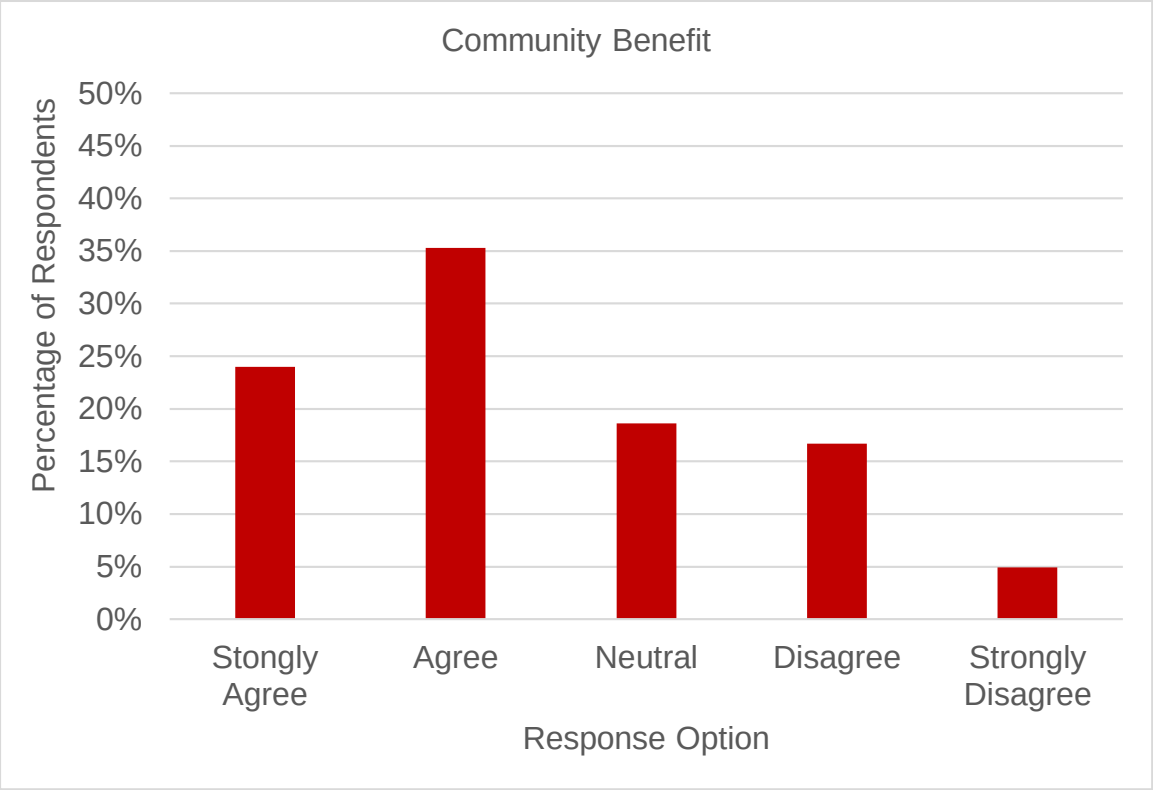


Figure 7.17 Community Benefit

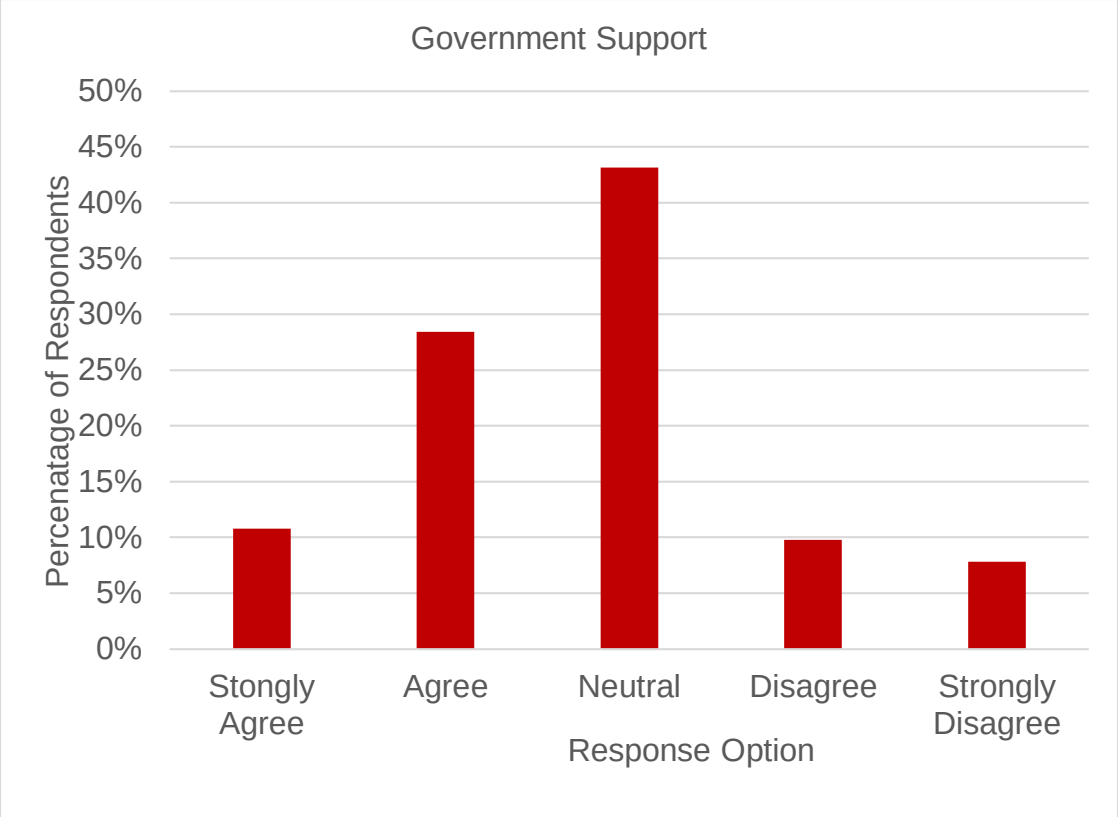


Figure 7.18 Government Support

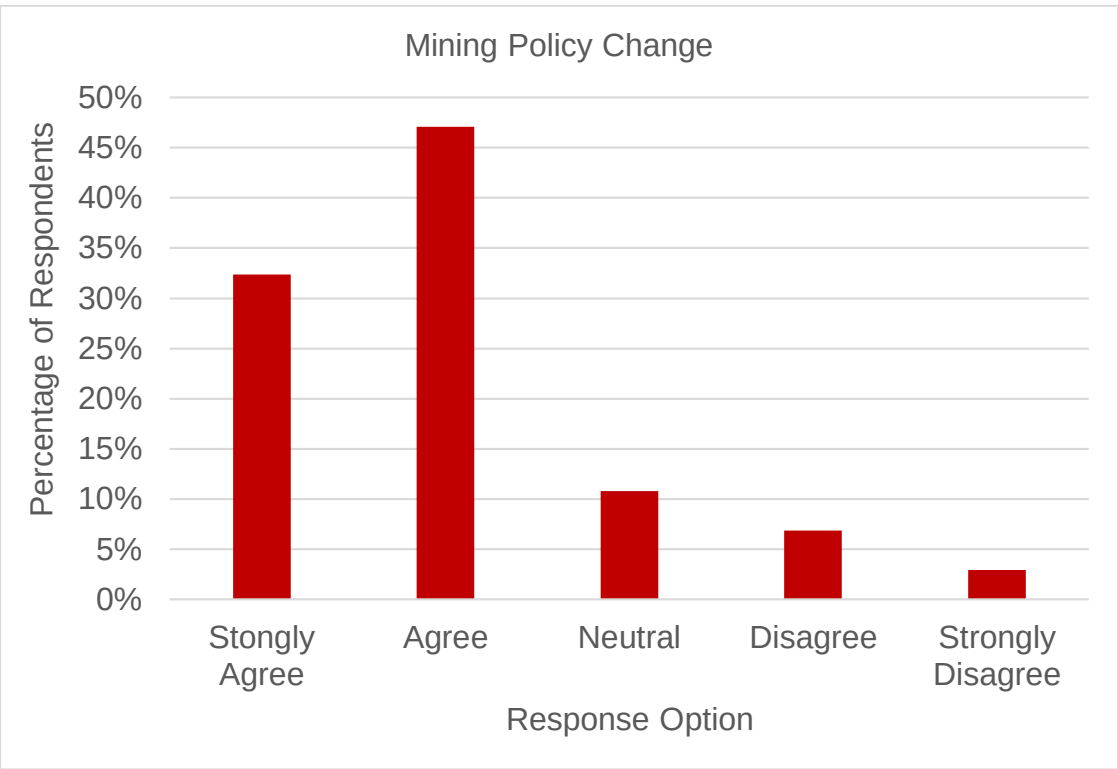


Figure 7.19 Mining Policy Change

Quantitative methods consider reliability, replication, internal consistency, and external validity for data validation. A validity test on the five scale type questions was performed to ensure reliability. Cronbach's Alpha indicates a result of 0.7, which is considered to be moderate, as shown in Table 7.1.

Table 7.1 Reliability Statistics

Cronbach's Alpha	**No of Items**
0.70	15

7.5 Bivariate Correlations

For this research study, it was essential to conduct a bivariate analysis to establish correlations between various independent and dependent variables of selected factors to explain the research questions. By applying Spearman correlation, it was possible to establish these relationships. The variables considered for the correlations and the results are summarised in Table 7.2

Table 7.2 Bivariate correlations

Variables	**Spearman Correlation Coefficient _rho (rs)**	**Significance** ***P*** **value**
Opencast Coal Mine "X" willingness to adopt automation and adoption not possible in less than 5 years	+0.41	0.02
Skills shortage and need to upskill and train	+0.26	0.01
Employment as a major adverse effect of automation, and Labour unions not support automation	+0.27	0.09

From these findings, the researcher identified a statistically significant positive correlation between opencast Coal Mine" X" willingness to adopt automation, but this

was not possible in less than 5 years. A statistically significant positive correlation was also observed between the shortage of skills and the need to upskill and train. A statistically significant positive correlation was also observed on the labour unions not supporting automation as long as employment is lost.

7.6 Qualitative Findings

The researcher designed eleven open-ended questionnaires for use in qualitative interviews as shown in Appendix D. Each of the 8 participants was asked to provide an example of their understanding of automation. The levels of understanding have been divided into Level 1 and Level 2, as shown in Appendix B. Of the 8 participants, 87% understood automation meaning, while 13% had a basic understanding.

The participants were further asked their opinions on the potential socio-economic effects of automation in the coal mining industry. All 8 participants (100%) agreed that automation is inevitable. Table 7.3 to Table 7**.**7 show the percentage of comments relating to each main theme and a representative quote. The themes generated by the 8 participants were all considered. The percentage was calculated as the number of comments coded to each theme out of the total comments provided (8).

7.7 Opinions on Implications/Socio-economic Effects of Automation

The participants identified the benefits and shortcomings of automation adoption in the mining industry and had common themes. However, the focus differed depending on the position on the mine and level of education. The summary frequency table as shown from Table 7.3 to Table 7.7, shows the percentage of comments about each theme from the interview.

Table 7.3 Automation Benefits

Automation Benefits	**%**	**Representative Quote**
Improvement in productivity cost-cutting to mining companies, improvements in efficiency, improved safety	100	"*I think it saves time and reduces errors. So, always in business; we want to be profitable".*
Safety	100	"*The first advantage is safety. Yes, you have no human factor in dangerous areas. So you would not have this thing of killing people."*
Training	87	*"I think there will be training for us on new machinery or such technology."*
Fatigue and health issues	13	"*Automation, it will be able to function 24 seven without any stoppage."*
Pandemic	13	*"Especially now with such virus outbreaks, one will look at such advantages to say, how can we do this better without you passing the virus to people."*
Carbon Emission	13	"*Automation will also greatly assist in terms of the carbon emission.*"
Growth in skills	13	*"I've seen a positive influence from technology in that our labour force in the mining industry has been upskilled."*

Table 7.4 Automation Negatives

Negative Impacts of Automation	**%**	**Representative Quote**
Employment loss	100	"*Cost-cutting can lead to a leaner workforce, meaning that most people, especially in lower-income brackets, who are usually either unskilled or uneducated, would tend to lose their jobs because the machines will take over those less skilled jobs." This can be for the short term. In the long term, roles change.*
High Capital	25	*"Capital is a challenge."*
Decrease in the GDP	13	"*Because then the mines would use less fuel and less locally produced resources, which will then reduce the GDP of the country, talking especially in South Africa where mining is a big pillar to the GDP."*
Automation Reliance	13	"*Automation cannot be relied upon, in a sense that there is a huge need of certain areas in society that will require human interaction."*
Employment entry-level high	13	"*I think the person who can come and be employed for automation, he or she must be more educated than current levels of education."*

Table 7.5 Local Communities Benefit from Automation

Community Benefits	**%**	**Representative Quote**
Minimal community benefit	75	"*There is no immediate benefit."*
	25	*"venturing into services industry such as tourism for local communities or training them to maintain and manufacture tools in line with automated industries is the way local communities can benefit from automation."*

Table 7.6 Potential Barriers to Automation Adoption

Barriers	**%**	**Representative Quote**
Education	100	"*I think we lack that because most things are not being taught in school."*
Labour unions	100	"*Labour unions, from a labour union perspective, our main objective or goal is to* ***preserve jobs****. Labour unions would come in to oppose full automation without the prior training of the current workforce."*
Specific skills	75	"M*y opinion is that we don't have the skill sets."*
High unemployment	50	*"Automation is going to take away jobs."*
Socio-economic inequality	25	*"In South Africa, socio-economic inequality and economic equality are at the highest peak. That will be the first barrier."*
Costly to implement	25	"So *I think the cost in the capital, it's also a challenge."*
Poor infrastructure/electricity shortage	13	*"In a South African context, we struggle with the Industrial Revolution technology, for instance, cell phone towers that most of this automation would require and with load shedding those types of towers tend to lose either reception, or go down entirely, and that would affect the mine for a couple of hours, which makes the mine less efficient*
Resistance to change	13	*"I think some of the challenges that I've just seen is the resistance, especially from the older generation, So there is that resistance and new technology."*

7.8. Ways to handle automation barriers

The researcher used probing questions to get more about the participants' opinions concerning ways to handle potential barriers to automation. Several themes were brought up by participants, as summarised in Table 7.7

Tabe 7.7 Barrier Handling

Handling the Barriers	**%**	**Representative Quote**
Education	100	"*Introduce the concept of technology, automation, fourth industrial revolution. specialize in IT, things like electrical engineering and software design, that's when you get exposed.*"
Training and Upskilling	100	"*Then when we look into existing labour adults, people already working. We need to start preparing them for that time for automation. This will be happening in the next ten years*."
Change Management (Awareness campaigns)	*75*	**"***Educating sending out information to the public about automation, like this research must be made available to layman people at the bottom of the barrel."*
Government support	25	"*So obviously, the government will need to start now looking into its policies. So the policies need to be investment friendly; there needs to be a lot of stability."*
Mine Support	13	"*Management support and buy-in from the floor"*
Labour unions	13	"*However, as labour, we are open to discussion, those who say, how can we implement automation."*
Economy diversification	13	"*South Africa, for instance, is dominated by the primary sector. Yeah, we need to add funds to develop and widen other sectors. For people to migrate seamlessly to the secondary and tertiary sectors.*

In the conclusion of the interviews, the participants were further asked how to better prepare for automation, and their opinions were aligned with ways of handling automation barriers.

7.9 Integration of Results

The integration of quantitative and qualitative findings from phases 1 and 2 is presented in joint tables showing quantitative and relevant qualitative findings. The mode of the quantitative survey was used as it was more representative of the participants' opinions, and an accompanying qualitative quote was also provided.

Table 7.8 Integration of Results

Themes and Quotes from Qualitative Findings	**Mode in Quantitative Survey**
Meaning of automation “Use of machines with minimal human involvement such as the use of a drone.”	42% (Agree category)
Education system alignment to automation “Introduce the concept of technology, automation, fourth industrial revolution. specialize in IT, things like electrical engineering and software design, those types of things, that's when you get exposed.”	42% (Agree category)
Major adverse effects “Cost-cutting can lead to a leaner workforce, meaning that most people especially in lower-income brackets, who are usually either unskilled or uneducated, would tend to lose their jobs because the machines will take over those less skilled jobs,” For the short term, people lose jobs but in the long term roles change.	49% (Agree category)
Skills Shortage “My opinion is that we don't have the skill sets.”	49% (Agree category)
Labour unions “Labour unions, from a labour union perspective, our main objective or goal is to preserve jobs. Labour unions would come in to oppose full automation without the prior training of the current workforce.”	27.5% (Disagree category)
Community Benefits “There is no immediate benefit.”	35% (Agree category)
Mining Policy Change “So obviously, the government will need to start now looking into its policies. So the policies need to be investment friendly, it needs to be a lot of stability into that.”	47% (Agree category)

Although there was a consensus that the education system is aligned with the automation courses during the quantitative interviews, the qualitative interview implies no alignment. Most of the themes in the quantitative survey aligned well with qualitative interview quotes.

7.10 Discussion of Results

This section discusses the results of the findings. The findings are linked to the literature review in Chapters 2,3,4, and 5 to answer the question set up in the aims and objectives of chapter 1. The two research phases, 1 and 2, had different respondents, with the quantitative survey having n=102 while the qualitative interviews had n=8 across various levels and sectors of mining production.

At the opencast, Coal Mine “X” males dominate with fewer female employees, as shown in Figure 7.1. The opencast Coal Mine “X” confirm what is already in the literature that the mining environment is male-dominated due to the nature of work which is labour intensive and demanding. It is anticipated that with automation, female employees will increase as employment opportunities with workloads not labour intensive and demanding for women are promoted through automation (Cosbey et al., 2016; Mutanga et al., 2021).

The developed countries have the old aged dominating the population. The dominating old age in developed countries has resulted in these countries sourcing for cheaper ways to improve production, hence the need for automation as this solves the high cost of employment (Meech and Parreira, 2011; Bellamy and Pravica, 2011; Cosbey et al., 2016; WEF, 2016). In SA, the demography is different. At Coal Mine, “X those aged between 20 and 40 dominate the workforce, typical for developing countries (Figure7.2).

The profile of respondents on the educational qualifications as shown in Figure 7.3 indicates only 4% are not holders of matric qualification with a third having a minimum of matric as a qualification and the rest are either diploma, degree or post, graduate holders. The educational qualification at Coal Mine “X” is relatively high, although matric qualification alone is not enough. The advantage of a qualification equivalent to matric or above is that people can further studies to acquire more automation skills

without much difficulty. In developing and developed countries, employees with low or medium-level education are at a high risk of job automation (Berriman and Hawksworth, 2017; Chang and Huynh, 2016). In Australia Rio Tinto in partnership with Universities have established an automation qualification (Rio Tinto, 2019). The education system in SA is educating people to be employed and is not yet at the level of training innovators. Therefore, more is needed in the education sector (Tyatya, 2019; Kayembe and Nel, 2019, Mutanga et al., 2021).

The diverse skills shown in Figure 7.4 enabled the sample of respondents to occupy various positions on the mine. The educational qualifications and skills at Coal Mine "X" fulfill literature findings that the coal mining industry has more skilled workers than hard rock mines (MCSA, 2018; CMM, 2020). In the quantitative survey, the operators dominate, which could introduce opinions heavily influenced by the operator level. Contrary to this, the literature reveals that the operator level of employees worldwide dominates in the mining industry and is likely to be negatively affected when automation is adopted (Cosbey et al., 2016). The second highest representation at the mine is the technical services people such as geologists and surveyors. Those in technical services will need reskilling and upskilling to use autonomous technologies (International Business Machines, 2018). Engineers are the least represented, and more must be done at the training institutions to generate additional enginners (Van Dam, 2017; Kayembe and Nel, 2019; Mutanga et al., 2021).

7.11 Coal Mine "X" Employees' Level of Understanding Automation

The researcher formed the question in response to the literature findings indicating that developed countries are advanced in automation adoption and research on the socio-economic effects of automation. Literature has shown that the developed countries population has highly educated people competent in specialised areas. According to NEDLAC (2019), commendable progress has been made in providing basic education to everyone in SA; however, the levels of education in SA are still considered low, implying that understanding of automation might be low. According to MCSA (2018), the coal mining industry has far more skilled workers than hard rock mines. This means that the level of education in the coal mines is better than that of hard rock mines. The research question was posed to assess the level of

understanding of coal mine employees concerning the meaning of automation and a provision of an example. The results of both a quantitative survey and qualitative interviews indicate that the participants were knowledgeable and aligned with the definition given in the literature (Hornby, 2005; Lynas and Hoberry, 2011; Janssen et al., 2019; Groover, 2020). The participants could also give examples of automation machinery during quantitative surveys and qualitative interviews (Tauber et al., 2018; Janssen et al., 2019; Strydom, 2019). Most of the participants' definition of automation was more aligned and explained in terms of full automation associated with 4IR rather than the low-level and middle-level automation (Ralston et al., 2014; Cosbey et al., 2016; Black Livingston et al., 2018; Rogers et al., 2019). Currently, the mining industry is benefiting from low-level automation and mid-level automation. Low-level and middle-level automation has been used at the coal mines for a while, although during the qualitative interviews, the participants had a low appreciation of low and middle automation. With the full level of automation, using machines such as driverless trucks, most people have not physically witnessed these autonomous machines, although, in the research, the participants appreciated these machines.

As part of this research, it was essential to establish the sources of automation information as most participants at Coal Mine “X” have not witnessed driverless trucks Information about automation from social media and the workplace has assisted the understanding of automation and associated machines in the mining industry as shown in Figure 7.7. Information flow through technologies, starting from 2IR to 3IR, has enabled communication and trade to be improved (Roberts, 2015; Taalib, 2018). Nowadays, people do not need to go to school to learn the basics of automation. Social media and the workplace assist in information sharing. Gender, educational qualification, and position at the mine do not play a significant role in the understanding of automation, as there were no differences in the responses from participants.

7.12 Potential Socio-economic Effects of Automation

This question was designed to establish if respondents know the potential socio-economic effects of adopting automation in the SA Coal Mine “X.” Automation is associated with specific benefits and challenges (McNab et al., 2013; Holcombe and

Kemp, 2019). Further, it was also essential to establish the level of difference in perception among participants' responses to the socio-economic effects of automation. Participants' perception of the socio-economic effects of automation was investigated as it sets the central core of this research.

The identified socio-economic effects among the different participants were closely related, although the researcher had not carried out a baseline survey on the levels of understanding of automation. The participants contributed their opinions based on their knowledge and best perception of automation. Most of the research work to date on potential socio-economic effects of automation has been carried out in developed countries, such as Australia and Canada, where the literacy levels (knowledge in specified areas) are considered high, and most people can comprehend automation effects better because of exposure (Cosbey et al., 2016). Based on the opinions given by the participants regarding the potential socio-economic effects of automation, for both quantitative and qualitative interviews, this baseline survey was not necessary as the participants understood the benefits and challenges associated with automation adoption.

As shown in the qualitative interviews, 100% of the participants (Table 7.6) believed that the education system was still lagging and was not embracing the curriculum for new technologies in the system. The difference between quantitative results and qualitative findings may be because, in the quantitative phase of the research, the respondents were given limited options to choose from based on the researcher's selection, which would not allow them to elaborate further as in qualitative interviews. Literature indicates that the SA education system is still misaligned to accommodate the 4IR needs (Tyatya, 2019; Kayembe and Nel, 2019; Mutanga et al., 2021).

Approximately 8 years ago, Accenture surveyed executives of 151 mining companies worldwide, and 85% strongly supported adopting digital technology because of the associated benefits (Sganzerla et al., 2016). For this study, the identified benefits and challenges were relatively similar across the spectrum of participants. In the quantitative interview, a limited option of benefits was provided to the participants by the researcher. Nevertheless, in the qualitative interview, the participants identified more benefits associated with automation and were able to elaborate during probing.

The findings from the qualitative interview were not different from the literature (MacNab et al., 2013).

During the qualitative interview, differences were noted in the participants' depth and scope of the benefits and challenges of automation adoption. This depended on the level of education and position at the mine. The participants in the middle management (foreman, overseer) to management (mining engineers, mining manager) positions had a diploma qualification or above, mentioned issues such as change management importance and the fact that employment loss is only for a short term, while in the long run, technology-enabled employees will be more (Burns and Church, 2019). The operator level with no matric or matric qualification focused more on safety as a benefit and loss of employment (backward linkage) as the major adverse effect of automation. One participant in the middle management strongly believed that fully automating the mines brings benefits, especially when pandemics such as COVID 19 are prevalent. This research acknowledges that different participants at different levels of qualifications and positions at the mine have different opinions and priorities on the effects of automation (Lynas and Horberry, 2011; Cosbey et al., 2016).

Literature dating back to 2IR and 3IR indicates a surge in productivity, efficiency, and reduction of costs when new technologies were introduced (Dickmanns, 2002; Humphrey, 2019). Participants in the qualitative interviews highlighted an improvement in efficiency by reducing fatigue for operators and overcoming challenges associated with health issues as a benefit of automating. Autonomous technologies were identified to be available most of the time. Literature has indicated that adopting new technologies in the mines has improved productivity by between 9%-23% (Moolman, 2018; Accenture, 2019; EY, 2019b). Mining companies in the developed world that have adopted automation have also noted improvements in safety and competitiveness (Rio Tinto, 2021a).

On further probing participants during the qualitative interview, 87% of the participants identified automation as an opportunity to be trained, grow in skills, and reduce errors in the system, thereby ensuring high-quality production as shown in Table 7.3. These align with the literature's benefits (McNab, 2013; MiHR, 2020). Another benefit 13% of participants identified is carbon emission reduction. High carbon emissions affect climate change, one of the biggest threats to economic stability worldwide (Harvey,

2019). In SA, high carbon emission is a challenge as the country relies heavily on thermal power generation for electricity (MCSA, 2018). Continuous use of coal for electricity generation might not favour SA in reducing carbon emissions, even if automation is adopted. One of the challenges in the coal industry is the introduction of the carbon tax (MCSA, 2022).

Another benefit of automating in developed countries such as Australia is replacing the aging workforce and solving the scarcity of operators (Bellamy and Pravica, 2011; WEF, 2016). Considering the demography at Coal Mine "X," the mode is aged below 40 years, an indication of a young aged population employed at Coal Mine "X". Demographically, SA, as a developing country, does not have a high percentage of an aging workforce, and neither is there a scarcity of operators. During the qualitative interview, there was no mention of the scarcity of operators as a benefit to automation in SA.

Technology and automation will alter how local communities benefit from mining companies (Burns and Church, 2019; Holcombe and Kemp, 2019). In the quantitative research, the respondents perceived minimal benefit for surrounding communities when mines automate. Most participants in the qualitative interview indicated no direct benefit to surrounding communities as shown in Table 7.5. A minority 25% of participants in the qualitative interview believed that the communities could benefit through employment, supplying goods to the mine related autonomous machines (Backward Linkages), training (Knowledge Linkages), offering tourism services (Consumption Linkages), (Cosbey et al. 2016; UNTCAD, 2017b). Evidence from the literature confirms that most mining companies will remotely control machines in operation centres thousands of kilometers away (Cosbey et al., 2016). When automation is adopted, local communities are at a disadvantage in terms of jobs and development, thus affecting the backward, consumption and fiscal linkages (McNab et al., 2013; Cosbey et al., 2016; Beare, 2017; Holcombe and Kemp, 2019).

The relationship between mining firms and states is based on a shared-value bargain that gives mining companies the SLO fulfilled through employment, procurement activities, and beneficiation (Cosbey et al., 2016;). Advances in technologies could support local communities by establishing technological infrastructure, which is

referred to as spatial linkage (Cosbey et al., 2016; Corneau, 2019). An indirect benefit to local communities, such as real-time data availability through technological infrastructure (spatial linkage), was not a finding by participants in this research (Cosbey et al., 2016).

On the negatives associated with automation adoption, the participants for both quantitative and qualitative surveys cited employment loss as the significant adverse effect of automation. The cross sectional analysis based on the “agree” responses for those aged 20-40 years and those aged 40-60 years did not show a difference as they all believed automation would bring employment loss. A 100% of the respondents in the qualitative interview agreed that loss of employment is a major adverse effect of automation. Advances in new technologies are capital intensive, require less labor, and are skill biased (Mining Review Africa, 2021; Roubini, 2021). The main risk the technologies are bringing would result in job losses. Employees currently doing repetitive jobs are likely to suffer more job losses, which are more severe for those above 45 years (Rogers et al., 2019; Ribeiro et al., 2021). When mines are fully automated, the workforce is reduced by 30-40% and is estimated to be as high as 75% in opencast mines (Bellamy and Pravica, 2010; MacNab and Garcia Vasquez, 2011). In this research, at Coal Mine “X,” the operators constitute the highest percentages of respondents and are likely to be negatively affected by automation. In contrast to this view, when Anglo-American adopted automation at the Sishen mine in 2014, there was no loss of jobs, but instead, a change in roles was experienced (SAIIM, 2018; Mutanga et al., 2021).

For this study, the age range below 40 dominates, and this age group's education qualification is matric or higher. The advantage of a younger population and matric qualification or higher is that the people can advance qualifications for other technologies. Automation will alter the workforce's size, roles, and location. The net effect of automation adoption is estimated to be insignificant as new jobs will be created (McNab et al., 2013; Cosbey et al., 2016). Although not focusing on the mining industry alone, Magwentshu et al. (2019) showed that there would be a net gain in jobs if jobs were automated in SA. NEDLAC (2019) findings allude to the fact that some jobs will be eliminated in the energy sector while there will be a higher demand for specific jobs.

During the qualitative interview, participants identified a decrease in the GDP as a negative in automation adoption. According to Cosbey et al. (2016), with automation adoption, it is anticipated that foreign mining companies will spend less in the host country where they are operating. There will be lower spending on local procurement for fuel or other resources that mining companies use to procure locally, affecting backward linkages, consumption linkages, and fiscal linkages (Cosbey, et al., 2016). Participants also highlighted high capital costs negatively affecting automation adoption. Developing countries such as SA are heavily reliant on international investments(United Nations Conference on Trade and Development, 2017a).

The other challenge was the heavy reliance on automation, as identified in the qualitative interview. Machines cannot carry out specific tasks in certain environments, and this work needs to be augmented by people. Due to the nature and complexity of the mining environment, it is not always possible to use automated machinery without human involvement in different scenarios. This supports the view that it is impossible to eliminate people from work even if automation is to be adopted (Dickmans, 2002; Lynas and Horberry, 2011; Rogers et al., 2019).

Participants identified the entry-level qualification to get employed in a fully automated mine as high. High education qualifications are a requirement to work in automated mines. Most low-level employees have matric qualifications in the Coal Mine “X” context. Being a matric holder is not enough qualification for working in an automated environment (Bruckner et al., 2017; Mutanga et al., 2021). In developed countries such as Australia, the government, Rio Tinto, and South Metropolitan have partnered to develop a nationally recognized Certificate IV in Autonomous control and automation, thus improving the skills needed in the automation era (Rio Tinto, 2019).

7.13 Critical Socio - economic Factors that May Impede Automation Adoption

The participants were also asked to identify the critical socio-economic effects that may be barriers to adopting automation. As literature has indicated, there are several impeding factors to automation (McNab et al., 2013; Cosbey et al., 2016).

As early as the 19th century and progressing into the 20th century, labour unions have resisted production technology in mining, car-making, shipbuilding, and cotton

weaving (Cosbey et al., 2016). During the 1IR, a group of "Luddites" recognized the threat of innovative technologies and rebelled (Archer, 2000). The participants identified the presence of a strong labour union in SA as a major barrier to automation adoption as the majority of respondents believed that labour unions would not support automation adoption, with the minority of participants remaining in the netral category suggesting that they are not fully aware of the reaction from the labour unions as shown in Figure 7.16. There is a statisticaly positive correlation between unemployment being the major adverse effect of automation and labour unions not supporting automation as shown in Table 7.2. During the qualitative interview, 100% of the participants indicated that the labour unions would not support automation adoption. The explanation given by participants during qualitative interviews for labour unions not supporting automation was that the labour union mandate is to "*preserve jobs*." and fear losing their members, primarily low-skilled workers. Hlatswayo (2017) argues that trade unions are aware that automating the mines can undermine their bargaining power.

On the ways to handle the negatives of automation adoption, the participants were of the view that it is not an outright "no" to automation adoption by the labour unions. There was an indication that if labour union members are educated and involved in discussing how automation can be adopted in the mining industry, the labour unions will support automation. Lööw and Johansson (2019) allude that workforce reduction needs to be managed in transparency with trade unions. As for developed countries, labour unions support automation as they can see opportunities associated with automation (O'Connor, 2020).

The skills availability was identified by participants as a major barrier to automation, as shown in Figure 7.14**.** According to WEF (2016), technological advances will result in skills mismatch and skills redundancy. Skills set meant for automation are currently not available in the SA. The bivariate analysis shows a statistically significant correlation between skills shortage and the need for upskilling and training as shown in Table 7.2. According to Sutherland (2020), mining companies identified that the data management systems in SA are not yet mature, and the workforce does not have the necessary skills to implement the novel technologies

According to Mining Technology (2017), high-performance communication is needed for remotely controlled equipment to succeed, as implemented at a Swedish Mine, the Kankberg gold mine. In this study, participants highlighted that part of the barrier to automation adoption in SA is inadequate infrastructure development in terms of the network and constant electricity supply as shown in Table 7.6. As identified by UNIDO (2016), the introduction of 4IR technologies requires a well-developed infrastructure in terms of networks. Developed countries have a well-developed and advanced infrastructure systems while developing countries have unreliable electricity supplies and lack decent network connectivity. Baxter (2015) alludes to the fact that energy costs in SA are ever-increasing. Sutheralnd (2020) also identified poor quality infrastructure as a challenge for the performance of automation in SA.

The initial high capital cost to implement automation has been identified as a potential barrier to automation. The initial costs of implementing automation are capital intensive (IGF, 2019; Groover, 2020). SA mining has been relying on FDI. In the previous years, FDI has decreased (UNCTAD, 2021). Not many investors might be coming in unless a favourable climate in terms of policy stability has been established (Baxter, 2015).

Resistance to change has been identified as a potential barrier as shown in Table 7.6. Literature reveals that in the SA context, the coal mining sector has been in the lead with adopting novel technologies. There is a need to ensure workforce acceptance of automation technologies from the development and deployment stages to identify and resolve issues that can contribute to acceptance (Lynas and Horberry, 2011). Participants in the quantitative and qualitative interviews highlighted the need for proper change management when new technologies are adopted. The literature, however, does not say much about how the coal mining companies were managing the change. There are suggestions that, probably due to internal change management, the coal mining companies could manage the socio-economic effects as these technologies were adopted Gumede, 2018).

Socio economic inequality has been identified as a barrier to automation adoption. SA is one country with unequal economies with a high socio-economic quality gap. This inequality gap is attributed to colonisation, racial segregation, and apartheid history. Literature has revealed that there has always been a socio-economic disruption and

inequality whenever there was an industrial revolution. As early as 1IR, the gap between the rich and the poor widened (Mohajan, 2019).

There is a general view among the participants for both quantitative and qualitative interviews that full automation adoption at opencast Coal Mine “X” is inevitable, although it will take more than 5 years. On further elaboration of the time frame of automation adoption, the majority were of the opinion that automation adoption would not occur in less than 5 years. The bivariate analysis shows a statistically significant correlation between SA opencast Coal Mine “X” willingness to adopt automation, but this not occurring in less than 5 years as shown in Table 7.2. The reasons for this delay in automation adoption are the barriers to automation adoption, such as high capital costs for initial setup, training, and acquiring the right skills. According to Barnewold and Lottermoser (2020), innovations with high initial costs and the possibility of impacting cash flows or SLO, most companies are cautious so much that take-up of technologies may be slow.

7.14 Possible Mitigation Measures to Better Prepare for Automation

The participants were also requested to identify possible mitigation measures to better prepare for automation adoption. As literature has indicated, several mitigation measures can be adopted to better prepare for automation adoption and the associated socio-economic effects (McNab et al., 2013; Cosbey et al., 2016; Bruckner, 2017).

Factors that may impede the adoption of automation in the coal mining industry will always be there. The participants in this study identified ways to better prepare for automation adoption, the need for changes in the education curriculum, training and upskilling of workers, carrying out proper change management through awareness campaigns, government support, and diversifying the economy as shown in Table 7.7. The identified ways to better prepare for automation are aligned with the findings in the literature (McNab et al., 2013, Bruckner, 2017)

In the qualitative interview,100% of the participants believed that the education system in SA needs realignment. Regarding the education system, there is a need to introduce subjects that directly link with the labour market, such as STEM from elementary, high

school, and college levels (Bruckner et al., 2017; Zervoudi, 2019; Mutanga et al., 2021). Policies promoting early education and lifelong learning skills such as mechatronics, systems approaches, and data management becomes crucial to equip people with the right skills (Zervoudi 2019). The WEF (2016) also emphasizes the need to invest in R&D for automation to succeed. In general, research and development funding in mining has been at low levels (Sanchez & Hartileb, 2020). For SA, funding research and development has been difficult (Singh, 2017) although in this research, the participants did not mention the need for R&D for automation to succeed.

In the quantitative interview, the majority of participants were of the opinion that to remain gainfully employed, there is a need to train and upskill. Training and upskilling remained a requirement for successful automation adoption. The WEF (2016) also emphasizes the need to invest in reskilling current employees for automation to be a success. The bivariate analysis as shown in Table 7.2 shows a statistically significant correlation between skills shortage and the need for upskilling and training. Lifelong training is the key to continuously upskilling and empowering workers (IGF, 2019). Collaboration between companies, government, and educational institutions are vital for training and upskilling. BHP Australia has set up training and upskilling opportunities for its employees at the IORC facility in Perth. Leeuw and Mtegha (2016) argue that with automation technology adoption, reskilling people that would have been made redundant by adopting automated and autonomous technology in the mining sector can be implemented.

Change management was one component identified by participants as necessary for automation. Participants in the qualitative interview suggested proper change management (awareness campaigns) as automation is being adopted. This assists with realignment with everyone who is to be involved. It is important to engage with the site workforce and emphasize opportunities associated with automation. Lynas and Horberry (2011) identified the need for operator acceptance and awareness when adopting new technologies.

Participants for both quantitative and qualitative interviews were aligned with the need for government support for automation adoption to succeed. Although most of the respondents were neutral on the government position during quantitative interviews,

the participants' explanations indicated that government is the pillar of change as the government is a major player in moderating activities between employers, employees, and the private sector. Mazzucato (2013) argues that governments are not only facilitators but also catalysts of technological innovation. Regarding mining policy changes, quantitative and qualitative survey participants indicated that mining policies need to change when automation is adopted. During the qualitative interview, the participant indicated that it was necessary to diversify the economy by looking at the secondary and tertiary industries. The need for forward, backward, horizontal, and spatial infrastructure linkages is vital for the development of the economy (Cosbey et al., 2016).

8. CONCLUSIONS AND RECOMMENDATIONS

8.1 Introduction

This chapter highlights the main findings from the research and provides a link between the research aim and objectives and the results. Included in this chapter are the recommendations and further research work suggested.

8.2 Principal Findings

This research indicates that the opencast "Coal Mine X" is male dominated, mainly by a population below 40 years old. Although the coal mining industry is currently male-dominated, literature has indicated that automation adoption will allow less labour-intensive work. It is inferred that this will allow more women to be employed in the mining industry.

The literacy level is commended as good as most participants are holders of matric qualification or above and are specialised in specific jobs. The young population with good literacy levels is advantageous in the coal mining sector as training and upskilling the workforce will be possible without much challenges.

The participants could see more socio-economic benefits of automation at Coal Mine “X.” Low-level and middle-level automation, already existent in the coal mining industry although not given much recognition and advantages compared to full automation. The participants' views of the benefits of automating were largely common and closely aligned as per literature findings. Besides improvements in productivity, efficiency, safety, and health, participants also identified training and upskilling in line with the new technologies as a benefit for fully automating the mines. Carbon emission reduction was identified as an added advantage to automation.

Concerning the negatives associated with automation, the participants identified more negatives at Coal Mine “X” than the same experience in the developed countries. Factors such as a decrease in the GDP in the host country and the requirements of high educational qualifications than what currently exists were some additional negatives identified.

Full automation adoption is inevitable at Coal Mine “X,” but this will only be possible five years from now. There are various barriers to full automation adoption. The identified barriers associated with automation include high socio-economic inequality, low literacy levels, high unemployment, skills shortage, high capital costs, labour unions resistance, poor infrastructure, and misalignment of the education curriculum to 4IR. Currently, there is minimal funding for R&D in the SA mining sector. In addition, the government and mining companies in the SA mining industry are working in silos. Developed countries fund R & D, and collaboration between different stakeholders in research is vital. The challenges in the SA mining sector are numerous, leading to the delay in adopting automation. The socio-economic effects of automation are anticipated to be worse in SA compared to developed countries.

To successfully adopt automation, the participants indicated the need to overhaul and realign the education system and train and upskill people. There is a need to slowly adopt change management processes through awareness campaigns at the mine. There is a need for management support at the mine and buy-in from shop floor workers on the automation adoption at a local level. On a national level, the government supports changes in mining policies to be in line with socio-economic changes brought about by automation. The participant believes that although the mandate for labour unions is to "preserve jobs," awareness and discussions with the unions need to be done to ensure everyone is aligned. The labour unions need buy-in on the idea of automation. Therefore, labour unions will not act as barriers to automation adoption.

The local communities benefiting from mining have been identified as disadvantaged if the coal mining companies are to automate. The existing SLP might not be applicable in the automation era. Participants indicated economic diversification as a possible solution to the socio-economic effects of automation adoption as SA heavily relies on primary industry.

The suggested factors to better prepare for automation are not new but have been identified in countries where automation has been adopted. The suggested factors for handling the barriers must be considered to better prepare for automation. Since automation in the 4IR is a new concept in SA, few published articles on the potential socio-economic effects of automation are available. The results of this research are

believed to be helpful for the coal mining industry, educational institutions, and the government.

8.3 Recommendations

Historically the mining industry has been focused on improvements in operational efficiencies, productivity, and safety concerning new technology. There has been minimal focus on the socio-economic effects of these technological changes. There is a need for a more comprehensive approach to the potential socio-economic issues of automating the coal mines. Work, education, welfare, risks, and policy concerns must be considered. This will make sharing information and resources easy and manage the different socio-economic effects.

There is a need to expand the research on the socio-economic effects of automation in other collieries in SA, including underground mines using the mixed method approach (qualitative and quantitative). Surrounding communities were not part of this research, and it is recommended to incorporate them for future research.

The government needs to set up a special task team solely responsible for automation adoption associated with the socio-economic effects of automation. The government needs to carry out extensive stakeholder consultation before automation adoption. There is a need to engage the labour unions more from planning to implementation. It is crucial to get the buy-in from the labour unions to face less resistance from union members.

There are no conclusions on the socio-economic issues of automation adoption in the coal mining industry as it is a relatively new and ongoing concept. Companies, stakeholders, and the government must collaborate to mitigate the potential socio-economic effects of automation. As for mining companies, there is a need to slowly incorporate the socio-economic changes brought about by automation in the change management programs.

8.4 Limitations of the research

The research was cross-sectional and at one specific mine attributed to a petite section of the opencast coal mine in SA. The results from this research might not

represent other opencast coal mines and might not be extrapolated or generalised to other areas.

Representatives from the communities and labour unions were not enough. There was no representation from the communities, as it was challenging to engage the community as these stay far from the mining premises. A true reflection on the communities' opinions is needed to represent such groups in research better. Only one union labour representative participated in the qualitative interview. The other labour unions might not have been represented enough in their views. Online interviews, as much as they are safe to use, not everyone has access to computers.

8.5 Suggestions for future research

An explanatory sequential method was used in this research, with the quantitative component being more dominant than the qualitative. Though inferences could be made from the prevalent quantitative survey, very minimal could be extrapolated in terms of participants' emotions, perceptions, and opinions. In the future, it is recommended that an exploratory sequential method be adopted with qualitative interviews being dominant and quantitative minimal to get as much information as possible on participants' opinions. This will assist in getting detailed information on ways to go forward.

Automation of opencast mines in developed countries has focused more on iron ore production and other hard rock mines. It is suggested that future research be carried out longitudinally and across many SA coal mine operations, unlike cross-sectional and being a case study. More information representative of participants' opinions on different mines is then obtained.

The other area of research to focus on in the future is the one that involves communities. Their opinions are equally crucial as mining companies are tied down with the SLP. Any changes in the SLP call for the participation of the communities. This will better guide all involved stakeholders in what changes to incorporate in the future.

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APPENDIX A: QUANTITATIVE QUESTIONNAIRES

Demographic information

Background Information

1.Gender

- Female
- Male
- Prefer not to say
- Other:

2. Age (Y)

- 20-30
- 31-40
- 41-50
- 51-60
- >60

3. Qualification

- No Matric
- Matric
- Diploma
- Degree
- Post Graduate

4. Position at the Mine

- Operator
- Artisan
- Foreman
- Mine Overseer
- Technical Services
- Human Resources
- Supply Chain
- Labour union Representative
- Management
- Other

Automation

Awareness of automation in mining

5. Automation is the use of appropriate technology to minimize direct human involvement

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

6. Driverless trucks in an opencast mine is part of autonomous technology

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

7. Social media and workplace provide information on automation in the mining industry

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

8. Schools, colleges and universities offer courses related to autonomous technology

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

Automation Adoption Implications Socio- economic effects

9. Opencast Coal Mine “X” is willing to adopt automation

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

10. Automation adoption at Opencast Coal Mine “X” will be in less than 5 years from now

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

11. The advantages of automation adoption at Opencast Coal Mine “X” includes improvements in productivity and competitiveness

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

12. The major adverse effect of automation adoption is unemployment

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

13. The alternatives to remain gainfully employed after automation is training, upskilling and reskilling.

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

14. There is not enough skills for automation adoption currently at Coal Mine “X”

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

15. Change management in automation adoption involves operator acceptance and awareness campaigns

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

16. The South African labour unions will support automation

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

17. There is minimal benefit for surrounding mining communities when automation is adopted.

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

18. The South African government is in support of automating at Coa Mine “X”

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

19. Mining policies will change when mining companies adopt automation

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

Back

Submit

Clear form

APPENDIX B: Quantitative Results

Table B 1 Gender of respondents

Gender	Frequency Count	Percentage	Cumulative Percentage
Male	72	70.59	70.59
Female	28	27.45	98.04
Prefer not to say	2	1.96	100
Total	102	100	

Table B 2 Respondents age

Age	Frequency Count	Percentage	Cumulative Percentage
20-30	14	13.73	13.73
31-40	57	55.88	69.61
41-50	16	15.69	85,3
51-60	15	14.71	100
Total	102	100	

Table B 3 Educational qualification of respondents

Qualification	Count	Percentage	Cumulative Percentage
No matric	4	3.92	3.92
Matric	34	33.33	37.25
Diploma	24	23.53	60.78
Degree	22	21.57	82.35
Postgraduate	18	17.65	100
Total	102	100	

Table B 4 Position at the mine

Response Position at Mine	Frequency Count	Percentage	Cumulative Percentage
Operator	28	27.45	27.45
Mine Overseer	7	6.86	34.31
Labour Representative	1	0.98	35.29
Other	15	14.71	50.00
Artisan	7	6.86	56.86
Foreman	10	9.80	66.66
Human Resources	6	5.88	72.54
Management	9	8.82	81.36
Technical Services	18	17.65	99.01
Engineer	1	0.98	100
Total	102	100	

Table B 5 Opinion on automation meaning

	Gender (Count)		
Response Option	Male	Prefer not say	Female
Agree	57	2	24
Neutral	12	0	2
Disagree	3	0	2
Total	72	2	28

Table B 6 Automated machinery example

Response Option	Qualification (Count)				
	Post Graduate	Degree	Diploma	Matric	No matric
Agree	15	19	15	30	4
Neutral	3	2	5	4	0
Disagree	0	1	4	0	0
Total	18	22	24	34	4

Table B 7 Automation information source

Response Option	Frequency Count	Percentage	Cumulative Percentage
Strongly Agree	22	21.57	21.57
Agree	44	43.14	64.71
Neutral	16	15.69	80.4
Disagree	15	14.71	95.11
Strongly Disagree	5	4.90	100
Total	102	100	

Table B 8 Education system alignment

Response Option	Frequency Count	Percentage	Cumulative Percentage
Strongly Agree	17	16.67	16.67
Agree	42	42.16	58.83
Neutral	34	34.31	93.14
Disagree	7	6.86	100
Strongly Disagree	0	0	100
Total	102	100	

Table B 9 SA opencast Coal Mine “X” willingness to adopt automation

Response Option	Frequency Count	Percentage	Cumulative Percentage
Strongly Agree	7	6.86	6.86
Agree	48	48.04	54.9
Neutral	27	27.45	82.35
Disagree	11	10.78	93.13
Strongly Disagree	7	6.86	100
Total	102	100	

Table B 10 Automation adoption time frame

Response Option	Frequency Count	Percentage	Cumulative Percentage
Strongly Agree	2	1.96	1.96
Agree	15	14.71	16.67
Neutral	25	25.49	42.16
Disagree	46	46.08	88.24
Strongly Disagree	12	11.76	100
Total	102	100	

Table B 11 Benefits of automation

Response Option	Frequency Count	Percentage	Cumulative Percentage
Strongly Agree	34	33.33	33.33
Agree	50	49.02	82.35
Neutral	8	7.84	90.19
Disagree	7	6.86	97.05
Strongly Disagree	3	2.94	100
Total	102	100	

Table B 12 Major adverse effects of automation by age

Response Option	Age 20-40 YRS	Age 40-60 YRS	Total
Agree	62	19	81
Neutral	10	4	14
Disagree	5	2	7
Total	77	25	102

Table B 13 Alternatives to remain gainfully employed

Response Option	Frequency Count	Percentage	Cumulative Percentage
Strongly Agree	28	27.45	27.45
Agree	54	52.94	80.39
Neutral	14	13.73	94.12
Disagree	5	4.90	99.02
Strongly Disagree	1	0.98	100
Total	102	100	

Table B 14 Skills availability

Response Option	Frequency Count	Percentage	Cumulative Percentage
Strongly Agree	31	30.39	30.39
Agree	38	37.25	67.64
Neutral	18	17.65	85.29
Disagree	10	9.80	95.09
Strongly Disagree	5	4.90	100
Total	102	100	

Table B 15 Change management

Response Category	Operators	Middle Management	Management
Agree	28	21	7
Neutral	12	16	0
Disagree	10	6	2
Total	50	43	9

Table B 16 Labour Unions

Response Category	Operators	Middle Management	Management
Agree	7	7	2
Neutral	8	15	3
Disagree	35	21	4
Total	50	43	9

Table B 17 Benefits to surrounding community

Response Option	Frequency Count	Percentage	Cumulative Percentage
Strongly Agree	25	24.51	24.51
Agree	36	35.29	59.80
Neutral	19	18.63	78.43
Disagree	17	16.67	95.10
Strongly Disagree	5	4.90	100
Total	102	100	

Table B 18 Government Support

Response Option	Frequency Count	Percentage	Cumulative Percentage
Strongly Agree	11	10.78	10.78
Agree	29	28.43	39.21
Neutral	44	43.14	82.35
Disagree	10	9.80	92.15
Strongly Disagree	8	7.84	100
Total	102	100	

Table B 19 Mining Policies

Response Option	Frequency Count	Percentage	Cumulative Percentage
Strongly Agree	33	32.35	32.35
Agree	48	47.06	79.14
Neutral	11	10.78	90.19
Disagree	7	6.86	97.05
Strongly Disagree	3	2.94	100
Total	102	100	

Table B 20 Level of understanding of automation and education qualification

Level Classification		**Education Qualification**	**(%)**
Level 1	Participants understand that there is the use of automated machinery through the provision of an example, without giving a definition	No Matric	13
Level 2	Participants understand automation to be the use of automated machinery with minimal human involvement adding relevant examples	Matric level	87

The comments below are for Table 1 to Table 19 and Table 22

Table 1 represents the gender of respondents. Of the 102 participants who completed the questionnaire, the male population of 72 (71%) is dominant, followed by females 28 (27%) and those that preferred not to say 2 (2%).

Table 2 shows the age categories of the participants who completed the survey question. The respondents generated a 102 (100%) response rate. The age ranged from 20 to 60 years, with the majority of the respondents 57 (56%) between 31-40 years representing the mode. This category is followed by the 41-50 age group

constituting 16 (15.69%). The 20-30 age group 14 (13.73%) and the 51-60 age group 15 (14.71%) are almost at par in terms of occurrence.

Table 3 shows the education qualification. The response rate was 102 (100%). The mode occurred in the category matric qualification with 34 (33,33%) followed by diploma with 24 (23.53%), a degree with 22 (21.57%), postgraduate with 18 (17.65%) and 4 (3.92) without matric respectively.

In Table 4, the multiple-choice question was part of the profile of respondents, and the response rate was 102 (100%). The mode occurred in the category of operators representing 28 (27,45%) occurrences, followed by technical services 18 (17,65%), other (contractors) 15 (14.71%), foremen 10 (9.80%), management 9 (8.82%) artisan and mine overseer both at 7 (6.86%), human resources at 6 (5.88 %) and labour union representative and engineer 1 (0.98%) respectively.

The researcher generated the question to determine the participants' understanding of the meaning of automation. As shown in Table 5 the question received a 102 (100%) response rate. A cross sectional analysis based on gender and understanding of automation did not bring a difference in the trend of responses on the agree category as there were 57 males, 2 prefer not to say and 24 females

In Table 6 the scale-type question had a response rate of 102 (100%). There was no difference in the trend in the agree category among the participants with different educational qualifications. 15 Post Graduate, 19 Degree holders, 15 Diploma holders, 30 Matric holders and 4 Non matric holders were in the agree category.

For Table 7 There was a 102 (100%) response rate with the mode of the respondents 44 (43.14%), indicating that social media and workplace provided information on automation. Only 16 (15.69%) are in the neutral category, 15 (14.71%) disagree, and 5 (4.90%) strongly disagree on the source of information.

For Table 8 The scale-type question was generated to establish participants' opinions on the role of the education system in courses offered for automation. There was a 102 (100%) response rate. Mode 42 (42,16%) was in the agree category, (17 (16,67%) in the strongly agree category, 34 (34,31%) neutral category, and 7(6,86%) were in the disagree.

Table 9 shows the response rate was 102 (100%) on the willingness of Coal Mine X to adopt automation, with the mode being 48 (48.04%) in agree category, 27 (27.45%) in the neutral category, 11(10.78%) of the respondents were in the disagree category, while 7 (6.86%) were for the strongly agree and strongly disagree category respectively at the Opencast Coal Mine “X”.

For Table 10 the questionnaire seeks to establish the time frame of SA opencast Coal Mine “X” to adopt automation. A 102 (100%) response rate was achieved with 46 (46.08%) in the disagree category, followed by 25 (25.49%) in the neutral category, 15 (14.71%) in the agree category, 12 (11.76%) in the strongly disagree, and 2 (1.96%) in the strongly agree category.

The opinion of participants was being sought on the advantages of automating SA opencast Coal Mine “X” through this question. Table 11 shows the response was 102(100%). The mode 50 (49.02%) were in the agree category, and 34 (33.33% were in the strongly agree category. Only 8 (7.84%) were neutral, 7 (6.86%) disagree, and 3 (2.94%) disagreed).

In Table 12 the majority of the respondents believed that the major adverse effect of automation is unemployment The responses of the 20-40 years and 41-60 years in the agree category followed the same trend.

The scale type question seeks to find participants' opinions regarding alternatives to remain gainfully employed if automation is accepted. Table 7.13 The response rate was 102 (100%) with the mode 54 (52.94%) in the agree category, 28 (27.45%) in the strongly agree, 14 (13.73%) in the neutral, 5 (4.9%) in disagree, and 1 (0.98%) strongly disagree.

The questionnaire sought to establish the opinion of participants on the availability of skills to be involved with automation. Table 14 shows the mode category 38 (37.25%) were in the agree category, with 31 (30.39%) in the strongly agree category. Only 18 (17.65%) were neutral, 10 (9.80%) disagree, and 5 (4.90%) strongly disagree.

The questionnaire sought to establish some steps to better prepare for automation adoption. Table 15 shows that the trend in the agree, neutral, and disagree category was similar for Operators, Middle Management and Management.

Table 16 shows The response rate was 102 (100%), with Operators (35), Middle Management (21), and Management (4) in the disagree category that the labour union will support automation. Of the Middle Management, 15 participants remained neutral.

Table 17 shows benefits to surrounding communities with the mode of the respondents was 36 (35.29%) were in the agree category while 25 (24.51%) were in the strongly agree, 19 (18.63%) were neutral, 17 (16.67%) disagree, and 5 (4,90%) strongly disagree.

The researcher designed scale type questionnaire to seek participants' opinions on the government position in terms of automation adoption. Table 18 shows the response rate was 102 (100%), with 36 (43.14%) of respondents in the neutral category, 28 (28.43%) in agree, 11(10.78%) strongly agree, 10 (9.80%) disagree, and 8 (7.84%) strongly disagree.

The questionnaire sought the opinion of participants on the mining policies if automation is to be adopted. Table 19 shows the mode 48 (47.06 %) were in the agree category, 32 (32.35%) in the strongly agree, 11 (10.78%) being neutral, 7 (6.86%) disagree, and 3 (2.94%) strongly disagree.

APPENDIX C: Spearman Rank Correlation in Excel

(Source Bradburn, H. 2021)

1. Calculate the ranks of the variables

=RANK.AVG (number, ref, [order])

2. Calculate the Spearman correlation coefficient in Excel

=CORREL (array1, array2)

3. Calculate the number of pairs

or large datasets; use the COUNT formula.

4. Calculate the t statistic

$$t = \frac{r_s \times \sqrt{n-2}}{\sqrt{1-{r_s}^2}}$$

=(ABS(r_s)*SQRT(n-2))/(SQRT(1-ABS(r_s)^2))

5. Calculate the degrees of freedom

6. Calculate the p-value

TDIST (x, deg_freedom, tails)

APPENDIX D: Qualitative Interview

Gender: M F Prefer not to say

Thank you for agreeing to participate in this Interview. As you have read in the Participation Information Sheet, the interview will take between 20 to 25 minutes, and you are allowed to discontinue the interview without any consequences if you feel so. The interview will be confidential. With your consent, can we proceed with the Interview?

1. What is your understanding of automation, and give 2 examples?
2. What is your opinion on the education systems in SA concerning automation?
3. Why would SA coal mines not be able to adopt automation in less than 5 years?
4. Automating the coal mines has the benefits of improvement in competitiveness. What are the other benefits?
5. What are the disadvantages of adopting automation?
6. What are the likely barriers to automation adoption?
7. In your opinion, how can these barriers be handled?
8. Why would labour unions not support automation in the coal mining industry?
9. How can surrounding communities benefit from automation?
10. What is the role of government in automation adoption?
11. In your opinion, what are the mitigation measures to better prepare for automation?

APPENDIX E: Ethical Clearance Certificate

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

Research Office

HUMAN RESEARCH ETHICS COMMITTEE (NON-MEDICAL)
R14/49 Dhege

CLEARANCE CERTIFICATE	**PROTOCOL NUMBER: H21/05/06**
PROJECT TITLE	The Fourth Industrial Revolution: Assessing the potential socio-economic effects of automation in the South African coal mining industry
INVESTIGATOR(S)	Mrs V Dhege
SCHOOL/DEPARTMENT	Mining Engineering/
DATE CONSIDERED	21 May 2021
DECISION OF THE COMMITTEE	Approved Risk level: Minimal
EXPIRY DATE	23 June 2024

DATE 24 June 2021 **CHAIRPERSON** J. Knight

(Professor J Knight)

cc: Supervisor : Professor M Hudson

DECLARATION OF INVESTIGATOR(S)

To be completed in duplicate and **ONE COPY** returned to the Secretary at Room 10004, 10th Floor, Senate House, University. Unreported changes to the application may invalidate the clearance given by the HREC (Non-Medical)

I/We fully understand the conditions under which I am/we are authorized to carry out the abovementioned research and I/we guarantee to ensure compliance with these conditions. Should any departure to be contemplated from the research procedure as approved I/we undertake to submit an amendment of the protocol to the Committee. **I agree to completion of a regular progress report. For Minimal and Low studies, this is due annually on 31 December. For Medium and High Risk studies, this is due twice annually on 30 June and 31 December.**

Signature

30/06/2021
Date

PLEASE QUOTE THE PROTOCOL NUMBER ON ALL ENQUIRIES

APPENDIX F: Electronic Consent Form Questionnaire

Title of project: *The Fourth Industrial Revolution: Assessing the potential socio-economic effects of automation in a South African coal mine- case study*

Name of Researcher: Varaidzo Esther Dhege

Please select your choice below:

- You have read the information in Appendix (G) Participation Information Sheet Questionnaire.
- You voluntarily agree to participate
- You are above 18 years of age

O Agree

O Disagree

APPENDIX G: Participant Information Sheet Questionnaire (online)

Dear Sir / Madam,

My name is Varaidzo Esther Dhege, and I am a Masters student in the School of Mining Engineering at the University of the Witwatersrand, Johannesburg. As part of my studies, I have to undertake a research project, and I am investigating: The Fourth Industrial Revolution: Assessing the potential socio-economic effects of automation in a South African coal mine under the supervision of Professor Mtegha.

As part of this project, I would like to invite you to take part in answering a questionnaire. This activity will involve selecting answers to the questions and will take around 15-20 minutes. Your survey answers will be sent to a link at Google forms.com, where data will be stored in a password protected electronic format. Google forms does not collect identifying information such as your name, email address, or IP address. Therefore, your responses will remain anonymous. No one will be able to identify you or your answers, and no one will know whether you participated in the study. Information collected from you is for data collection purposes only.

There will be no personal costs to you if you participate in this project. You will not receive any direct benefits from participation, but there are no disadvantages or penalties if you do not choose to participate or withdraw from the study. However, your responses may help us learn more about The Fourth Industrial Revolution and assessing the potential socio-economic effects of automation. You may withdraw at any time or not answer any questions if you do not want to. The questionnaire will be confidential and anonymous as I will not ask for your name or any identifying information. The information you give me will be held securely and not disclosed to anyone else. I will use coding to represent your participation in my final research report.

If you have any questions during or afterward about this research, feel free to contact me at the details listed below. This study will be written up as a research report available online through the university library website. If you wish to receive a summary of this report, I will be happy to send it to you. The data collected from this research project will be stored on a secure server at the University and kept for two years. Other researchers may use the data collected from this research project in an anonymised format with your permission. If you have any concerns or complaints regarding the ethical procedures of this study, you are welcome to contact the University Human Research Ethics Committee (Non-Medical), telephone +27(0) 11 717 1408, email hrecnon-medical@wits.ac.za

Yours sincerely,
Varaidzo Esther Dhege

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