



A human-centric approach to Industry 4.0 adoption within the South African mining industry

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DECLARATION

I, Buhle Sinton Baloyi, declare herewith that the thesis/dissertation/mini-dissertation entitled A human-centric approach to Industry 4.0 adoption within the South African mining industry, which I herewith submit to the North-West University complies with the requirements set for the degree Master of Engineering in Industrial Engineering is my work, has been text-edited by the requirements and has not already been submitted to any other university.

Signature of Student:



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Signed on this day, 20 November 2024.

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ABSTRACT

Due to its negative environmental impact, the mining industry has faced declining profit margins and a damaged public image. This is partly exacerbated by the slow adoption of Industry 4.0 technologies compared to other heavy industries such as manufacturing, oil, and gas. These technologies could improve both perception and actual environmental impact. This study explores how African Rainbow Minerals (ARM) can adopt Industry 4.0 technologies to improve productivity, public perception, and overall work environment while staying competitive.

A Systematic Literature Review (SLR) identified best practices for implementing Industry 4.0 technologies. A mixed-methods approach followed using qualitative and quantitative data from a survey of industry experts. The survey evaluated steps for implementing Industry 4.0, derived from the literature, and adapted them for the South African context. Experts rated each step in a proposed roadmap and provided feedback on necessary modifications.

Qualitative responses were analysed using thematic analysis, which revealed three key themes:

1. Overall agreement on the importance of all steps,
2. Suggestions for additional steps
3. Some uncertainty or indifference toward the roadmap.

These themes highlight a consensus among respondents while identifying areas for improvement and feedback for refining the roadmap.

Through descriptive statistics, the study analysed quantitative responses, summarised them, and tested for significance through two-proportion hypothesis tests. The study also used Analysis of Variance, T-tests, and Chi-square tests to identify response differences across demographic groups (age, experience, and gender). These tests confirmed the robustness of the findings through demonstrated statistical significance testing.

A pilot study refined the survey and ensured its validity and reliability by removing spelling errors and improving conciseness. The final results showed that most respondents supported the roadmap, with agreement rates between 87.1% and 96.8% for each question. No significant demographic differences were found, except for question 19,

where more experienced respondents were more likely to agree that training services should be part of the system calibration, testing, and integration phase.

In conclusion, the participants mostly supported the roadmap, with only minor suggestions for improvement. Future iterations of the roadmap should consider these suggestions and reevaluate under similar conditions. These findings suggest that ARM can confidently proceed with Industry 4.0 implementation, with further iterations of the roadmap accounting for the expert feedback. Technology adoption is crucial for ARM to maintain competitiveness and enhance its operational efficiency in the evolving mining industry.

Keywords: Technology roadmaps; New technology; Industry 4.0 adoption; Mining

LIST OF ABBREVIATIONS

Abbreviation	Full name
4IR	Fourth Industrial Revolution
AI	Artificial Intelligence
ANOVA	Analysis of Variance
AR	Augmented Reality
ARM	African Rainbow Minerals
AVE	Average Variance Extracted
BI	Behavioural Intent
CAD	Computer Aided Design
CDMO	Contract Development and Manufacturing Organisation
CFM	Confirmatory Factor Analysis
CI	Confidence Interval
CPS	Cyber-Physical Systems
CR	Composite Reliability
DoS	Denial of Services
DSC	Digital Supply Chains
EFA	Exploratory Factor Analysis
FDS	Functional Design Specifications
FMEA	Failure Mode and Effective Analysis
FMS	Fuel Managing System
FSW	Friction Stir Welding
HMI	Human-Machine Interface
HSD	Honestly Significant Difference
ICT	Information and Communication Technology
Industry 4.0	Fourth Industrial Revolution
IPL	Intellectual Property Law
IROC	Integrated Remote Operations Centre
IT	Information Technology
KBDCs	Knowledge-Based Dynamic Capabilities
KMO	Kaiser-Meyer-Olkin

KPIs	Key Performance Indicators
M2M	Machine to Machine
METS	Mining, Equipment, Technology and Service
MHSA	Mine Health and Safety Act of 1996
MIMACS	Monitoring and Control System
Mining 4.0	Fourth Industrial Revolution in Mining
ML	Machine Learning
MSA	Measurement System Analysis
NGOs	Non-Governmental Organisation
NWU	North-West University
OHS	Occupational Health and Safety
OPC	Open Platform Communication
PGM	Platinum Group Metals
PICOS	Participants, Interventions, Comparisons, Outcomes, and Study
PMBOK	Project Management Body of Knowledge
PRISMA	Preferred Reporting Items for Systematic reviews and Meta-Analyses
PsyCap	Psychological Capital
QbD	Quality by Design
QUOROM	Quality of reporting of meta-analyses
R&D	Research and Development
SAIIE	Southern African Institute for Industrial Engineers
SCADA	Supervisory Control and Data Acquisition
SDGs	Sustainable Development Goals
SDSS	Smart Decision Support Systems
SIGCS	Safe, Intelligent, Green Climate-Smart Practices
SLR	Systematic Literature Review
SWOT	Strengths, Weaknesses, Opportunities, and Threats
TAM	Technology Acceptance Model
TRA	Theory of Reasoned Action
TRIZ	Theory of Inventive Problem Solving

TSF	Tailings Storage Facility
UJ	University of Johannesburg
URL	Uniform Resource Locator
USA	United States of America
UTAUT	Unified Theory of Acceptance and Use of Technology
UTAUT2	Unified Theory of Acceptance and Use of Technology
VIF	Variance Inflation Factor
VR	Virtual Reality
VSM	Value Stream Map
WMI	Wits Mining Institute
XSS	Cross-Site Scripting

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CHAPTER 1 BACKGROUND AND MOTIVATION

1.1 Background

There is a move towards using Industry 4.0 technology in mining. Industry 4.0 is the integration of digital technologies into a value chain to automate a process that results in improved optimisation and operational efficiency (Bag et al., 2021); (Ajayi and Laseinde, 2021). The advantages involve reducing resources such as money, time and waste whilst reducing risk (Ediriweera & Wiewiora, 2021). This move towards technology is due to a decline in the quality of the mined resources, which means that more and more energy is required to extract these resources, producing more waste. Therefore, innovation is necessary to solve these challenges (Daly et al., 2022). The new technology in the mining industry could prevent pollution and result in cleaner production methods. The movement towards cleaner production across the entire value chain of the business could reduce environmental impact (Ediriweera & Wiewiora, 2021).

Limited research is available on technology integration that could revolutionise mining industry technology, reduce the environmental impact of mining, and increase profitability in developing countries such as the Republic of South Africa. However, there is plenty of visible growth in Industry 4.0 technology research, as shown by a rise in patent registration for developed countries and countries that are not necessarily relevant to the mining industry, such as Japan, South Korea, and several European countries. Economies specialising in mining, such as Chile, Russia, and South Africa, have seen a decrease in mining-related innovation (Daly et al., 2022). There has also been a steady decline in the availability of resources required by the mining industry for operational purposes. Once abundant resources have become less readily available, pressurising the mining industry to optimise their use (Mathews et al., 2002). A critical consideration in the context of developing countries is how they will use mixed approaches to Industry 4.0 technology implementation (using automation and humans collaboratively to complete a task) (Coetzee and Veldsman, 2022). That necessitates people being a central focus when implementing these technologies.

According to Attaran & Celik (2023), there has been an exponential growth in the adoption of Digital Twin technology, resulting in changes in how businesses run operations. According to a Gartner (2019) survey, 75% of companies are implementing the Internet

of Things (IoT) or using Digital Twin technology in their operations. The study further states that 13% of the respondents were implementing Digital Twin technology, with another 62% planning to integrate it into their operations within one year of survey publication. Digital Twin technology can replicate all aspects of a product, process, or service, creating a digital world copy of the real-world setting whose results are analysed to make judgments faster than was previously not possible when using classic methods (Attaran & Celik, 2023). Many more Industry 4.0 technologies, such as the Internet of Things (IoT), Cyber-Physical Systems (CPS) and Big Data in mines, are under implementation, or plans to implement them are underway, and they provide an industry-wide solution to the problems the industry faces (Sishi, 2017). IoT is the integration of internet into machinery for both decision making and monitoring processes.

The mining industry has had limited research on barriers and enablers of these new technology adoptions in the mining sector, further highlighting the need for studies focusing on Industry 4.0 technology adoption steps.

1.2 Motivation

1.2.1 Company background

African Rainbow Minerals (ARM) is a leader in South African mining, with operations in Malaysia and South Africa. The various sets of minerals mined by the company include iron ore, manganese ore, chrome ore, platinum group metals (PGM), nickel and coal, with a strategic gold investment with Harmony Gold Mining Company (African Rainbow Minerals (ARM), 2023). ARM's Ferrous has South African operations locations in Limpopo, Northern Cape, KwaZulu-Natal, and Mpumalanga provinces. The company has another operation in Sarawak, Malaysia (African Rainbow Minerals (ARM), 2023).

ARM has attempted to implement Industry 4.0 technology, but the company has struggled to succeed. The Industry 4.0 technologies listed in section 1.2.2 below are some previous attempts. The failed implementation attempts resulted in storing technological equipment for long periods without successful use. Among suspected causes were a lack of training resources on the new equipment, resistance to change by the people using the equipment, lack of planning for the recently acquired equipment and insufficient resources allocated for the implementation. Therefore, ARM is investigating technology adoption strategies for current and future technology adoption that will lead to the

successful use of purchased technology already available and in future cases where new technological equipment is purchased.

1.2.2 Research motivation

The African Rainbow Minerals Ferrous division (the focus of this study) has purchased the following technologies:

- Automated Drilling Machines (Pit Vipers)
- S2 Boomers-automated underground drilling machines
- Mobilaris-data collection systems for real-time information monitoring
- Integrated Remote Operations Centre (IROC) replacing traditional control rooms as in Figure 1-1.
- Battery Electric Machines (Loaders and Trucks)



Figure 1-1: Image of an Integrated Remote Operations Centre (iROC) in use (African Rainbow Minerals (ARM), 2023).

The goals of the implementation of these technologies were the following:

- Improve employee safety, health, and working environment
- Reduce operating costs by reducing labour costs
- Improving operational efficiencies
- Remain competitive

- Obtain real-time data for fast decision-making

Implementing such technologies has caused issues that hamper the timely implementation and has affected the workforce. The effects that need accounting include best practices for implementing technology, how people's jobs were affected, how to overcome resistance to technology, and how the workforce receives the necessary skills for Industry 4.0 technology.

1.2.3 Research problem, question, aim, and objectives

1.2.3.1 Research problem and background

Technology growth is rapid. Technologies, including the Internet and sensors, allow physical and cyber systems interconnection. Industry 4.0 is relatively new, with much to ultimately discover. Prinsloo et al. (2019) showed a significant potential for the mining industry to apply Industry 4.0 technology. Figure 1-2 shows the progression of industrialisation from mechanisation in Industry 1.0 to digitalisation of Industry 4.0 within 100 years. Industry 4.0 is the placement of varying and rapidly advancing technologies when developing autonomous systems (Coetzer et al., 2020). Aghimien et al. (2022) mention that the question moved from digital technology being a or not to how to make it a reality. That leaves companies with no choice but to go digital.

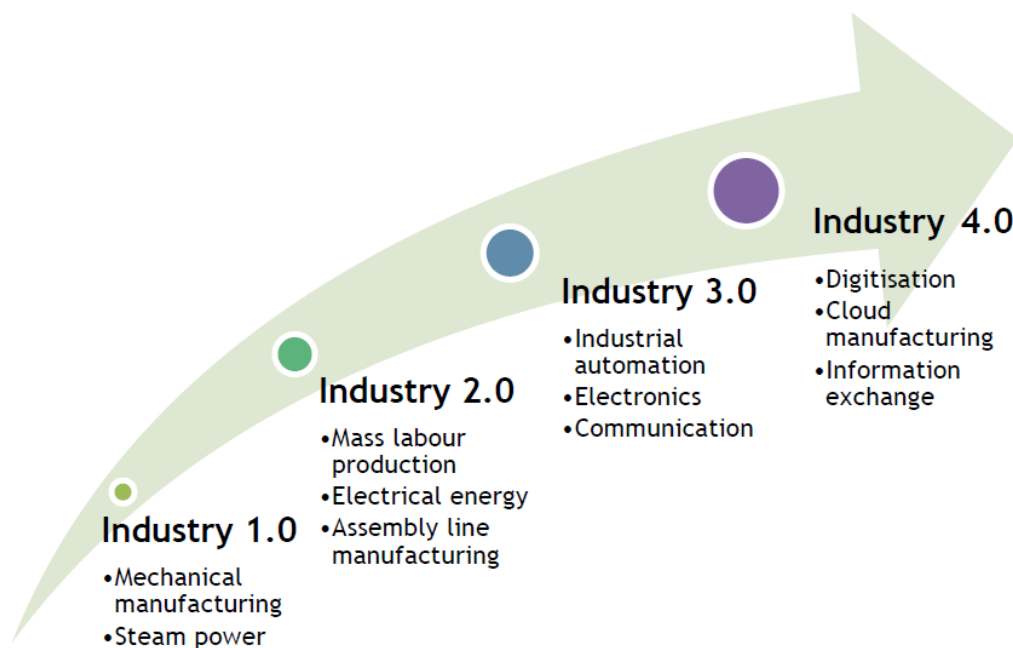


Figure 1-2: Progression of the Industrial Revolution (Prinsloo et al., 2019).

The mining industry is adopting Industry 4.0 technology to improve its operations and revenue. This adoption leads to challenges in the implementation steps and a disconnect between the applied technology and the human resources that use this technology to achieve set goals or objectives. African Rainbow Minerals (ARM) is not immune to the problem of trying to consolidate technology and the people who use it in its operations.

A. Challenges faced by the mining industry

One of the pillars of the South African economy is mining, which contributes R400 billion annually (Mpofu & Nicolaides, 2019). Mining industry challenges include low productivity, longer haul distances, low ore grade, and limited opportunity to improve with conventional methods. That also includes time-consuming, labour-intensive, and expensive mining activities and the limited amount of optimisations mining activities have. Industry 4.0 technologies, such as drone surveys and automated machines, have not been a priority in South African mining activities, and the decreasing profits in mining have made it more difficult to apply such technology (More et al., 2020; Maasz and Darwish, 2018). However, adopting such technologies could have an adverse social impact on job security for low-skill workers.

Nell et al. (2019) cite the financial pressure experienced by deep-level gold mining to maintain working temperatures in deep mines while still meeting production targets as a challenge. The study also notes the decline in production in South African mines compared to the worldwide trend due to socio-economic challenges, mining activity depth, environmental conditions and legal requirements. The decline in production means a decrease in revenue and a knock-on effect on South Africa's overall economy, so these issues are consequential beyond mining and require solutions.

B. Research problem

Organisations in developing countries (South Africa for this study), such as ARM, find it challenging to adopt Industry 4.0 technology. These struggles include people's fears, lack of training, understanding of the technology, and planning for the adoption. ARM's attempt at adopting Industry 4.0 technology resulted in Industry 4.0 technology purchases not being successfully integrated within its multiple operations.

1.2.3.2 Critical research question

How can the mining industry best move towards implementing Industry 4.0 technology that includes people?

1.2.3.3 Research aim

Investigate the implementation of Industry 4.0 technology strategies that consolidate technology and the people who work with it.

1.2.3.4 Objectives

The main objective of the research is to understand how best to apply Industry 4.0 technology in the South African mining industry. Accomplishing the main objective follows from completing the following minor objectives:

- Execute a Systematic Literature Review (SLR) on technology adoption in the South African heavy industry.
- Develop a roadmap for adopting technology for the South African mining industry to implement new technology based on literature from developed and developing countries.
- Test the roadmap against experts in the South African mining industry to determine whether the roadmap is suitable for the country.
- Develop the technology adoption roadmap further based on experts' opinions.

1.3 Significance of the study

This study is significant in that it brought a method to test a roadmap for the implementation of new technology in mining in a developing country, namely South Africa. Many available roadmaps focused on developed countries, so further developing and testing one for a developing country was crucial. The study also focused on adding expert's opinions on the roadmap that could lead to a better roadmap for future use.

1.3.1 Engineering bodies of knowledge covered by the study

This study covers the industrial engineering bodies of knowledge (Institute of Industrial and Systems Engineering Body of Knowledge, 2021) as follows:

- Ergonomics and Human Factors
 - Improving human safety

- Operations Engineering and Management
 - Organisational issues
- Engineering Management
 - Leadership, teamwork, and organisation

1.4 Chapter division

Chapter 1: Introduction and Background

This chapter outlines the introduction, background, and objectives of this study.

Chapter 2: Literature Review

This chapter outlines the literature used for this study based on studies examining technology adoption in heavy industries, particularly mining, their benefits and challenges in mining and examples of successes and failures of implementing technology across different countries with economic structures similar to South Africa. Lastly, the literature examined previous technology implementation roadmaps or models to develop a roadmap for South African mines, which was used in this study to collect data.

Chapter 3: Research methodology

This chapter details the methodology used, from data collection through an online survey to data analysis through qualitative and quantitative methods. The data was collected using a 5-point Likert scale (quantitative data). Opinions, through long sentences (qualitative data), were also collected on suggested improvements to the roadmap. The analysis converted the survey responses to inferences.

Chapter 4: Validity and verification

This chapter details the methods used to validate and verify the survey results, such as survey pre-testing, data triangulation, tests of statistical assumptions, tests for survey internal consistency and factor analysis.

Chapter 5: Results

This chapter outlines the study results from the survey responses summaries, hypothesis testing, and validity and verification of the roadmap.

Chapter 6: Limitations of this study

This chapter outlines the limitations associated with the study results and the steps taken to reduce their impact.

Chapter 7: Discussion

This chapter discusses the study findings, from the literature to the roadmap and the adjustments made, highlighting the significance and meaning of the study findings.

Chapter 8: Conclusions and Recommendation

This chapter describes the conclusions and recommendations for this study that ARM can use. This chapter also included a possible approach to further studies on the topic covered that this study scope could not cover (how another study can broaden the findings alongside those derived from this study).

Appendix A: Survey design

This appendix shows the survey with questions about the roadmap sent to the industry experts who participated in the study.

Appendix B: Summary statistics of qualitative responses

This appendix shows the summary statistics of survey responses to the quantitative questions relating to the roadmap sent to the industry experts who participated in the study.

Appendix C: Publication from this study

This appendix shows the publication that came from this study.

1.5 Chapter summary

The mining industry has problems implementing Industry 4.0 technology, and the South African mining industry faces similar challenges. Therefore, strategies are required to implement these technologies in a developing economy such as South Africa using strategies implemented in developed and developing countries. The study aims to investigate the strategy applicable to South African mines, test steps from past research on South African mines through a survey of mining experts on their opinions on these steps and lastly, what steps the survey respondents suggest should added to improve the roadmap.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

Mining technology has come a long way, from people using tools such as animal horns to a point where 300-tonne trucks with computerised schedules do the work. That shows the importance of innovation in the mining industry. The modern industrial basis of society are the materials sourced from mining, sent through roads and power plants to our homes (Daly et al., 2022).

The products produced by the mining industry are critical in maintaining the standard of living, but the processes involved in mining are increasingly frowned upon. There are high risks associated with investing in research in the mining industry due to the extended lead times and the likelihood of the competitor's better implementing the innovations (Hitzman, 2002). Mining is a critical economic activity for both developing and developed countries. That has been the case for hundreds of years. It is down to innovation in mining for the sector to move forward while still delivering reliable supplies of raw materials while saving on cost and remaining socially acceptable despite the challenges (Daly et al., 2022).

The rise in the standard of living of people and the growing population resulted in a growth in the demand for these mineral resources. According to (Daly et al., 2022), the demand for mineral resources such as copper in 1990 was 10.7 million tonnes, and as of 2017, the need for copper has grown to 23 million tonnes (more than double in 27 years). If the current growth rate persists, the study predicts 36 million tonnes of demand by 2030.

The harmful nature of mineral extraction to the environment and its economic implications leads the mining industry to seek strategies to extract minerals with minimal environmental damage. The mining industry has seen growth in implementing environmental sustainability programmes and has improved how mining operations are conducted to gain a competitive edge (Bai et al., 2017; Ediriweera and Wiewiora, 2021).

The fact that there is a depletion of access to extractable resources exacerbates the need for innovative solutions in the mining industry. Implementing technological innovations reduces costs and dampens the environmental impact while increasing productivity and mineral recovery (Ediriweera & Wiewiora, 2021). There has been a decline in the quality of the mined resources, which means that more and more energy is required to extract these resources, producing more waste, and innovation is necessary to solve these

challenges (Daly et al., 2022). The new technology in the mining industry could reduce this waste, prevent pollution, and result in cleaner production methods. The movement towards cleaner production across the entire value chain of the business could reduce environmental impact (Ediriweera & Wiewiora, 2021).

Limited research is available on technology that could revolutionise mining industry technology, reduce the environmental impact of mining, and increase profitability specific to developing countries (Daly et al., 2022). However, there is plenty of visible growth in Industry 4.0 technology research, as shown by a rise in patent registration for developed countries and countries that are not necessarily relevant to the mining industry, such as Japan, South Korea, and Europe. Economies specialising in mining, such as Chile, Russia, and the Republic of South Africa, have seen a decrease in mining-related innovation. The move towards an era of Industry 4.0 technology was demonstrated in the growth of the number of patents published in the mid-2000s and onwards (Daly et al., 2022). Due to operational efficiencies offered by Industry 4.0 technology, this provides solutions to adverse environmental impacts from mining activities.

2.2 Mining industry economics

The availability of monetary resources to acquire the technology, train the people on the technology and maintain the technology over time will determine the adoption capability of Industry 4.0 technology. That means economic factors require consideration during the planning. Daly et al. (2022) lists the following five contributors to the financial factor of mining.

2.2.1 Minerals are not renewable

Once mined, the resources are not replenishable. However, there is a way to recover minerals through recycling. Deterioration still occurs, and the industry has to work continuously to keep up by increasing efficiency and reducing costs (Daly et al., 2022; Mateus and Martins, 2019; Steinbach and Wellmer, 2010).

2.2.2 The distribution of minerals is not even across the globe

Rarely is it possible to find a sufficient concentration of minerals in a single location to provide viable mining operations. The best technology is required to extract these resources from these scattered locations. That means additional incurred costs, political

and transportation issues, to name a few, add to concerns (Daly et al., 2022; Dushyantha et al., 2020).

2.2.3 Mining is capital intensive

Mining activities require a lot of resource investment before generating revenue. That means that the industry needs cost-effective methods to remain operational. Mines are long-term projects requiring the technology applied to last along with the mine once they commit to starting mining (Daly et al., 2022; Mamo et al., 2017).

2.2.4 Miners are price takers

Global markets sell resources produced through mining, which the mining industry has limited control over. That means that mines must concentrate on activities within their operations that they can control for profit. Mining, Equipment, Technology, and Service (METS) has a higher response rate to adopting innovation when there are higher-than-average price changes in the mining industry (Daly et al., 2022; Mamo et al., 2017).

2.2.5 Local impacts of mines

The mining industry can lead to economic growth in the community through its activities, such as creating infrastructure and jobs. On the other hand, it impacts the environment by removing tonnes of earthly materials, leading to large amounts of solid waste. These issues were likely to increase with the growing demand for mineral resources and the community's expectations for more responsible mining. There is also a faster growth rate in the waste produced compared to the number of mineral resources produced. More innovative methods to reduce this waste and satisfy affected communities are required to keep up with these pressures (Daly et al., 2022; Mateus and Martins, 2019; Menegaki and Damigos, 2020).

2.2.6 Investment in mining

There are six stages to mining industry investment which are (Mamo et al., 2019):

1. Grassroots investment
2. Exploration investment
3. Advanced exploration investment
4. Prefeasibility investment
5. Feasibility investment

6. The construction investment

The expenditure on research and development (R&D) in the mining sector was around \$140 billion for over ten years, with the countries contributing the most to R&D being China with 47% of the total, followed by the United States of America (USA) with 22% of the total, followed by Australia with 17% of the total, followed by Canada and Europe as a whole with 8% and 5%, respectively (Daly et al., 2022).

The study shows that the mining industry has seen an upward trend in investment in exploration and transportation technologies while demonstrating a decline in investment in refining technologies. There is an increase in innovations in automation technology (Daly et al., 2022).

2.3 Technology in mining

A major pathway for innovation in the mining industry involves technology integration into equipment, suppliers' inputs, and services. The price of the minerals, the long-term performance of innovation and the success of adopting Industry 4.0 technology are linked. That is due to the mineral rent application. The study found that countries specialising in mining tend to adopt innovation slowly (Fernandez, 2022).

METS companies are critical contributors to technology in the mine life cycle. These technologies include those designed to reduce risk, costs, cost of new mine creation, sustainable performance improvement, and reduction of environmental impact (Fernandez, 2022; Daly et al., 2022). A two-thirds majority (66.67%) of mining innovation is accomplished by established mining organisations with METS. And a third (33.33%) through academic institutions (Daly et al., 2022). The mining industry uses an open innovation process that not only relies on internal knowledge to innovate but also on external sources of innovation, such as public patents, competitors, and other external agents (Fernandez, 2022). Other mining industry channels for innovation are venture collaboration, outsourcing through R&D spin-offs, and suppliers' input acquisition of embedded equipment services technology (Fernandez, 2022).

A positive long-term mineral price link exists between new inventions for processing, environmental impact, transporting minerals, mining operations, and exploration technology. There is a predominant influence on long-term mineral prices by exposure to mineral rents by country, based on country know-how, internationalisation of inventions,

and inventors' experience. There are also high concentrations of innovation in some companies and research institutions worldwide (Fernandez, 2022).

2.4 Technology implementation in developed countries' mining industry

Gruenhagen et al. (2022) discuss barriers and enablers to adopting innovative technologies in a developed country. Section 2.4 is entirely based on Gruenhagen et al. (2022). Figure 2-1 shows barriers and enablers of technology adoption in developed countries.

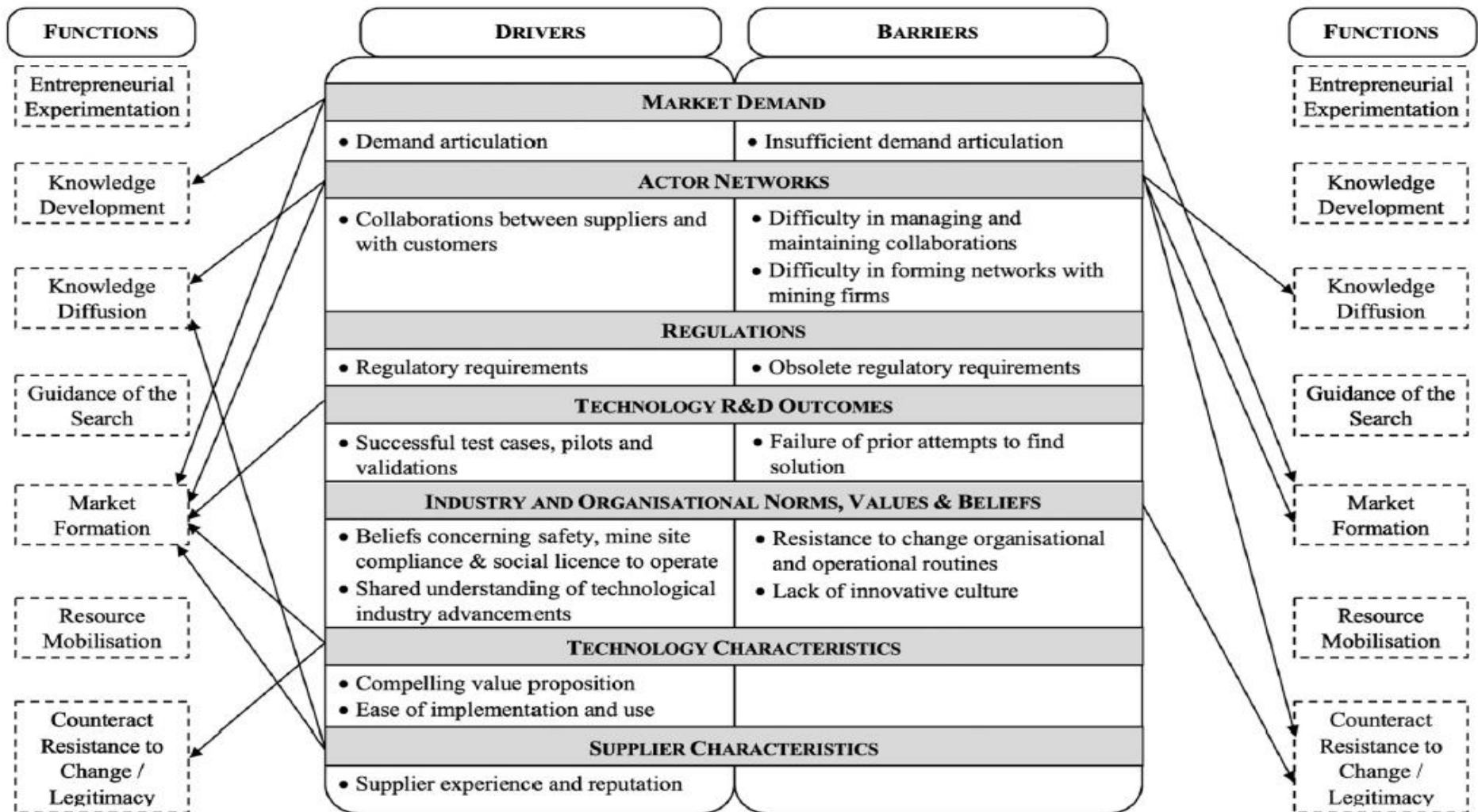


Figure 2-1: Summary of barriers and enablers of technology in a developed country (Gruenhagen et al., 2022).

The following section details factors influencing technology implementation in developed countries, from people, laws, research, how an individual organisation functions, and technology itself.

2.4.1 Stakeholder networks

Collaborative relationships between suppliers and customers implementing innovative technology are crucial in spreading knowledge. Respondents to Gruenhagen et al. (2022) noted that mining suppliers, compared to other suppliers when doing innovative technology work, work closely with their customers (the mining company) when supplying specialised equipment to the mining company.

Challenges arising in forming networks were due to the differing goals of decision-makers, the complex structures of mining companies, the prolonged decision-making process, and the high staff turnover rates. Bureaucracy was a challenge, with a respondent saying, 'You need ten yeses' before making a final decision. The respondent also noted that once the decision has gone through several decision-makers, and when some of them leave, the process has to be reset or redone in some cases.

2.4.2 Regulations

Regulation act as both a motivator and a barrier to the adoption of autonomous technologies in mining. Some regulations make innovation possible, while obsolete regulations block this innovation. These regulations are necessary for compliance with health and safety standards, and companies are creating innovative technology solutions along with these regulations.

2.4.3 R&D results

A presentation of successfully validated and tested pilots acts as a signalling tool towards implementing new technology based on the pilots. The mining industry avoids risks, so when providing proof in advance of the potential benefits and applications of the technology increases the likelihood that companies will move toward this technology. There is also peer influence in technology adoption, so the persuasion of other companies applying this technology leads to more Industry 4.0 technology adopters, while failures in other companies lead to a lack of legitimacy.

2.4.4 Values and beliefs of industry and individual organisations

Not only do regulations influence technology implementation, but social influences such as NGOs involved in developing such technology, cultures, and routines within the organisation, such as lack of innovation and regular routines in place, play a role. The workforce can resist adopting technology due to perceived increased workload, job loss fears, and the lack of training required for this technology, often leading to adoption failures.

2.4.5 Characteristics of the technology

The ease of implementation, ease of use, and value provided are crucial in technology adoption. If using or adopting the technology is not easy, it leads to resistance to the adoption of the technology. The other characteristics that the new technology promises are lower investment costs and higher productivity, which encourage its use.

2.4.6 Characteristics of the suppliers

The more established a supplier and the relationships formed with mining companies, the more likely trust is in their capability to implement the technology under consideration.

2.4.7 Strategies mitigating barriers to technology implementation

The lack of articulation of the demand for technology is a fundamental barrier to Industry 4.0 technology development. A solution suggests better communication and articulation of the need for technology, raising awareness that the technology is viable and desirable. A method of spreading the information is through conferences, collecting testimonials and presentations on the safety, financial, and operational benefits the technology brings. Cooperation between the mining company and suppliers is a solution that leads to the successful technology implementation.

The regulatory barrier is difficult to overcome as institutions change slowly, so the education of mining companies and regulators leads to improved technology implementation.

2.5 Technology implementation in developing countries' mining industry

Developed countries like the United States of America and Australia have adopted automated systems, and there has been a recent research push for similar technology

preparedness and awareness among African countries' by mining stakeholders (Ali & Ur Rehman, 2020).

2.5.1 Pakistan's implementation

The mining industry in Pakistan was the subject of Ali and Ur Rehman (2020), addressing overall preparedness and the social impacts of technology. The basis for this section is entirely on Ali and Ur Rehman (2020). This study is relevant as it addressed the implementation barriers and enablers of Industry 4.0 technology in a developing country like South Africa.

Most respondents in Ali and Ur Rehman (2020) supported adopting new technology due to the perceived safety and productivity improvements that Industry 4.0 technology brought. The main objections to this technology were fear of job losses and unemployment. Another main concern was the level of skill training available for this technology in academia. This study recommended amendments to the curriculum and a collaborative effort between government, industry, and academia to address existing gaps in Pakistan.

2.5.1.1 Autonomous mining systems awareness

Most of the respondents to Ali and Ur Rehman (2020) were aware of the implementation of autonomous mining systems. These technologies are automated haul trucks, automated drills, drones, and robotics, with 81.6%, 45.8%, 43.6% and 21.2% of respondents saying they knew each technology, respectively.

Large proportions of the respondents learnt these technologies from social networks (49.2%), followed by word of mouth from colleagues, friends and academia (43.6%). The last most used method to spread knowledge of these technologies was direct workplace interactions. When referring to education in the engineering field, respondents acknowledged that they lack education on autonomous mining systems in their degree programmes.

2.5.1.2 Stakeholder preparedness

Most of the respondents to this Ali and Ur Rehman (2020) mention that they view implementing semi-autonomous mining systems (68.1%) in the future. On the other hand, 15.1% view a 'fully autonomous mining system' in the Pakistani mining industry, with a

supermajority of the respondents (72.3%) favouring implementing these autonomous systems and a minority (6%) against the implementation.

The reasons for supporting Industry 4.0 technology implementation are safety improvements, productivity, and operational cost reduction, with 77.4%, 83.5% and 43.9% of respondents giving credit to each of these reasons (the percentages coming from those supporting this technology), respectively. Those against technology cited knowledge gap and unemployment, with 46.8% and 53.2% of respondents, respectively (the percentages coming from those against this technology).

A large proportion of respondents to this study say that they have the necessary skills required to remain employed when autonomous systems are in place, with 46.7% of the respondents. The rest of the respondents do not believe they have the skills, with 21.8% of the respondents and 31.6% unsure of their employability after Industry 4.0 technology implementation. The overwhelming majority of the respondents, 90.2%, indicated they were willing to receive training for the new technology-based work environment. A minority, 4.2%, were willing to leave their jobs to start businesses or seek new employment opportunities. When assessing the availability of the training, 44.9% of the participants indicated that the training was unavailable in Pakistan, and only 22.1% of the participants believed that the necessary training was available in the country's institutions.

2.5.1.3 Impact of implementing autonomous mining systems

Ali and Ur Rehman (2020) respondents highlighted the positive and negative impacts on Pakistan of Industry 4.0 technology, with a large majority of those having a negative outlook (63.4%). They identified unemployment as the adverse effect they faced. 65.6% of the respondents believed the government supported the implementation of the Industry 4.0 technology, while 34.4% did not believe in such support. The reasons respondents cited for their perceived possible government support were that implementation positively impacted the country's GDP and increased productivity, with 59.4% and 46% of respondents, respectively, citing these reasons. Respondents who did not believe in government support cited increased unemployment, political loss, and possible labour unrest as the reasons they did not believe in government support for new autonomous technology systems, with 80.6%, 84.7% and 52% of respondents, respectively. A 2.1%

minority cited health and safety concerns as reasons the government did not support this technology.

2.5.1.4 The skillset required for autonomous mining systems

51.1% of the Ali and Ur Rehman (2020) respondents state that IT skills and software are the most crucial for Industry 4.0 technology, while 27.4% believe that operational skills and equipment maintenance are the most critical. A small minority of the respondents (6.45%) considered managerial skills more crucial.

2.5.1.5 The curriculum in mining engineering

According to Ali and Ur Rehman (2020), only 11.5% of engineering courses at the undergraduate level prepared students with the skills necessary to work with the new technology. The degree of education at the graduate level is 59.4% core mining courses and 40.1% electives, with no courses on AI, process automation, ML, data mining, and database management and design (Industry 4.0 technologies).

2.5.2 India's implementation

Bhattacharyya and Shah (2022) examined the challenges and solutions to implementation in the Indian mining industry and identified the following themes. The basis of section 2.5.2 is entirely on Bhattacharyya and Shah (2022). This study is relevant as it addressed the implementation barriers and enablers of Industry 4.0 technology in a developing country like South Africa.

1. Technology adoption must be an organisational event.
2. Providers of reliable emerging technology were critical to the promotion of such technology.
3. The mining industry seeks to implement new technology partners who have proven their capability in this regard.
4. The first step towards emerging technology has been the digitalisation of data from mining operations.
5. The public sector mining companies were slow to implement technology because their main objective was to create jobs, and the nature of Industry 4.0 technology replacing jobs hampered the new technology implementation.

6. Strategies for long-term industry goals and implementing Industry 4.0 technology do not align.
7. The mining industry operates in difficult geographical and geological areas, making it hard to implement Industry 4.0 technology.
8. The lack of skilled employees in Industry 4.0 technology acts as a barrier.
9. An improved legal environment for technology adoption could lead to faster technology adoption.
10. The lack of economies of scale in the Indian mining industry due to natural factors is a barrier to Industry 4.0 technology.
11. The bureaucracy in the approval process and legal restrictions hamper the implementation of new technologies.
12. The most implementable emerging technologies in India were data analytics and cloud computing.
13. The imitation of solutions from developed countries did not apply to the Indian mining industry, which required uniquely Indian solutions.
14. Managers always seek to extract complete value from current technology rather than upgrading to Industry 4.0. That slowed the implementation of emerging technology.
15. The entire organisation is affected by the implementation of Industry 4.0 technology.
16. Industry 4.0 technology implementation requires substantial initial investment.
17. Mining activities need to be enabled by the new Industry 4.0 technology.
18. Industry 4.0 technology providers must understand the economic context of a mining company.
19. The conditions in which mining activities are carried out in, including geological and geographical conditions, must be understood by technology suppliers.
20. The benefits of new technology are unclearly defined, and suppliers of such technology need to clarify the benefits.

- 21. Organisational culture plays a crucial role in the implementation of new technology.
- 22. Mining managers lack awareness of emerging technologies.
- 23. If emerging technologies were to be used to solve the problems currently faced by mining companies, then adoption would be widespread.
- 24. Benefits such as cost reduction, faster delivery, and better quality increased the likelihood of adoption.

2.5.3 South Africa's implementation

Letaba et al. (2018) developed an "innovation profile" for developing countries, including South Africa, using a technology road mapping practitioner's viewpoint. This study detailed the positive and negative factors influencing technology roadmap innovation. This study was relevant as it added context to the influences expected during technology roadmap development. Figure 2-2 shows the critical factors that positively influence the innovation roadmaps, and Figure 2-3, on the other hand, shows the negative critical factors according to respondents to Letaba et al. (2018).

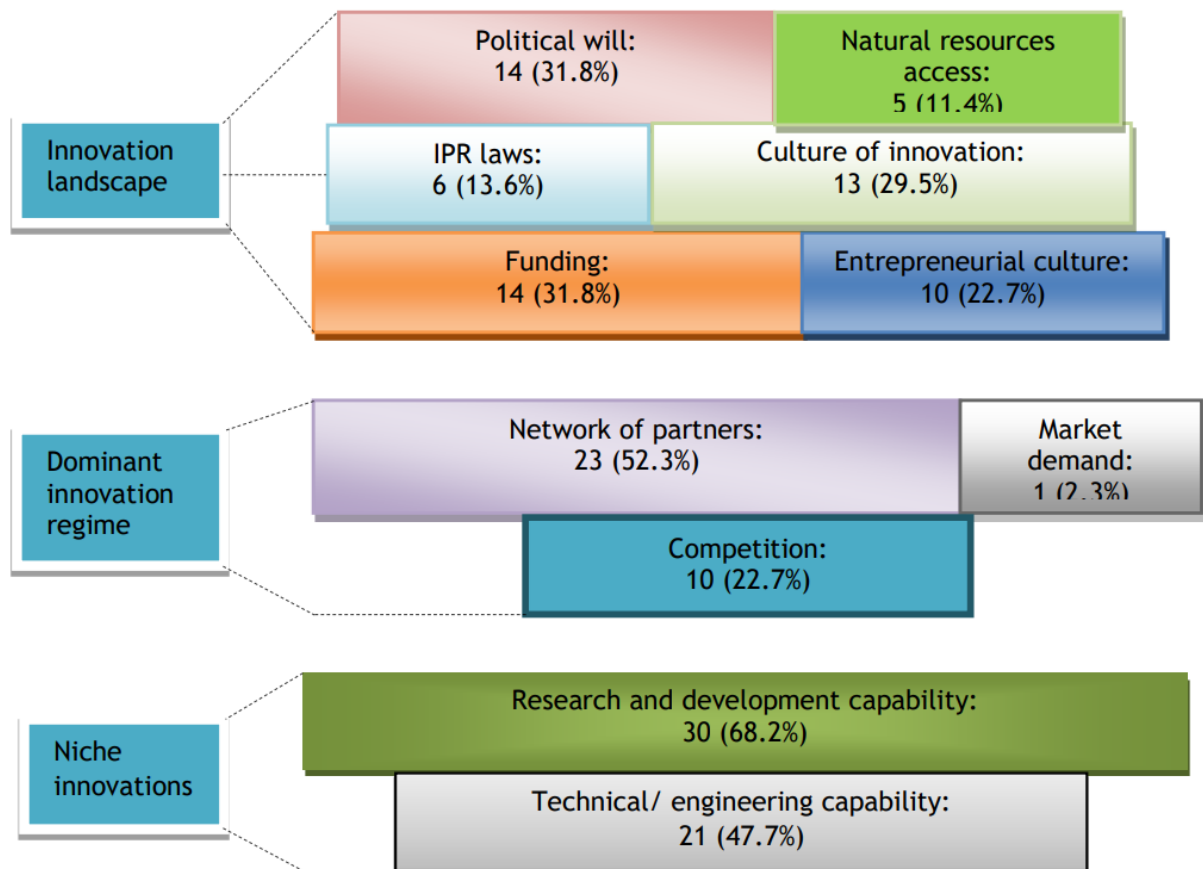


Figure 2-2: Positive influences on technology innovation roadmaps (Letaba et al., 2018).

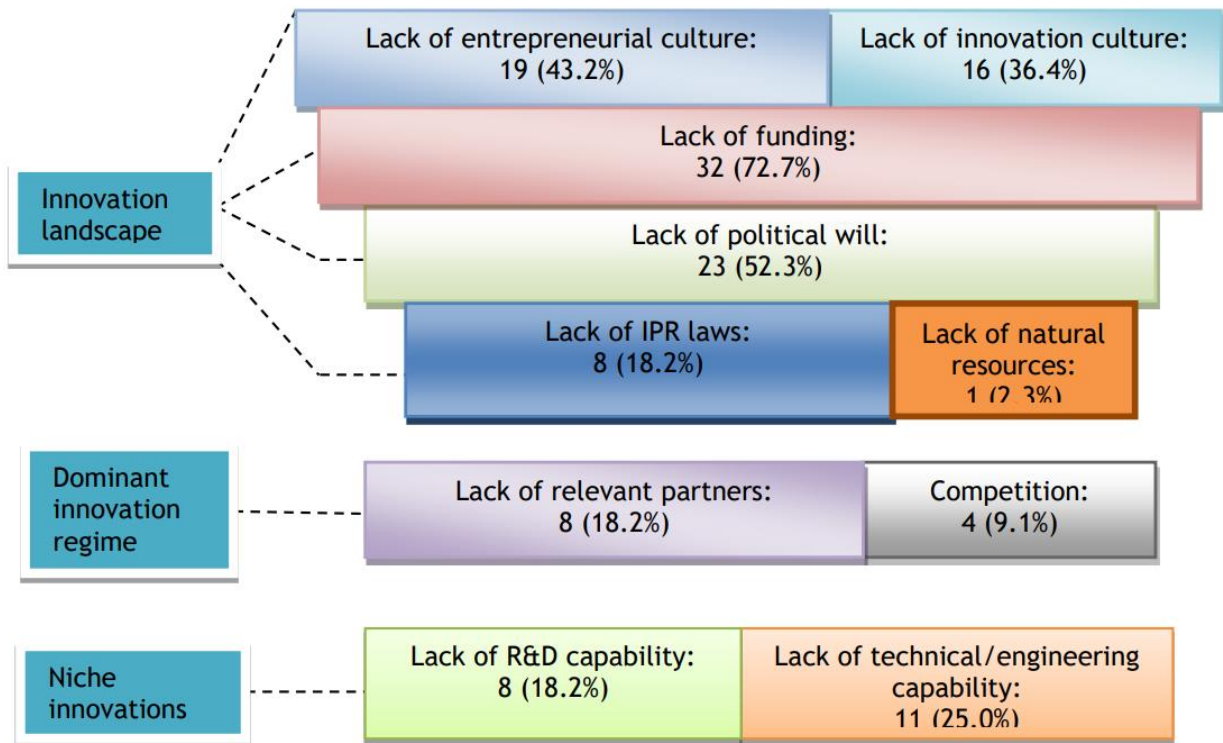


Figure 2-3: Negative influences on technology innovation roadmaps (Letaba et al., 2018).

The most significant enablers of technology implementation and their level of influence, according to Letaba et al. (2018), are shown in Figure 2-2. They are an abundance of political will, culture, funding, Intellectual Property Laws (IPL), partnership networks, competition, market demand, R&D capacity, engineering capacity, and access to natural resources. The lack of these enablers acts conversely, and their level of influence, according to Letaba et al. (2018), are listed in Figure 2-3.

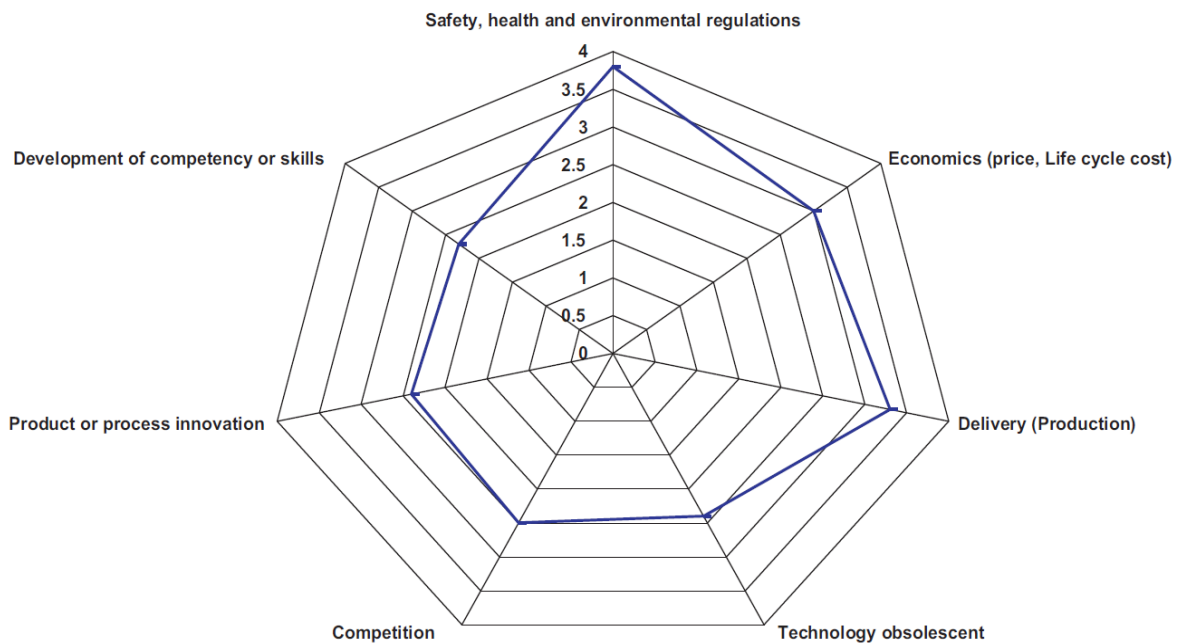


Figure 2-4: Critical factors influencing technology implementation in coal mining (Amadi-Echendu et al., 2011).

Figure 2-4 shows the respondents in a coal mining survey of the drivers of innovation. According to the survey respondents, health, safety, and environmental regulations were the main drivers of innovation.

2.5.3.1 Political, social, and economic factors that affect technological adoption in the local South African context.

Kyobe (2011) investigated the influence of capacity, international environment exposure (foreign investment) and government policies in South African adoption of Information and Communication Technology (ICT). The study found that the most significant impact on ITC adoption was due to capacity, followed by international environmental exposure. Lastly, government policies had a negative but insignificant influence on ICT adoption, similar to other developing countries. Kyobe (2011) also noted the need for South Africa to grow economically to allow for technological advancements that lead to sustained competitiveness on the international stage. According to Oduniyi (2022), the slow technology adoption in developing country agriculture threatens productivity.

According to Kyobe (2011), South Africa is liberal about internet access. The limitations that do exist are for controlling abuse of information and fraud. The pricing of internet services requires improvement so they are accessible and reliable.

Zerihun (2020) investigated the adoption of agroforestry innovation in the Eastern Cape province of South Africa. The study found that positive influences on the adoption were access to credit, information exchange, extension services, social group participation, trust in institutions locally and prior technology exposure.

Qi and Yang (2023) studied the influences of green innovation among BRICS nations using the Triple Bottom Line Theory (environmental, social and economic influences). The study found that all three factors significantly led to green innovation with time. The study found that a 1% increase in economic factors led to a growth of 0.29% in green innovation. Environmental concerns led to 0.438% in green innovation. Social factors had a low influence, with a 0.175 increase, and globalisation led to a green innovation increase of 0.310%. The study noted that government interventions only increase in the long term, and so does its influence.

2.5.3.2 Comparing technology implementation in developing countries with South Africa

Improved safety and productivity due to Industry 4.0 technology implementation are why people in South Africa and other developing countries are for this technology, as demonstrated in sections 1.1 and 2.5 above. Knowledge from developed countries on this implementation affects South Africa and other developing countries as the skills and know-how often implemented in developing countries follow success stories in developed countries, as demonstrated in section 2.4 and 2.5.

The common concerns prevalent in South Africa and other developing countries were job losses, lack of training, specialised skills and training facilities. South Africa's internet services are not restrictive to access, which could give it an advantage over more restrictive developing countries. The biggest concern regarding internet access in South Africa is the pricing. The Internet is a critical part of Industry 4.0 technology adoption.

Qi and Yang (2023) found that social factors in South Africa affected technology implementation, but even though this effect had limited impact, it still requires attention as social unrest can negatively affect the implementation of Industry 4.0 technology.

2.6 General technology adoption barriers and enablers

Many areas of science and technology have seen an increase in funding from their respective industries and the government, while the natural resource sector, including the mining industry, has seen a decline in such funding from all sources. The funding opportunities for research and development have declined due to smaller corporate profit margins (Hitzman, 2002). According to Ediriweera and Wiewiora (2021), studies looking at technology “barriers and enablers to innovation” in the mining industry offered an improved understanding of “industry-specific barriers and enablers” faced.

Adoption Barriers to technology within the mining industry include remote mining sites, the level of risk associated with the change, the uncertainty of the industry as a whole, the volatility of commodity prices of the mined minerals and the possibility of inflicting physical harm on the environment and people. Changes in technology could also affect daily production targets, and employees may be reluctant to compromise as they affect their bottom lines. The study notes that ground workers focused on their production goals to protect their work rather than risk it with unproven technology applications (Ediriweera & Wiewiora, 2021). The mining industry business cycle and the fluctuation of commodity prices are linked. Variations in commodity prices are more likely to affect countries that specialise in mining when the perception is that innovation is a long-lasting shock (Daly et al., 2022). Mining innovation follows a cycle with highs when the price of commodities is high and reduces as soon as the prices go down (Daly et al., 2022). Another difficulty in innovation is that the stakeholders who make the decisions may be proponents of the innovative solution or be against the new idea (Ediriweera & Wiewiora, 2021).

An insufficient relationship with external stakeholders discourages the adoption of technology. An example given is when an external stakeholder determines the commercial value of a technology, and the mining companies try to close off the technology for their benefit alone, believing that they gained a competitive advantage with the technology while not realising that the only accrued advantage is being the first in the industry to use the technology; others caught on eventually (Ediriweera & Wiewiora, 2021).

Mining companies hesitate to trust the skills, capabilities, and knowledge of participants who input their skills from outside the mining industry, and this disrupts collaborative

research efforts to co-create solutions (Ediriweera & Wiewiora, 2021). There is not enough communication between the mining industry and the external stakeholders. That is due to limited information made available by the industry on its METS, which allows companies to build new technology. The engagement of external stakeholders has low priority within mining power structures, which is an obstacle to maximising technology adoption (Ediriweera & Wiewiora, 2021).



Figure 2-5: Generalised technology barriers and enablers (Ediriweera & Wiewiora, 2021).

The complexity of mining operations presents other barriers to technology adoption, such as a possible failure of the technology, which could risk the mine not meeting its daily objectives. That means that the people in charge of the operations may opt out of adopting the technology as they avoid applying the technology that is not guaranteed to work and that the mining industry is highly susceptible to risk. Mining experts say they might not adopt the technology because they do not trust the accuracy of the data from the Industry 4.0 technology before implementation (Ediriweera & Wiewiora, 2021).

New technology disrupts old established methods, such as collaborations with external partners. That can be during the peaks and troughs of the economic cycle. During the highs of these economies, suppliers have more customers to supply, which means they can raise their prices. The rise in price limits the amount the mining companies can make available for technology adoptions, as they need that additional money to keep buying supplies, and during troughs, mining companies do scale back on expenditure to continue afloat (Ediriweera & Wiewiora, 2021).

The findings of Ediriweera and Wiewiora (2021) suggest that earthly locations are a barrier to the mining industry adopting new technology. The study found that the distance between the main office and the mining operation site hindered technology adoption due to the difficulty of information flow between the two and the limited access to resources.

The mining industry is capital-intensive, meaning there are many resource requirements for mining operations. That intense resource intake means the mining industry is limited when investing in Industry 4.0 technology as costs go towards equipment, machinery and building new plants (Ediriweera & Wiewiora, 2021).

The mining industry has a non-negotiable objective to satisfy shareholders. Adopting new technologies obstructs that key objective, as short-production-term targets take a back seat due to disruptive technologies that target more long-term goals, which becomes a hurdle to adopting Industry 4.0 technology (Ediriweera & Wiewiora, 2021). The mining industry is unwilling to adopt new technology due to its unproven nature. Industry managers prefer to stick with proven strategies rather than take the risk associated with the technology that could negatively influence performance. This risk is more likely to be taken if the technology is not too disruptive. Safety risk is also a significant factor since no implementation of technology advancements occurs if they risk the safety of employees (Ediriweera & Wiewiora, 2021).

The study found that limited trust between the employees at the mining site and those based at the head offices is also a factor in adopting technology in the mining industry. The fact that the head office and site are so far apart also adds to the distrust between the two. The mining sites are so remote that interaction with the head office is limited (Ediriweera & Wiewiora, 2021).

The mining industry emphasises efficiency and effectiveness and has little to no emphasis towards creativity and learning. The study found that employees find creative ways to operate and solve problems, but employees do not emphasise these out-of-the-box methods and shy away from suggesting disruptive changes (Ediriweera & Wiewiora, 2021).

The basis of key performance indicators (KPIs) is volumetric production, and none are technology adoption or creative idea implementation. There is little to no reward for riskier and unproven ideas. Studies show that KPIs are compartmentalised, where the KPIs of

a particular unit do not align with other departments on the production line. People focus on their KPIs rather than thinking about the effect on the entire production. A solution could be to have KPIs that look at the system in its entirety, and a more holistic view is adopted, looking at the efficiency as a whole rather than focussing on small units that disregard other parts (Ediriweera & Wiewiora, 2021).

There is limited autonomy in decision-making for people who work in mining operations daily. There is no empowerment for employees to take calculated risks or develop methods to improve methods to achieve objectives unless the improvements affect efficiency gains. Pushing through technology adoption-related decisions is through higher management in the head offices. Although the implementation within the mining site and those who make the decisions have limited oversight over the implementation process, those implementing have limited decision insights or authority for decision-making, causing a gap in information between the two (Ediriweera & Wiewiora, 2021). A summary of “barriers and enablers of technology” is in Figure 2-5.

2.6.1 Innovation adoption

Ediriweera and Wiewiora (2021) break down innovation adoption into the following stages: understanding, persuasion, the decision to reject or adopt the technology, implementation, and confirmation.

- **Understanding:** Understanding is getting to grips with an opportunity for innovation and realising when to act on it.
- **Persuasion:** Navigating around the fact that the environment is allowing innovations to thrive or the environment is not allowing it.
- **Adopting or rejecting the technology decision:** Adopting or rejecting the technology decision: Deciding on whether or not to use move forward with the innovation.
- **Implementation:** Applying innovative solutions to solve the problem aligned with the organisation's objectives.
- **Confirmation:** The process in which the level of success or failure of the solution is quantified.

2.6.2 Results of technology adoption

According to the diffusion of innovation theory, the following five groups determine the results of technology adoption: compatibility, relative advantage, observability, complexity, and traceability (Ediriweera & Wiewiora, 2021).

- **Compatibility:** The level of fit that the innovations had with the values of the business and its operations.
- **Relative advantage:** The relative level of improvement the innovation has on the current methods of achieving the goal.
- **Observability:** Observability of the noticeable change caused by innovations observed by others outside the building process.
- **Complexity:** Complexity is the perceived difficulty of applying the solution and the degree of understanding of the innovation.
- **Trialability:** Trialability is the allowance that innovation provides for experimentation with its usage.

Figure 2-6 details the effects of the level of automation on efficiency, data and the human risk involved in the system. This figure shows that efficiency increases while human risk decreases. The amount of data grows as a result of growing automation.

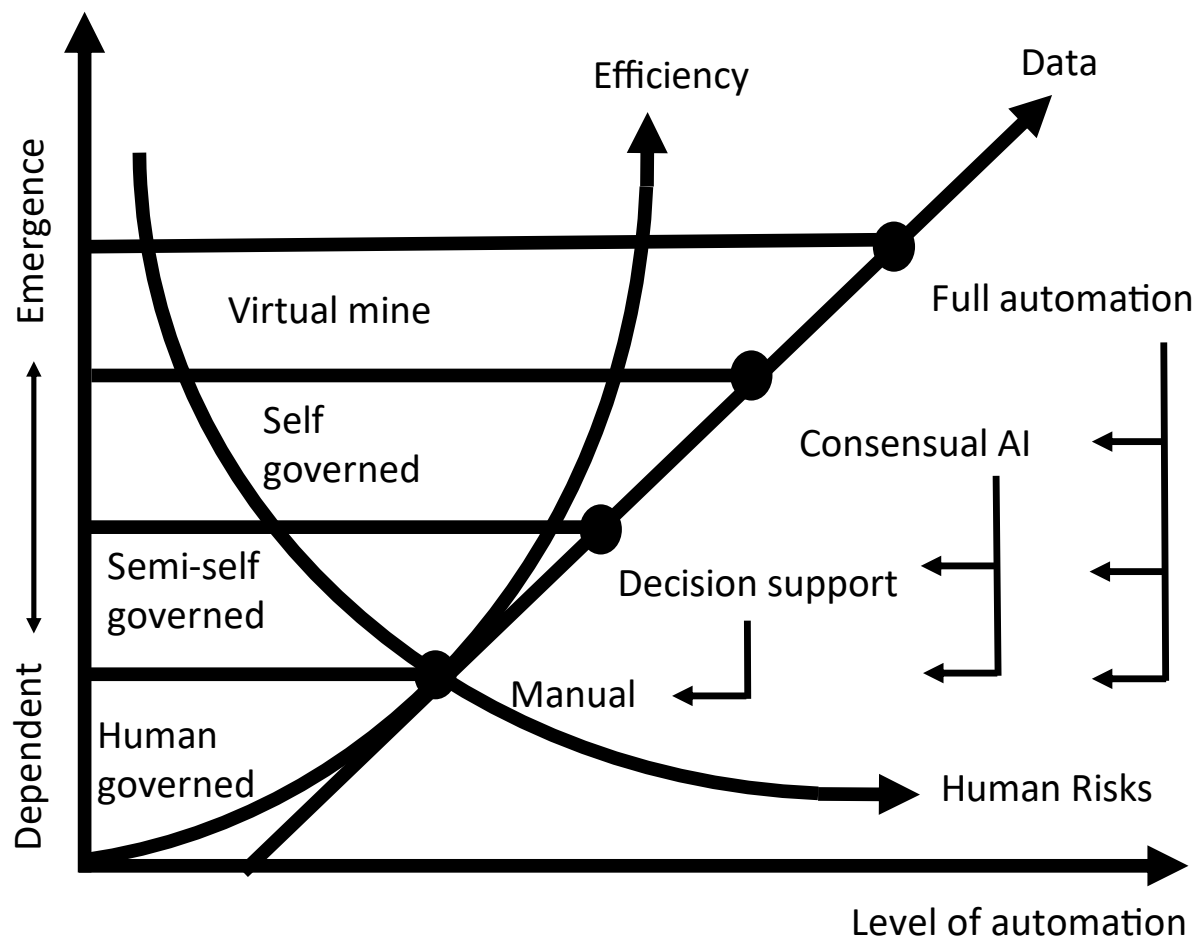


Figure 2-6: The effects of automation (Yaqot & Menezes, 2022).

2.6.3 Other enablers of technology adoption

The study found five mining industry enablers for technology adoption: employee empowerment, a learning culture, reward and recognition of innovation, cross-discipline knowledge sharing, and external stakeholder engagement (Ediriweera & Wiewiora, 2021).

2.6.3.1 Learning culture

Ediriweera and Wiewiora (2021) found that a learning culture that allows experimentation, testing, and room for the occasional tolerance for failures in technology implementation was successful. It was necessary to create testing sites to evaluate technology performance and impact; these sites provide an opportunity to take risks and manage them without severe consequences.

2.6.3.2 Knowledge sharing across disciplines

Ediriweera and Wiewiora (2021) found that knowledge sharing between the different work units resulted in more transparent operations and information assimilation while improving the adoption of Industry 4.0 technology. These differing units learn from each other and have an opportunity for collaborative solution-building efforts.

2.6.3.3 External stakeholders engagement

Collaborative work between external stakeholders provides for sharing knowledge or knowledge creation and is essential to adopting technology. The relationship with external stakeholders, including those with suppliers and research organisations, allowed the sharing of knowledge through mutually beneficial agreements. These relationships lessen risk when adopting technology due to the different expertise shared, and over time, trust builds through frequent information exchange and communication (Ediriweera & Wiewiora, 2021).

Ediriweera and Wiewiora (2021) found that the participants suggested that a combined KPI that supports innovation was beneficial, with combined KPIs meaning that they are based on the production system entirely and not just single unit performance. Recognising innovative ideals could also encourage those who are not necessarily innovative to participate in creating new ideas.

According to Ghebrihiwet (2019), companies in the natural resource sector were likely to initiate innovation if they were involved in agreements with foreign suppliers or customers.

2.6.3.4 Employee empowerment

Ediriweera and Wiewiora (2021) found that given more autonomy, employees adopted more problem-solving methods. The study found that employee empowerment requires three mechanisms. These are providing employees oversight of the process, assigning them decision-making capabilities, and providing more flexibility. Another way to empower employees is to allow them to learn from other areas of the mining industry to acquire a more comprehensive knowledge base on mining operations. Operational staff should also be involved in generating new ideas for running the mining operations and solving preexisting problems.

2.6.3.5 Government regulations

The government plays a noticeable role in advancing innovation, such as allowing for a well-organised patent-obtaining system. Another way the government can aid innovation initiatives is by introducing tax incentives and supporting research institutions through sponsorships (Daly et al., 2022). Introducing environmental regulations leads to mining organisations developing clean technologies within the production line (Andersen & Noailly, 2022). Acts such as the MINER Act led to more patents towards safety innovation. The MINER Act led to a 51% decrease in injuries and days off work for miners in the United States of America (Toole et al., 2022). A similar applicable law for the South African context is the Mine Health and Safety Act (MHSA) of 1996.

2.7 Similarity and differences between developing and developed countries

This section details the main consequence from sections 2.4 to 2.6 that show literature on how developing and developed countries use technology. The concern with technology adoption for developing and developed countries is bureaucracy, as it hampers technology adoption by slowing the movement towards new technologies in both developing and developed countries. Job losses and unemployment are other main concerns people have with the adoption of new technologies in both developing and developed countries. The benefits for both developing and developing countries are safety, cost reduction and productivity improvements as the main benefits of the technology. Regulations assist and hamper the adoption of new technology in both developing and developed countries.

A collaborative effort between suppliers and their customers aids technology adoption in both developing and developed countries. The mining industry is risk averse, meaning demonstrations of the success of the technology help in its adoption for both developing and developed countries. Social influences affect technology adoption, such as people's opinions on the benefits and costs of the implementation for both developing and developed countries. The perceived usefulness of a technology helps in its adoption for both developing and developed countries.

Concerns unique to developing countries are lack of resources and skills to implement the technology, social and political unrest due to the changing technology and the lack of education and institutions to train individuals.

2.8 Fast-tracking technology implementation

The potential is plentiful for modern technology to improve productivity and optimise mining practices. Mining industries must adopt skills and technology from other alternative industries (Daly et al., 2022). Vertommen (2018) studied the implementation of fast-tracking technology in the pharmaceutical industry. The project was carried out under urgent circumstances when the French authorities decided to suspend the manufacturing licence of a critical product encapsulating site that affected patients in France. As a result of the limited supply of the drug, the new site had to use a short time frame to regain approval from the regulators and replenish supplies before the market ran out of stock.

The fast-tracking of the implementation of the new site was done in three phases and completed in 9 months. The phases were:

- Phase 1: Planning and feasibility (approximately two months)
- Phase 2: Submission to the health authority after execution (approximately four months)
- Phase 3: Obtaining regulatory approval for the release of the product (approximately three months)

While the project was underway, six critical factors led to its success, namely:

- Robust product knowledge
- Strong project leadership
- Trust and transparency
- Planning and management
- Established Quality-by-Design (QbD) processes
- Risk mitigation and management

2.8.1 Robust product knowledge

Project success required plenty of technical knowledge about the product. There was a precise “understanding of what was critical and what was not critical in the technology transfer process” (Vertommen, 2018).

2.8.2 Strong project leadership

The responsibilities and roles of the two partners, the Contract Development and Manufacturing Organisation (CDMO) and the pharmaceutical company, were clearly

defined. CDMO provided expertise in capsule development and manufacturing while bringing the knowledge needed to implement the quality-by-design approach (QbD) (Vertommen, 2018). The study also highlighted the need for a well-connected project leader who maintains high priority toward the project, as a project without this level of attention would likely be delay-riddled.

2.8.3 Trust and transparency

The open conversations between the pharmaceutical company and CDMO were of paramount importance, as demonstrated by the weekly conference calls in which the partners participated. The trust resulted in rapid issue resolution (Vertommen, 2018).

2.8.4 Planning and management

The study noted the importance of maintaining documentation, expertise requirements, and strengthening team seniority. The project was exceptionally detailed, from resources to budget (Vertommen, 2018).

2.8.5 Established Quality-by-Design (QbD processes)

The project relied on QbD knowledge for its success. From the beginning of the project, time was invested in understanding and developing QbD collaboratively, leading to an easy transition to the feasibility stage, as by the time to feasibility, an established understanding of QbD was already in place (Vertommen, 2018).

2.8.6 Risk mitigation and management

Since the project was about meeting regulatory standards, the regulatory body needed frequent participation as a risk mitigation strategy. Meetings were held from the beginning of the project and throughout its implementation. The project also used preexisting risk aversion strategies when carrying out the project. The result was a successful delivery of soft gel capsules into the supply chain within nine months and customer satisfaction. The success was due to the teamwork applied between the partners (Vertommen, 2018).

Fast-tracking Industry 4.0 technology implementation in the mining industry would invoke steps similar to those applied in the pharmaceutical industry, detailed in Vertommen, (2018)'s study. Therefore, adopting and adapting these steps would result in similar fast-tracked results.

2.9 Human-centred technology adoption approach

This section details efforts to include humans in Industry 4.0 technology implementation throughout different sectors.

2.9.1 Effects of new technology on ergonomics

Any new technology introduced to a workspace will interact with people working in and around the space at some point. This interaction should be as comfortable as reasonably possible for the people, which motivates the inclusion of ergonomic considerations during the implementation of such technology.

Hunt and Ivergard (2014) stress the importance and requirement of service design that leads to harmony and balance between the activities of people and the natural world. The study examined ergonomics and its relationships with humans and complex technology systems. According to Hunt and Ivergard (2014), ergonomics is the science of looking for ways to fit people with the technology they use. Ergonomics creates a balance between people and technology. Ergonomics in the work environment aims to avoid disturbances and catastrophic accidents.

According to the study, the following criteria points evaluate ergonomics:

- Security, health and safety
- Ease of use
- Comfort level
- Aesthetics
- Level of Complexity
- The pleasure brought
- Level of desire or craving
- Motivation

The study's findings also mention the importance of the user in enabling them to apply the technology successfully.

Hunt and Ivergard (2014) highlighted that good ergonomics fits all different people, where the characteristics of individuals are physical strength, physiological dimensions of people, and mental attributes. The study also mentions the need for organisations to factor in environmental factors, giving examples such as lighting and acoustics. The

design of an ergonomic approach should be inclusive of all people, regardless of any circumstances. The study findings also mention the importance of the user's ability to apply the technology successfully. The study also mentions the need for organisations to factor in environmental factors, giving examples such as lighting and acoustics.

Hunt and Ivergard (2014) emphasise the paramount importance of health and safety in many sectors or industries. The study also highlighted the importance of elements considered less often, such as the comfort and well-being of the employees. Failure in these elements does not have life-threatening consequences, but comfort and well-being failure provisions can lead to emotional strain and, in some instances, accidents. The study also mentioned how several industries changed when public confidence waned in managing a crisis, showing the influence of public opinion on decision-making.

Hunt and Ivergard (2014) mention information and communication technology (ICT) as a tool to improve the user experience for people, but there has been a focus on cognition and learning for young people (excluding other populations in the age demographics). The focus on younger generations for these technologies means that older generations had difficulties with the technology, as the systems are more difficult for older generations to adapt to. The focus on the young demonstrates that the senior management of organisations relies upon younger assistants and their secretaries to interface with the technology they struggle with personally (the usability in these systems is lacking).

Hunt & Ivergard (2014) mention the importance of leadership to employees, leaders who know the value of the well-being of employees. The study goes on to say that the well-being of employees is the precondition for high levels of motivation for workers to work at the highest level or any quality, for that matter. The study mentions the term Psychological Capital (PsyCap), which is the development and reinforcement of positive traits within the workplace. This results in a general increase in performance. The study mentioned a positive workplace as a source of employee confidence, hope, happiness, and emotional intelligence. This positive environment is the responsibility of leaders.

There are negative consequences to not building a positive workplace. The study noted an example case where employees saw managers as insensitive and uncaring of workers' welfare. Employees look for more confirmation of their grievances (looking for more examples to confirm their case, a knock-on effect). The study also mentioned how

the employees looked for ways to "get back at the institutions" as a form of payback for the wrongdoings of the organisation in their view. Another consequence is that employees compare their working conditions with the conditions of rival organisations.

Hunt and Ivergard (2014) also highlighted how negative feelings toward an organisation can spread, leading to short-term motivation loss and, in the long term, organisational reputational damage. That shows the need to account for all those involved when the decision-making process is underway. A warning from the study was that when an organisation allows the seed of a gloomy workplace to grow, they end up working for rival organisations and further highlight the disparities between organisations, leading to further reputational damage to their former organisation.

Hunt and Ivergard (2014) also mentioned how often there is a divide between the strategy of senior managers or executives compared to the concerns of everyday employees. There is a need to address these day-to-day concerns, such as the comfort of the workplace, which leads to more employee commitment towards the main objectives. For employee involvement and the future direction of an organisation, communication with employees is critical for employees to join the plan. There should not be an overwhelming emphasis on working machinery, and the well-being of people at work should be of the utmost importance.

2.9.2 Issues and benefits to people during new technology implementation

According to Ratshidi et al. (2022), technology applications fail for the most part during the implementation stage due to human and context-related contributors. Carayannis et al. (2024) claim that Industry 4.0 technology is not considered human-centric because of its ignorance towards the human element in process optimisation. These all lead to job losses, digital exclusion, job market transfers, digital divide and environmental damage (Carayannis et al., 2024; Arıcı and Kitapci, 2021).

Siemieniuch et al. (2015) discuss issues faced by people in manufacturing when Industry 4.0 technology is being implemented, such as skill issues, job content and ethics. Human beings play a critical role in sustainability as customers, creators and operators, but their involvement in socio-technical systems is unaddressed. Ergonomics are crucial for both the operation and design of sustainable systems (Siemieniuch et al., 2015; Gervasi et al., 2022; Verma and Singh, 2024; Olvera et al., 2021; Arıcı and Kitapci, 2021). Holzinger et

al. (2024) noted that agricultural development of Industry 4.0 technology also experienced automation that often marginalised workers' involvement. Industry 4.0 technology implementation impacts workers and the work environment requiring investigation. Categories of Occupational Health and Safety (OHS) implications are cognitive, technological demands and organisational as in Figure 2-7. The impacts related to affecting the workers the most were psychological (mostly stress) (Bispo and Amaral, 2024; Kadir and Broberg, 2020; Arıcı and Kitapci, 2021). The psychological impact includes psychological pressure, increased mental demand, resistance to technology, lack of cognitive skills and difficulty adapting.

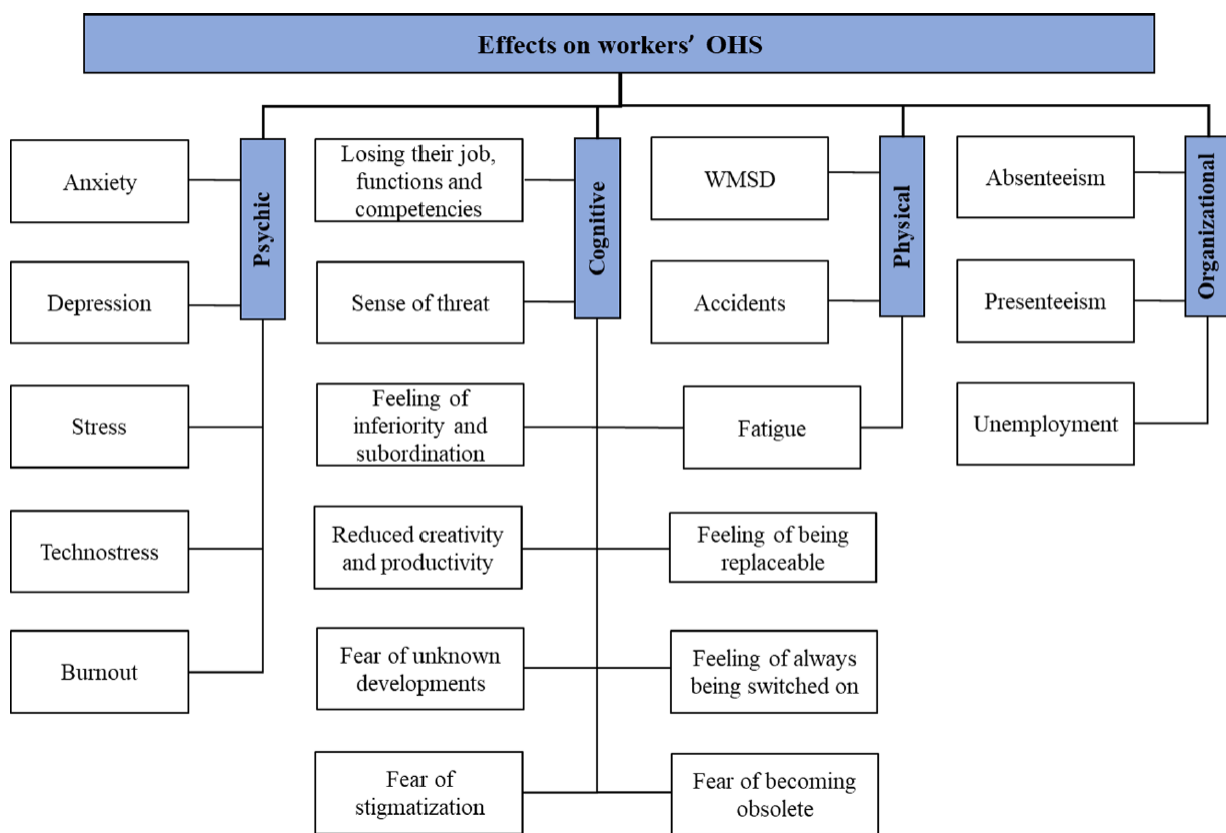


Figure 2-7: The psychological impact on workers by new technologies (Bispo & Amaral, 2024).

The competencies required for Industry 4.0 technology will be increased intellectual development. The workers will acquire more responsibility for the operation of these technologies that were not in existence previously, meaning the operator will require more skills and competencies to operate and effectively work in the Industry 4.0 environment (Bispo and Amaral, 2024; Arıcı and Kitapci, 2021). These developments rely on individual self-development, multitasking, autonomous individual decisions and working with real-

time information. Other hazards include cyber risks and physical hazards (not very significant) (Bispo & Amaral, 2024).

Collaborative robots are an Industry 4.0 technology seeking to support workers with four types of interactions, including cooperation, synchronism, coexistence and collaboration. Industry 4.0 implementation in most companies that are in the early stages focuses on replacing or substituting the human worker. These technologies also deskill workers, reskill and upskill in different cases depending on the goals of implementing the collaborative robots as in Figure 2-8 (Dornelles et al., 2023; Arıcı and Kitapci, 2021).

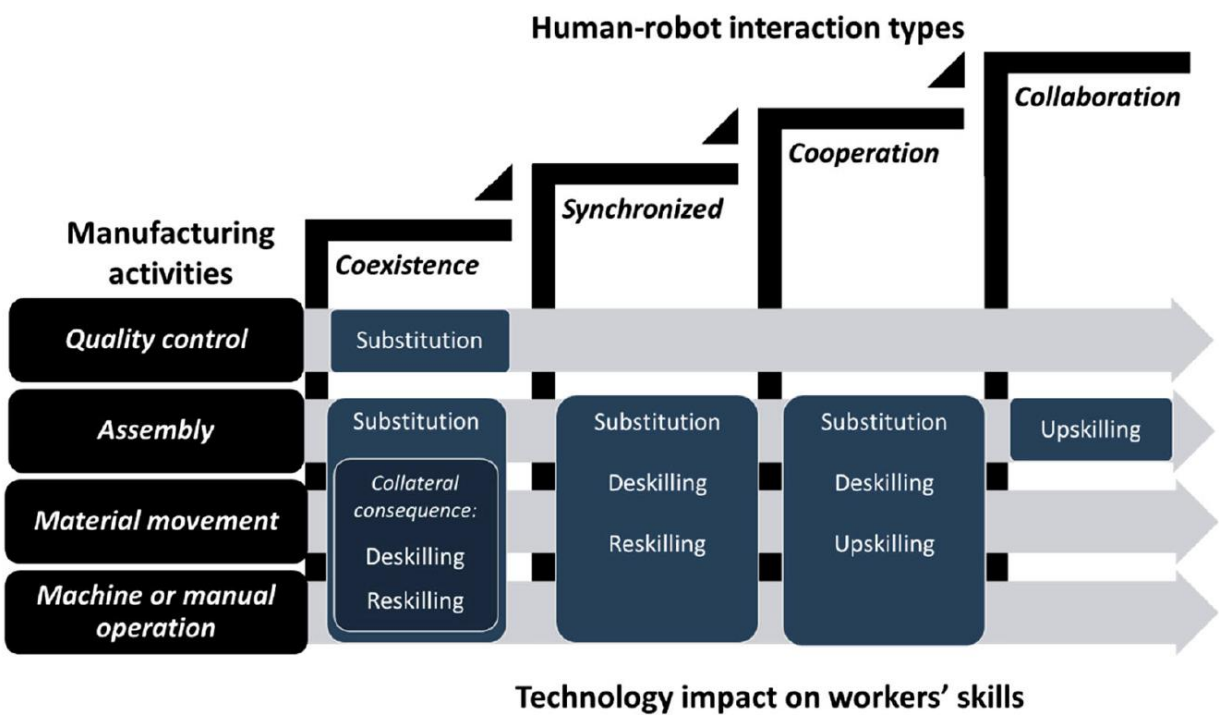


Figure 2-8: Different human and robot interactions and their effects (Dornelles et al., 2023).

Tran et al. (2023) used an SLR to assess heart rate variability research to assess real-time work-related stress during industrial work. That demonstrated that not only can Industry 4.0 technology work with people but also monitor people's conditions in the workplace, improving such working conditions. Collaborative robots used directly with people to understand their work and how to improve it are still limited to expensive equipment (Ni et al., 2023).

Tortorella et al. (2024) found that AI could positively influence employee engagement physically, emotionally and cognitively when the environment is human-centric as in Figure 2-9. AI and employee engagement could also positively influence psychological

conditions such as availability, safety and meaningfulness (Tortorella et al., 2024; Papetti et al., 2020).

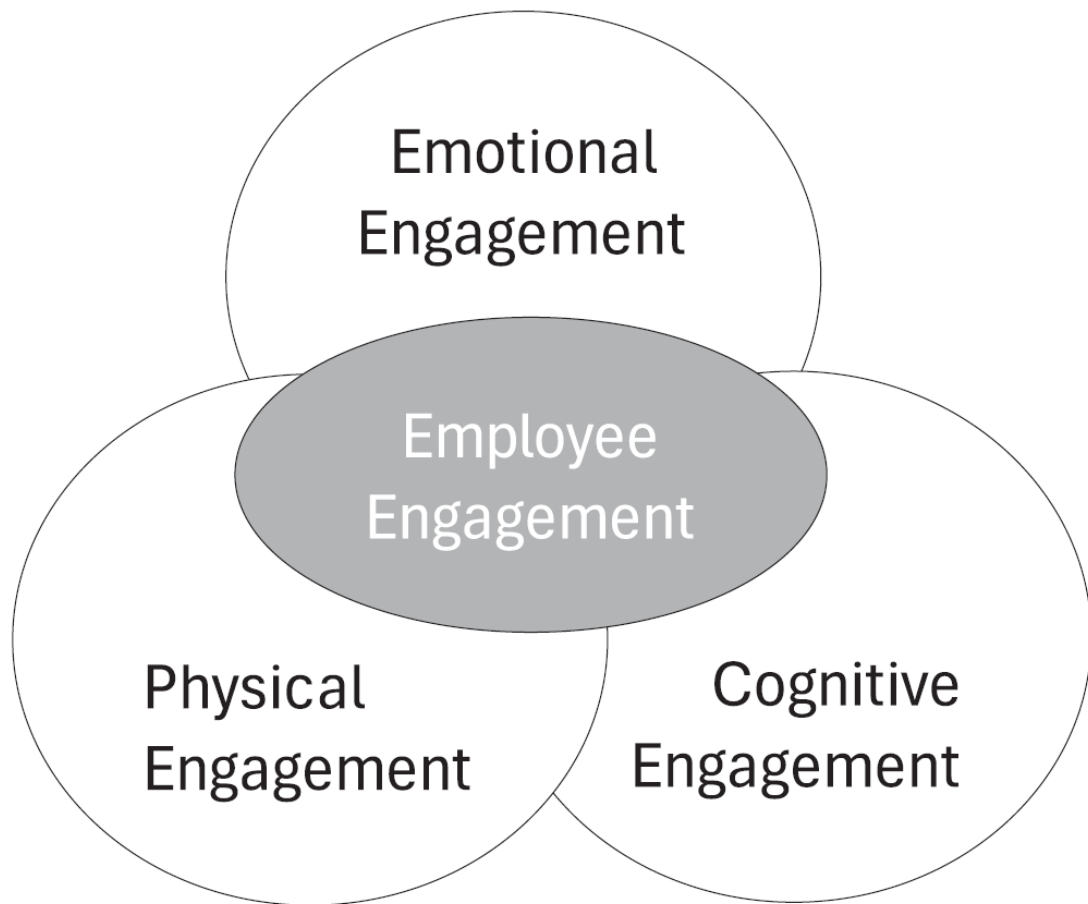


Figure 2-9: Technology influence on Employee Engagement (Tortorella et al., 2024).

Rautiainen et al. (2022) mention the need for more modalities of human-robot collaboration, such as speech, bodily gestures and touch. The study concluded that the personalisation of input methods from persons to machines reduced mental workload and physical exhaustion in the human participant using the technology, and the participants preferred this personalised system. The study also notes that there are no significant workload reductions by personalisation. The use of IoT systems with people had benefits such as appeal to stakeholders and savings in resources such as people, money and time (Rautiainen et al., 2022; Papetti et al., 2020; Abdous et al., 2023).

Industry 4.0 implementations requires many changes in Human resource management without reducing their significance. No automation is possible without the input of people

and has been from the first industrial revolution and will be in the 4th industrial revolution (Papetti et al., 2020; Arıcı and Kitapci, 2021).

Karuppiah et al. (2023) identified the following as the main challenges to human and robot collaborations:

1. Robustness
2. Scalability issues
3. Initial investment cost
4. Maintenance cost
5. Technical concern
6. Energy consumption
7. Programming approaches
8. Safety of data transmission
9. Sensors
10. Task allocation and task planning
11. Flexibility Concern
12. Safety interaction
13. Lack of reliability
14. Selective collaborative operation modes
15. Reality enhancement
16. Input modes
17. Control laws
18. Level of automation
19. Workplace design
20. Operator training

Kadir and Broberg (2020) looked at the effects of technology implementation in three phases, namely before (pre-implementation), during (implementation) and after (post-implementation) demonstrated in Figure 2-10.

In the pre-implementation phase, most companies had informed their employees of the upcoming changes, which created excitement and uncertainty. Informing the workers was positive overall as workers appreciated the information, and there was general excitement and started their independent research on the technology. The negative aspect of the

pre-implementation phase was the uncertainty created by the news. Several workers from Kadir and Broberg (2020) expressed concern over the new technology, and they expressed their concern over their inability to keep up with the Industry 4.0 systems, with some expressing concern over their capacity to learn the necessary skills. Technologies like robots also raise the concern of physical harm as the people share the workspace with these machines and job losses.

In the implementation phase, workers respond positively to involvement, learning and working with new technologies. The workers are negatively affected during this phase by a lack of information, their reluctance towards Industry 4.0 technology, worry, and the change in the division of workloads (Kadir & Broberg, 2020).

In the post-implementation phase, workers are positively affected by improved ergonomics introduced by the new technology. Workers enjoy the new working mode, they appreciate improved safety, and during this stage, they worry less about job losses. The lack of commitment from management and the lack of standardisation and training frustrate workers at this stage of implementation (Kadir & Broberg, 2020).

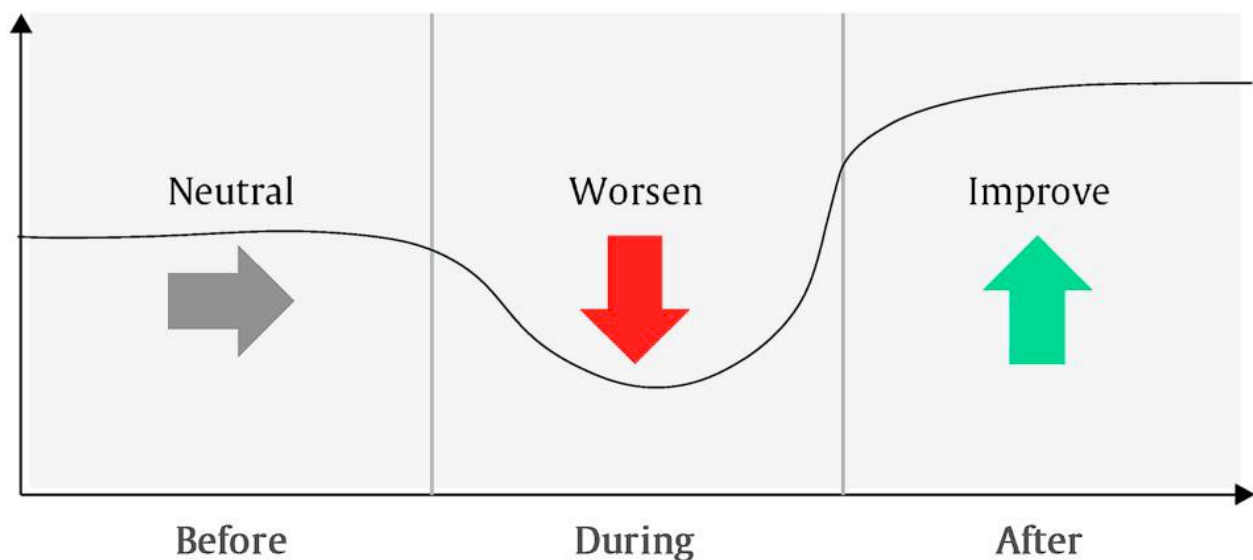


Figure 2-10: Perceived well-being and the system's overall performance through the three phases of implementation (Kadir and Broberg, 2020).

Kadir and Broberg (2020) recommended the following in the pre-installation phase:

1. Strategic objectives should be linked to digital strategies.
2. Inform all stakeholders of the reasons for the digital technologies.

3. Evaluate workforce competencies for the new technology, determining whether or not more training is necessary.
4. A systematic approach should be developed and followed for the new technology.
5. Understand the interactions of the target system and determine the effects it could have on worker well-being.
6. Follow a human-centred design approach that involves affected employees from the onset.

Kadir and Broberg (2020) recommended the following implementations in the pre-installation phase:

1. Follow an iterative, systematic approach.
2. Resources should be planned and allocated accordingly.
3. Continuously update and inform the organisation of changes.
4. Ensured workers know how to operate the new digital technology.
5. Continuously capture user feedback.
6. Gather sufficient data on the system to determine its limitations.

Kadir and Broberg (2020) recommended the following implementations in the post-installation phase:

1. Standardise working with the digital technology.
2. Develop standard procedures for the new system and clean up the site.
3. Develop a training system for the workers.
4. Ensure maintenance, continuous improvement and updates to the system through a life cycle management plan that collects data on the system from usability to performance.

2.10 Technology implementation roadmaps

This section introduces some of the approaches to developing roadmaps. It follows with examples of roadmaps for technology implementation in manufacturing and construction industries, South African mining and generic roadmaps. The study included these roadmaps because they were in a developing country context and because of the type of industry they were designed for.

2.10.1 Building roadmaps

Amadi-Echendu et al. (2011) respondents listed technology road mapping as one of the techniques they were aware of the most, but it was the least widely applied, as in Figure 2-11.

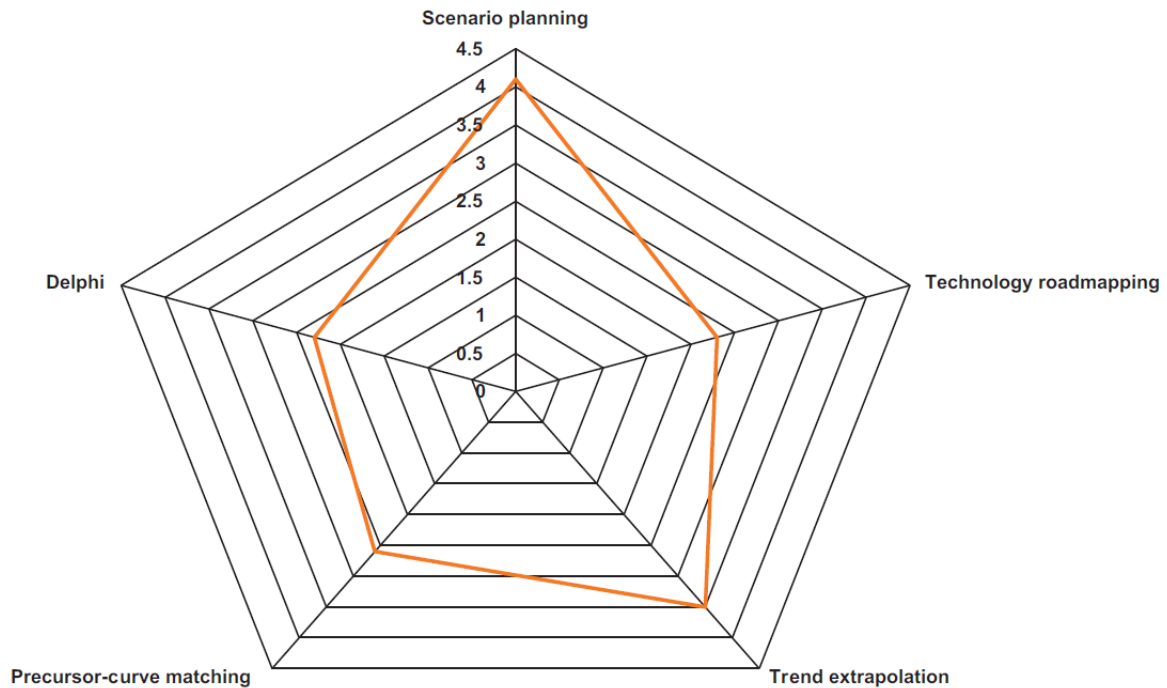


Figure 2-11: The levels of applications of technology implementation plans in mining (Amadi-Echendu et al., 2011).

Technology implementation roadmaps are visual representations of the strategy applied during the implementation, linking the organisation's technology strategy with the business strategy. For the technology roadmap to successful implementation, clear objectives custom to each organisation require establishing alignment with the organisation's culture (Gerdri et al., 2010).

The development of the implementation technology roadmap can be divided into three phases, as shown in Figure 2-12. The first phase is the initiation phase, followed by Development and Integration.

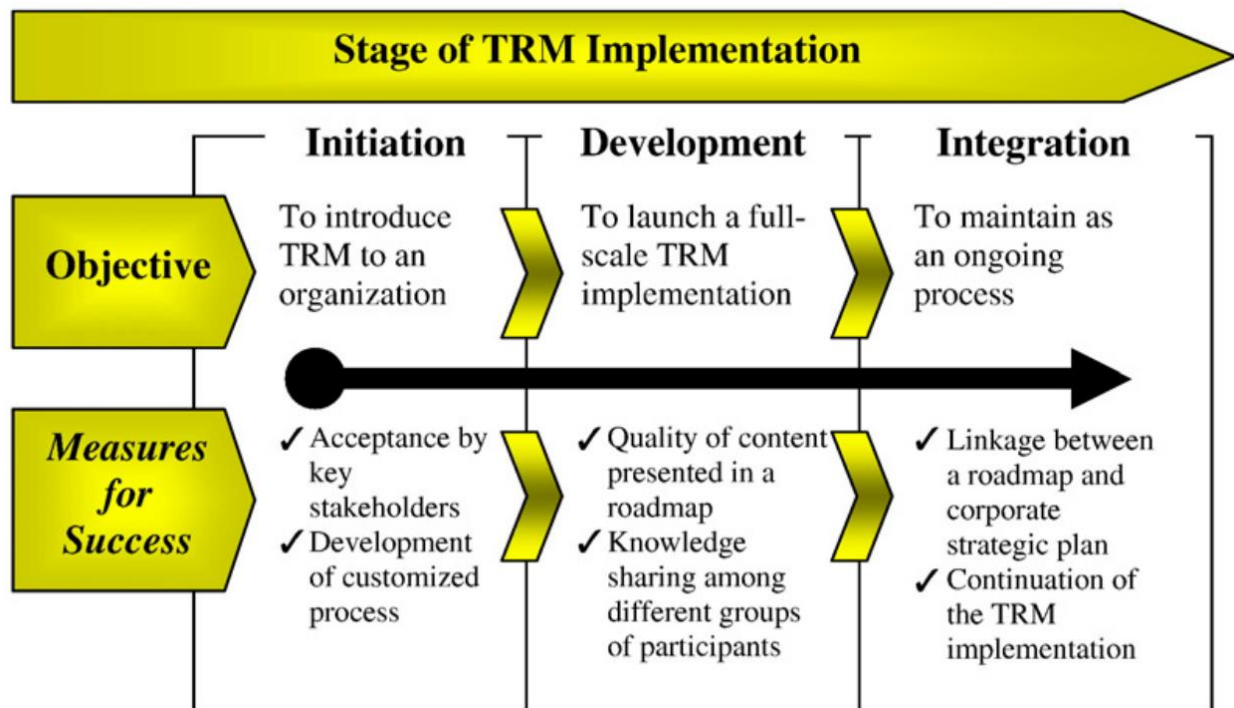


Figure 2-12: Phases of the technology roadmap development (Gerdsri et al., 2010).

A. Initiation phase

This phase gathers information for the follow-up phases of the technology implications roadmap. In this phase, key stakeholders combine into a team responsible for developing the organisation's roadmap for implementing the new technology. The success of this phase was quantified using the degree of acceptance by stakeholders of the customised roadmap that fits the organisation (Gerdsri et al., 2010).

B. Development phase

This phase gathers data from both external and internal sources, where stakeholders meet to analyse the data and present them in a roadmap form for implementing the technology. This phase may require several iterations. Measuring the success of this phase through the quality of the roadmap content, the experience and knowledge contributed by the stakeholders involved in the roadmap development (Gerdsri et al., 2010).

C. Integration phase

This phase integrates the roadmap of technology implementation with business operations. The success measure of this phase was through the level of alignment of the

roadmap with the business strategy, the quality of the roadmap, and the continuous day-to-day development of the roadmap (Gerdsri et al., 2010).

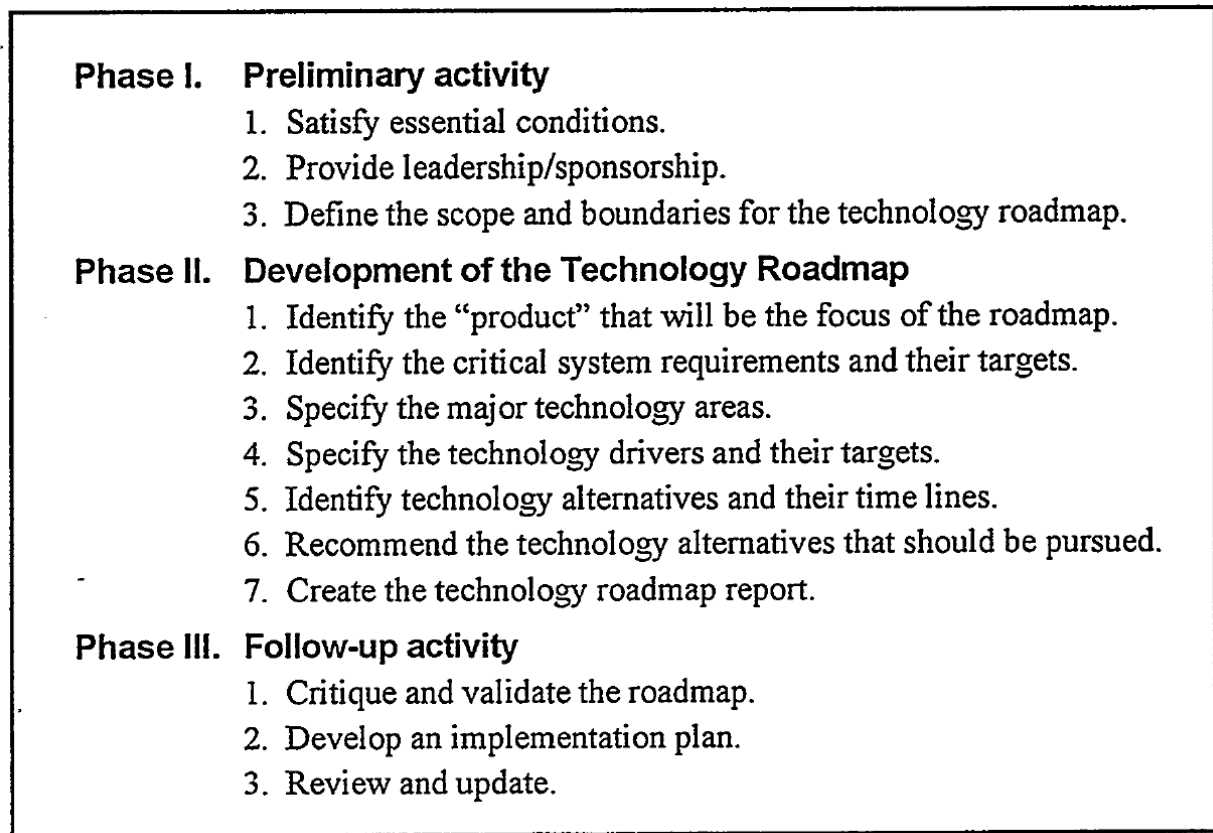


Figure 2-13: Steps for developing a technology implementation roadmap (Garcia and Bray, 1997).

Figure 2-13 summarises the above-mentioned technological development roadmap steps. Using technology road mapping develops consensus on the technological needs and how they are satisfied, forecasts technology developments, and provides a framework for planning technology developments (Garcia and Bray, 1997).

2.10.2 Industry 4.0 implementation roadmaps

2.10.2.1 Industry 4.0 implementation roadmaps in the manufacturing industry

A. First roadmap for the manufacturing industry

Figure 2-14 shows some common Industry 4.0 technologies implemented in manufacturing.

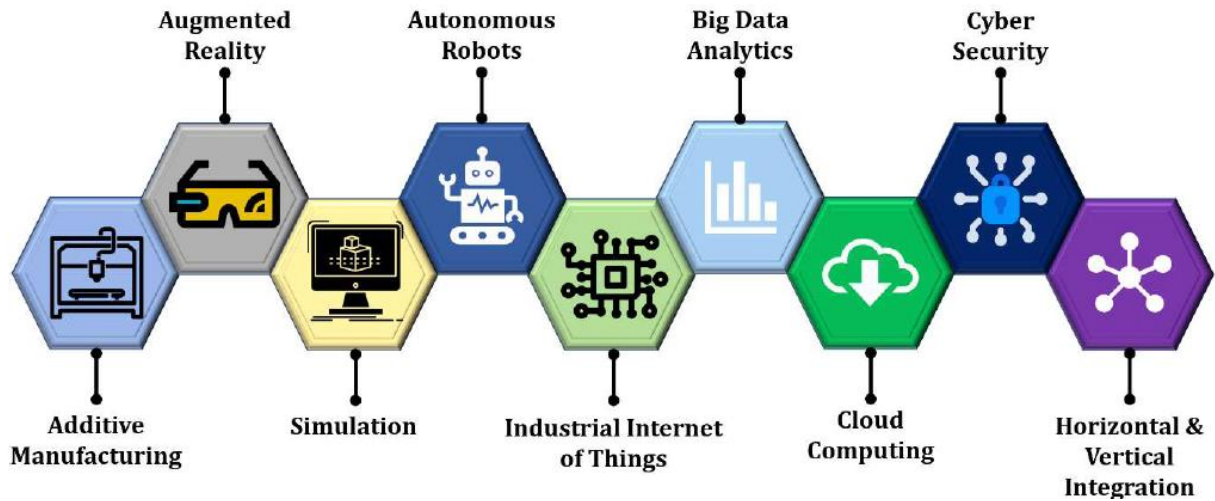


Figure 2-14: Examples of Industry 4.0 enabling technologies (Butt, 2020).

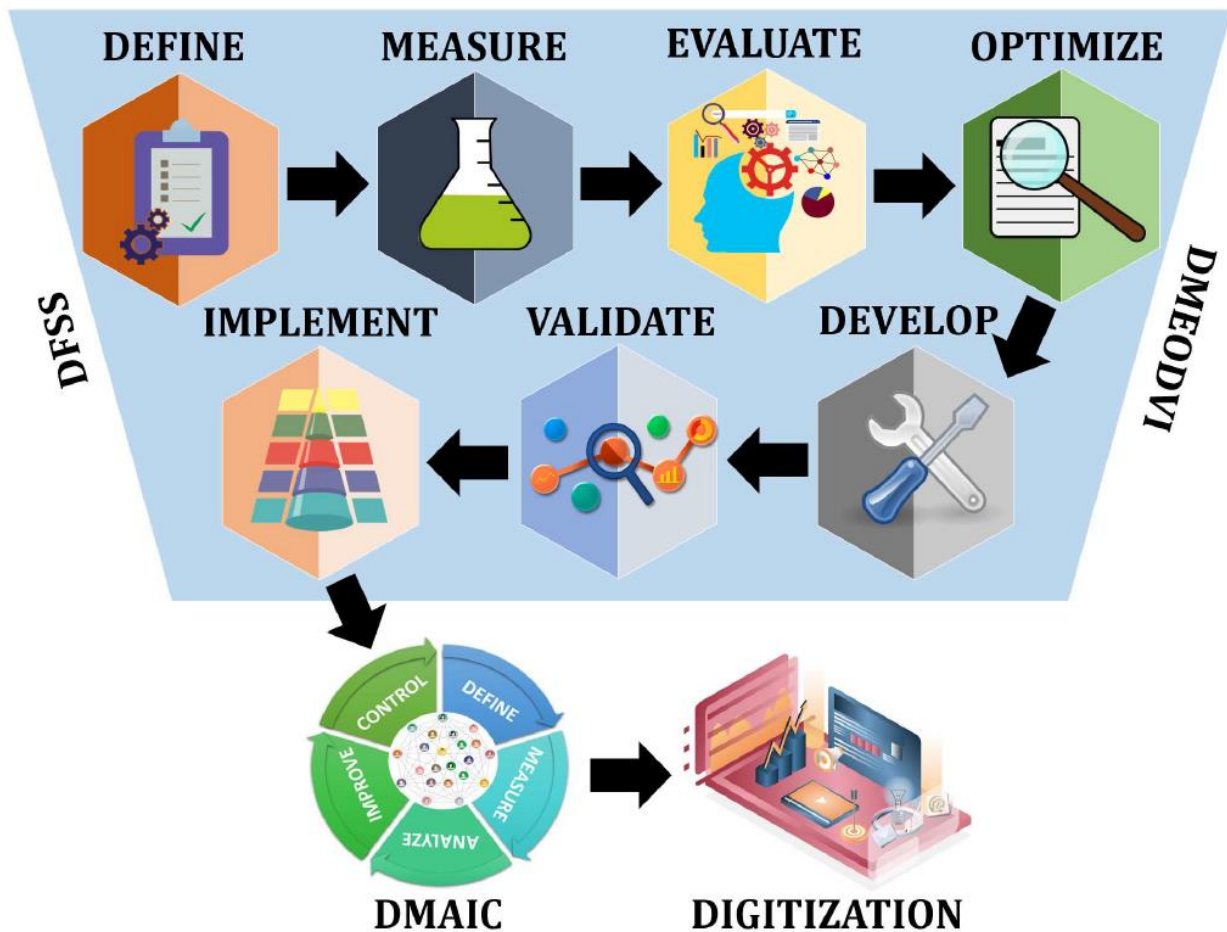


Figure 2-15: Manufacturing roadmap for Industry 4.0 steps (Butt, 2020).

Figure 2-15 shows details of the roadmap by Butt (2020) developed for manufacturing and details of the roadmap are below. Choosing an approach people are familiar with when implementing Industry 4.0 technology helps encourage more positive responses to

the new technology in the workforce. Modifying this approach to fit the unique company needs.

Butt (2020) presented a roadmap for Industry 4.0 technology in manufacturing. The seven phases of this roadmap were as follows:

- First phase: DEFINE
- Second phase: MEASURE
- Third phase: EVALUATE
- Fourth phase: OPTIMISE
- Fifth phase: DEVELOP
- Sixth phase: VALIDATE
- Seventh phase: IMPLEMENTATION

i. First phase: DEFINE

This phase involves defining the problem, identifying existing resource limitations, and developing a scope for Industry 4.0 technology. This phase should include external and internal stakeholders, such as management, customers, employees, and suppliers. Develop a transition team from all business sectors to ensure a uniform vision. The different steps in the transition should be mapped out in detailed project plans, with the work involved in each phase clearly stated. Identify strategies for the long-term, mid-term, and short-term Industry 4.0 technology (Butt, 2020).

This phase also involves defining the skill and training levels in the organisation required to compensate for the shortages in Industry 4.0 technology knowledge. There is also a need for a change management strategy for a smooth digital transition from traditional methods. 'Digitalisation' characterises Industry 4.0. Therefore, the IT department will be under pressure. The IT department must have a team responsible for organising the budget, strategy, execution, controlling, and reporting progress in the Industry 4.0 projects (Butt, 2020).

The supply chain must adapt to the changes introduced by Industry 4.0 technology. That implies that the suppliers that supply the digital technologies the implementing entity is applying should also adopt the approaches. The legal framework should include the

changes introduced by Industry 4.0 technology. With these changes, a risk management strategy to minimise the risk introduced was required (Butt, 2020).

ii. Second phase: MEASURE

This phase focuses on gathering data to understand the external and internal requirements of the company implementing the technology. Then addressing these requirements and Butt (2020) suggests using the Quality Function Deployment (QFD) to capture the requirement of the commissioning company. Butt (2020) recommends a Measurement System Analysis (MSA) to capture a realistic view. MSA assesses a measurement process typified by experiments that seek variation. The MSA elements investigated are stability, bias reproducibility, repeatability, and stability. This study recommends a Value Stream Map (VSM) for this phase.

iii. Third phase: EVALUATE

This phase benchmarks and documents the readiness of Industry 4.0 technology within an organisation. This phase can also compare critical quality processes with market leaders. From the benchmarks, develop new concepts. Butt (2020) recommends using Failure Mode and Effective Analysis (FMEA), cause-effect analysis, and others for the design process with the R&D team along with experts.

The Theory of Inventive Problem Solving (TRIZ) can solve frequent problems and save R&D time. After generating ideas for Industry 4.0 implementation, use the Pugh matrix to evaluate and identify the best design (Butt, 2020).

iv. Fourth phase: OPTIMISE

This phase involved building a detailed design. That is, performance is statistically and numerically analysed using software such as Anylogic for process flow CAD designs using Autodesk, among others (Butt, 2020).

v. Fifth phase: DEVELOP

This phase involves building a prototype based on the findings of the previous steps. This phase should evaluate the hardware and software demands from management and the IT department. Then, gather the resources and skills necessary for the prototype and an economic plan. Develop prototypes according to the findings of the simulations in previous steps and use these simulations as a validation tool. The prototype development

should be separate from the production line and should not disrupt the production line (Butt, 2020).

vi. Sixth Phase: VALIDATE

This step involves testing the prototype against the simulation model. The prototype is used as a means of risk mitigation, testing the actual performance of the new system in a controlled environment and confirming or disproving expectations before full implementation. Upon improvements at this stage, stakeholders can witness demonstrations of the new system, making convincing arguments for their application. Opinions of all stakeholders are necessary through this process (Butt, 2020).

A risk assessment is made based on the results of the pilot, and then, when the results are favourable, full-scale implementation can take place (Butt, 2020).

vii. Seventh Phase: IMPLEMENTATION

This step involved the full-scale implementation of the system with the necessary adjustments from the previous step. The implementation should focus on saving costs and applying the prioritisation matrix to select the priority steps. The biggest hurdle facing this will be resistance to change. Once the project meets the requirements set out at the beginning, standardise the processes used in this implementation. Then, a training plan for users follows. And a definition of new processes. The final system should be continuously improved and refined accordingly (Butt, 2020).

B. Second Roadmap for the Manufacturing Industry

Ghobakhloo (2018) developed a roadmap for technology adoption, detailed in Figure 2-16. The image shows the strategies from management, marketing, human resources, IT, manufacturing, and the entire supply chain.

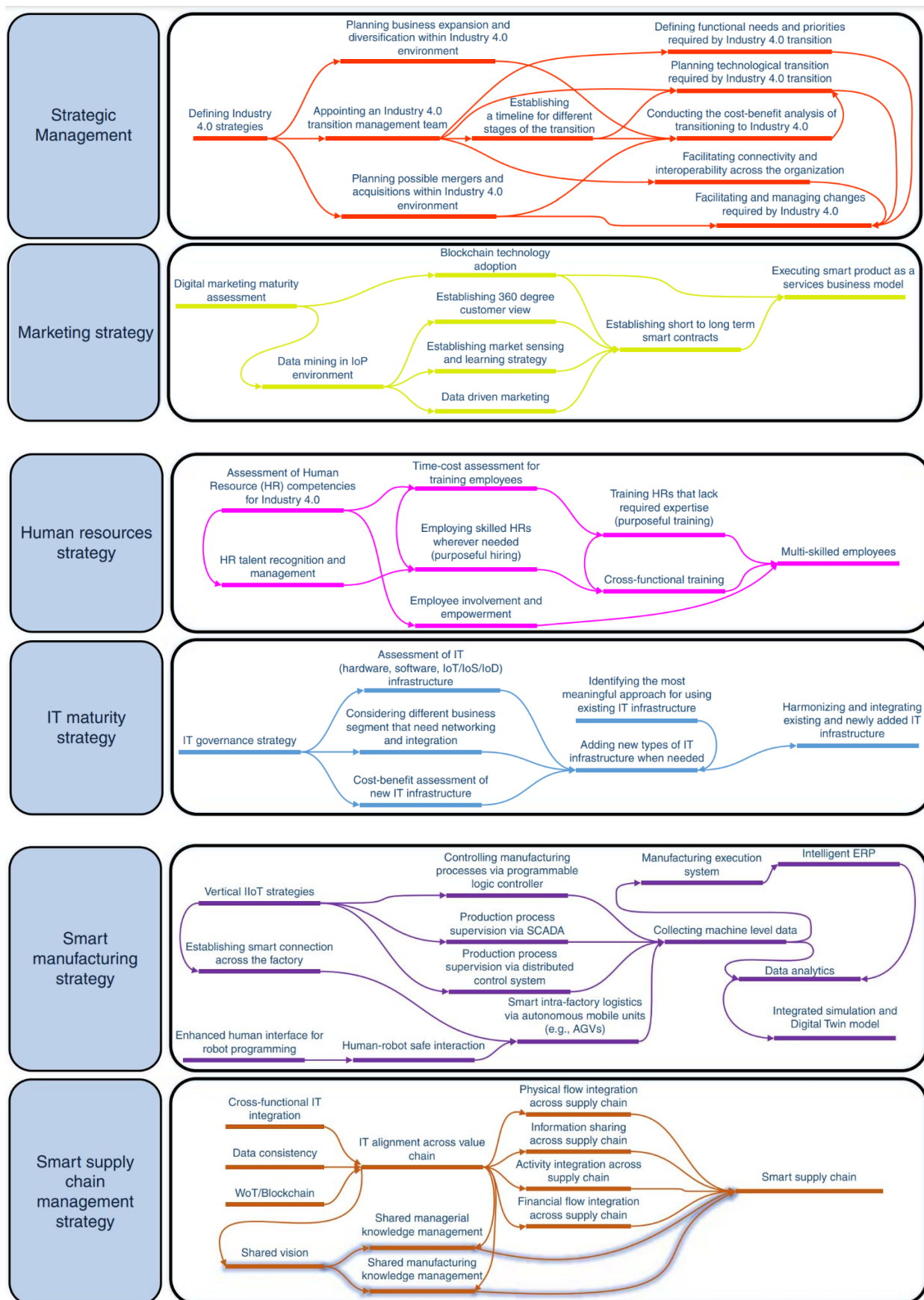


Figure 2-16: A strategic roadmap for transitioning into Industry 4.0 (Ghobakhloo, 2018).

C. Third roadmap for the manufacturing industry

Figure 2-17 shows a 10-step roadmap for technology adoption in manufacturing.

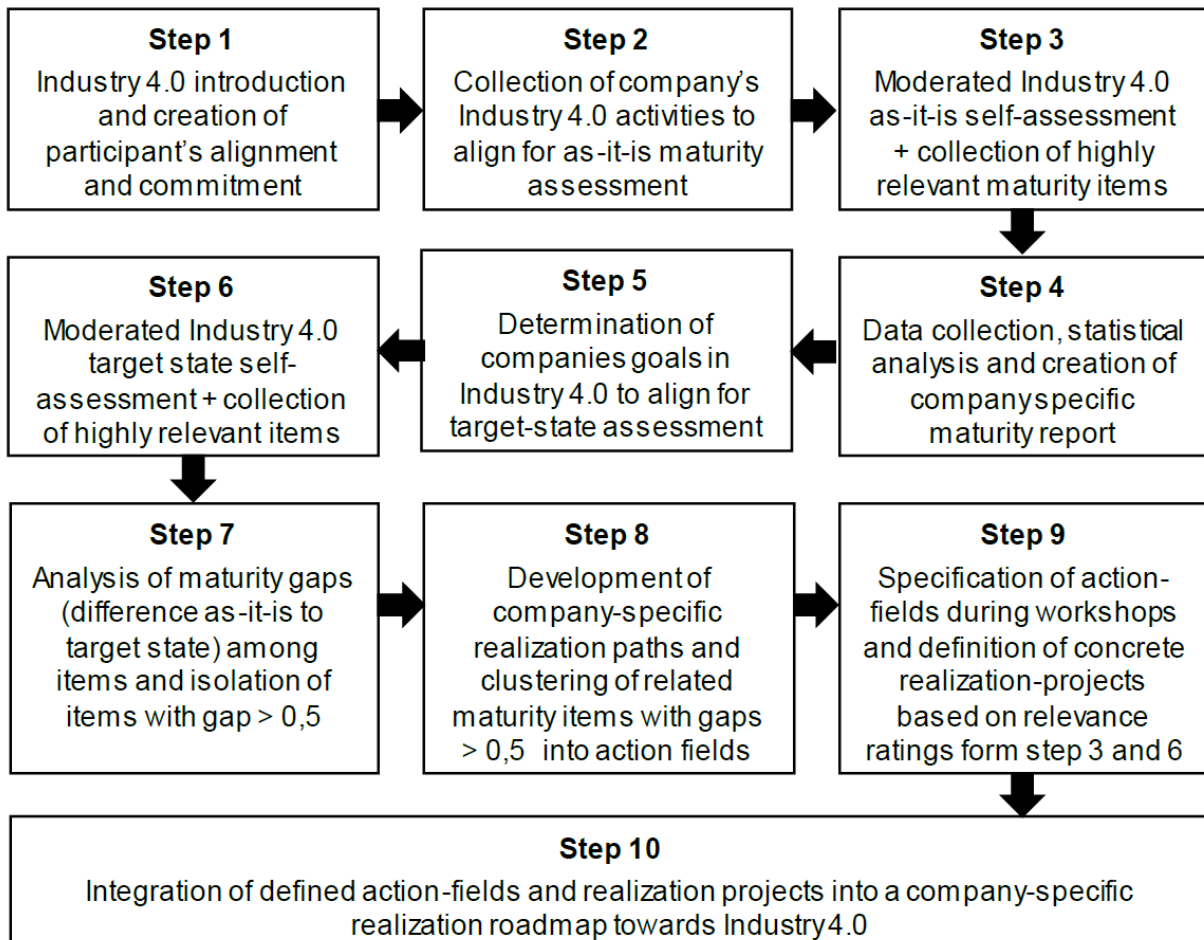


Figure 2-17: Manufacturing roadmap for Industry 4.0 steps (Schumacher et al., 2019).

2.10.2.2 Industry 4.0 implementation roadmaps in the construction industry

Figure 2-18 shows three different roadmaps for adopting technology for construction developed by Lau et al. (2019).

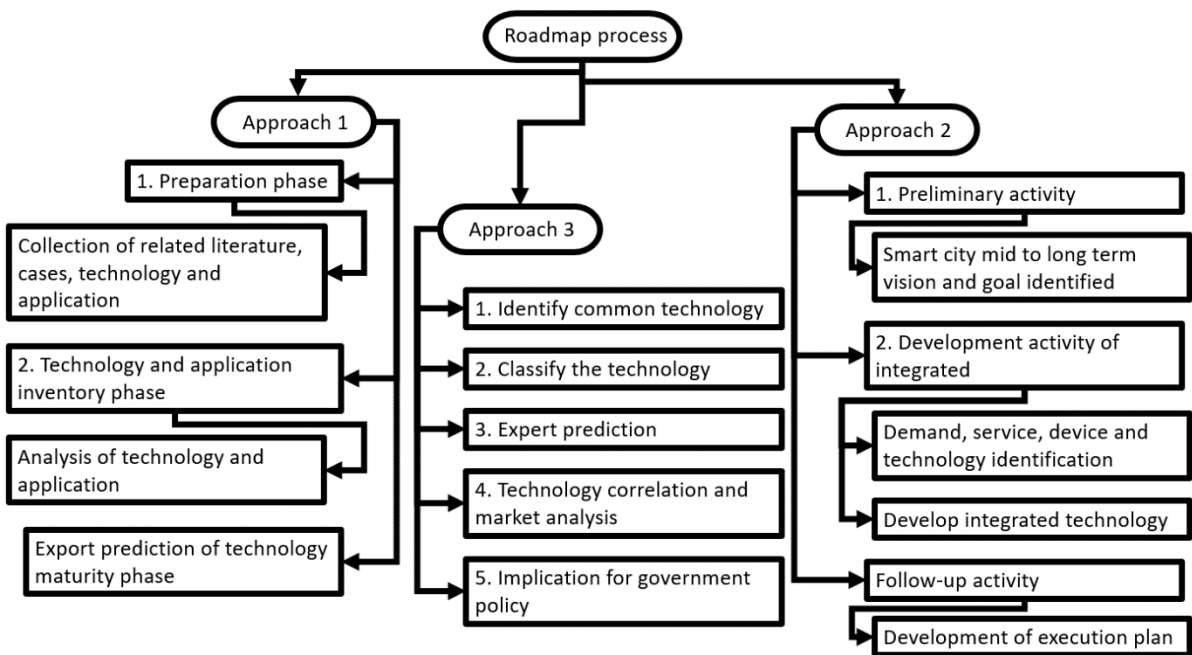


Figure 2-18: Differing roadmap approaches for the construction industry (Lau et al., 2019).

2.10.2.3 Generic Industry 4.0 roadmap

Figure 2-19 details a generic roadmap for technology adoption by Pessl et al. (2020).

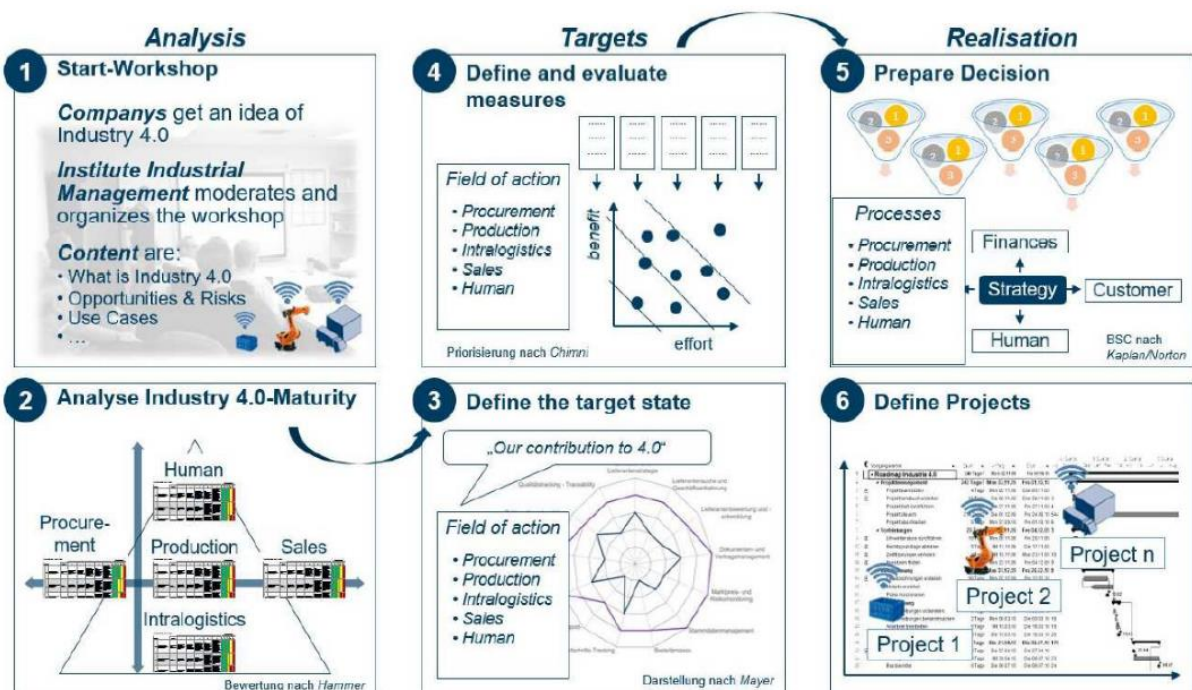


Figure 2-19: A generic roadmap for technology adoption (Pessl et al., 2020).

Pessl et al. (2020) developed a road map in three phases. The phases were analysis, goal setting, and implementation. Sequentially conducted these steps further divided the

roadmap into six steps. These further steps on the roadmap address production, purchasing, intralogistics, human resources, and sales.

The first step is to create awareness within the organisation, and employees should be involved. SWOT analysis should be part of this step. The second step is to gather data on the company's capabilities to implement Industry 4.0 technologies. The third step involved defining the target states by industry experts. Some techniques used in this step are morphological analysis and brainstorming. The fourth step must include drafting documents and measures to evaluate the differences between the expectations and the final results of the technology. Evaluating measures rating efforts and benefits from low to high with estimated costs. Step five involves the definition of objectives, their relevance, and the change they will add to the organisation. Step six involves connecting projects in Industry 4.0 implementation with budgets and using pilot projects recommended to gain the necessary experience before planning the next steps. That will allow for solving problems early in the implementation (Pessl et al., 2020).



Figure 2-20: Human resource development areas (Pessl et al., 2020).

Figure 2-20 shows the areas of development in human resources when implementing new technologies in a business environment.

2.10.3 South African Industry 4.0 implementation roadmaps

Fan (2019) developed a roadmap for effectively implementing technology in South African mines, focussing on the findings of a case study conducted at the Wits Mining Institute (WMI). The study examined the errors and acceptable judgments when installing Schauenburg's Mine-Wide Integrated Monitoring and Control System (MIMACS) II system. Figure 2-21, Figure 2-22, and Figure 2-23 show the roadmap for technology implementation.

Similar to the development steps of the roadmap detailed in section 2.10, the roadmap in Figure 2-21, Figure 2-22, and Figure 2-23 is in three phases.

Blueprint contents				
Main-phase	Sub-phase	Main-tasks	Check (tick)	Remarks
1. Pre - installation phase for technology system				
	1.1 Gather information on the actual entity's capacity	1.1.1 Commissioning entity's capacity		
		1.1.2 Commissioning entity's technological gap		
		1.1.3 Commissioning entity's expectations		
	1.2 Evaluate vendors, identify the potential technology systems	1.2.1 Information gathering on vendors and technology systems		
		1.2.2 Assessment and selection procedures for vendors and technology systems		

Figure 2-21: Pre-installation phase (Fan, 2019).

Blueprint contents				
Main-phase	Sub-phase	Main-tasks	Check (tick)	Remarks
2. Adoption phase for new digital technology				
	2.1. Legal documents drafting	2.1.1 Agreement drafting		
		2.1.2 Contracts drafting		
	2.2 Preparation work for adoption	2.2.1 Documents required for running the system		
		2.2.2 System requirement documents need to be prepared by vendors (Cawood, 2017)		
		2.2.3 Requirement for infrastructure upgrade		
	2.3 Adoption of new digital technology	2.3.1 Ensure implementation of legal documents		
		2.3.2 Budget control		
		2.3.3 Design and quality of civils work		
		2.3.4 Support & cooperation (communication)		

Figure 2-22: Installation phase (Fan, 2019).

Blueprint contents				
Main-phase	Sub-phase	Main-tasks	Check (tick)	Remarks
3. Post-adoption phase for new digital technology				
	3.1 System calibration, testing, and integration	3.1.1 System calibration		
		3.1.2 System testing		
		3.1.3 System integration		
	3.2 After sale services	3.2.1 Activities required to maintain continuous system functionality		
		3.2.2 Exit strategy		

Figure 2-23: Post-installation phase (Fan, 2019).

The three phases listed in Fan (2019) each have their challenges. In each of the phases, these were the challenges that each phase encountered.

Pre-installation challenges

- The appropriate identification and selection of technologies
- Budget overspends

Challenges of the installation phase

- Overspending
- Civil works construction delay
- Poor system compatibility
- System malfunction
- Unreliable communication system
- Faulty hardware design
- Restrictions on remote access
- Interruption in overall system functionality
- System integration problem

Post-installation phase challenges

- Poor after-sales support
- Insufficient provisions for future upgradability and system maintenance

2.10.4 Other roadmaps

Gerdsri et al. (2010) developed a technology implementation roadmap that combined Kotter's eight steps of change and Prosci's elements of change. The details of the roadmap are in Figure 2-24 and continued in Figure 2-25.

Change management concepts		Action plan to support the three-stage TRM implementation process	Stage of TRM implementation	Key success factors (KSFs)
Prosci's elements of change	Kotter's eight steps of change			
Awareness Desire Knowledge	Step 1: Create a sense of urgency	✓ Understand the value of applying TRM in the organisation	Initiation	✓ Acceptance of the initiative by key stakeholders ✓ Development of a customised TRM process
	Step 2: Form a guiding coalition	✓ Build awareness of why TRM implementation is needed		
		✓ Discuss the details of TRM concept		
		✓ Raise urgency of why TRM implementation is immediately necessary to all participating members		
	Step 3: Develop vision and strategy	✓ Develop a vision, objective, and scope of TRM implementation for the organisation		
		✓ Set the plan to roll-out TRM implementation		
		✓ Gain acceptance and sponsorship from top-management		
	Step 4: Communicate vision and strategy	✓ Communicate the vision for the buy-in and support from key players		
		✓ Form a working group responsible for activities related to TRM implementation		
		✓ Provide the fundamental concept of TRM to all participants		
		✓ Prepare all participants to be ready to implement the TRM process. Training sessions may be provided.		
		✓ Customise the generic TRM process to fit with the organisational setting		
Ability	Step 5: Empower people	✓ Plan and organise a series of workshop sessions to develop a roadmap	Development	✓ Content quality presented in the roadmap

Figure 2-24: A technology roadmap developed using change management concepts (Gerd Sri et al., 2010).

Change management concepts		Action plan to support the three-stage TRM implementation process	Stage of TRM implementation	Key success factors (KSFs)
Prosci's elements of change	Kotter's eight steps of change			
	Step 6: Create short-term wins	✓ Allocate responsibilities to each individual in the group as well as set up ground rules for the group participation ✓ Maintain the momentum and energy from all participants throughout the TRM development process ✓ Remove barriers blocking participants from carrying out their TRM activities ✓ Conduct debriefing and review sessions		✓ Knowledge sharing among different groups of participants
Reinforcement	Step 7: Consolidate gains	✓ Consolidate roadmaps into one master roadmap (if needed) ✓ Establish the procedures to review and revise a roadmap so that a roadmap can be kept alive	Integration	✓ Linkage between roadmap and corporate strategic plan
	Step 8: Anchor new approaches	✓ Integrate TRM process into organisation's existing processes ✓ Transfer ownership of the process to the proper group of people		✓ Continuation of technology roadmapping

Figure 2-25: A technology roadmap developed using change management concepts (Gerdri et al., 2010) Continued.

Figure 2-26 shows the level of effort required to develop a roadmap in technology, with the most effort in the initiation and integration steps matching the challenges mentioned by Fan (2019).

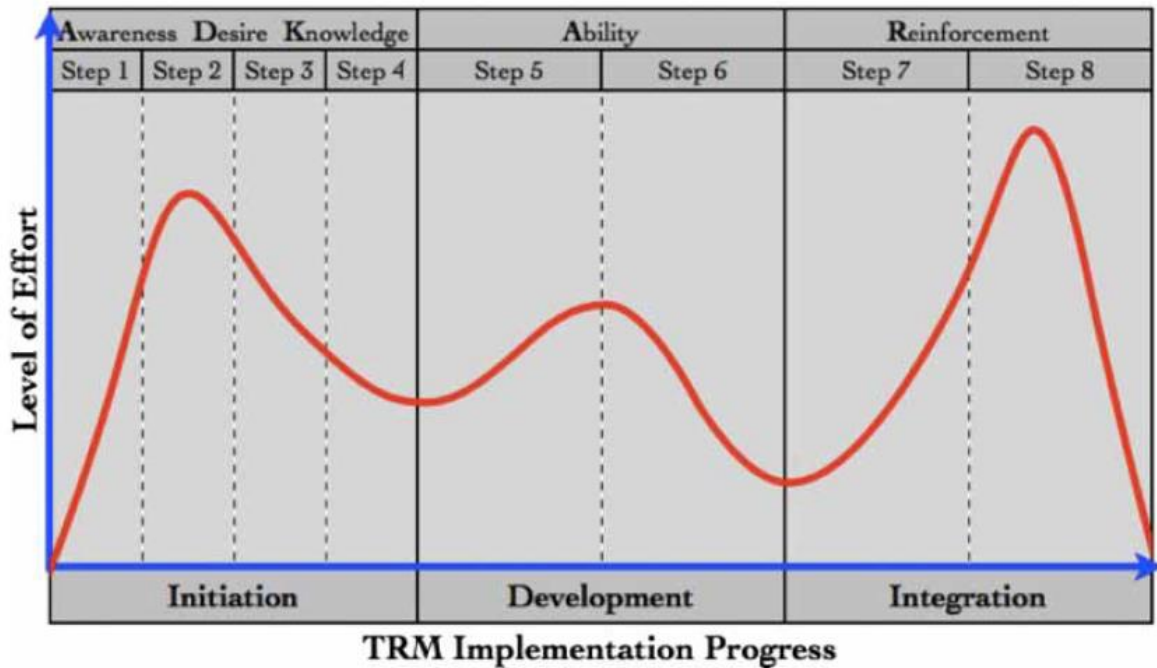


Figure 2-26: The effort levels required for each phase and step in implementing technology (Gerdson et al., 2010).

2.11 Technology Adoption/Acceptance Models (TAM)

2.11.1 Technology Acceptance Model (TAM)

According to the Theory of Reasoned Action (TRA), an individual's performance when performing a specialised action is labelled as behavioural intent (BI), which is influenced simultaneously by a person's attitude and subjective norm (Davis et al., 1989). Figure 2-27 details the TRA model.

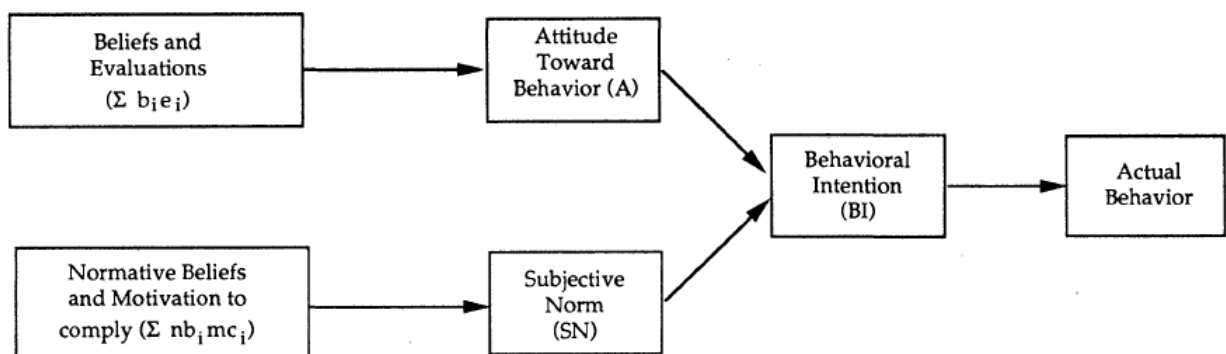


Figure 2-27: Theory of Reasoned Action TRA Model (Davis et al., 1989).

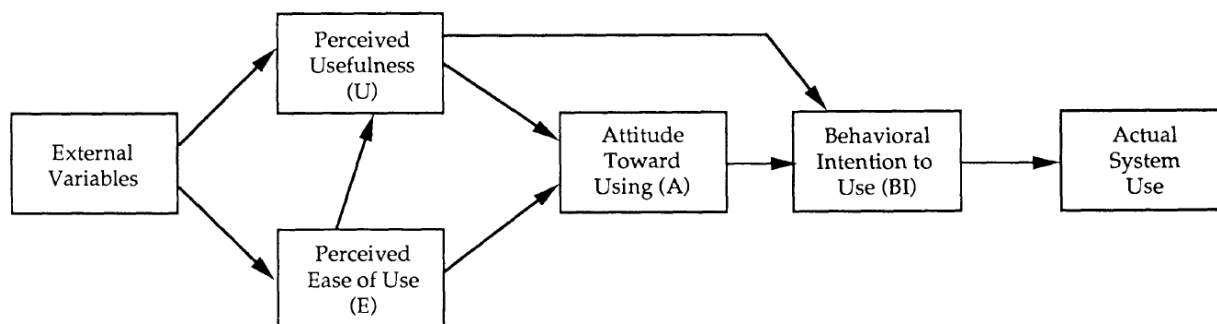


Figure 2-28: Technology Acceptance Model (TAM) (Davis et al., 1989).

Figure 2-28 details TAM found when investigating the use of computers. Davis et al. (1989) found that people's use of computers was predictable through their intentions, perceived usefulness determines people's use of computers, and perceived ease of use is a significant secondary influence on intention.

Important determinants that influence the use of the system are perceived ease of use and perceived usefulness. Perceived usefulness is when people tend to use or decide not to use an application based on whether it helped improve job performance. Perceived ease of use is the user's belief about the difficulty a system has when in use. Negative perceptions resulting from the level of effort outweigh the benefits of the performance. Perceived usefulness is a user's belief in a system that it improves their job performance. Perceived ease of use is the level at which an individual believes a system's usage was free of effort (Davis, 1989).

Perceived usefulness and ease of use were significantly correlated with self-reported use by respondents of Davis (1989). In the same study, usefulness was associated strongly with usage rather than ease of use. This study concluded that there was a direct correlation between user acceptance of new technology and perceived usefulness, affecting people designing a system or implementing one. Therefore, ease of use was of greater significance than usefulness, which was more significant than actual usage (Davis, 1989).

The lack of acceptance by users has hindered the successful implementation of information systems (Davis, 1993).

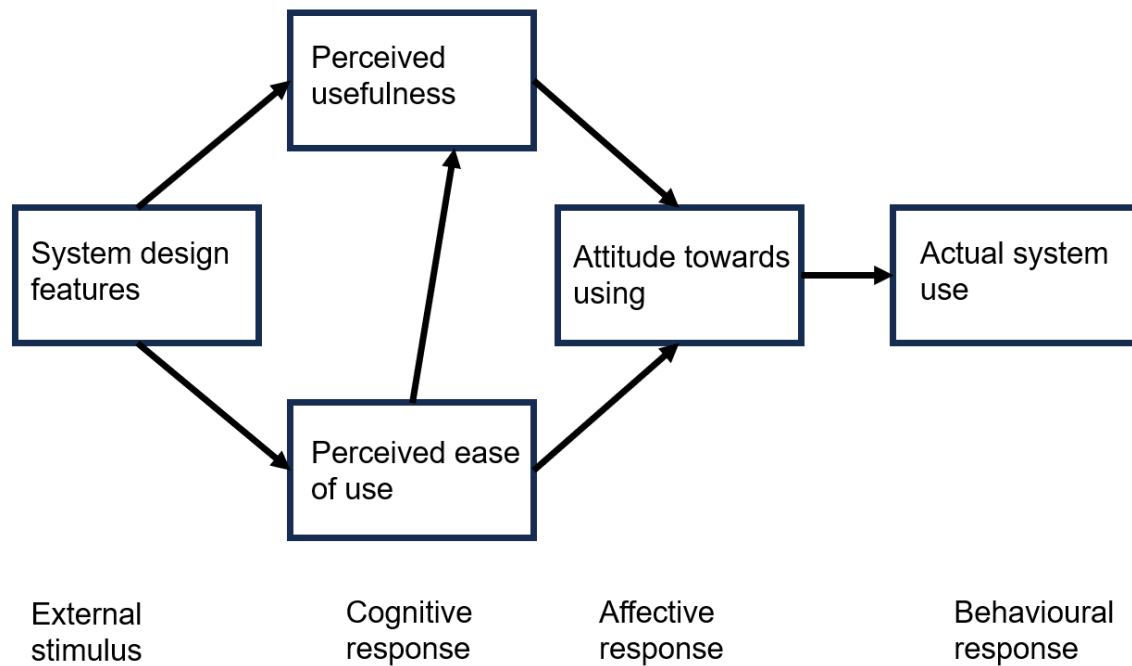


Figure 2-29: Technology Acceptance Model (TAM) (Davis, 1993).

Figure 2-29 shows a generic TAM. Characteristics such as perceived usefulness and ease of use influence behaviour but do not directly influence actual use. According to Davis (1993), usefulness influences direct use twice as much as attitudes toward use. Usefulness influences attitude four times more than ease of use.

Perceived ease of use compared to usefulness has little effect on attitudes, with attitudes indirectly influenced by usefulness (Davis, 1993). The ease of use affects the usage through usefulness. The cost of using a system to a user is the effort of use and is the opposite of ease of use (Davis, 1993).

2.11.2 Technology Acceptance Model (TAM) extension

Applying the TAM, Venkatesh and Morris (2000) explored differences between genders in the individual's adoption and continual usage of technology in the workplace, presented in Figure 2-30. In this figure, H1 to H6 represent the hypotheses about technology implementation influence due to gender in that study. H1 was that there was more influence on men than women from perceived usefulness on behavioural intention. H2a was that there was more influence on women than men from perceived ease of use on behavioural intention. H2b was that there was more influence on men than women from perceived ease of use to perceived usefulness. H3 was that there was more influence on

women than men from subjective norms on behavioural intention. H4 was that there was more influence on men than women from perceived usefulness on behavioural intention due to increasing experience. H5a was that there was more influence on women than men from perceived ease of use on behavioural intention due to increasing experience. H5b was that there was more influence on men than women from perceived ease of use on perceived usefulness due to increasing experience. H6 was that there was no influence on women or men from subjective norms on behavioural intention due to an increase in experience.

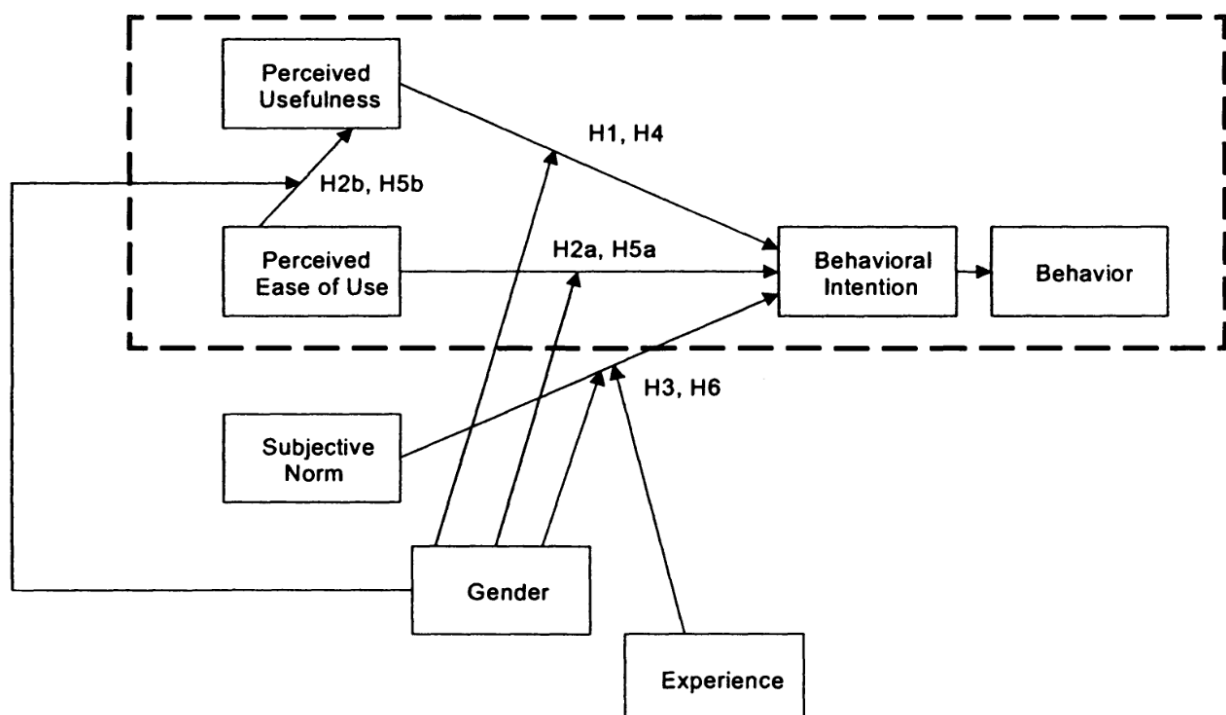


Figure 2-30: TAM extension (Venkatesh and Morris, 2000).

Perceived ease of use affects intention through a direct effect on intention and indirectly through perceived usefulness. That suggests that perceived ease of use could positively influence user acceptance (Venkatesh and Morris, 2000). The subjective norm is the level of an individual's belief in what people important in their lives think, which influences their performance or behaviour. Peers and superiors strongly influence subjective norms (Venkatesh and Morris, 2000).

Men consider perceived usefulness more than women in the decision to use new technology in the long and short term. The perceived ease of use influenced women more than men in the training stage and continues with more experience. Over time, perceived

ease of use for men increased with experience, while it decreased for women (Venkatesh and Morris, 2000).

At no stage were men's decision-making influenced by subjective norms. On the other hand, women considered this influence in the initial stages of technology implementation for up to a month, while after three months, subjective norms no longer influenced them (Venkatesh and Morris, 2000).

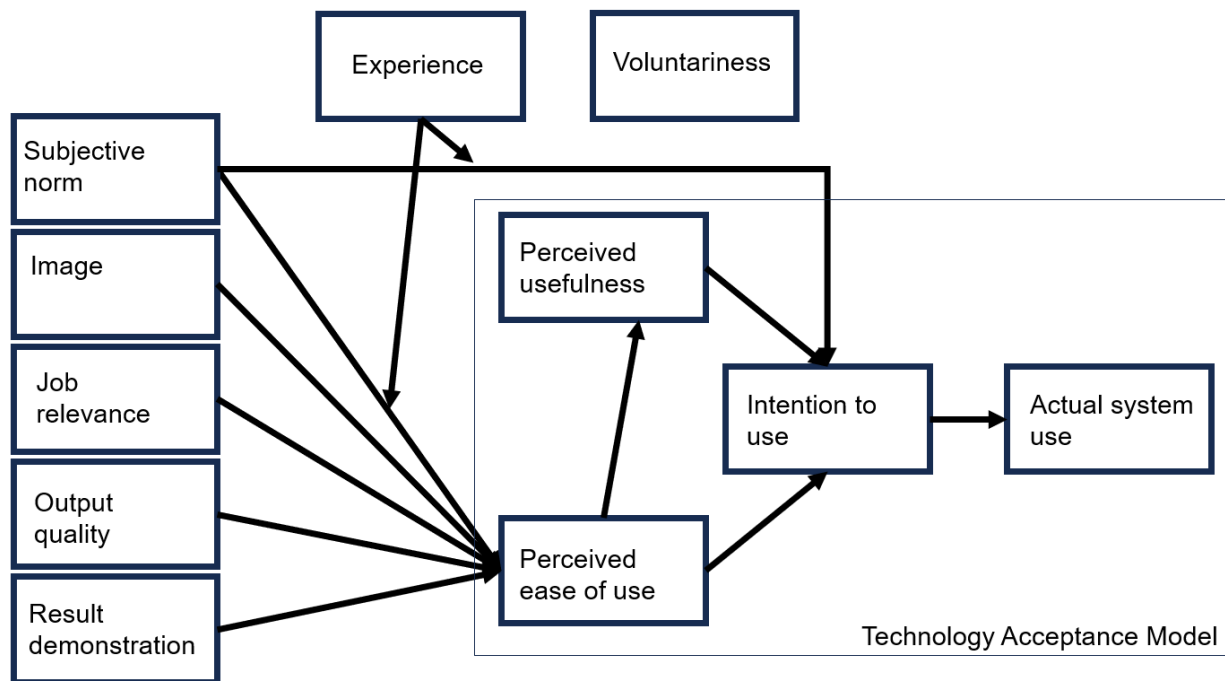


Figure 2-31: TAM2 Extension to TAM (Venkatesh and Davis, 2000).

Venkatesh and Davis (2000) also confirmed that perceived usefulness was a significant determiner of intention to use, while perceived ease of use was a secondary determinant. Venkatesh and Davis (2000) measured the support of TAM2 across three organisations through three phases. These phases were pre-implementation, implementation, and post-implementation.

TAM2 is an extension of TAM, showing that subjective norm influences usage intention more than perceived ease of use and perceived usefulness when the implemented systems are mandatory and not voluntary (Venkatesh and Davis, 2000). Subjective norms determined the influence on perceived usefulness. Social influence goes towards usefulness perception, which is called internalisation, and identification is when people

use a system to gain influence and status among their peers, with improved performance (Venkatesh and Davis, 2000).

As people gain experience with a system, they rely less on social influence on intention and perceived usefulness, but people still judge the usefulness on their potential status from using the system (Venkatesh and Davis, 2000). The output quality from a system and job relevance determine the perceived usefulness, which meant that judgment on the usefulness of a system was affected by the match between job goals resulting from system use, influence lasting over time, unlike social influences (Venkatesh and Davis, 2000). Figure 2-31 shows the extension of the TAM.

2.11.3 Unified Theory of Acceptance and Use of Technology (UTAUT)

Figure 2-32 details the underlying principles influencing users' technology acceptance.

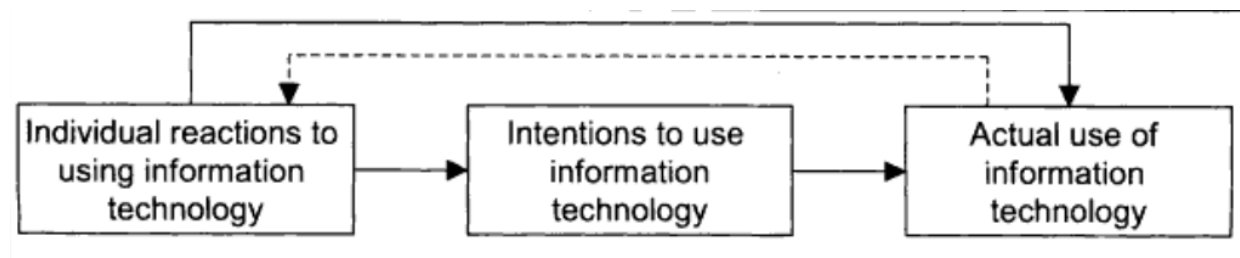


Figure 2-32: User acceptance model underlining principles (Venkatesh et al., 2003).

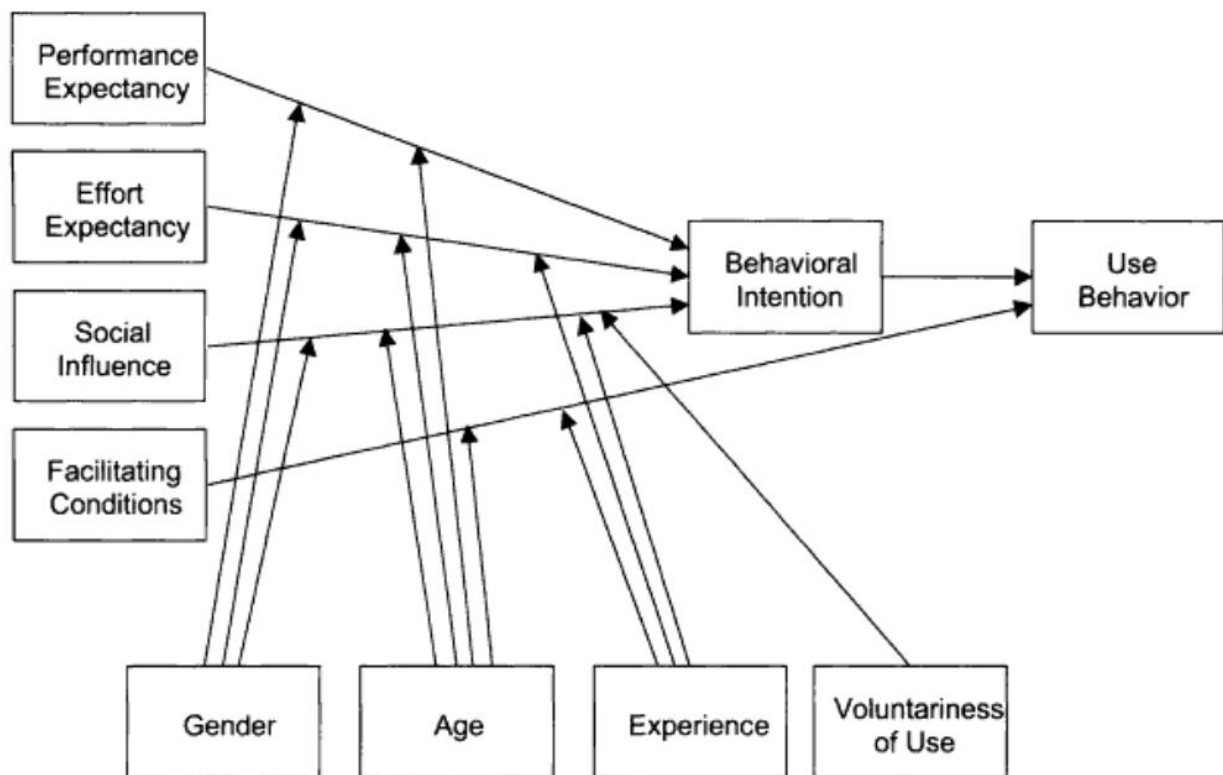


Figure 2-33: Unified Theory of Acceptance and Use of Technology (UTATU) (Venkatesh et al., 2003).

The formulation of the Unified Theory of Acceptance and Use of Technology (UTATU) consisted of seven constructs, with only four significantly influencing usage behaviour. These constructs were social influence, effort expectancy, performance acceptance, and facilitating conditions (Venkatesh et al., 2003). UTATU is in Figure 2-33.

In most situations, performance expectancy determines intention, and gender influences it along with age, but it is perceptible in younger workers and men. The influence of the expected effort on intention is determined by gender and age, with influence more significant on women and older workers, meaning its influence diminishes with experience (Venkatesh et al., 2003).

Performance expectancy is the extent to which the application of technology benefits the user when performing certain activities. **Effort expectancy** is the degree of ease with which the user uses the technology. **Social influence** is the degree to which users perceive the importance of technology to others, such as friends and family. Facilitating

conditions are the user's perceptions of the support and resources available for facilitating using the technology (Venkatesh et al., 2012).

2.11.4 Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)

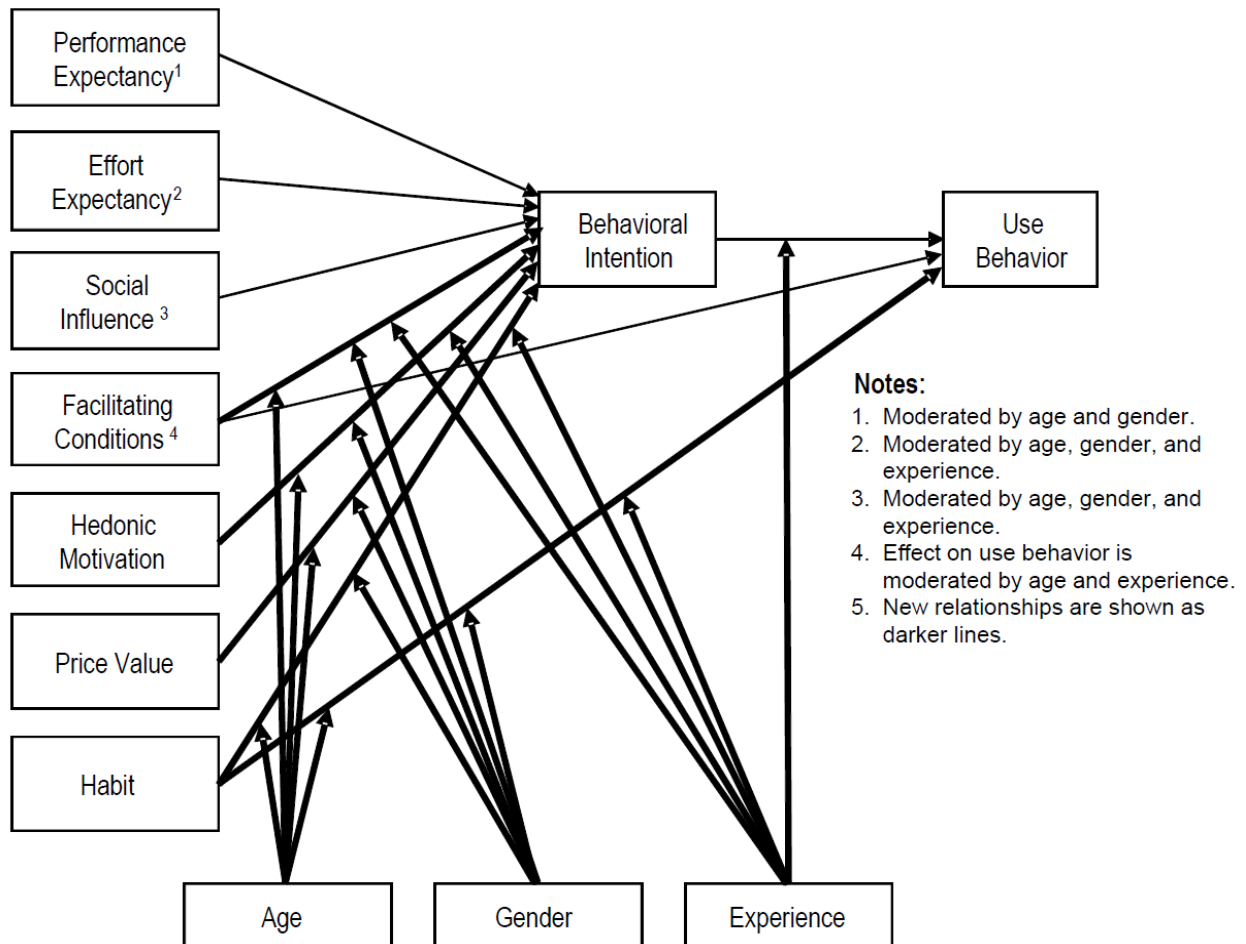


Figure 2-34: Unified Theory of Acceptance and Use of Technology (UTAUT2) (Venkatesh et al., 2012).

Figure 2-34 shows the UTAUT2 model. **Hedonic motivation** is the pleasure of using technology and shows the influence on technology use and acceptance (Brown and Venkatesh, 2005). The **price value** is the cost and pricing structure imposed on consumers of technology in the no-organisation setting, unlike in UTAUT, where there is no cost associated with purchasing the technology for the worker. Price can influence the use of technology (Venkatesh et al., 2012).

In the non-organisation context, performance expectancy is a less important driver of technology usage than hedonic motivation. Hedonic motivation influences younger men

with limited experience with technology, while price value influences mature women more (Venkatesh et al., 2012).

2.12 Technology implementation interventions

Technology implementation with intervention consequences can be controllable, with some interventions before or after resulting in positive results. These interventions are detailed below.

2.12.1 Pre-implementation interventions

You can reduce initial resistance by implementing previews similar to the future system so that users can be familiar with the system and its benefits to their work (Venkatesh and Bala, 2008). **User participation** is critical, especially in complex systems that cause significant changes to the work environment. Users directly or indirectly involved through their representatives in the implementation steps, such as prototype testing, can judge the system's relevancy, the quality it provides and the results, which are determinants of perceived usefulness. The involvement of the final user in the developing technology helps communicate top management's views on the system to the user, forming a social pressure that influences subjective norms (Venkatesh and Bala, 2008).

Hands-on experience with an implemented system may reduce users' anxiety due to system unfamiliarity. This can enhance users' perceived enjoyment, perception of external control, and subjective usability due to experience and familiarity with the new system (Venkatesh and Bala, 2008).

Management support is an individual's perceived degree of commitment from management towards "the successful implementation and use of a system". Due to the transformative nature of implementing the new systems, top management's support is crucial through communication and commitment. That legitimised the process of implementation and provided a morale boost. Management's direct involvement in the implementation reduces anxiety towards the system's use and impact (Venkatesh and Bala, 2008).

Incentive alignment needs to be in place for users to use the new system, as there may be a situation where the system is in place with users having a positive outlook towards the system in the form of users accepting the new technology, but it may not influence

the organisation's outcomes due to users lacking incentives to use the new system (Venkatesh and Bala, 2008).

2.12.2 Post-implementation interventions

Post-implementation interventions must provide employees with comfort with the new system and help them perceive it as an opportunity to improve their work performance. They should use the system with as little effort as possible, meaning all necessary resources associated with the system should be provided (Venkatesh and Bala, 2008).

Training may be one of the most critical post-implementation interventions, leading to more system success and user acceptance. Training takes place pre-implementation and post-implementation. Training can positively influence perceived usefulness and ease of use (Venkatesh and Bala, 2008).

Organisational support refers to informal or formal activities or functions that help employees effectively use a new system. The forms of support an organisation can provide include creating help desks, providing infrastructure, providing off-the-job training, and hiring system experts. This support is crucial, especially for the implementation of complex systems. Organisational support can influence perceived usefulness and perceived ease of use. Support can reduce the anxiety associated with using the new system (Venkatesh and Bala, 2008).

Peer support refers to co-workers' activities that help them to use a new system effectively. This support can help with the acceptance of the new system (Venkatesh and Bala, 2008).

2.13 Chapter summary

Many factors influence the mining industry's move toward Industry 4.0 technologies, including finances or investment, availability of minerals mined, geological and geographic locations of mines, the difficulty of mining, and environmental and social impacts, among others. These influences vary depending on the level of development that a country has achieved.

Both developed and developing countries have barriers and enablers to adopting technology. Barriers and facilitators in developed countries are prevalent in developing countries. However, developing countries do have barriers specific to developing

countries. These include the lack of awareness of the new technology, the level of skills required for the technology, the specialised education on the technology, the lack of financial resources, and the lack of understanding of the potential benefits, among others. That makes the case that adopting Industry 4.0 technology in developing countries requires a specific approach that fits the context of a developing country.

There was limited research on roadmaps and approaches to technology adoption specific to developing countries compared to developed countries. Most of the roadmaps included in this literature had three main phases in adopting technology. These were pre-installation, installation and post-installation. The pre-installation phase focused on planning, stakeholder involvement, gathering and evaluating resources. The installation phase focused on building pilots, testing and final implementation of the new technology. Lastly, the post-installation phase focused on support services for the latest technology systems. This study used the roadmaps in the literature to develop the roadmap in section 5.3. The full roadmap development details are in Chapter 5.

This literature review examined the TAM to understand the engagement between the human South African participants in the technology acceptance and the technology they will interact with as also strengthened by centre technology adoption (section 2.10). That together with the rest of the literature on other developing countries' technology implementation and developed countries on technology implementation, barriers and enablers to technology adoption, fast-tracking technology implementation and technology interventions (section 2.4 - 2.9), formed the basis for the different interactions the people of South Africa will potentially come to terms within an environment where Industry 4.0 technology is in the planning process of implementation, is being implemented and after the technology is already in place.

The details of these approaches are beyond the scope of this study, but they informed the approach to this study, which was technology implementation road mapping. The Technology Implementation Road mapping literature was the basis for the road map design, which was then sent to participants alongside insights from the additional literature, as mentioned previously. The central focus was on the human element from the literature to the survey from the literature on human subjects to the final participants. The roadmap was a step-by-step process for each phase, with additional details for each

step requiring additional study not covered in this study. The details of the method are in the chapter that follows.

CHAPTER 3 HUMAN-CENTRED ADOPTION OF MODERN TECHNOLOGY IN DEVELOPING COUNTRIES: A SYSTEMATIC REVIEW

3.1 Abstract

Implementing Industry 4.0 technology is the next step in innovation, and the mining industry is no exception. To examine the cutting edge of this technology, a systematic review of English articles using the PRISMA approach, searching Scopus and Web of Science databases, studies dated between 2018 and 2024, and searching titles, keywords and abstracts was conducted. The final studies were selected individually based on inclusion criteria based on context and relevancy. Results show limited available literature in developing countries on implementing Industry 4.0 technology and even less literature focusing on the mining industry specifically. Requirements for the successful implementation of Industry 4.0 technology are partnerships between all stakeholders, good leadership, research and development while overcoming challenges like people's hesitation towards the new technology and the lack of examples in the context of developing countries.

3.2 Introduction

Perceptions suggest there has been little research on modern technology adoption in general. That suggests the mining industry is suffering a similar fate. Mining companies are seeking methods to apply to their operations to fast-track such technological advancements, setting the basis for this study. That is a systematic literature review (SLR) surveying the literature on mining industry technology adoption in recent years in developing countries' mining or similar industry contexts. That was to find methods applied across the industry to gain a competitive edge or keep up with competitors within the space, as this is crucial.

Recent developments include using Industry 4.0 technology, such as simulation modelling, Digital Twins, and virtual reality, among others. Constant exploration of these technologies and their general directions is necessary.

There is a concern regarding how to use technology in a developing country like South Africa in the best possible manner. This study aims to address set concerns by surveying

literature around South Africa and other developing countries on how to successfully implement Industry 4.0 innovation in the mining industry while addressing the worries, including how to apply the technology in mining, this includes how to include the people in the process and keep up with the increasing demand over time of this technology among others. Since there is little to no literature on the mining industry specifically, this study included other similar industry literature. This review will add to the limited number of studies on technology adoption in developing countries and provide the latest trends in the sector.

Research question

- What are recent trends in using Industry 4.0 technology in developing countries' mining industry through a systematic literature review across publications?

The research question in this section relates to the research objectives in section 1.2.3.1 by giving background information on how best to apply Industry 4.0 technology in the developing countries context, which could be more suitable to the South African mining industry.

3.3 Method

3.3.1 Protocol

The SLR protocol for this study was an adapted version from Moher et al. (2010) and de Paula Ferreira et al. (2020). That is alongside snowball sampling for additional relevant literature. Snowball sampling was used in the study, as purposive sampling through the SLR did not yield adequate relevant literature. This study used the s stage k name Snowball sampling method by looking at references from literature identified in the databases in the initial search to name k additional relevant literature on Industry 4.0 technology implementation, and this can carry on in stages until an adequate sample size is gathered (Goodman, 1961a).

3.3.1.1 Background

An SLR can justify further investigation in a covered area and aggregate empirical studies, which are critical for academic inquiry (Moher et al., 2010; Kitchenham et al., 2010; Xiao and Watson, 2019). SLRs are methodologically rigorous research reviews of results, and their purpose is not just to gather existing evidence but also to develop

evidence-based guidelines (Kitchenham et al., 2009). Assessing the value of SLR research is done by considering the conduct of a study, its findings and how encompassing the reporting is. The quality of SLRs differs across studies, which hampers the audience's ability to gauge the strengths and weaknesses of SLRs (Moher et al., 2010). Literature reviews help identify the frontier of research and help build on it. Literature reviews should be repeatable, valid and reliable (Xiao and Watson, 2019).

SLRs are required to be transparent and repeatable. SLR follow four phases:

1. Planning
2. Sampling
3. Analysis
4. Reporting

The planning phase involves justifying objectives and scope. Then, screening central articles. The sampling is searching and selecting articles. The analysis is the extraction and coding of data. The last step of reporting is writing the report and putting the evidence collected into practice (Kitchenham et al., 2009).

3.3.1.2 PRISMA meeting

A group of international collaborators met in 1996 to discuss meta-analyses of suboptimal reporting methods. They developed a guidance method called QUOROM Statement (quality of reporting of meta-analyses). The QUOROM Statement was updated by (Moher et al., 2010) to PRISMA (preferred reporting items for systematic reviews and meta-analyses). The PRISMA approach was to solve practical and practical advances in the science of SLRs.

Outcome-level versus study-level risk of bias assessment

Both a study-level and outcome-level risk of bias assessment are required. To complete an outcome-level evaluation of bias, data reliability and validity checks for each critical outcome by determining methods used in the original individual study are necessary (Moher et al., 2010).

The importance of reporting bias

The SLR method aims to be unbiased by being repeatable and auditable (Kitchenham et al., 2010). All reporting biases may negatively affect an SLR's conduct and interpretation. Consider bias such as selective reporting of complete studies (bias towards certain publications/gain for publication from only reporting beneficial information) and outcome reporting bias (reporting results that omit other results) when reporting SLR results. It is critical to indicate whether an SLR is an update of an existing SLR and a description of the changes made to the procedures from the original protocol (Moher et al., 2010).

The PRISMA statement

The PRISMA statement is a 27-item checklist alongside a four-phase flow diagram. Although PRISMA was developed originally for randomised trials, it can be used in other types of research, especially in assessing the success of an intervention. However, PRISMA cannot gauge the quality of a SLR. Modification of the checklist is necessary depending on the circumstances surrounding the SLR at hand (Moher et al., 2010).

Table 3-1 details the adapted PRISMA checklist for SLRs from Moher et al. (2010). The adapted PRISMA checklist used in this study omitted items 13, 14, 19, 20, 21 and 22. That was due to the nature of this research, and these checklist items related to meta-analysis were not included in this SLR.

Table 3-1: Checklist of steps completed in the SLR. Adapted and modified from (Moher et al., 2010).

Section/topic	Item number	Checklist item	Reported on page #
TITLE			
Title	1	Identify the report as a systematic review, meta-analysis, or both.	Page 74
ABSTRACT			
Structured summary	2	Provide a structured summary including, as applicable, background, objectives, data sources, study eligibility criteria,	Page 74

		participants, and interventions; study appraisal and synthesis methods; results; limitations; conclusions and implications of key findings; systematic review registration number.	
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of what is already known.	Page 74
Research question	4	An explicit statement addressing questions regarding participants, interventions, comparisons, outcomes, and study design (PICOS).	Page 74
METHODS			
Protocol and registration	5	Indicate if a review protocol exists, if and where it can be accessed (e.g., Web address), and, if available, provide registration information, including registration number.	Page 75 and page 81
Eligibility criteria	6	Specify study characteristics (e.g., PICOS, length of follow-up) and report characteristics (e.g., years considered, language, publication status) used as criteria for eligibility, giving rationale.	Page 81 to page 83
Information sources	7	Describe all sources (e.g., databases with coverage dates, contact with study authors to identify additional studies) in the search and the date last searched.	Page 81 to page 82

Search	8	Present a fully electronic search strategy for at least one database, including any limits used, for it to be repeatable.	Page 81 to page 82
Study selection	9	State the process for selecting studies (i.e., screening, eligibility, included in the systematic review, and, if applicable, included in the meta-analysis).	Page 81 to page 85
Data collection process	10	Describe the method used for data extraction from reports (e.g., piloted forms, independently, in duplicate) and any processes for obtaining and investigators confirming data.	Page 81 to page 85
Data items	11	List and define all variables for which data were sought (e.g., PICOS, funding sources) and any assumptions and simplifications made.	Page 89 to page 119
Risk of bias in individual studies	12	Describe methods used for assessing the risk of bias in individual studies (including specification of whether done at the study or outcome level) and how usage of this information and any data synthesis will occur.	Page 88
Risk of bias across studies	15	Specify any assessment of the risk of bias that may affect the cumulative evidence (e.g., publication bias, selective reporting within studies).	Page 88
Additional analyses	16	Describe methods of additional analyses (e.g., sensitivity or subgroup analyses,	Page 88

		meta-regression), if done, indicating which were pre-specified.	
RESULTS			
Study selection	17	Give the number of studies screened, assessed for eligibility, and included in the review, with reasons for exclusions at each stage, ideally with a flow diagram.	Page 89 to Page 117
Study characteristics	18	For each study, present characteristics for which data were extracted (e.g., study size, PICOS, follow-up period) and provide the citations.	Page 85
Additional analysis	23	Give results of additional analyses if done (e.g., sensitivity or subgroup analyses, meta-regression [see Item 16]).	Page 109 to Page 117
DISCUSSION			
Summary of evidence	24	Summarise the main findings, including the strength of evidence for each principal outcome; consider their relevance to critical groups (e.g., health care providers, users, and policymakers).	Page 89 to page 115
Limitations	25	Discuss limitations at the study and outcome level (e.g., risk of bias) and the review level (e.g., incomplete retrieval of identified research, reporting bias).	Page 88

Conclusions	26	Provide a general interpretation of the results in the context of other evidence and implications for future research.	Page 117 to page 120
FUNDING			
Funding	27	Describe funding sources for the systematic review and other support (e.g., data supply) and the role of funders for the systematic review.	Page 121

Figure 3-1 details the flow diagram to follow when using the PRISMA approach for SLR research.

3.3.1.3 Scopus Search and Web of Science

The search keyword used was Mining 4.0 to ensure that the search results were on implementing Industry 4.0 technology in mining. The search fields in Scopus and Web of Science searches were limited to document titles, abstracts and keywords (Albliwi et al., 2014). To restrict the search scope to the latest research, the range of years was between 2018 and 2024, which ensured that the studies were at the cutting edge of research. All researchers selected affiliated with research institutions in developing countries as a limiting criterion for the searches in line with the study objective. The language for all papers was English. More details are in Table 3-2 below.

Table 3-2: Search protocol for Scopus and Web of Science search.

Purpose of the study	To identify recent trends in the use of Industry 4.0 technology in developing countries' mining industry through a systematic literature review across publications.
Inclusion criteria	- Industry 4.0 implementation in the mining industry or similar industry. - Studies published between January 2018 and 29 October 2024.

Exclusion criteria	• No full-text available • Not in English
Keywords	• Mining 4.0 • Developing countries (article focusing on developing countries).
Search fields	• Title • Abstracts • Keywords
Document types	• Journal articles, • Conference papers • Books
Search databases	• Scopus • Web Of Science

3.3.1.4 Text mining techniques

The software tool used to create “maps based on network data and for visualisation” is VOSviewer. This software can create visualisations of individual publications, journals, research organisations, keywords, co-authorship, co-citations, and countries through databases like Scopus, ScienceDirect and Web of Science (van Eck and Waltman, 2023).

3.3.2 Eligibility Criteria

Study focus area: Upon initial review, the studies included had to have an Industry 4.0 application in mining or similar industries, as this is the primary area of focus of the study. The scope also had to fit a final review and final inclusion in this review. Table 3-3 below details this further.

3.3.3 Study Selection Steps

The basis for the study selection is the abovementioned criteria. Table 3-3 and Figure 3-1 below detail the study selection from all studies identified to the number of studies used in the final analysis.

3.3.4 Data Collection for Quantitative Analysis

Data collection was in two phases. The first phase was the quantitative stage of the study, and the second was the qualitative stage. Data collection for the quantitative analysis was from the search fields mentioned in Table 3-2 used for search in Scopus and Web of Science. The initial search yielded 248 studies.

3.3.5 Data Collection for Qualitative Analysis

The inclusion and exclusion criteria from Table 3 were used in this study phase. The basis for the exclusion and inclusion criteria is what was deemed relevant to the objective of this study by the author. If a study meets the inclusion criteria, it features in the qualitative analysis stage of this study.

Of the original 248 studies, 158 were from the Scopus search and 90 from the Web of Science search. The researcher scanned through the titles, abstracts, and keywords of the studies and accordingly selected studies relevant in that they were in the context of a developing country, in the mining or similar industry, focusing on Industry 4.0 applications. This phase relied on the author's discretion to select whether a study was relevant to this study.

From the list of 248 studies, excluding 94 due to the unavailability of full text. Then, an additional 124 exclusions based on inclusion and exclusion.

3.3.5.1 Detailed Search Protocol

Scopus search

The search steps were detailed in section 3.3.1.3. The search resulted in 158 publications, with 29 used in the final qualitative analysis. All found studies used quantitative analysis.

Web of Science search

The search steps were detailed in section 3.3.1.3. The search found 90 publications, with one used in the final qualitative analysis. All publications were already found in the Scopus search.

Table 3-3: Inclusion and exclusion criteria.

Criteria	Description	Total occurrences	
		Scopus	Web of Science
Exclusion criteria (E)	E1: Excluded due to not meeting any inclusion criteria.	154	107
Inclusion criteria (I)	I1: Industry 4.0 implementation in the mining industry.	14	4
	I2: Industry 4.0 implementation in industries similar to the mining industry.	15	5
The total included in the qualitative analysis		29	9

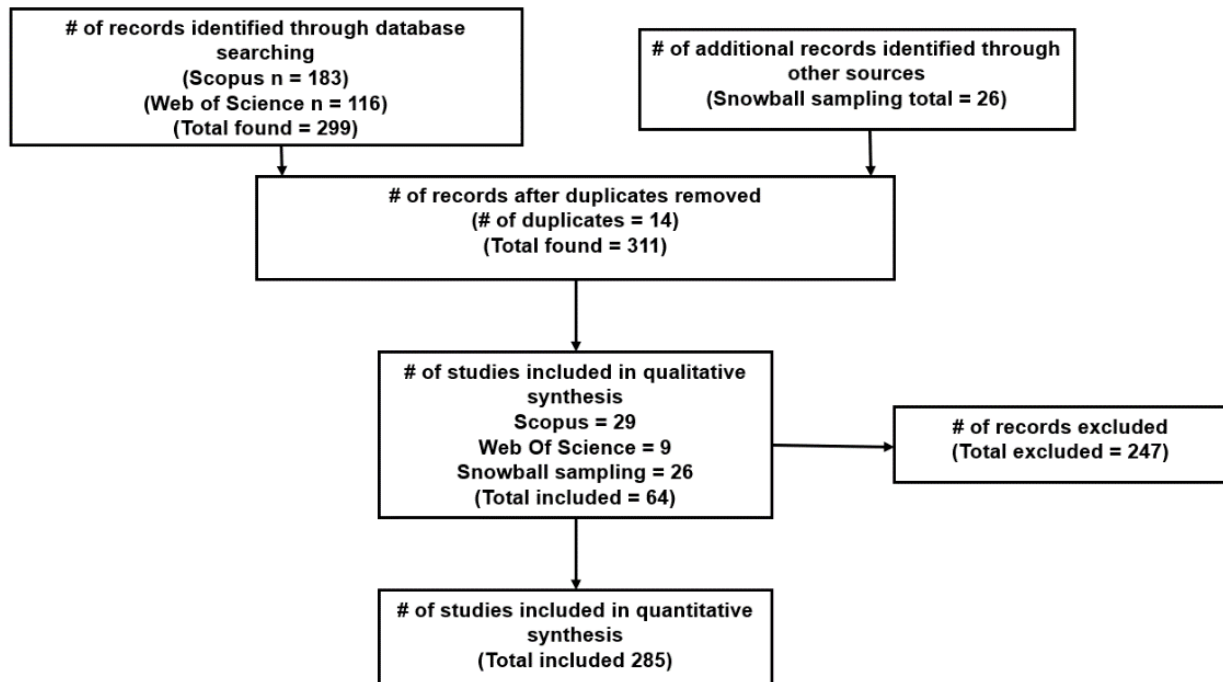


Figure 3-1: Adapted PRISMA flow diagram in (Moher et al., 2010). The study steps from study selection to write-up.

Figure 3-1 details all the literature found and used for the qualitative analysis, while Table 3-3 totals only include literature used for the qualitative analysis.

3.3.5.2 Study characteristics (qualitative analysis)

Table 3-4: The characteristics of selected studies.

Characteristics for which data were extracted	Study citation
1. Move towards Industry 4.0 technology	(Adenuga et al., 2020); (Aghimien et al., 2022); (Bag and Pretorius, 2022); (Bag et al., 2018); (Bag et al., 2021); (Botha, 2019); (Bowie, 2022); (Coetzer et al., 2020); (Coetzer et al., 2023); (Coopasamy and Botha, 2022); (Kohl and Swartz, 2019); (Maasz and Darwish, 2018); (Marnewick and Marnewick, 2020); (Mayer and Oosthuizen, 2020); (More et al., 2020); (Mpofu and

	Nicolaides, 2019); (Nell et al., 2019); (Nkonyana et al., 2019); (Oláh et al., 2020); (Prinsloo et al., 2019); (Ramdass and Mokgohloa, 2022); (Thekkoote, 2022); (Tissir et al., 2023); (Murugaiyan and Ramasamy, 2021); (Tavana et al., 2022); (Malik et al., 2023); (Hosseini et al., 2023); (Lin et al., 2023); (Dhamija, 2022); (Shamim et al., 2019); (Bag et al., 2020); (Buddhan et al., 2019); (Ajayi and Laseinde, 2021); (Hoffmann Souza et al., 2020); (Sivanuja and Sandanayake, 2022); (Telukdarie and Sishi, 2018); (Laosiritaworn and Chattinnawat, 2019); (Agbehadji et al., 2021); (Kamalakannan et al., 2024); (Cacciuttolo et al., 2023)
2. Effect of Industry 4.0 technology on people	(Aghimien et al., 2022); (Bag et al., 2022); (Bag et al., 2018); (Bag et al., 2021); (Botha, 2019); (Chidoori and Van Belle, 2020); (Coetzee and Veldsman, 2022); (Coetzer et al., 2020); (Coetzer et al., 2023); (Coopasamy and Botha, 2022); (Maasz and Darwish, 2018); (Marnewick and Marnewick, 2020); (Mayer and Oosthuizen, 2020); (More et al., 2020); (Mpofu and Nicolaides, 2019); (Oláh et al., 2020); (Oosthuizen, 2022); (Prinsloo et al., 2019); (Ramdass and Mokgohloa, 2022); (Roberts et al., 2022); (Uys and Webber-Youngman, 2019); (Bag and Pretorius, 2022); (Maganga and Taifa, 2023); (Buddhan et al., 2019); (de Moura et al., 2021); (Ajayi and Laseinde, 2021); (Ammirato et al., 2023); (Al-Banna et al., 2023a)
3. Benefits of Industry 4.0 technology	(Adenuga et al., 2020); (Bag and Pretorius, 2022); (Bag et al., 2022); (Botha, 2019); (Bowie, 2022); (Coetzer et al., 2023); (Maasz and Darwish, 2018); (Marnewick and Marnewick, 2020); (Mayer and Oosthuizen, 2020); (More et al., 2020); (Mpofu and Nicolaides, 2019); (Nkonyana et al., 2019); (Oláh et al., 2020); (Ramdass and Mokgohloa,

		2022); (Aghimien et al., 2022); (Malik et al., 2023); (Hosseini et al., 2023); (Lin et al., 2023); (Bag et al., 2020); (de Moura et al., 2021); (Jiskani et al., 2023); (Wang et al., 2019); (Xie et al., 2022); (Agbehadji et al., 2021); (Liu et al., 2024); (Tripathi et al., 2024); (Cacciuttolo et al., 2024); (Restrepo-Arias et al., 2022); (Sadiq et al., 2021); (Laiton-Bonadiez et al., 2022);
4. Challenges with Industry 4.0 implementation		(Bag et al., 2022); (Bag et al., 2018); (Mayer and Oosthuizen, 2020); (More et al., 2020); (Mpofu and Nicolaides, 2019); (Prinsloo et al., 2019); (Roberts et al., 2022); (Aghimien et al., 2022); (Bowie, 2022); (Coetzer et al., 2020); (Chidoori and Van Belle, 2020); (Sivanuja and Sandanayake, 2022); (Sellami et al., 2020); (Agbehadji et al., 2021); (Al-Banna et al., 2023a); (Joshi et al., 2024); (Sajjad et al., 2024); (Liu et al., 2024); (Sadiq et al., 2021)
5. Types of implemented technology		(Adenuga et al., 2020); (Bag and Pretorius, 2022); (Bag et al., 2022); (Dhamija and Bag, 2020); (Maasz and Darwish, 2018); (Mondejar et al., 2021); (More et al., 2020); (Nkonyana et al., 2019); (Prinsloo et al., 2019); (Oosthuizen, 2022); (Murugaiyan and Ramasamy, 2021); (Buddhan et al., 2019); (Laosiritaworn and Chattinnawat, 2019); (Xie et al., 2022); (Liu et al., 2024); (Tripathi et al., 2024); (Laiton-Bonadiez et al., 2022)
6. Method		(de Paula Ferreira et al., 2020); (Moher et al., 2010); (Goodman, 1961a); (Kitchenham et al., 2010); (Xiao and Watson, 2019); (Kitchenham et al., 2009)

3.3.6 Summary Measures

3.3.6.1 Phase 1

The primary measure for the qualitative analysis was to determine the direction of Industry 4.0 implementation in developing countries and how it applies to mining and related industries today.

3.3.6.2 Phase 2

The primary measure of the quantitative analysis was to determine the amount of research by researchers in developing countries on Industry 4.0 implementation strategies and general trends in the amount of research in recent years. Visualisations of the relationships between the articles used VOSviewer and Excel software and graphics developed by the author from the search results (van Eck and Waltman, 2023).

3.3.7 Limitations

3.3.7.1 Risk of bias in individual studies

Akin to the methods used in Bag and Pretorius (2022), the researcher used Scopus and Web of Science databases as the core data sources. Relying on these two sources of information limits the search, introducing the possibility of missing out on other literature on other databases, so snowballing was used in addition to the articles identified on the two databases.

First, a single author reviewed all the research studies used in this study (an additional two co-authors reviewed the SLR after it was compiled with by the first author). That meant a decrease in bias or risk of bias introduced to the study because there were independent secondary reviewers of the selected studies. To limit the risk of additional bias introduction, the author relied on the search string results only, and no introduction of subjectively selected studies was for examination. The author also thoroughly examined the titles, abstracts and keywords of the studies included and those excluded to ensure that they met the criteria for such exclusion or inclusion for this study.

3.3.7.2 The need for more literature

As mentioned by Bag et al. (2021), interpreting this study's findings should be done in the context of an emerging economy, as the topic requires further exploration. There's a lack of research on adopting Industry 4.0 technology in sustainable manufacturing and circular

economies (Bag and Pretorius, 2022). Bag et al. (2022) suggest employing their findings by other comparable manufacturing companies to aid the progression of digital transformation. This study was also limited to an emerging economy, and the literature suggests that such economies lag in digital manufacturing compared to more developed economies.

Mpofu and Nicolaides (2019) explained the lack of literature on Industry 4.0 adoption and its impact on humans relating to South Africa (SA context). There is limited research on the application of digital technology in mines. There is a need for further research into Big Data analytics throughout the mining production cycle (More et al., 2020). The lack of literature relating to instances of machine innovation is a limitation (Botha, 2019). There is still a need for more understanding of digitalisation and its influence on the construction industry in South Africa. South Africa has limited digital know-how, making it difficult to implement digital tools (Aghimien et al., 2022). This study also mentions the need for more literature on the perceptions of the South African public on how they believe Industry 4.0 will affect them (Roberts et al., 2022).

The mentioned literature shows the limits of doing a digital technology study in developing countries like South Africa and how far behind developing countries are in researching the topic. The lack of literature limits its reliability as the studied surveys themselves needed more information to build upon.

3.4 Results and discussion

3.4.1 Qualitative analysis

3.4.1.1 Background of Industry 4.0 implementation in developing countries

Technology has rapidly grown. Businesses look to use technology to avoid physical contact between people and machines (Agbehadji et al., 2021). Technologies, including the internet and sensors, allow for physical and cyber systems and interconnections. The industry is relatively new, and there is still plenty to discover with this technology. There's significant potential for the mining industry to apply Industry 4.0 technology (Prinsloo et al., 2019). Industry 4.0 is the placement of varying and rapidly advancing technologies when developing autonomous systems (Coetzer et al., 2020). The question has moved from choosing digital technology or not towards how to implement digital technology

(Aghimien et al., 2022). That leaves companies with no choice but to move in the digital route.

The move towards adopting industrial technology to remain competitive is unavoidable globally, including sectors in South Africa (Maasz and Darwish, 2018; Mayer and Oosthuizen, 2020). That brings the need for the country to keep up with such advancements. Reducing capital expenditure is the principal method for the mining industry to remain profitable (Prinsloo et al., 2019). One of the pillars of the South African economy is mining, which contributes R400 billion annually (Mpofu and Nicolaides, 2019). This systematic literature review will be used as a stepping stone to an in-depth observation of the applications of Industry 4.0 in mining and other related fields, as there is a lack of literature specific to mining.

According to Maasz and Darwish (2018), there is plenty of potential for applying Industry 4.0 technology in the South African mining industry as the technology is becoming more readily available. According to Bag et al. (2021), firms are encouraged to adopt smart manufacturing and consider its potential impact on a circular economy. A circular economy takes waste as input towards another economic activity, reducing waste. The common perception is that the mining industry has no use for these new technologies. That is due to the remote nature of mining operations and the regulations the mining industry is under that limit the use of technology underground.

Countries such as South Africa seek ways to take full advantage of the adoption of Industry 4.0 innovations. That will help grow their developing economy while improving people's quality of life. Rising demand for Industry 4.0 technology has led to companies needing to integrate such technology vertically and horizontally (Bag et al., 2018). There is also a need to establish collaborations for research and development for modern technology (Bag et al., 2018). The United Nations' Sustainable Development Goals (SDGs) are achievable through implementing Industry 4.0 technology, such as the Internet of Things (Mondejar et al., 2021). The market is moving towards more customised products for the consumer, which leads to massive competition to meet customer demands (Tissir et al., 2023).

3.4.1.2 Drivers to Industry 4.0 implementation

An industry like mining, where accidents often occur, requires the implementation of automation despite the challenges this technology introduces (Kamalakannan et al., 2024). Monitoring safety and sustainability in mining are high priorities to reduce socio-environmental effects, use renewable energy, reduce the carbon footprint, efficiently use water, reduce fatalities and accidents and reduce waste (Cacciuttolo et al., 2023). Using Industry 4.0 technology helps strategically tackle unplanned, undesired and unexpected situations (Al-Banna et al., 2023a).

This study recognises sensors, automation and analytics as the predominant drivers of Industry 4.0 (Murugaiyan and Ramasamy, 2021). Requirements for successful transformation to Industry 4.0 technology include transformation, integration, collocation, policies, skills and operator (Murugaiyan and Ramasamy, 2021). Digital Supply Chains (DSC) that involve Machine learning, Blockchain technology, and IoT moved forward during the COVID-19 pandemic, and firms adopted remote working and digital technologies. The study also noted the lack of case studies to guide firms in adopting these technologies (Tavana et al., 2022). The impact of DSCs on company management includes openness, flexibility, agility and security. With the help of these technologies, managers can track stakeholders' real-time feedback from customers (Tavana et al., 2022).

The top motivations for this new technology are customer satisfaction, product improvement, process improvement (continuous improvement), waste reduction, decision-making assistance and improved transparency (Maganga and Taifa, 2023).

3.4.1.3 Challenges when implementing Industry 4.0 technology in industry

Despite recognising the potential benefits, mining companies struggle with technology adoption and fail to consider broader perspectives in decision-making and implementation objectives. There is a slow introduction of the latest disruptive technology in the mining environment (More et al., 2020). There is an advantage to exploiting South Africa's mineral resources, but this should benefit the environment and the people. The move towards Industry 4.0 technology has implications for employees and employment practices (Joshi et al., 2024). Therefore, labour rights and human rights considerations are required (Mpofu and Nicolaidis, 2019). Other challenges the mining

industry faces are low productivity, longer haul distances, low ore grade, and the limited opportunity to improve with the conventional methods (More et al., 2020; Maasz and Darwish, 2018; Liu et al., 2024). Challenges also include the time-consuming nature of mining, labour-intensity and expensive mining activities, and the limited amount of optimisations in mining activities (Maasz and Darwish, 2018). That study further says that modern technologies, such as drone surveying and automated machines, have not been a priority in South African mining activities, with decreasing profits in mining making it more difficult to apply such technology.

The financial pressure experienced by deep-level mining includes maintaining the temperature in the deep mines while meeting production targets (Nell et al., 2019). The study also notes the decline in production in South African mines compared to the worldwide trend. The decline in production means a decrease in revenue and a knock-on effect on South Africa's overall economy.

The effect of Industry 4.0 is so massive that it swallows up the entire business, which means that the organisation with this technology will be affected in different areas. These positive and negative changes need consideration when adopting the technology (Ajayi and Laseinde, 2021). Bag et al. (2022) identified seven categories of challenges to Industry 4.0 adoption. The categories were human resources, financial, collaboration, technology, security and leadership. The security risk and information privacy when using external data were identified as barriers to digital manufacturing. Technological issues were identified as the most impactful in Bag et al. (2022), followed by financial challenges. According to More et al. (2020), the mining industry is driven towards adopting Industry 4.0 by growing challenges such as low commodity prices, rising electricity costs and pressure from NGOs for mining companies to provide monitoring data. Some reasons for challenges in developing countries when it comes to adopting Industry 4.0 technology involve the lack of technology and the lack of maturity for that technology in the country (Sajjad et al., 2024). According to Sajjad et al. (2024), Pakistan is at 3.39 manufacturing maturity. Meaning it is not well suited for Industry 4.0 technology.

Mayer and Oosthuizen (2020) participants also noted that South Africa and Africa have unique challenges when implementing Industry 4.0, compared to European countries. The study notes that South Africa needs to expand employee skills, processes, and systems to deal with the implementation of Industry 4.0 (Mayer and Oosthuizen, 2020).

The study mentioned the need to evaluate the environmental and societal advantages and disadvantages of Industry 4.0 implementation (Mayer and Oosthuizen, 2020). When organisations overcome barriers to adopting sustainable digital technology, they can implement effective strategies and policies and improve profits (Bag et al., 2022).

Sivanuja and Sandanayake (2022) surveyed experts in the maintenance sector on their knowledge of Industry 4.0 technology. A survey respondent to Sivanuja and Sandanayake (2022) said that the early stages of new technology implementation are always challenging. Another respondent alluded to the hesitation of large manufacturing firms to invest in set technology due to the unknown risks associated with the technology investment. During the implementation of Industry 4.0, technology must run parallel with the old system (Sivanuja and Sandanayake, 2022). Another respondent to the survey in Sivanuja and Sandanayake (2022) mentioned the need to secure data generated through Industry 4.0 technology.

Laosiritaworn and Chattinnawat (2019) was a survey looking at Thai firms implementing Industry 4.0 technology, which concluded that the country is struggling with implementation. This study found gaps in Machine to Machine (M2M), Big Data, and sensor technology with the firms surveyed implementing some Industry 4.0 technology. The move to full adoption is still far from perfect in Thailand, with noteworthy research and development gaps and Information Technology. Addressing these gaps can involve preparing the workforce with the necessary skills (Laosiritaworn and Chattinnawat, 2019).

Challenges that can disturb the adoption of Industry 4.0 in heavy industries are subdivided into two categories. The two are Major physical challenges and Major psychological challenges, with each subdivided as follows (Prinsloo et al., 2019):

- **Major physical challenges**
 - Interoperability
 - Security and privacy
 - Accessibility
- **Major psychological challenges**
 - Impact on labour or personnel
 - Technical skill sets and education

- Financial perspectives

The security and privacy of digital systems are critical to adopting digital technology and should be a high priority point when such technology is applied (Prinsloo et al., 2019). The increased move towards Industry 4.0 comes with increased cybercrimes, namely, SQL injection, Malware and Phishing attacks, Denial of Services (DoS), Credential Reuse, Cross-Site Scripting (XSS), and Ransomware, with phishing being the most commonly used attack. These attacks can harm entire businesses and individuals alike (Sadiq et al., 2021). Sadiq et al. (2021) examined state-of-the-art Phishing attack defence systems and determined that the five major categories of defence against these attacks were the Blacklisting-whitelisting approach, Data Mining, URL Scan-Based Approach, and Search Engine-Based Approach. Other challenges associated with Industry 4.0 technology involve data privacy, lack of skilled labour, and poor data analysis and management (Agbehadji et al., 2021).

Maganga and Taifa (2023) surveyed the Tanzanian manufacturing industry and its struggles with implementing Industry 4.0 technology in the context of quality in manufacturing. The respondents stated that the top challenges faced are reliable electricity, government policy, high-speed internet, skilled workforce, investment, support from top management and awareness of the concept, data management, culture, and cultural change.

3.4.1.4 Solving the challenges of using Industry 4.0 technology

In looking for ways to improve productivity, organisations examine how human resources can add value while embracing Industry 4.0 technology to create a multi-skilled working environment (Ramdass and Mokgohloa, 2022). Out-of-date methods of mining that endured for decades without change are proving costly in the modern era, demonstrated by a sharp decline in productivity. The introduction of automation, machine communication and data analysis requires exploration (More et al., 2020). According to More et al. (2020), Smart mining requires exploring inter-connected communication and real-time data in all aspects of mining production.

People remain a critical resource to South African mines, but literature such as Botha (2019) states that the introduction of machine intelligence raises an important question. Should humans stay in primary control of innovation as machine intelligence may work

alongside human intelligence or replace human intelligence altogether? This study sees all three innovation methods prevailing in the future.

According to Malik et al. (2023), the advancement of technology has led to strides in development that went along with devastation to the environment. There have been policies such as carbon pricing, limits on polluting industries and mandates for renewable energy to guide the movement towards sustainable development. To further aid these policies, incentives for research and development in this development direction are economically viable to pursue these environmentally friendly policies (Malik et al., 2023).

Al-Banna et al. (2023a) notes that both under-investment and over-investment in Industry 4.0 technology can lead to undesired outcomes, so striking a balance between the two to avoid any undesired outcomes is necessary. Therefore, current regulations, cybersecurity, and scalability are critical considerations during this technology adoption.

Convincing stakeholders of the benefits of Digital Supply Chain Resilient technologies is difficult. Other challenges include a lack of knowledge, limited resources to implement the technology and resistance to the technology (Al-Banna et al., 2023a). Strategies to mitigate the resistance to Industry 4.0 technology include education on the benefits of these technologies and a cost-benefit analysis of the return on investment due to the technology presented to stakeholders, shareholders, and collaborative effort between the commissioning entity and its supplier can lead to the identification of the technology that best fits the particular application and lastly, pilot cases of the new technology to determine benefits before full implementation as proof of concept for the different stakeholders (Al-Banna et al., 2023a).

3.4.1.5 Resources needed for successful Industry 4.0 adoption

The findings in Bag et al. (2021) suggest that the most critical resources for the South African context are big data analytics, green design, collaborative relationships and production systems. Human factors, resources, and capabilities are paramount in adopting Industry 4.0 (Bag and Pretorius, 2022). There is a need for laws and regulations around Industry 4.0 adoption (Bag and Pretorius, 2022; Agbehadji et al., 2021). Understanding barriers to Industry 4.0 technology will lead to easier adoption of digital manufacturing in a circular economy (Bag et al., 2022). This study recommends

outsourcing IT infrastructure to store, preserve, and process personal data relating to customers and networks securely (Bag et al., 2022).

There's a need for a blended workforce between older and younger employees. More experienced workers possess engineering knowledge, while younger ones own technical technology know-how. With such disruptive technology as Industry 4.0, employees need to increase their specialisation or skills and also increase their work speed, according to the study participants (Mayer and Oosthuizen, 2020).

There is seldom a study on Industry 4.0 adoption, according to (Bag et al., 2018). Enablers for supply chain sustainability include support by the government, management, IT security standards improvement, change management, focus on people, standardisation, horizontal and vertical integration, third-party audits and corporate governance (Bag et al., 2018). The implementation of Industry 4.0 technology demands new machinery, hardware and software. These can be highly expensive in the developmental stage, with benefits that outweigh these costs in the long run (Oláh et al., 2020).

Analysis from Hosseini et al. (2023) determined the order of importance for all the criteria for Industry 4.0 implementation in mining. The most and least critical criteria are implementation cost and resource evaluation. This study also noted the most important policies listed, with IoT ranked highest for the Mining 4.0 policy.

Lin et al. (2023) examined the Chinese manufacturing industry. This study found that large and private firms are more motivated to adopt Industry 4.0 technology, with subsidies from the government having no significant influence on the decision to do so. Embracing this technology increases financial performance and innovation but does not significantly improve the supply chain.

Government involvement in state-owned companies has sparked criticisms of subsidies viewed to favour these companies. However, the findings from this study indicate that this criticism is unfounded. This study also found that implementing Industry 4.0 technology has a positive relationship with company share prizes, with companies with such technology valued higher (Lin et al., 2023).

This study focused on the South African implementation of Industry 4.0 technology. This study notes that the SA government is interested in strategically embracing science and technology to use local and international resources (Dhamija, 2022).

3.4.1.6 Benefits of Industry 4.0 Adoption

The implementation of Industry 4.0 costs can be compensated for by incomes generated during the improved mining processes. The added benefits of mining 4.0 are not limited to profits but also improved safety, desirable societal impact, and employment opportunities for local communities (Hosseini et al., 2023). Liu et al. (2024) showed that using autonomous vehicles resulted in reduced idle time and an increase in total output. Tripathi et al. (2024) showed that IoT from Industry 4.0 with Machine Learning predictions-based dust monitoring systems had positively improved worker safety and environmental disaster.

Mining operations generate many data points. This data can monitor Tailings Storage Facilities (TSF) (Cacciuttolo et al., 2024). TSF accidents across the globe have led to the introduction of Industry 4.0 technology in mining. Of the large amounts of data generated in the mining industry, only a small portion is used for TSF monitoring, signifying large room for improvement (Cacciuttolo et al., 2024).

3.4.1.7 What is needed from leadership for successful technology implementation?

To implement Industry 4.0 technology successfully, an organisation requires data analytics, collaboration, scalability, connectivity, compliance, leadership, organisational culture and training. These need to be implemented methodologically by the organisation (Thekkoote, 2022).

Leadership

The PMBOK guideline affected by the implementation of new technology is project resource management, which involves acquisition and people. The management of people becomes more complex with Industry 4.0 technology that needs accounting for (Marnewick and Marnewick, 2020).

Human resources, project management, management leadership and collaborative relationships are crucial to Industry 4.0 adoption (Bag et al., 2021). There needs to be a

clear goal for implementing digital innovation set by top management, and they need to look for new emerging technologies and their potential benefit (Aghimien et al., 2022). Leaders are seeking ways to keep up with the emergence of this Industry 4.0 technology within their organisations. The study found that for a leader to thrive in this new environment, they must move away from authoritarian, bureaucratic and task-oriented leadership styles towards people-oriented, transformational and charismatic styles (Coopasamy and Botha, 2022).

There's a need to equip managers with the knowledge to manage a changing environment due to Industry 4.0 technology. That will enable them to motivate and coach the workforce. There is also a need for people and machines to work hand in hand (Ramdass and Mokgohloa, 2022). There's an emphasis on constructive and positive employee management as paramount to implementing Industry 4.0 technology, suggesting the importance of considering employee opinions in decision-making (Mayer and Oosthuizen, 2020).

Successfully implementing Industry 4.0 for an organisation depends on being self-driven, flexible, driven by data and willing to learn. The organisation using this technology changes completely, from people to work methods (Kohl and Swartz, 2019). That study found that there is already an integration of technology in workplaces in South Africa, with examples such as remote work. It also highlights the need for these workplaces to take all employee's inputs (Coetzee and Veldsman, 2022). That study found skills needed in Industry 4.0 for people's intrapersonal and interpersonal skills and integration of digital competencies (Coetzee and Veldsman, 2022). South Africa and other developing countries still use mixed environments (using automation and humans collaboratively to complete a task). More research on collaborative decision-making performed in a manner that workers find acceptable within an organisation needs to be conducted (Coetzee and Veldsman, 2022).

Management must prioritise investment and support that help the move towards this technology. That includes applying new employment models and continuously improving systems (Bag et al., 2018). The managers working with Industry 4.0 technology need to constantly receive information and work on making adjustments accordingly (Marnewick and Marnewick, 2020). Firms in developing countries can learn Industry 4.0 technology

from their more developed counterparts through Knowledge-Based Dynamic Capabilities (KBDCs) (Shamim et al., 2019).

Types of leadership

Almost every business has been affected by the advent of Industry 4.0 innovation. Ramdass and Mokgohloa (2022) focused on the clothing industry and found that the basis for management techniques was machine-age paradigms. Unless it moves to the digital age, an organisation will not be competitive (Ramdass and Mokgohloa, 2022). There's also a need for the mining industry to adopt new kinds of leadership approaches, as most current leadership models are unsustainable (Uys and Webber-Youngman, 2019).

Leadership styles during the transition

There are differences in phases in current work methods compared to when implementing Industry 4.0. These results indicate that the various implementation methods also required different leadership styles (Coopasamy and Botha, 2022). Democratic leadership styles were deemed more effective in Industry 4.0 implementation, especially in the transitional phase between pre-Industry 4.0 and Industry 4.0 (Coopasamy and Botha, 2022). Managers must develop new ways of managing in the digital age and hybrid workplaces. They also need new digital skills to work in a technology-enabled environment (Coetzee and Veldsman, 2022). Once an organisation fully implements Industry 4.0, Coopasamy and Botha (2022) recommends adopting transformational, people-oriented and charismatic leadership styles and ensuring a considerable connection between leaders and those under their leadership. That will confirm strong links between people in a digital environment.

What is required is a new leadership style in the 21st century, with the current applied leadership styles not suited for the current environment. Uys and Webber-Youngman (2019) suggests the new leadership model adopted for Industry 4.0 be the tetrahedron, where the base is SELF, which represents the leader's interpersonal dimension, WORK (vocation), PEOPLE and the IMPACT panels. The explained differing interactions between elements on the tetrahedron are in Uys and Webber-Youngman (2019).

Getting the right people

There's a need for organisations to not only invest in acquiring technology but also for the right people to use this technology. There is a need to consider the people side of

technology. These people need to be trained and retrained. More investment is needed in this regard. The construction industry necessitates the people dimension to have the ability to attract personnel, retain the personnel and have a digital culture (Aghimien et al., 2022).

Preparing the people

Coetzee and Veldsman (2022) focused on applying industrial psychologists' skills and roles to help companies in South Africa while they move towards Industry 4.0. That study showed limited research on the application of psychologists in digital-enabled companies. Knowledge management is also a requirement when looking to digitalise (Aghimien et al., 2022). Top managers need to support digital transformation alongside improving their technical knowledge of technology (Aghimien et al., 2022).

An organisational culture promoting innovation will encourage existing and future employees, easing their fear of joblessness due to contemporary technology (Aghimien et al., 2022). The study also highlighted the lack of digital culture, training, and analytical and predictive-driven production thinking as significant factors in the sustainability of a digital business (Bag et al., 2022). Personnel training and education in Industry 4.0 is essential and costly (Marnewick and Marnewick, 2020). Training should enable the necessary skills development of Industry 4.0 technology (Joshi et al., 2024).

A re-evaluation of the relationships between employers and employees when implementing Industry 4.0, as pressure is to apply to governing organisations. Encourages ethical practices when implementing Industry 4.0 technology and discourages side-lining employees for machines when introducing set technology (Mpofu and Nicolaides, 2019).

Getting partners

There's a need for a coordinated, collaborative effort between the mining industry, research institutions and academia to develop a skilled workforce capable of building and maintaining such Industry 4.0 technological systems (Prinsloo et al., 2019; Mayer and Oosthuizen, 2020). There's also a need for financial support for such new technologies, as has been the case that technologies are not receiving support due to their novelty. Investors often invest in methods that have proven to work in the past instead of unproven ones (Prinsloo et al., 2019).

There is a need for partnerships with other organisations, particularly those with digital tools. There is the inclusion of academia and industry partnerships, where digital talent is recognised early, and they progress into the organisation with technical skills. The advantage of investing in academia will be that these new members of the organisation will have a background in the organisation's direction, and they will integrate easily (Aghimien et al., 2022). Literature is scarce in the manufacturing industry on Industry 4.0 adoption, so literature from other heavy engineering industries is necessary as long as they practice Industry 4.0 in developing countries like South Africa (Bag et al., 2021).

This study mentions the need for policymakers to pursue mining sector investments that are socially responsible, sustainable and environmentally conscious policies regarding Industry 4.0 technology. There is a required focus on data privacy, information sharing and privacy of data (Bag et al., 2020).

3.4.1.8 Impacts of Industry 4.0 on the workplace

More et al. (2020) highlight the importance of employing smart mining to ensure mines remain market competitive. However, there is a reluctance to complete the adoption of Industry 4.0, or organisations wait for other mining companies to adopt the technology. There's a view that digital labour is a potential driving force towards economic and technological advancement for developing countries like South Africa, addressing unemployment, low wages and lack of demand (Chidoori and Van Belle, 2020). This study, however, also mentions the possibility of digital labour bringing unfavourable effects such as the exploitation of workers, unguaranteed remuneration or none at all. This study's findings lean towards a positive attitude towards digital labour influenced by the expected compensation these individuals would receive for their digital work (Chidoori and Van Belle, 2020). People have contrasting beliefs on how Industry 4.0 will affect organisations. Some believe it will improve efficiency, quality of life and productivity, while others think it will lead to job losses, social exclusion and inequality (Roberts et al., 2022). Rapid developments come alongside the adoption of Industry 4.0 innovations. This study also names organisations needing to adapt to the challenge, especially its human rights implications (Mpofu and Nicolaides, 2019).

The mining industry seeks to improve worker safety, effective maintenance and safe reconnaissance missions during emergencies (Buddhan et al., 2019). In this study, AR

uses real-time sensor data to predict emergencies and alarms set off in cases of emergency (Buddhan et al., 2019). The Implementing Industry 4.0 technology aids in planning for maintenance and reduces operational costs and the number of unexpected shutdowns in a plant. Increases reliability, safety of personnel and reliability (de Moura et al., 2021).

Organisational change due to Industry 4.0 technology

Mayer and Oosthuizen (2020) explored the implications of companies applying Industry 4.0 innovation in South Africa. Findings from this study show five core themes in innovation in the country: employee management, innovative technological change and systematic change, the organisation of work, environment, networks, and cooperation. The study also mentioned that the relationship between humans and machines seemed to build a critical block towards socio-technological change and the work environment. This study also examined methods an organisation can employ strategies that lead to a constructive movement towards Industry 4.0 implementation. This study also notes the need to inform employees when introducing noteworthy changes to the working environment or organisation. A requirement is for organisations to focus on balancing the human-machine interaction if Industry 4.0 implementation is to take place successfully. There should be a conscious act towards not replacing humans but ensuring that humans play an integral role in the control and programming of machines (Mayer and Oosthuizen, 2020).

Human and machine innovation

Botha (2019) aimed at investigating the evolution of innovation from human-only to the human-machine initiative progressing to machine-produced. This study found that innovation will evolve from human-only innovation inputs to where humans and machines co-innovate. Lastly, we see machines innovate autonomously with growth in machine intelligence. The future of machine innovation focuses on social, sustainable, disruptive, and integration innovations. That study also notes that the technology required for machine innovation is available to some extent, and more is still under development. Clients need faster delivery and more customised products, increasing the demand for more intelligent machines (Botha, 2019).

Coetzer et al. (2020) found a lack of collaborative effort in decision-making when using digital tools and solved by introducing human and technological approaches in the decision-making process. This study also tested the use of human-only decision-making, then computer-only decision-making, and lastly, a scenario where a combination of computers and humans is used. The study found that using humans and computers is the most effective decision-making tool.

Human-machine interactions

The digital age reduces costs and waste while improving effectiveness, efficiency, production quality, safety, the organisation's agility, and production amounts (Ramdass and Mokgohloa, 2022). There has been more research on machines and digital systems, each studied independently, but most industries still apply a mixed environment where machines and people work together (Coetzer et al., 2023). This study showed that processes utilising autonomous systems alone were 20% slower than when humans were involved. Including workers in Smart manufacturing systems allows opportunities for workers who would otherwise lose their jobs due to the new technology to acquire new skills and training. However, this study highlighted the need for more research in that area (Coetzer et al., 2023). Training programs must be agile, linked and open to the constantly changing demands (Joshi et al., 2024).

Positive impacts of Industry 4.0 on the workplace

The benefits of Industry 4.0 implementation include the skills the employees will have to learn when switching towards Industry 4.0, creating job opportunities and requiring more qualifications for the new positions the employees occupy (More et al., 2020). That study foresees increased safety and security of mining sites using Industry 4.0 technology. The sum of humans and machines will eradicate or reduce mistakes (Mayer and Oosthuizen, 2020). Significant impacts of Industry 4.0 implementation include humans, costs, processes, material resources, products, and business models (Ajayi and Laseinde, 2021).

Industry 4.0 can drive sustainable manufacturing, aid with improving economies and the environment, and have social benefits (Bag and Pretorius, 2022). Human resources positively impact Industry 4.0 adoption (Bag et al., 2021). "Smart technologies" are expected to positively affect the mining industry in the long run, simplifying how mines

reach their full-scale production targets (More et al., 2020). The ability to collect more and more data is becoming more readily available (Maasz and Darwish, 2018). Innovation can improve efficiency, use of materials, labour, safety and profits (Maasz and Darwish, 2018). Some of Mayer and Oosthuizen (2020)'s participants said that they do not see Industry 4.0 as a threat to human employees but as an aid to the people that will help speed up production.

The implications of Industry 4.0 improve environmental sustainability and help stakeholders and companies address their environmental impacts (Oláh et al., 2020). Integrating new technology entails more efficient processes, with fewer hours for human workers in factories. Departments synchronise with others, and there is minimal use of resources and energy (Oláh et al., 2020). Using machinery for mundane tasks frees people to explore more complex activities, allowing for optimal use of resources. Teams continuously learning and adjusting will allow the team a competitive advantage (Marnewick and Marnewick, 2020).

Negative impacts of Industry 4.0 on the workplace

There has been an overwhelming acceptance of the World Economic Forum's 4IR strategy on economics skills development and growth, but there has been criticism (Bowie, 2022). Industry 4.0 technology is a fledgling approach, with skills still under development (Maasz and Darwish, 2018). The lack of institutional measures can hamper the progression of Industry 4.0 adoption. An example was Brazil, where there was a lack of workforce skills in the area. Developing countries need to look at producing institutions that aid the development of Industry 4.0 (Bag and Pretorius, 2022). The study Mpofu and Nicolaides (2019) is less optimistic about the opportunities that Industry 4.0 implementation will bring as they state that there will be opportunities. However, those who benefit will be few and far between. There's an acknowledgement of the changes that will come with Industry 4.0 to the way of life and work worldwide (Mpofu and Nicolaides, 2019). Stating that the consequences will far exceed any changes from prior industrial revolutions, bringing along uncertainty, volatility and chaos. Other dark implications of Industry 4.0 during the pre and post-installation stages include job losses, lack of Industry 4.0 knowledge in the supply chain, dip in morale, and lack of funding for the technology and IT security standards (Bag et al., 2018).

The criticism behind Industry 4.0 technology is also on the motive behind the implementation of such technologies and its "socio-technical effects". The critique is on the so-called "hype", characterised as a neo-liberal ideology. Critics of this approach claim that the attention this approach has garnered is unjustified. It is a trend, not something based on analytical rigour (Bowie, 2022).

The push for implementing Industry 4.0 technology is seen as an elitist religious push towards it while ignoring other social issues plaguing countries like South Africa. This article mentions that the other industrial revolutions have not been successful, but there is already a push for implementing Industry 4.0. This study also highlights the dangers that implementing Industry 4.0 may bring, such as mass surveillance, anxiety towards AI, and data encryption (Bowie, 2022).

The implementation of technology may not always bring benefits to an organisation. Therefore, adopting technology must align with the organisation's objectives, allowing for benefits from the technology and considering the reliability aspect of Industry 4.0 (Hoffmann Souza et al., 2020). This study said that the move toward Industry 4.0 technology risks the possibility of human resources/people being sidelined and forgetting their central role (Ammirato et al., 2023). This study mentioned the need for deeper understanding in areas such as employee engagement, ethics and fairness in the digital workplace, impact on employee well-being and the role of human resources in digital transformation when implementing Industry 4.0 (Ammirato et al., 2023).

Technology on people's jobs

Implementing digital technologies could be at the expense of many mine workers as more autonomous equipment is used instead of human labour (Mpofu and Nicolaidis, 2019). Introducing Industry 4.0 technology within an organisation will pose plenty of challenges to all members (Mayer and Oosthuizen, 2020). Technological innovations such as introducing robots lead to replacing human labour, raising the issue of joblessness in society (Botha, 2019). Employee concerns include employee retrenchment, machines taking over control, and an unsafe working environment, which are challenges that need addressing when organisations apply Industry 4.0 technology (Mayer and Oosthuizen, 2020).

Two-thirds of jobs available today will be replaced by Artificial Intelligence (AI) and robotics (Oosthuizen, 2022). The study also mentions that robots will manage twice the work humans currently handle. The study also notes that 85 million replaced jobs by robots by 2025 and 97 million new job types for the new division of labour between humans and machines (Oosthuizen, 2022). There remains a lack of knowledge or awareness in the area (half of the South African population lacks understanding), leading to a negative perception of modern technology implementation (Roberts et al., 2022).

Roberts et al. (2022)'s findings suggest familiarity with Industry 4.0 in South Africa depends on age, class, perceptions towards labour market vulnerability, scientific knowledge and people's confidence in the government and their ability to handle any counterproductive impacts of the implementation of Industry 4.0. Roberts et al. (2022) found that older people are less likely to accept automation. The study also mentions that the more familiar with technology the individual is, the more likely they will be receptive towards automation in South African society. That study also found that the individuals more likely to be moved by automation were less open-minded to automation and hostile towards technological change overall. Roberts et al. (2022) found that socioeconomic standing influences attitudes towards technology implementation, with individuals on the lower side of the standing less receptive, while those on the higher end were more receptive towards new technology.

3.4.1.9 Application areas of Industry 4.0

Industry 4.0 technologies apply to many industries, such as education, manufacturing, mining, business, healthcare, society and agriculture (Agbehadji et al., 2021). Industries such as the manufacturing industry are moving towards Industry 4.0 technology with technological interests such as big data analytics, machine automation, Cyber-Physical Systems, virtual reality (VR), Wireless networks, augmented reality (AR), decentralised computing and the Internet of Things (IoT) Nkonyana et al. (2019), Prinsloo et al. (2019), Adenuga et al. (2020), Maasz and Darwish (2018), Dhamija and Bag (2020) and Liu et al. (2024). The manufacturing industry heavily relies on fault detection to reduce the number of errors encountered (Nkonyana et al., 2019; Oláh et al., 2020). Reducing imperfections leads to better profitability, and reducing environmental impact and applying Industry 4.0 technology can lead to better decision-making (Adenuga et al., 2020; Nkonyana et al., 2019).

The manufacturing industry uses sensors to collect operational data and intelligent devices (Maasz and Darwish, 2018). The manufacturing industry needs to produce high-quality products safely while reducing costs (Nkonyana et al., 2019). Machine learning techniques are used in manufacturing to analyse the collected data from intelligent systems (Nkonyana et al., 2019). Faults are studied with the data and aid the decision-making process. Adenuga et al. (2020) examined the application of Industry 4.0 technology to monitor energy consumption and modelling, which impacts energy efficiency. The designs for the current methods of heat expulsion are different for a period from what is required currently, and there is a need for a change to such systems. That is where to apply Industry 4.0 technology, bringing dynamic heat monitoring in the deep mines (Nell et al., 2019). Safe, Intelligent, Green Climate-Smart practices (SIGCS) require adoption in the mining industry to remain future-fit (Jiskani et al., 2023). Sadiq et al. (2021) showed that Industry 4.0 sensor-based monitoring systems were applicable to monitor Friction Stir Welding (FSW), leading to the tracking of data on temperature, force, power, torque, vibrations, imaging, current and acoustic vibrations. This real-time data collection allowed for control, precision and quality control.

Data drives digital manufacturing, including simulation, 3D data visualisation, analytics, and collaboration tools when producing products (Bag et al., 2022). Bag et al. (2022) give the example of enhanced efficiency resulting from Industry 4.0 adoption, where different manufacturing activities are combined while reducing data-related errors, which is impossible in paper-based record keeping. Managers could benefit from the fast procedure turnarounds within the value chain. Adopting Industry 4.0 technologies offers managers the ability to make decisive decisions. The basis for these decisions is real-time results and offers testing at an earlier production stage. More et al. (2020) lists the Internet of Things, Wireless Sensor Networks, Artificial Intelligence, swarming drones and the application of autonomous machines as the most widely used technologies in the mining industry. This study also states there has been a rise in automation in the mining industry, seeing tasks preserved for humans done by machines in an improved fashion and safer. The mining industry uses supervisory control and data acquisition (SCADA) for data collection, where the data is stored and analysed off-site (Prinsloo et al., 2019). A challenge is the analysis of large amounts of data to help with the decision-making process. Sellami et al. (2020) looked at a general approach to predicting machine failure.

This study suggests that information not shared in real-time makes informed decision-making difficult (Telukdarie and Sishi, 2018).

This study also outlined the different levels involved in Industry 4.0 technology, starting with level 0, where the physical systems/processes occur, and then level 1, where the wireless and wired actuators, sensors and analysers. Level 1 to level 2, where the Human-Machine Interface (HMI), Supervisory Control and Data Acquisition and Open Platform Communication (OPC). The next is Level 3, where systems like the Fuel Managing System (FMS), Modular Systems, etc., are connected to Level 2 and Level 4. The last level is Level 5, where the Business Intelligence (BI). That is where visualisation and analysis of the data from the subordinate systems take place. The data flows from Level 0 to 5 and vice versa (Telukdarie and Sishi, 2018).

Implementing Industry 4.0 technology in the Chinese coal mining industry would lead to automated mining with useable energy transported to the surface while waste is dealt with underground (Wang et al., 2019).

Steps towards Industry 4.0 Implementation

For the successful implementation of Industry 4.0 technology, according to Prinsloo et al. (2019), the mining industry will need to decentralise while developing wireless interconnections. This study also says that interconnected systems will allow for the development of virtual copies of mining operations (Digital Twins), the next step in managing mining operations.

Prinsloo et al. (2019) found the following Industry 4.0 principles:

Framework principles

- Decentralisation
- Real-time capability
- Modularity
- Interoperability
- Virtualisation

This study showed application simulations to a high degree in real-time in Mining 4.0, with high-level decisions based on the simulation results. This study demonstrated improved capabilities with AI operations used to select optimum strategies (Xie et al., 2022).

Inland Waterway Transport applies Industry 4.0 technology in analytical Big Data, Smart Navigation, Cybersecurity, Traffic Monitoring and Emission Reduction (Restrepo-Arias et al., 2022). The railway industry uses Industry 4.0 technology for control and maintenance, such as IoT, Big data, Cybersecurity, AI, Simulations and modelling, Virtual Reality, Smart Decision Support Systems (SDSS), Cloud Computing, and Computer Vision (Laiton-Bonadiez et al., 2022).

3.4.2 Quantitative analysis

3.4.2.1 Results

This section details the results from the quantitative analysis of literature found for the SLR, such as trends in publication over the years, prominent authors, countries and affiliations, keywords and subject areas.

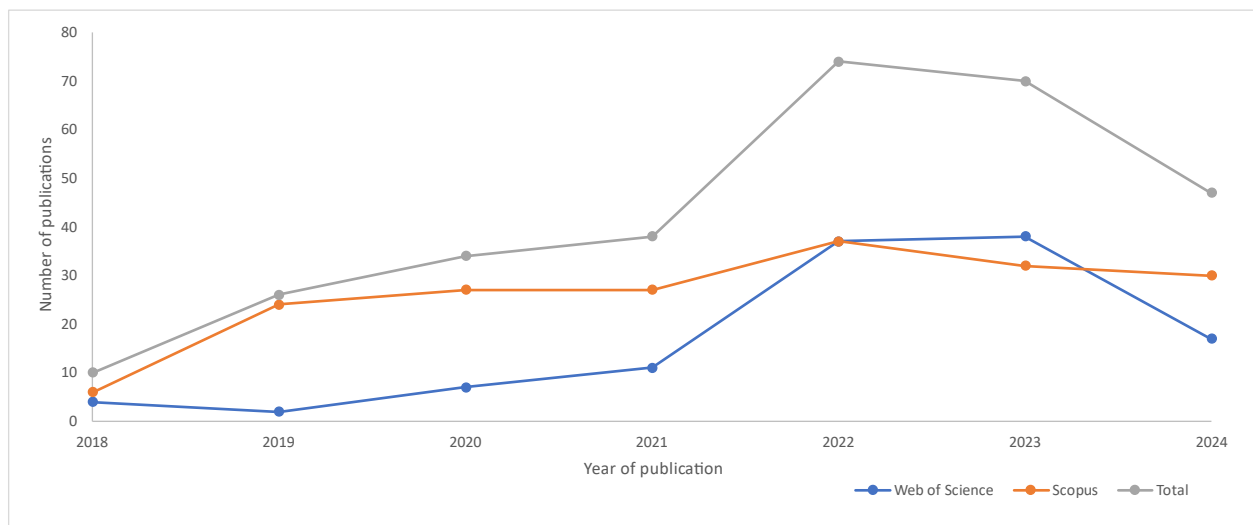


Figure 3-2: Studies published per year.

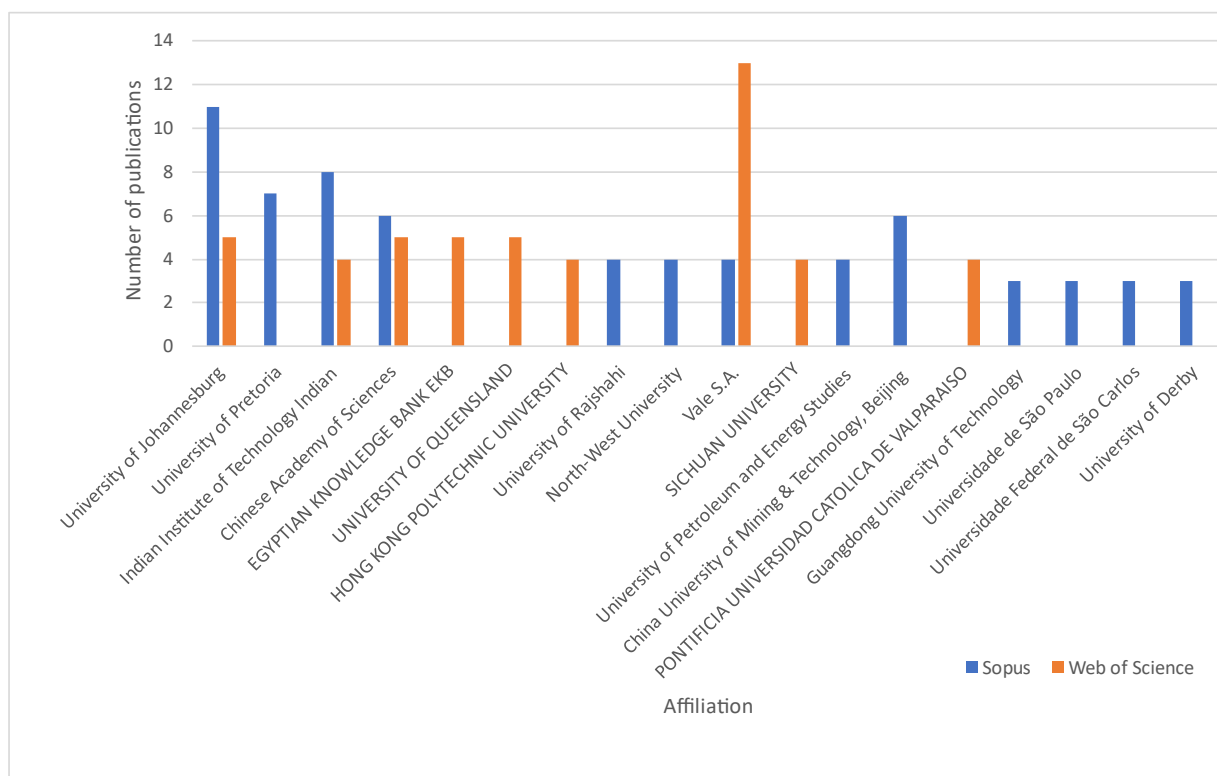


Figure 3-3: Studies published per institution.

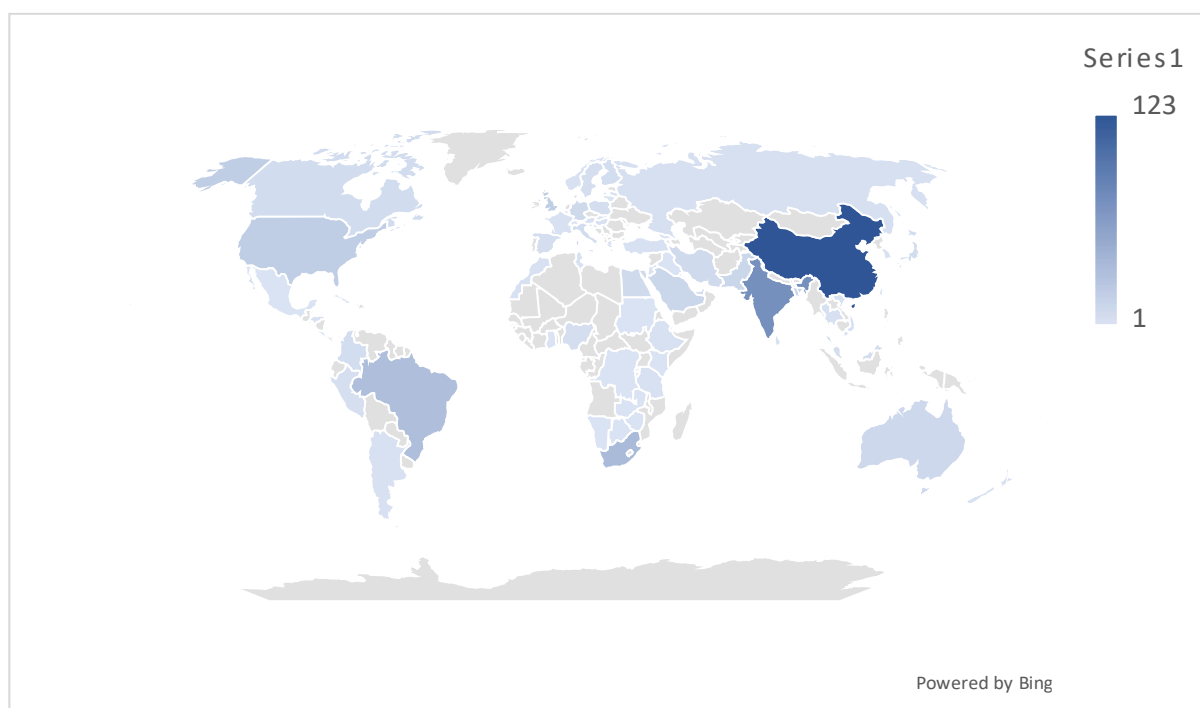


Figure 3-4: Number of collaborations between developing countries and international researchers.

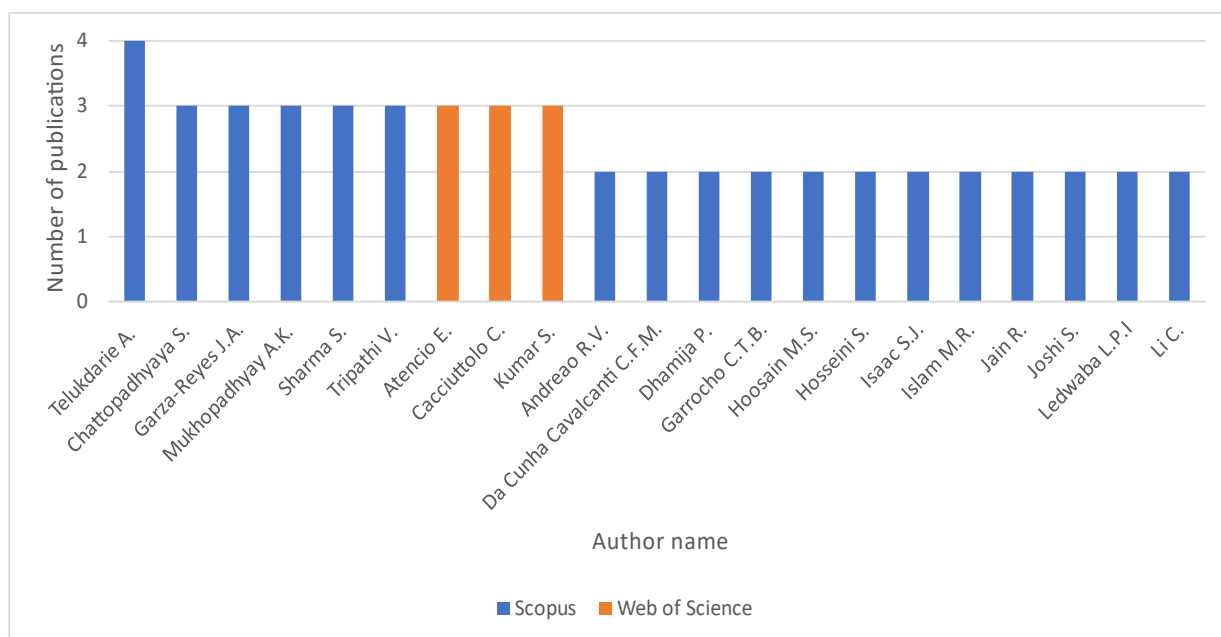


Figure 3-5: Number of publications per author.

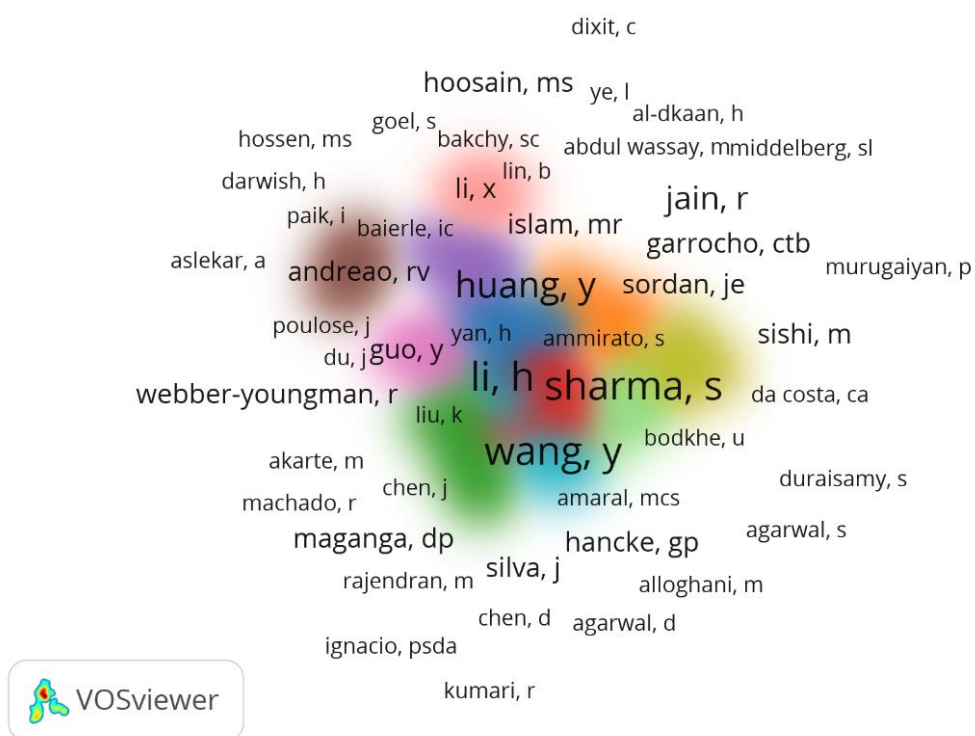


Figure 3-6: Cluster density visualisation of co-authorship Scopus.

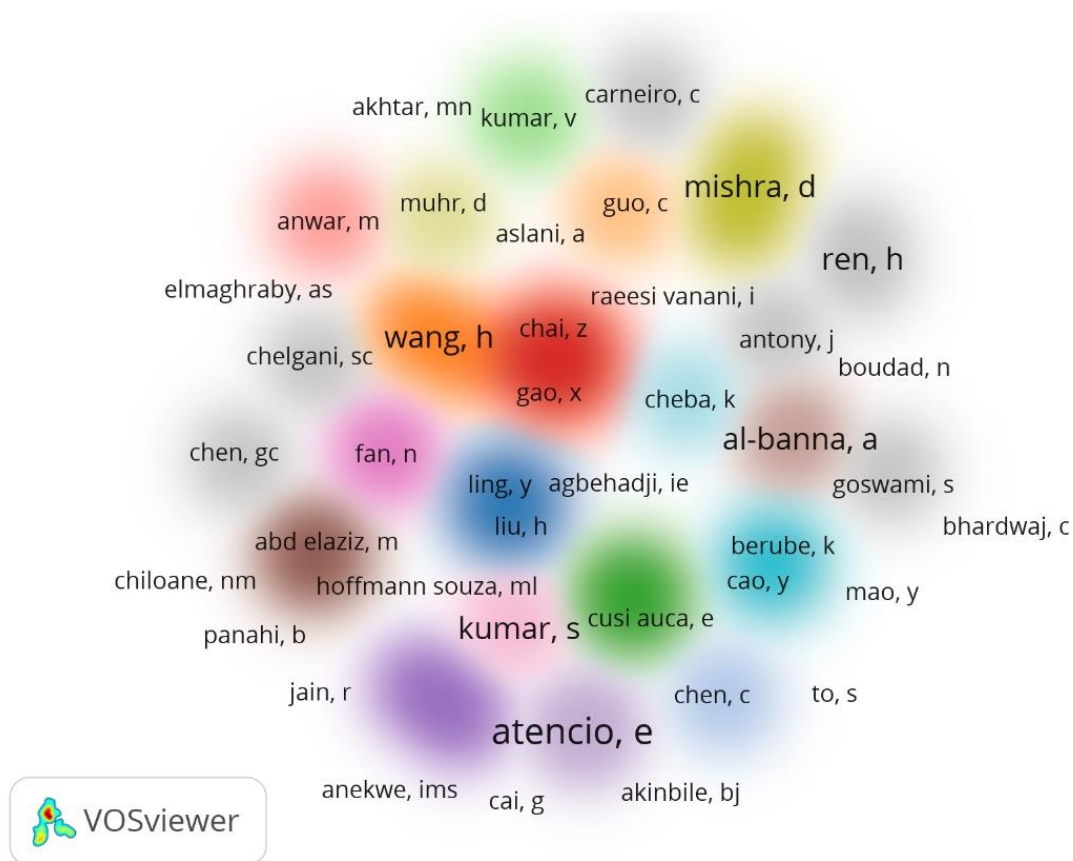


Figure 3-7: Cluster density visualisation of co-authorship Web of Science.

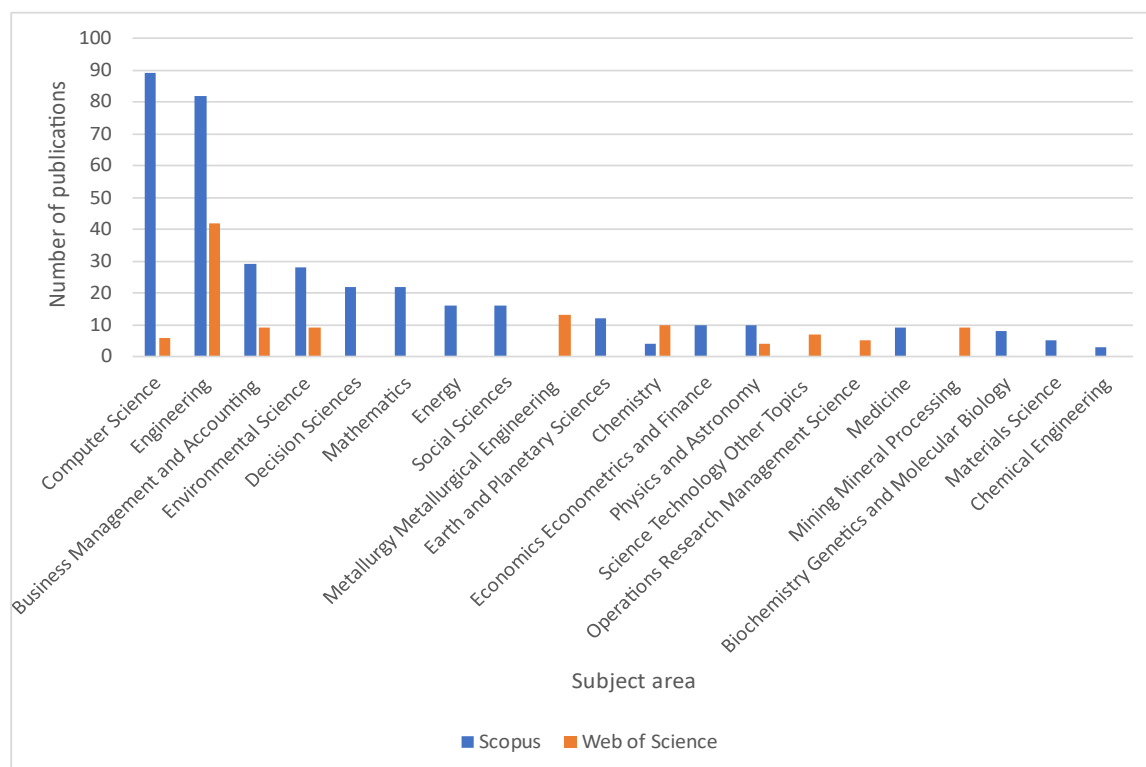


Figure 3-8: Publications per subject area.

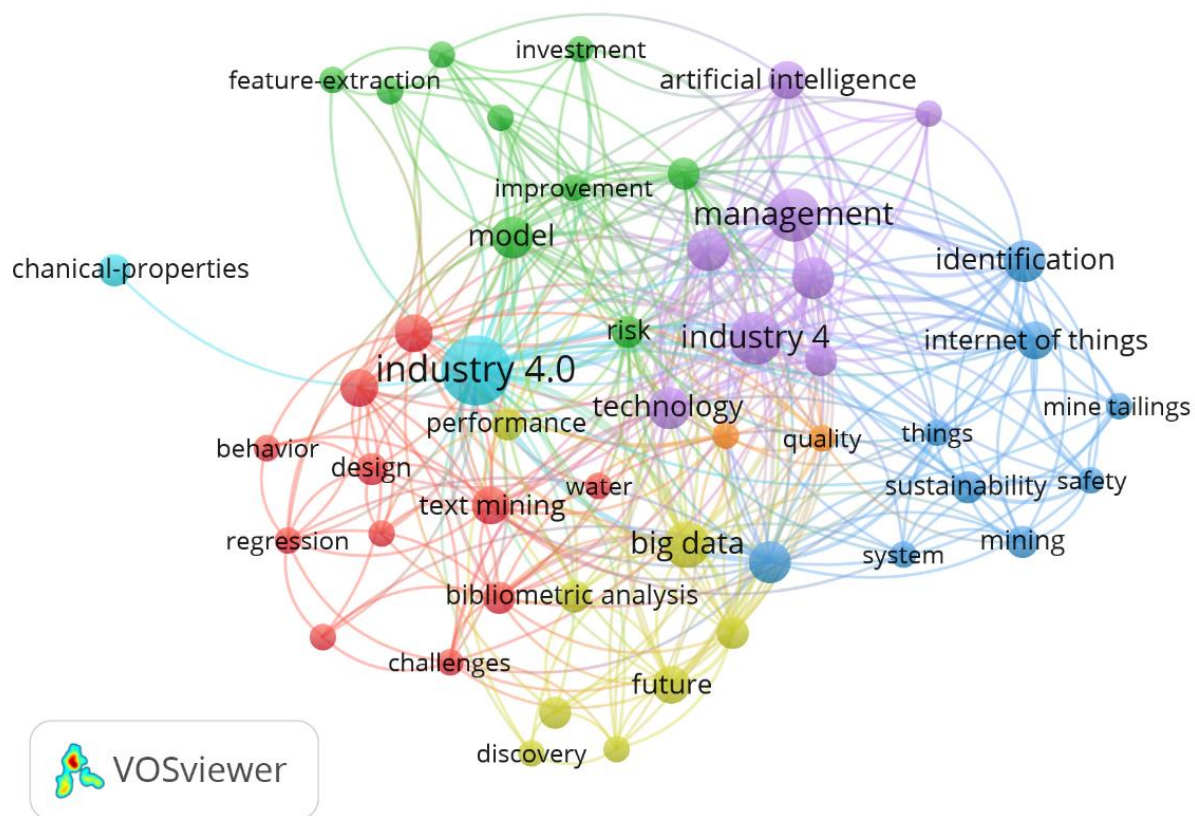


Figure 3-10: Cluster density visualisation of keywords used in the study titles and abstracts Web of Science.

3.4.2.2 Discussion

As demonstrated by Figure 3-2, there has been a steady rise in the number of publications focused on Industry 4.0 and its implications from authors from developing countries. The graph shows a steady increase in the number of publications from 2018 to 2022 (from 10 publications in 2018 to 74 publications in 2022), followed by a slight decrease from 74 to 70 publications between 2022 and 2023. In 2024 so far (up until the date of this study), there have been 47 publications.

Even though the number of publications is trending upward, the low number of publications covering Industry 4.0 implementation from South African authors or in the context of South Africa indicates that there is room for more research. That shows the infancy of the topic in the country and how more studies can close the gap and attempt to solve the modern technology adoption problem faced by South African industries.

Figure 3-3 shows that the leaders in Industry 4.0 applications study affiliates are Vale S.A. with 17, and the University of Johannesburg (UJ), with 16 publications.

Figure 3-3 shows the low involvement of research institutions in the research of Industry 4.0 adoption. However, this could mean private companies withhold research to stay ahead of their competitors, as their funded research studies may remain within their organisations.

Figure 3-3 demonstrates the lack of publications from universities outside the countries like China, South Africa and India, as an overwhelming majority are from universities within these countries. There could be a benefit from studies from other parts of the world that could bring insights that researchers from the mentioned regions could have missed. That could be from personal experience, environment, etcetera.

Figure 3-4 shows the number of publications per developing country and international collaborations between developing country-affiliated researchers and their developed country counterparts. The most frequent publishers are China, India, South Africa and Brazil. The most frequently collaborating developed country with these developing countries in the developed world is the United States of America and the United Kingdom.

Figure 3-4 demonstrates the lack of international collaboration between developing country authors and developed country authors on Industry 4.0 adaptation strategies. When there's international collaboration, it is limited in the number of publications and the number of countries involved.

Figure 3-5 shows the leading researchers by the number of publications each has. The most prominent authors being Telukdarie, A., Chattopadhyaya, S., Mukhopadhyay, A.K., Sharma, S., Tripathi, V., Chen, Y., Kumar, S. and, Atencio, E.

Leading researchers by the number of publications like A.P. Botha is also highly cited, with publications like Bag et al. (2021) having 138 citations thus far. That indicates the level of expertise and reputation the author has among other authors.

Figure 3-6 and Figure 3-7 show groups of authors and their close relationships. The links show the co-authored articles between the authors.

Figure 3-8 shows the split of the publications according to the subject area. The subject area with the highest publication numbers was the engineering field, with 124, closely

followed by computer sciences, with 95 publications. The third highest number of publications by study field was from the Business Management field, with 38.

Figure 3-8 also demonstrates that the sciences are leading in research on Industry 4.0 adoption. However, there is a lack of studies focusing on mining specifically. There is room for more studies to add to the existing literature.

Figure 3-9 and Figure 3-10 show the most common terms used in the titles, authors key keywords and publication abstracts examined. The image illustrates five to six distinct colours of the relationships between the terms.

3.5 CONCLUSIONS, RECOMMENDATIONS AND OPPORTUNITIES FOR FUTURE STUDIES

3.5.1 Conclusions

The literature suggests that organisations need the option to choose between digital technologies and alternatives. Otherwise, the obsolescence of the organisation will follow shortly. Models such as circular economies fit well with implementing Industry 4.0 technology as they look at ways to improve waste management. Industry 4.0 technology is very effective at tracking all kinds of processes in a firm, including waste management and redistributing such waste.

3.5.1.1 The people dimension

There is still a need for people in a mixed economy in developing countries such as South Africa, which means that these people will need to be managed accordingly in the changing environment brought upon by implementing Industry 4.0 technology. The literature suggested that managers must seek methods to train people in the changing environment and keep them updated regularly. The literature also mentions the need to move from outdated management styles towards people-oriented leadership methods (Section 3.4.1.7 details the different leadership styles for each stage of Industry 4.0 implementation) that consider the opinions of all involved in the value-adding process they undertake. Human labour working hand in hand with technology is what literature recommends. The literature suggests more benefits from the human-machine partnership than when leaving machines to their devices.

Implementing Industry 4.0 will bring along many changes to the work culture. These changes will require more resources, such as psychology departments trained in the new working environment. There will also be a need to form partnerships between organisations looking to digitalise and specialists in digitalisation. That will aid in developing the necessary digital skills within a short period. Whether that will be cheaper requires further evaluation. Other forms of partnerships suggested by the literature were between organisations looking to digitalise and academia. More partnership suggestions by the literature were between organisations looking to digitalise and academia. The benefit of such a partnership would be the development of the necessary know-how for the organisation and the academic partner, addressing the need for more know-how in digital technology tools highlighted by the literature.

The literature suggests that there are still fears about introducing technologies such as automation due to fears such as replacing the workforce. Such fears require addressing with education and clear communication of plans for implementing such technology before introducing the technology.

3.5.1.2 Industry 4.0 implementation resource needs

Due to the landscape change of the working environment caused by the implementation of Industry 4.0 technology, as suggested by the literature, require new and old equipment to be altered or replaced. That is where the partnership mentioned in 3.4.1.7 above comes in handy, as these organisations will have set equipment and the technical knowledge to use them.

All new partnerships between businesses, people who do the work and policymakers will be required. Knowledge from experienced implementers of Industry 4.0 technology will help new adopters, especially in developing countries, as they can adopt knowledge from developed countries that lead the way in adopting set technology.

3.5.1.3 Benefits and risks of Industry 4.0 implementation

According to the literature, Industry 4.0 implementation will result in safer work practices, faster and more abundant production, waste reduction, high-skill job opportunities, improved costs, and improved environmental impacts, among other benefits. These benefits will ease the pressure on heavy industries such as mining, which have experienced a reduction in productivity while upgrading their public image as they are

among the largest polluting industries. The mining companies that move towards implementing Industry 4.0 technology will also gain the advantage of not being rendered obsolete. However, there is a risk for early adopters as there have been a low number of instances where Industry 4.0 technology in mining has been applied successfully in an emerging market such as South Africa. Most of the technology is new, and early adopters risk costly mistakes associated with introducing new technology with little information on how to apply it in an economy such as South Africa. The lack of literature highlighted this issue.

Using the new technology could potentially reduce the number of accidents and human errors in mining using real-time data collected across mining activities. Despite all these benefits, people are still reluctant to adopt new technology due to the risks posed to their job security. These people need reassurance by demonstrating how the technology will benefit them and how they will work alongside technology instead of technology replacing them.

3.5.2 Conclusions and recommendations

- Implementing Industry 4.0 is critical to the mining industry. However, such technology comes with many risks. Therefore, mining companies must slowly apply the technology to small parts of the mining value chain. Optimising technology use in the selected section before transforming another part of the value chain.
- Partners with Industry 4.0 technology technical know-how need to be involved in implementing Industry 4.0 technology. That requires acquiring new resources, meaning partnerships should include companies having set resources available.
- Leadership plays a pivotal role during technology adoption, so leaders must evolve with the changes and involve all stakeholders.
- South Africa, a developing economy, needs to use a mix of digital technology and people. These people will need proper training in the changing environment, and the leadership needs to change alongside them. Leadership styles relevant to Industry 4.0 -enabled workplaces are also required. The people will need training on utilising, maintaining and continuously improving the new technology.

- Mining companies need to invest more in research and development of Industry 4.0 methodologies and applications specific to the mining industry as there is a lack of such research readily available, especially research focusing on emerging markets such as South Africa.
- People are still hesitant to introduce disruptive technology. They need more information about the technology and implications for their work. Considering people's inputs during all stages of such technology implementations is crucial, from the introduction of plans to the final steps.
- Industry 4.0 technology often fails due to a lack of planning before implementation. A solution is improving the planning methods required before implementing the technology, which will determine the need for the technology and whether the technology will be successful in the organisation.
- Roadmaps for adopting Industry 4.0 developed to some extent in South African literature but lacked rigorous testing to prove their applicability.
- The use of simulations or pilot plants in Industry 4.0 technology can help identify opportunities and weaknesses of new technology before implementing the technology at full scale.

3.5.3 Opportunities for further exploration

- This study highlighted the need for more literature specific to the mining industry in South Africa on Industry 4.0 technology implementation. A future study could be a case study on implementing Industry 4.0 technology in a subsystem within a mining operation. That can involve simulating a process within the mining operation and examining how to incorporate it into the subsystem step by step. The advantage of using a simulation model would be the evaluation of the subsystem without immediately disrupting it. A paper on building and evaluating this subsystem can then be published, adding to the much-needed literature.
- This literature review was limited to researchers from developing countries only. Therefore, other researchers can take a broader look at other developed countries and identify literature on the emergence of Industry 4.0 technology in mining that could support this study's findings and add to set results. Other researchers can

also alter the search criteria, inclusion criteria, etcetera used in this study to identify different sources of literature that this study could have missed.

- The literature review found recommendations for roadmaps for developing countries like South Africa, but these roadmaps were not rigorously tested or evaluated. A future study could evaluate these roadmaps using interviews with industry experts or testing their application on a project for technology adoption.

3.5.4 Funding sources

A bursary from African Rainbow Minerals (ARM) was the funder for this study.

CHAPTER 4 RESEARCH METHODOLOGY

4.1 Introduction

This study used two research methods to gather data. The first step was a desktop study completing a Systematic Literature Review (SLR) on implementing new technologies in the South African mining industry (Submitted for conference review). The second research method used an online survey on a roadmap for the successful implementation of Industry 4.0 technology. The survey participants were industry experts who were asked for their opinions on the technology implementation roadmap and asked to rate the steps in the roadmap.

4.2 Qualitative part philosophical assumptions

This research followed the constructivist social worldview (Creswell, 2009). This worldview holds that people have different worldviews, with individuals seeking to understand the world they work and live in. This worldview states that individuals construct subjective meanings of experience. That allows for differing interpretations and the researcher the ability to explore complexity in the views that would otherwise not work if categorising responses (limiting responses to a few categories). This research worldview aims to rely primarily on participant responses as much as possible with broad general questions that allow participants to construct meaning (Creswell, 2009).

The researcher administered a survey with open-ended questions sent online to participants (Creswell, 2009). The details of the methods for gathering qualitative data from the survey are in section 4.8.3. Figure 4-1 shows the qualitative research approach.

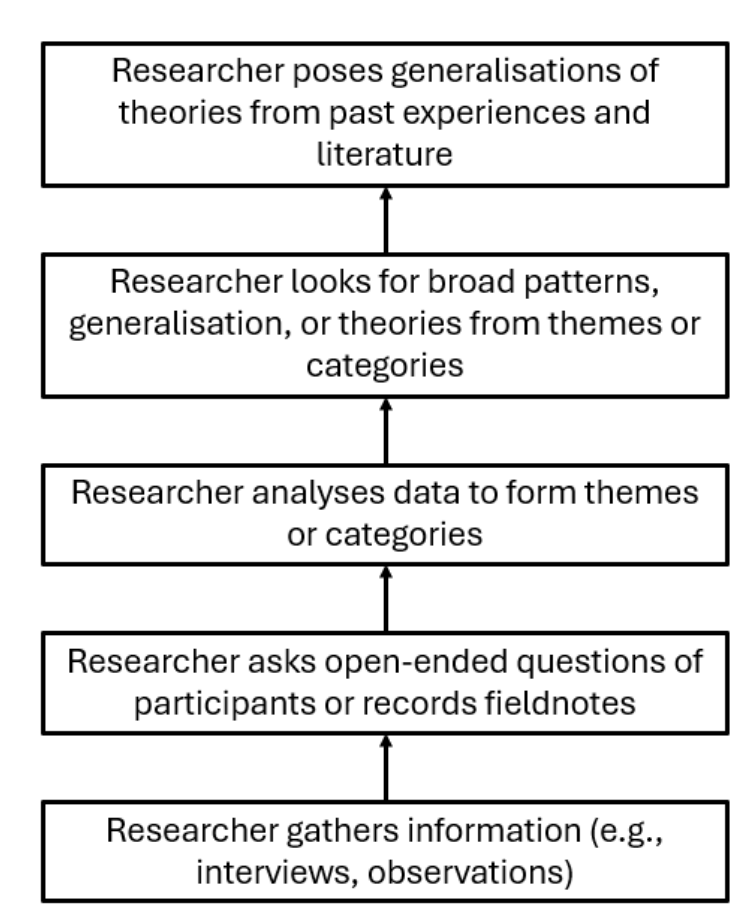


Figure 4-1: Qualitative research approach (Creswell, 2009).

4.3 Quantitative part philosophical assumptions

In addition to open-ended questions, closed-ended questions were added to the survey to ease respondent's efforts when they completed the online survey. The postpositivist worldview is the traditional research method commonly used for qualitative research. That is what the scientific method is. This approach recognises that people cannot be "positive" about claims about knowledge when studying human actions and behaviours (Creswell, 2009).

A postpositivist follows a deterministic philosophy where cause determines the effect, meaning problems studied in postpositive research identify and assess causes that influence results. This approach is reductionist, meaning forming subsets of a problem ideal for testing, and then variables are developed. Then, form research questions and hypotheses. In this approach, the researcher formulates theories, and data is collected that refutes or confirms the theories with necessary tests and revisions (Creswell, 2009). Babbie (1990) says it is possible to study society scientifically. The effectiveness of

probability sampling makes this point relevant. With just 1500 voters, researchers can accurately predict outcomes for tens of millions of voters. Figure 4-2 shows the quantitative research approach.

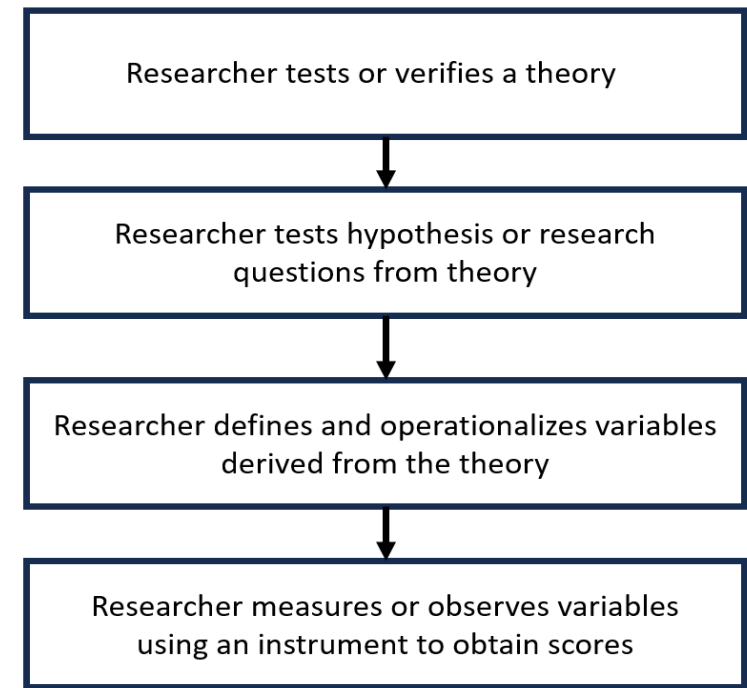


Figure 4-2: Quantitative research approach (Creswell, 2009).

4.4 Mixing the philosophical assumptions of quantitative and qualitative

Concurrent mixed methods

This method merges qualitative and quantitative research approaches for comprehensive research problem analysis. This approach collects both forms of data simultaneously and interprets the data as a whole (Creswell, 2009). Figure 4-3 shows the approaches to research and how they link to formulate mixed methods.

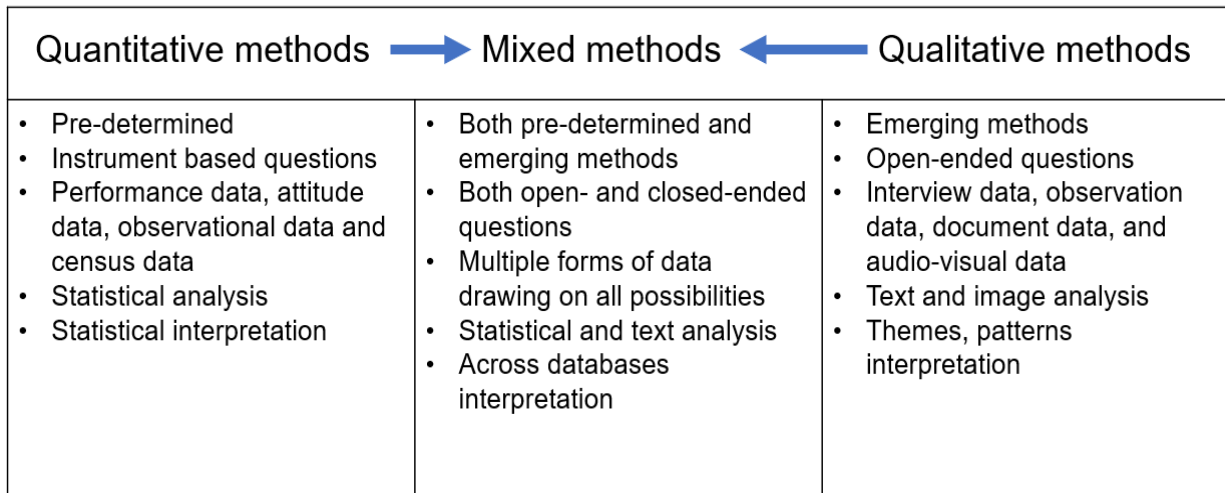


Figure 4-3: Three approaches to research methodology (Creswell, 2009).

The researcher combined qualitative and quantitative methods to collect data because they allowed as many participants as possible without inconveniencing their work and dissuading them from participating in the study. The quantitative questions in the survey allowed the participant to rate the steps in the roadmap presented through the roadmap. That also allowed simplicity due to the online administration. The participants could answer the questions at their own time and pace with no input from the author. The qualitative questions allowed the participants to expand on their responses to the steps in the roadmap, and the questions explicitly asked for additions suggested by the participants that could improve the roadmap.

4.5 Research methods

The following are the methods and materials used in this study. The researcher split this study into two parts, the first being a desktop study on Industry 4.0 implementation strategies in the mining industry, including other heavy industries. The second part was a survey examining the practical implementation of best practices from the literature. Figure 4-4 shows the details of the method from how the research was split between the SLR (finding research gap) and the dissertation. The research gap split identified barriers and enablers to technology implementation while the main dissertation analysed industry experts' opinions on a roadmap developed in this study.

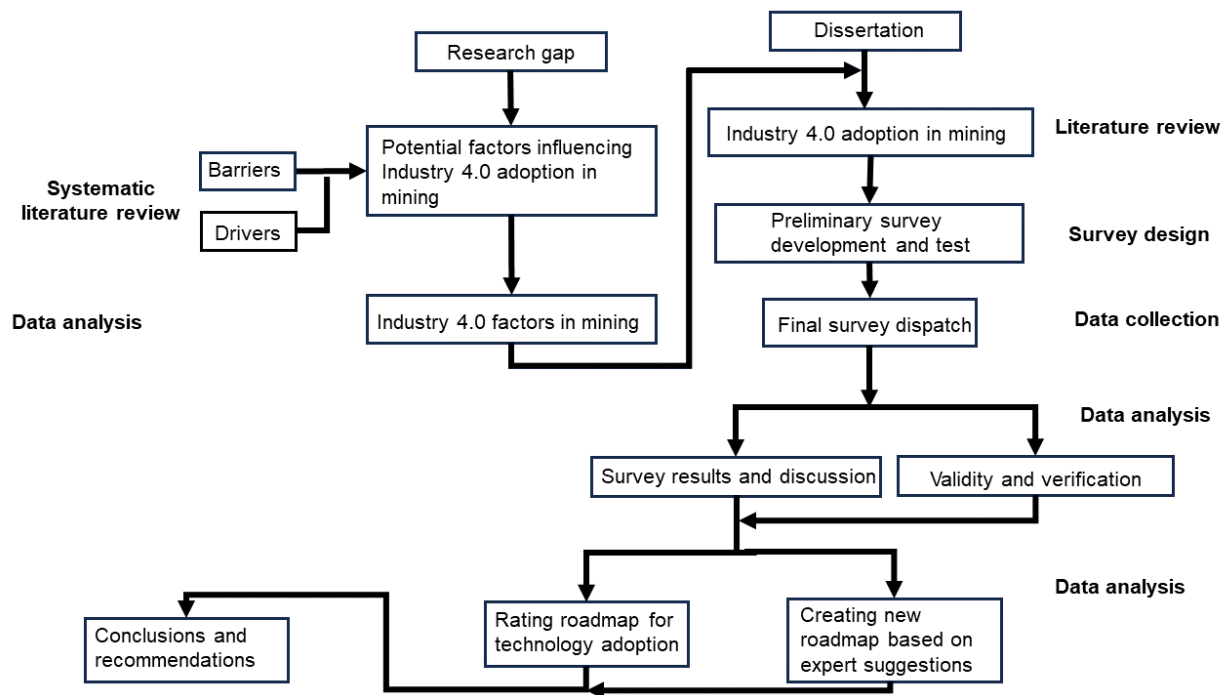


Figure 4-4: The split of the research method into phases.

4.5.1 Resources used for the study

- Computer specifications:
 - Processor 13th Gen Intel (R) Core (TM) i5-1335U 1.30 GHz
 - Installed RAM 16.0 GB (15.6 GB usable)
 - Operating system Windows 11 Pro
 - 64-bit operating system, x64-based processor

4.5.2 Software used for the study

- Python codes for some statistical analyses
 - ChatGPT for code generation
- Microsoft Excel for some statistical analyses
- Microsoft Word for report writing

4.6 SLR data collection procedures

SLR is the collection of relevant evidence on a topic in line with pre-described eligibility criteria to answer a formulated research question; this goes along with meta-analysis, where statistical methods determine inferential and descriptive summaries on the area of

interest (Mengist et al., 2020). Figure 4-5 shows the SLR selection flow diagram where the literature was included or excluded according to these predetermined criteria.

The systematic review of the literature of this study was used as a stepping stone for an in-depth look at the applications of Industry 4.0 in mining and other related fields, as there is a lack of specific literature for mining. The study further states that there was an advantage in exploiting South Africa's mineral resources, but this should benefit the environment and people. Therefore, labour and human rights considerations are required when introducing Industry 4.0 technology in the mining sector.

The study looked at the literature on how technology has been applied to South African industries using large equipment and having many people working for them, similar to and including mining in the past. Below are considerations for the implementation of such technology:

- The benefits of technology adoption.
- The challenges encountered when adopting new technology within an organisation and staff using the technology.
- How can the organisation correctly adopt the new technology and bridge the gap between the technology and the people who, in the end, use the technology?

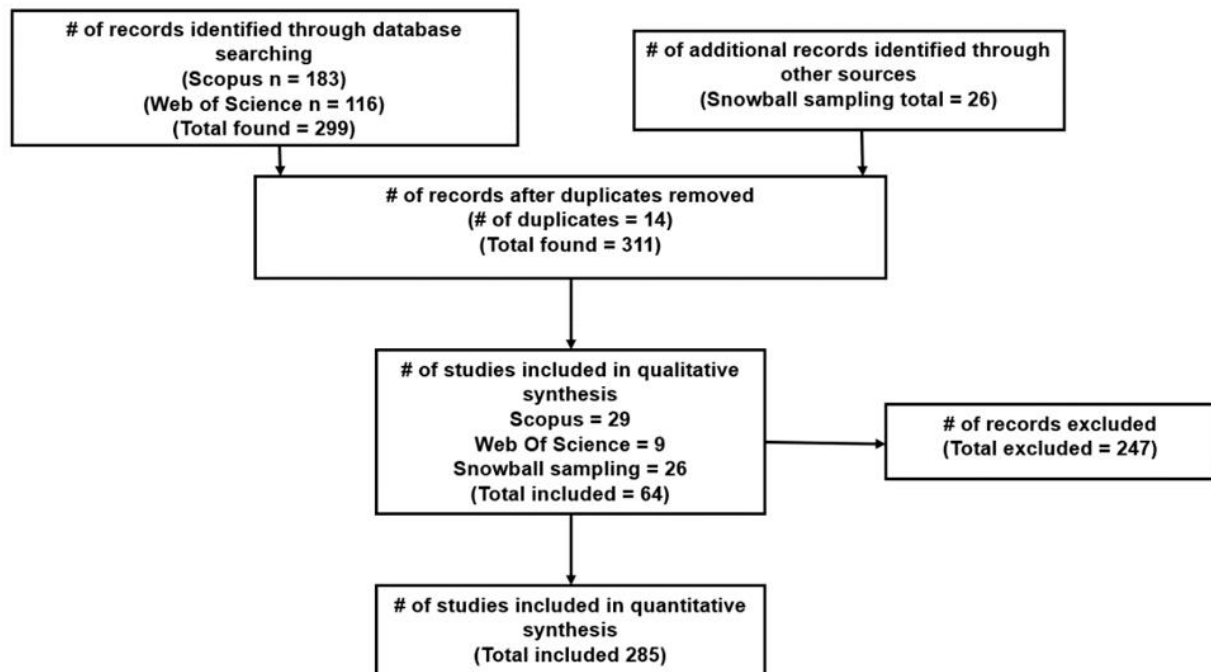


Figure 4-5: Study selection steps used for the SLR.

4.7 Survey data collection procedures

This research used grounded theory (Creswell, 2009). This strategy gathers abstract and general process theory, interactions, or actions based on participants' views. The characteristic of this research design was to compare the data with theoretical sampling and the categories that emerge from responses that look to make the most of the differences and similarities (Creswell, 2009).

Qualitative research is applied to investigate and understand people's ascribed meaning to human and social phenomena. Data collection through participants (people) and data analysis is inductive, gathering general themes from participants. Qualitative research is warranted if the phenomenon or concept requires better understanding because little research exists (Creswell, 2009; Taylor et al., 2015). This study used qualitative research methodology. That is because the nature of the research collected human opinions on a process that leads to adopting new technology in the mining industry, achieving this through a qualitative survey with industry experts (Creswell, 2009; Taylor et al., 2015).

4.7.1 Survey design

Reasons for surveys. In the last 50 years, there has been a move towards using online surveys as the most dominant form of survey methodology to collect data in research, coinciding with the growth of the Internet (Toepoel, 2015). That is a more convenient method to gather information due to the long distances between surveyors, and the respondents can be from each other during the survey period. Using online surveys provides convenience, as respondents can participate at a time convenient to their schedule. The study distributed the survey through Google Forms, which stores responses in real time, freely, and data can be easily exported (Melo, 2023; Synodinos, 2003; Watson, 1998; Ritter and Sue, 2007; Wegner, 2012).

Surveys gather primary data from direct questions to respondents. Survey instruments measure attitudinal-type data such as opinions, preferences, awareness, perceptions, motivations, etcetera (Wegner, 2012). Surveys eliminate interviewer bias, allowing respondents more time and ensuring the anonymity of respondents, meaning more honest answers (Wegner, 2012; Synodinos, 2003; Watson, 1998).

Some of the drawbacks of electronic surveys (e-surveys) include the lack of personal communication between the responders and the researcher, limited influence over the

collection procedure, they have a limited response rate, and there is no provision for clarity for the respondents. Surveys need to be simple and short, meaning fewer data are collected. There is limited control over final respondents, increasing bias, and there is no chance of further probing of respondents (Wegner, 2012).

Surveys need thorough testing before use. The researcher's responsibility is to ensure they ask only relevant questions in the form of questions, wording, and sequence. The study asked knowledge questions about a topic based on roadmaps for technology adoption in the mining industry (Toepoel, 2017).

The survey's basis was a roadmap developed through the literature in section 2.10 on roadmaps for adopting Industry 4.0 technology in the mining industry. This research tested whether the roadmap was sufficient for the South African mining industry. The survey took approximately 15 to 20 minutes to complete using Google Forms.

The survey was the measurement tool used in this study. The survey measured whether the combined roadmap applies to the mining industry in South Africa by gathering the opinions of industry experts in a South African mine. The survey is available in Appendix A.

4.7.2 The rationale for selecting questions in the survey

Oduniyi (2022) showed that gender was statistically significant in sustainable land management practices adoption. There was also a correlation between sustainable land management practices adoption and age. Lastly, years of experience in farming negatively affected the adoption of sustainable land management practices. The study also showed that farmers were unwilling to adopt new technology due to the fear of the unknown.

The demographic questions selected in the survey collected data on years of experience, type of work experience in mining, age, and gender. The years of experience alongside the kind of work experience data provides context on the credibility of the years of experience in decision-making on implementing technology in the mining industry. That provided background on the level of decision-making they were involved in and responsibilities in the implementation they had. The inspiration for the gender and age demographic questions were studies such as Oduniyi (2022), and Venkatesh et al.

(2003), which showed differences in responses due to gender and age on how technology implementation should take place.

The basis for the qualitative questions was the literature in section 2.10. The three phases of the survey were to break down the steps into milestones. Leading to better milestone tracking during the technology implementation. These three phases were the pre-installation, installation, and post-installation phases.

The pre-installation phase questions summarised the steps in Section 2.10, literature on technology implementation planning. These questions encapsulated the steps in which the commissioning entity, its stakeholders, and its vendors would interact to plan the execution of the new technology. The installation phase questions encapsulated the steps of the commissioning entity, its stakeholders, and the vendor during the Industry 4.0 technology system installation. The post-implementation phase questions captured the after-sales services the vendors provided to the stakeholders and commissioning entity after the technology was installed, from maintenance and servicing to the training on the use.

The survey was pretested and refined based on the feedback with details in section 6.3.

4.7.3 Sampling

The sampling method used for the study was purposive sampling. That sampling method falls under the non-random (or non-probability) sampling based on experience, common sense, expertise, and researcher intention (Neetij and Bikash, 2015).

The type of purposive sampling

The type of purposive sampling used in the study was expert sampling. This sampling method gathers data in a particular area of expertise. Applying expert sampling when high uncertainty is involved is useful (Neetij and Bikash, 2015). The participants in this study were experts familiar with the implementation technology of the mining industry in the mining sector. The sampling included industry experts with experience applying new technology in South African mines.

4.7.3.1 Snowball sampling

Snowball sampling was used in the study since purposive sampling did not produce an adequate sample size. This study applied the s-stage k name Snowball sampling method

by asking the individuals identified in the purposive sample to name k additional individuals with the necessary expertise (technology implementation), and this can carry on in stages until gathered is an adequate sample size (Goodman, 1961a). That yielded 31 participants to the survey.

4.7.3.2 Sample size for qualitative responses

Francis et al. (2010) found that when purposive "diversity sampling" with only ten interviews, a further three yielded no significant change in observing common themes. A study investigating behavioural beliefs requires only 15 interviews, while normative belief studies require 13 interviews, and, lastly, when examining control beliefs, only 14 interviews sufficed. Setting a sample size of at least 13 interviews records beliefs, subjective norms, and perceived behavioural control (Francis et al., 2010).

Guest et al. (2006) identified 94% of the common themes within six out of 60 interviews, and 12 are sufficient to determine 97% of common themes out of 60 interviews. Hennink and Kaiser (2022) identified 23 articles on saturation, and a range of 9 to 17 interviews are sufficient for saturation and 4 to 8 participants in focus groups. Most of the studies in Hennink and Kaiser (2022) were homogeneous populations. This study resulted in 18 respondents to the 31 total responding to the qualitative part, and saturation was reached (Most qualitative responses were repetitive).

Please note: Participants did not receive any incentive to participate. KMO is detailed in section 6.6.1 to determine the sample size adequacy for quantitative responses (interval data) to the survey.

4.8 Data analysis

4.8.1 Systematic Literature Review

The SLR subdivision consisted of two parts (quantitative and qualitative parts). The full details were presented in Chapter 3.

4.8.1.1 Qualitative

The first part was a qualitative study of the available literature on applying Industry 4.0 technology in South African heavy industries.

4.8.1.2 Quantitative

The quantitative part of the SLR develops insights such as which industries invest heavily in Industry 4.0 implementation, the leading institutions and researchers in the area, and the level of research done in developing countries, including the prominent researchers in the field.

4.8.2 Online survey qualitative response analysis

The study developed themes from the participant's responses through coding. These themes were interpreted and reported in Figure 4-6. Therefore, coding themes determine similarities and differences in the responses to the survey.

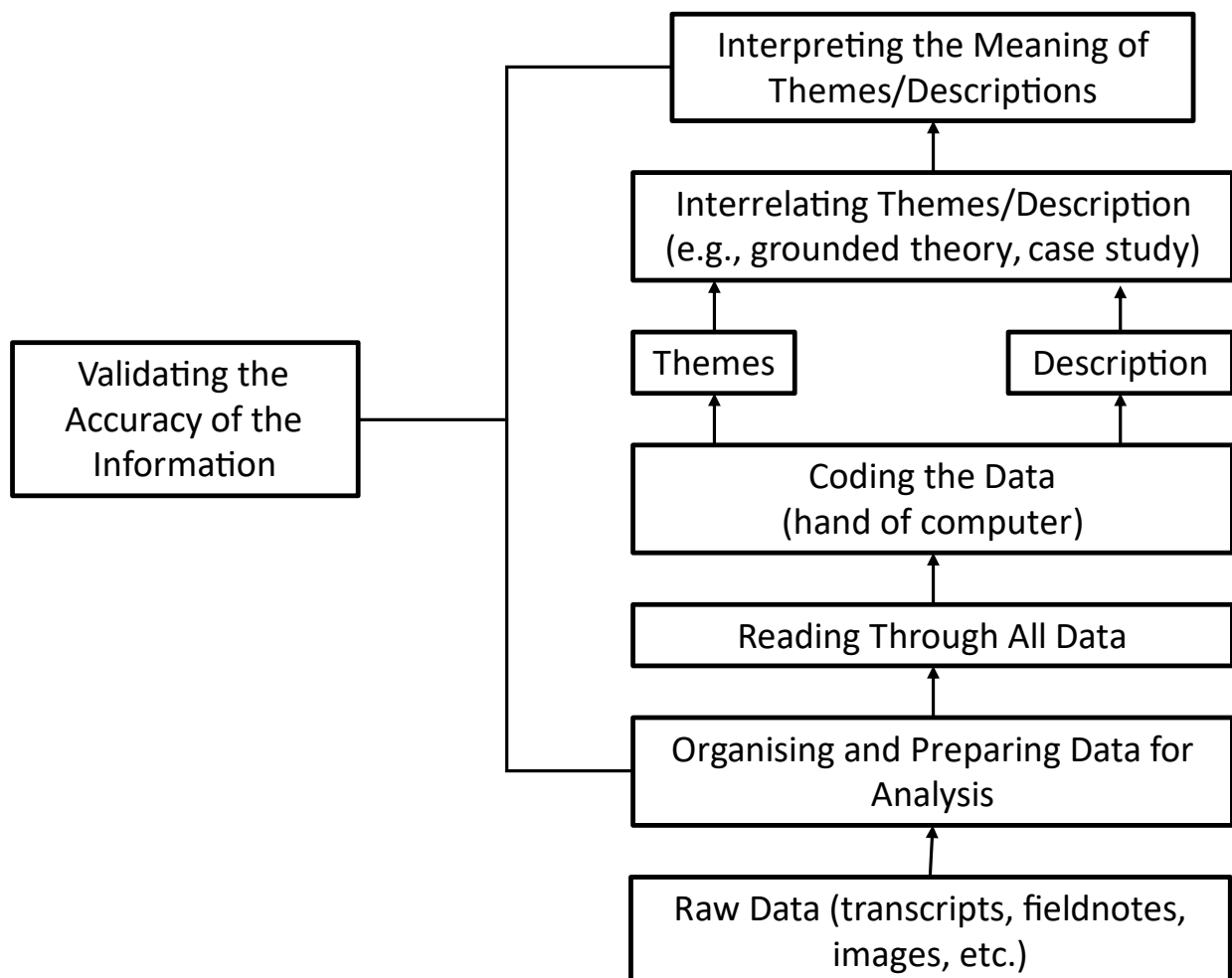


Figure 4-6: The development of themes from raw data (Creswell, 2009).

4.8.2.1 ChatGPT for thematic analysis

ChatGPT is a generative AI software product. ChatGPT was found practical and useful in research by students (Xu et al., 2024; Firat, 2023). ChatGPT has transcript data coding ability to generate themes from code lists. Therefore, this tool can perform thematic analysis. This analysis required a human researcher to intervene if necessary (Lee et al., 2024; Turobov et al., 2024). The researcher inserted the survey's qualitative responses into ChatGPT. It formed themes that were reviewed and confirmed by the researcher.

4.8.3 Quantitative response analysis of online surveys

Nominal data are categorical data. If all categories are equal in importance, they are referred to as nominal-scaled data (for example, male and female) (Wegner, 2012). This study collected this data to separate different demographics among the respondents.

Interval data are numerical and quantitative random variables used in surveys to measure respondents' motivations, preferences, perceptions, and attitudes (Wegner, 2012). This study used this data to measure levels of agreement or disagreement with the roadmap steps presented in the survey.

Please note: The quantitative responses used statistical summaries to summarise the survey responses.

4.8.3.1 The Student t-distribution

When the unknown is the population standard deviation and requires an estimate through sample standard deviation, the student t-distribution applies to obtain limits for confidence intervals (Wegner, 2012).

Population proportion (p) confidence interval

For nominal data, the measure of central location is proportion. The following equation gives a confidence interval:

$$p - z \sqrt{\frac{p(1-p)}{n}} \leq \pi \leq p + z \sqrt{\frac{p(1-p)}{n}} \quad \dots(1)$$

Here, the sample proportion (p) is given by $p = \frac{x}{n}$, and n sample size. The z-limits correspond to the specified confidence level. The final interval is a percentage (Wegner, 2012).

4.8.3.2 Hypothesis testing

Sample data are gathered and analysed, and based on sample findings, hypothesised claims are either accepted as likely correct or rejected as likely false. That is hypothesis testing (Wegner, 2012). When using a parametric one-sample t-test and non-parametric Wilcoxon Rank Signed test, Baran (2021) found no differences in statistical significance between the parametric and non-parametric tools when analysing Likert scale data. Murray (2013) made a similar observation, where parametric Pearson and non-parametric Spearman correlations yielded similar results after analysis. Hypothesis testing was used in this study to determine the levels of agreement respondents had with the steps in implementing technology in mining.

4.8.3.3 Survey section B hypothesis based on the roadmap

The study proved the expert's agreement with the steps in the implementation roadmap by testing the hypotheses made below.

Null Hypothesis (H_0): The proportion of respondents who agree or strongly agree with each question is less than or equal to 50%.

- **The null hypothesis (H_0):**

$$H_0 : p \leq 0.5 \quad \dots(2)$$

where π_1 is the mean proportion of respondents that agree or strongly agree and π_2 is the proportion of respondents that disagree or strongly disagree.

Alternative Hypothesis (H_1): The proportion of respondents who agree or strongly agree with each question is greater than 50%.

- **The alternative hypothesis (H_1):**

$$H_1 : p > 0.5 \quad \dots(3)$$

Note that hypothesis tests for the difference between two proportions assess differences and similarities between two populations (Wegner, 2012).

4.8.3.4 Hypothesis test for the difference between two or more groups

Analysis of Variance (ANOVA) is "to determine whether there is a statistical relationship between the factor and the response variable", meaning is there statistically significant independence between two measures (Wegner, 2012).

For each question Q_i where i ranges from 1 to 21, comparing mean score across groups:

- **The null Hypothesis (H_0):**

$$H_0 : \mu_1 = \mu_2 = \mu_3 = \dots = \mu_k \quad \dots(4)$$

where μ_i is the mean score of the i -th group.

- **The alternative Hypothesis (H_1):**

$$H_1 : \mu_1 \neq \mu_2 \neq \mu_3 \neq \dots \neq \mu_k \quad \dots(5)$$

A. Age difference hypothesis

Null Hypothesis (H_0): There is no significant difference in the mean scores among different age ranges for each question:

- **The null Hypothesis (H_0):**

$$H_0 : \mu_1 = \mu_2 = \mu_3 = \dots = \mu_k \quad \dots(6)$$

Alternative Hypothesis (H_1): There is a significant difference in the mean scores among different age ranges for each question.

- **The alternative Hypothesis (H_1):**

$$H_1 : \text{At least one } \mu_i \text{ is different} \quad \dots(7)$$

B. Years of experience difference hypothesis

Null Hypothesis (H_0): There is no significant difference in the mean scores among different years of experience ranges for each question:

- **The null Hypothesis (H_0):**

$$H_0 : \mu_1 = \mu_2 = \mu_3 = \dots = \mu_k \quad \dots(8)$$

Alternative Hypothesis (H_1): There is a significant difference in the mean scores among different years of experience ranges for each question.

- **The alternative Hypothesis (H_1):**

$$H_1 : \text{At least one } \mu_i \text{ is different} \quad \dots(9)$$

C. Tukey's HSD test depending on ANOVA test

Controlling type I errors in comparison tests of multiple variables is crucial. Many statistical tests provide differences in system structure while minimising error rates and providing accuracy and meaningful conclusions. Tukey's honestly significant difference is one of the tests that provide these benefits and is one of the most used (Nanda et al., 2021).

A commonplace research problem is the comparison of multiple treatments to determine which has the best performance. One of the tests used to determine the result of the performance test is the ANOVA. This test determines the significance of a test and shows that at least one group in the multiple groups the test performed on was significant. However, it does not specify which exact group means are significantly different in the collective of tested groups. This problem in ANOVA analysis is solved by pairing the test with a pairwise comparison. Pairwise comparison allows the ability to distinguish which mean groups are significantly different from each other as individual pairs. The most commonly used of these tests is Tukey's Honestly Significant Difference (HSD) (Prasad and Chari, 2011; Abdi and Williams, 2010; Nanda et al., 2021).

The HSD test uses sample data to examine differences between population means. The HSD involves assessing confidence levels to determine statistical differences between mean groups. The confidence interval establishes the statistical and practical significant differences between group means. If zero is not part of the confidence interval, we reject the null hypothesis, stating there is no difference between means (Nanda et al., 2021; Abdi and Williams, 2010).

$$HSD = \frac{M_i - M_j}{\sqrt{\frac{MSW}{N}}} \quad \dots(10)$$

$M_i - M_j$ is the pair of means differences (M_i should be more than M_j in the calculation). M_{sw} is the mean square within groups, and N is the number of individuals within the group (Nanda et al., 2021).

The study performed a Tukey's Honest Significant Difference (HSD) test for all ANOVA results showing significance. That was to determine which groups in the data differ from each other. Only the experience groups showed significance for the ANOVA test. Therefore, the HSD test was only for the experience groups that showed significance.

Null Hypothesis (H_0): There is no significant difference in the mean scores between any two experience groups for each question.

- **The null Hypothesis (H_0):**

$$H_0 : \mu_i - \mu_j = 0 \quad \dots(11)$$

Where μ_i and μ_j are the mean scores of the i -th and j -th experience groups, respectively.

Alternative Hypothesis (H_1): There is a significant difference in the mean scores between at least one pair of experience groups for each question.

- **The alternative Hypothesis (H_1):**

$$H_1 : \mu_i - \mu_j \neq 0 \quad \dots(12)$$

D. Hypothesis test for the difference between genders

Venkatesh and Morris, (2000), and Venkatesh et al. (2003) suggested that gender plays a critical role in the issues faced when implementing technology. Does this apply to the steps in the roadmap in the survey? Does gender play a crucial role in the responses?

Null Hypothesis (H_0): There is no significant difference in the mean scores between males and females for each Likert question Q_i . Where i ranges from 1 to 21 and testing against both means.

- **The null hypothesis (H_0):**

$$H_0 : \mu_{male} - \mu_{female} = 0 \quad \dots(13)$$

where μ_{male} is the mean response of males and μ_{female} is the mean response of females.

Alternative Hypothesis (H_0): There is a significant difference in the mean scores between males and females for each question.

- **The alternative hypothesis (H_1):**

$$H_1 : \mu_{male} - \mu_{female} \neq 0 \quad \dots(14)$$

4.8.3.5 Chi-square hypothesis tests

The Chi-squared hypothesis test tests the "independence of association between categorical variables". It also tests the proportions equality between multiple populations. And lastly, it is used as a goodness-of-fit test (testing if data follows a particular distribution). The basis for this test is the frequency data count collected from random samples. The chi-square statistic measures the difference between observed frequency and expected frequency. When the difference is slight, the null hypothesis is probably accepted and probably rejected if the difference is sizeable. The following equation calculated the chi-square statistic (Wegner, 2012):

$$\chi^2 = \sum \frac{(f_0 - f_e)^2}{f_e} \quad \dots(15)$$

Where f_0 is the frequency observed of the "category of a categorical variable", and f_e is the expected frequency of the categories of the categorical variable (Wegner, 2012). The chi-square test can also test the equality of several proportions (Wegner, 2012). In this study, the Chi-square test was used as an alternative or triangulation tool to verify the findings of the hypothesis tests mentioned earlier in section 4.8.3.

For each question Q_i where i ranges from 1 to 21:

Null Hypothesis (H_0): The question responses are independent of the demographic variable (gender, age range, or years of experience).

- **Null Hypothesis (H_0):**

$$H_0: \sum \frac{(f_0 - f_e)^2}{f_e} = 0 \quad \dots(16)$$

Alternative Hypothesis (H_1): The question responses depended on the demographic variable (gender, age range, or years of experience).

- **Alternative Hypothesis (H_1):**

$$H_1: \sum \frac{(f_o - f_e)^2}{f_e} \neq 0 \quad \dots(17)$$

4.9 Ethical considerations

Since human participants were involved in the study, the researcher respected their rights, needs, desires, and values. The research objectives were disclosed to the participants in writing, with permission to participate in the study gathered from the participants. The researcher maintained the anonymity of the participants during the reporting process (Creswell, 2009; Ritter and Sue, 2007). The only conflict of interest to declare was ARM's sponsorship of this study. The study got ethics clearance from the ENG-REC committee. The ethics clearance was granted, with the ethics number NWU-00229-23-A3.

4.10 Chapter summary

The research method used started with an SLR that guided the direction of this research, identifying the trends that developing countries follow to implement Industry 4.0 technology. The researcher then designed a survey from the literature on roadmaps for technology implementation in South Africa. The survey collected both qualitative and quantitative data. The qualitative data collected opinions from the participants on what they deemed necessary additions to the roadmap. The quantitative data collected were five-point Likert scale ratings of the roadmap steps.

The researcher then sent the Google Forms survey to mining industry experts to gather their opinions on the roadmap and its applicability in the South African mining industry. Google Forms online (internet) collected the responses. The researcher used a purposive sample of mining industry experts to select respondents, people working in the mining industry with experience in how the mining industry approaches adding new technologies. This study's survey aimed to test the roadmap by gathering industry expert's responses to the roadmap as is. The survey also provided a platform for additions to the roadmap if the respondents deemed it necessary by strengthening areas where the roadmap was lacking in terms of South African adoption-specific steps necessary. The study used thematic analysis for common themes to analyse the qualitative responses for additions

to the roadmap. The study's analyses of Likert scale questions for ratings of the existing roadmap steps used quantitative methods, including hypothesis testing and statistical summaries.

CHAPTER 5 SURVEY DESIGN

5.1 Introduction

This chapter details how the survey was designed, from the literature to its final form.

5.2 Survey design

The survey consisted of qualitative and quantitative questions. The qualitative questions collected information that would help improve the study for future use and improve shortfalls identified by the participants, such as what the roadmap was missing sections to remove, sections to add, and sections that needed combination due to them addressing the same issue.

5.2.1 Qualitative questions

The qualitative questions in the survey collected data on whether the participants agreed with the steps included in the study's survey. These questions also collected additions to the roadmap.

5.2.2 Qualitative questions

The survey questions had three-phase subdivisions. These were the Pre-installation, Installation and Post-installation phases. This was in line with what Gerd Sri et al. (2010), Garcia and Bray (1997), Ghobakhloo (2018) and Fan (2019), their approaches split the steps into three phases. The other approaches presented by Butt (2020), Schumacher et al. (2019), Lau et al. (2019) and Pessl et al. (2020) were step by step by step approaches that involved up to ten steps one after the other. That made it difficult to track progress when compared to a phased approach. The phased approach also made it possible to gauge progress and allowed the assessment of whether further steps were still worth pursuing based on the current progress (stakeholders have a chance to evaluate the implementation after each phase).

5.3 Final survey

The following lists detail the roadmap questions sent to survey participants. The 21 qualitative questions and the three quantitative questions are listed. The order of the qualitative questions matches that of the detailed analysis. The actual online survey questions are in Appendix A.

- **Pre-installation phase (gathering and evaluating implementing entity's capacity and potential partners) questions**
 1. Define the business problem
 2. Identify the technological gap
 3. Identify the commissioning entity's expectations and capacity
 4. Evaluating information on the necessary technology and vendors
 5. Assessment and selection procedure for vendor and technology selection
 6. Compiling short-term, medium-term, long-term and risk management strategies
 7. Drafting agreements and contracts
 - a. Do you agree with the listed checklist items and their order for gathering and evaluating the information above?
- **Installation phase questions**
 8. Design and evaluate concepts for a simulation, create a numeric simulation of the technology scenario
 9. Evaluate the numeric simulation against expectations
 10. Prepare prototype designs for possible implementation based on simulation separated from normal operations
 11. Validate the prototype against simulation expectations, choosing optimal (if the results of the prototype are unfavourable terminate the project)
 12. Gathering system requirement documents from the vendor
 13. Gathering system requirements for infrastructure upgrade
 14. Ensure implementation of legal agreements
 15. Implement budget control measures
 16. Constant checks of design and quality of civil works
 17. Provide support and cooperation (communication)

- b. Do you agree with the listed checklist items for developing a detailed project plan above?
- **Post-adoption phase (System calibration, testing, integration and after-sale service) questions**
 - 18. System calibration, testing and integration
 - 19. Providing training services
 - 20. Activities required to maintain continuous system functionality
 - 21. Exit strategy
- c. Do you agree with the listed checklist items for system calibration, testing and integration above?

The Pre-installation phase questions looked at the steps in the planning phase of the technology implementations. These ranged from defining the problem the technology addressed to the legal agreements between the vendors and the organisations acquiring the technology. This phase examines the feasibility and the requirements for the technology. The second phase was all about the implementation or installation of the technology. This phase had steps ranging from designing a simulation of the implementation of the technology to planning for post-implementation support. The last phase involved steps that would follow after implementing the technology. The steps in this phase ranged from testing and calibrating the system to the final exit strategy (commissioning the new technology).

5.4 Conclusion

The technology implementation roadmap had a subdivision of three phases of questioning. These simplified the approach. These phases were the pre-installation phase, installation and post-installation phase. The questions in the survey were both qualitative and quantitative. The qualitative questions collected information on improving the roadmap, and the quantitative questions gauged the level of agreement the survey participants had with the roadmap.

CHAPTER 6 VALIDATION AND VERIFICATION

6.1 Introduction

This chapter details the methods used to validate and verify the study methods. From the data collected, data cleansing, and the final analysis.

Measurement error is the level at which an observation does not represent the 'true' value. This error is associated with sources such as measurement imprecision and the inability of respondents to respond (Hair et al., 2009; Hubley and Zumbo, 2011). Validity and reliability are associated with reducing the error. Validity is “the degree to which a measure accurately represents what it is supposed to” (Hair et al., 2009). The reliability definition is “the degree to which the observed variable measures the true value and is error-free”. Thus, the opposite of error (Hair et al., 2009).

6.2 Systematic Literature Review (SLR)

Triangulation seeks convergence from different data sources (Creswell, 2009). Triangulation increases the validity of a study and allows for more confidence in researchers' findings (Guion et al., 2011; Jick, 1979). Investigator triangulation involves the use of multiple investigators to analyse data. When the findings of each evaluator reach the same conclusion, the confidence in the findings is increased (Guion et al., 2011). The systematic literature review included multiple reviewers/co-authors involved in the review process. The co-authors determined whether the literature selection methods were fair and inclusive of all available literature on South Africa's mining or similar industries. The co-authors also reviewed the literature as a whole and adjusted it accordingly. Triangulation of multiple databases, namely Scopus and Web of Science, was used for the systematic review search. That ensured an exhaustive list of sources of the literature surveyed for the study.

6.3 Survey validation and verification strategies

The strong emphasis on validity, generalisability, and reliability of results ensures that the observed effects are of the actual causes. Results are valid if explanations capture the true nature of what was occurring. The results are reliable if they remain consistent through multiple investigations under different circumstances. Lastly, results are

generalisable if they remain actual in a prespecified wide range of circumstances beyond the research (Gibbs, 2007).

6.3.1 Constant comparisons

Using constant comparisons is critical for creating codes, and in the earlier stage of code creation, this served as a means of checking within and between different cases (Gibbs, 2007). For validation, both comprehensive treatment of data and dealing with deviant cases are essential (findings not in line with the general point the researcher is trying to make) (Gibbs, 2007).

This study used **constant comparison** to compare the consistency of the responses offered over time. That provided the ability to confirm if different participants understood the survey similarly or if the questions were unclear. When questions appear confusing to participants, then answers diverge from expected outcomes. The researcher adjusted questions in this study's survey to prevent diverging answers.

6.3.2 Survey pre-testing

Environmental triangulation involves using different settings and locations in a study to see if the findings are similar across divergent settings. When the findings are the same or similar, then validity is established (Guion et al., 2011). The researcher completed a pilot study to pre-test the survey. A pre-test is where a small set of participants in the intended sample before the final participate in an earlier version of the survey (Toepoel, 2017). Pre-test surveys and editorial reviews confirm clarity, readability, consistency, grammar, and punctuation errors (Considine et al., 2005). The survey used in this study, similar to Shrestha (2021), was designed to collect primary data. The pre-test study by Shrestha (2021) was on students and academics to identify errors and improve the survey, improving the Cronbach alpha. Therefore, the pre-test achieves similar objectives in this study. The survey pre-test involved five people unfamiliar with the investigation. The responses were consistent across participants and in line with expected outcomes. The researcher concluded that the survey was valid and reliable (Guzman and Balcazar, 2010; Synodinos, 2003; Ritter and Sue, 2007).

6.3.3 Qualitative data reliability and validity

Theory triangulation involves the use of multiple perspectives to interpret data. That can include involving people of different disciplines. That brings about different positions from

differing disciplines interpreted similarly, bringing about validity (Guion et al., 2011). Multiple stakeholders and industry experts were involved in the study to ensure varying responses. There were limited response rates. Therefore, triangulation applied to findings from similar surveys across the literature. Therefore, supplementing responses from this study (Creswell, 2009). The credibility of the data also comes from close collaboration between researchers and participants. Collaboration can mean involving participants in the study as co-researchers or in less formal roles. This validity viewpoint brings the participant's views into the study (Creswell and Miller, 2000). Methodological triangulation involves the use of multiple methodologies, both quantitative and qualitative. If the findings from each method are the same, then validity is established (Guion et al., 2011). Verification of transcription errors kept the codes consistent while the researcher coded the themes. The multiple coding methods allow for shared analysis and cross-checking of codes from different sources (Creswell, 2009). The researcher clarified personal bias from his background and perspective (Creswell, 2009). Research reported all positive, negative, and discrepant results (Creswell, 2009).

6.4 Test for statistical assumption associated with multivariate analysis

6.4.1 Outliers in multivariate analysis

Mahalanobis distance measures distance or divergence differences between groups with multiple characteristics. This measure is applied where two group differences are of interest. The following equation describes the measure in the case of sample measurements (McLachlan, 1999):

$$\mathbf{S} = \frac{[(n_1 - 1)S_1 + (n_2 - 1)S_2]}{N} \quad \dots(18)$$

$N = n_1 + n_2 - 2$ and n_1 and n_2 are the random sample sizes of each group (two distinct groups). S_1 and S_2 are the respective sample covariances of the two groups (Ren et al., 2021). The Mahalanobis Distance D^2 is given by the following equation:

$$D^2 = (\bar{x}_1 - \bar{x}_2)^T \mathbf{S}^{-1} (\bar{x}_1 - \bar{x}_2) \quad \dots(19)$$

Where $\bar{x}_1$ and $\bar{x}_2$ are the respective sample means of the groups, and $(\bar{x}_1 - \bar{x}_2)^T$ is the transposes difference between the two. $\mathbf{S}$ is the estimated covariance matrix between the

groups. Mahalanobis distance applies to classification in most cases. The Mahalanobis distance can assess whether a random sample x_i is an outliers, and was used for this purpose in this study (McLachlan, 1999; Ren et al., 2021; De Maesschalck et al., 2000).

The first assumption in the analysis was that the data contained no outliers. Mahalanobis D^2 measures the distance in multidimensional space, measured from the mean centre of the overall observations (Hair et al., 2009). Conservative threshold levels for significance as low as 0.001 or 0.005 for data to be considered outliers. That means $\frac{D^2}{df}$ for small samples should be 2.5 and 3 or 4 for large samples (Hair et al., 2009). The researcher used Mahalanobis D^2 measures to identify outliers in the collected data in this study.

H_0 : For each question Q_i the Mahalanobis distance (D^2) follows a chi-squared distribution with (k) degrees of freedom. Therefore, they are not outliers. Where i ranges from 1 to 21.

- **The null Hypothesis (H_0):**

$$H_0 : D^2 \sim \chi_k^2 \quad \dots(20)$$

Where (k) is the number of variables.

Alternative Hypothesis (H_0): The Mahalanobis distance (D^2) does not follow a chi-squared distribution with (k) degrees of freedom. Therefore, they are outliers.

- **Alternative Hypothesis (H_1):**

$$H_1 : D^2 \not\sim \chi_k^2 \quad \dots(21)$$

6.4.2 Normality assumption test

In multivariate analysis, normality is the most fundamental assumption. It is the distribution shape compared to the normal distribution (Hair et al., 2009). Testing for normality involves looking at the probability plot to identify if it follows a normal distribution, and additionally, statistical tests for normality, such as kurtosis and skewness, assess normality (Hair et al., 2009). Kurtosis and skewness were used in this study to identify whether or not the data used for analysis followed a normal distribution.

The following equation calculated the value of skewness $z_{skewness}$:

$$z_{skewness} = \frac{skewness}{\sqrt{\frac{6}{N}}} \quad \dots(22)$$

The most used $z_{critical}$ values are $\pm 2,58$ for 0.01 significance level.

The following equation calculated the value of kurtosis $z_{kurtosis}$:

$$z_{kurtosis} = \frac{kurtosis}{\sqrt{\frac{24}{N}}} \quad \dots(23)$$

H_0 : For each question Q_i , the Skewness is equal to zero. Therefore, they are symmetrical. Where i ranges from 1 to 21.

- **The null Hypothesis (H_0):**

$$H_0 : Skewness = 0 \quad \dots(24)$$

Where (k) is the number of variables.

Alternative Hypothesis (H_0): The Skewness is not equal to zero. Therefore, they are not symmetrical.

- **Alternative Hypothesis (H_1):**

$$H_1 : Skewness \neq 0 \quad \dots(25)$$

H_0 : For each question Q_i the Kurtosis is equal to zero. Therefore, they are normal kurtosis distributed. Where i ranges from 1 to 21.

- **The null Hypothesis (H_0):**

$$H_0 : Kurtosis = 0 \quad \dots(26)$$

Where (k) is the number of variables.

Alternative Hypothesis (H_0): The Kurtosis is equal to zero. Therefore, they are not normal kurtosis distributed.

- **Alternative Hypothesis (H_1):**

$$H_1 :: \text{Kurtosis} \neq 0 \quad \dots(27)$$

Shapiro-Wilk test is a measure used to test the normality of data, and it confirmed normality in the results of the Likert scale responses (Shapiro and Wilk, 1965).

In analysis, the assumption of normal distribution in observations is often the case, and this usually leads to the entire analysis being invalid once this assumption is proven false. So, it is critical to confirm this assumption (Rani Das, 2016).

Shapiro-Wilk test is a popular method for testing the normality assumption in analysis. It has a basis in correlation alongside corresponding normality scores. The following equation defines the W statistic in the Shapiro-Wilk test (Rani Das, 2016):

$$W = \frac{(\sum_{i=1}^n a_i y_{(i)})^2}{\sum_{i=1}^n (y - \bar{y})^2} \quad \dots(28)$$

Where $y_{(i)}$ represents the i th statistic, and a_i represents the expected i th normalised order statistic. The W statistics is always less or equal to 1, and if the W statistic is much less than 1, then the hypothesis of normality is rejected (Rani Das, 2016). The Shapiro-Wilk test strength diminishes with rising sample sizes (Yazici and Yolacan, 2007; Kwak and Park, 2019; González-Estrada and Cosmes, 2019).

$$(a_i, \dots, a_n) = \frac{M^T V^{-1}}{(M^T V^{-1} V_m^{-1})^{1/2}} \quad \dots(29)$$

Where $M = (M_1, \dots, M_n)^T$ and the $M_1, \dots, M_n$ is the order statistic expected values of identical and independent randomly distributed variables from the normal distribution. V is the covariance matrix of those order statistics.

In clinical research, one of the critical assumptions is the normality of the data and often, results are published that do not test the assumption of normality before presenting findings. Another issue is that the sample sizes are usually less than 30 participants due to cost and time constraints, requiring robust methods for testing normality (Kwak and Park, 2019).

H_0 : For each question Q_i the data follows a normal distribution. Where i ranges from 1 to 21.

- **The null Hypothesis (H_0):**

$$H_0 : \text{The data follow a normal distribution} \quad \dots(30)$$

Where (k) is the number of variables.

Alternative Hypothesis (H_1): The data does not follow a normal distribution.

- **Alternative Hypothesis (H_1):**

$$H_1 : \text{The data does not follows a normal distribution} \quad \dots(31)$$

6.4.3 Linearity assumption test

Linearity is the assumption for correlation-based association measures. The identification of linearity relationships used in this study was the Spearman correlation (Hair et al., 2009). Spearman correlation (a non-parametric measure) calculates correlation for Likert scale data (Murray, 2013). Linearity is an implicit assumption for multivariate analysis (Hair et al., 2009).

Multicollinearity the extent to which variables explain other variables in the analysis. An increase in Multicollinearity complicates interpretation as it is more difficult to point to a single variable explaining the effect due to the variables' interrelations (affecting factor analysis). Variance Inflation Factor (VIF) was used in this study to determine multicollinearity. VIF is given by the following equation (Murray et al., 2012; Hair et al., 2009):

$$VIF = \frac{1}{1 - R_{m(k)}^2} \quad \dots(32)$$

Where $R_{m(k)}^2$ is the multiple correlation coefficient.

H_0 : For each question Q_i there is no multicollinearity among the predictor variables, therefore VIF is close to 1. Where i ranges from 1 to 21.

- **The null Hypothesis (H_0):**

$$H_0 : VIF \leq 1 \quad \dots(33)$$

Alternative Hypothesis (H_1): There is multicollinearity among the predictor variables.

- **Alternative Hypothesis (H_1):**

$$H_1 : VIF > 1 \quad \dots(34)$$

6.5 Measuring internal consistency

The study used **Cronbach alpha** to prove accuracy and dependability, referred to as the reliability measure. The reliability coefficient test shows whether the designed test was correct when expecting to collect data to interpret individual differences. Measuring the accuracy of a measure involves creating two independent measurements compared to each other (Cronbach, 1951). Cronbach's alpha estimates 'the internal consistency of responses in multi-item bipolar scales'. And is given by the following formula (Vaske et al., 2017):

$$\alpha = \frac{N}{N-1} \left(\frac{\sigma_X^2 - \sum_{i=1}^N \sigma_{Y_i}^2}{\sigma_X^2} \right) \quad \dots(35)$$

Where:

N is the number of surveys in the scale, σ_X^2 is the variance of the observed total scores and $\sigma_{Y_i}^2$ is the variance of items i for person y (Vaske et al., 2017).

The Cronbach alpha is the most commonly used estimate for the internal consistency of scale items. It measures the degree of correlation of responses with each other, described as the variance proportion consistent or systematic in survey responses (Vaske et al., 2017). The Cronbach alpha measures the reliability of a survey by providing a simple method to measure whether a score is reliable. The Cronbach alpha measure applies under the assumption of multiple items that measure the same underlying construct (Shrestha, 2021). By convention, the alpha values considered adequate are between 0.65 and 0.80 when human dimension research is the subject of study, and a high value shows a high correlation of items (Vaske et al., 2017; Shrestha, 2021). Positive alpha values mean that the items measure the same theoretical concepts, while a negative alpha occurs when there is no correlation and may also mean that the respondents are answering inconsistently (Vaske et al., 2017).

6.6 Factor analysis

Factor analysis is a necessity in instances where research administers surveys. Factor analysis aims to simplify complicated data sets, determining correlations between the variables. The results of this analysis set out several factors whose meaning must be created based on the factor loadings. Factor loadings are correlations between the variable and the factors. Factor loadings greater than 0.6 are high, and those greater than 0.3 are considered moderate, with any loading less than 0.3 being insignificant and therefore ignored (Gie Yong and Pearce, 2013; Kline, 1994).

Factor analysis extracts a few relevant factors from a larger related group. This analysis can help remove irrelevant questions from a survey (Shrestha, 2021). The two main methods for factor analysis are Confirmatory Factor Analysis (CFM) and Exploratory Factor Analysis (EFA). EFA is used to check the dimensionality in the early stages of research, gathering data on interrelationships between variables (Shrestha, 2021; Hair et al., 2009). The factor analysis used in this study is Exploratory Factor Analysis (EFA).

Factor analysis steps:

1. Assessing suitability of data
2. Extraction of factors
3. Rotating factors and interpretation

6.6.1 Assessing the suitability of data for factor analysis

A. Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy

KMO was used to measure the suitability of data for factor analysis, which also means that it tested the adequacy of the sample size. KMO measured the sampling adequacy for both individual variables and the complete model. KMO values greater than or equal to 0.8 indicated an adequate sample value, while values between 0.6 and 0.69 are in the middle and values less than 0.6 are mediocre. Samples with fewer than 300 participants need commonality testing of the retained items. A commonality value > 0.6 is acceptable for samples < 100 , and an average value between 0.5 and 0.6 for sample sizes between 100 and 200 is acceptable (Shrestha, 2021). The sample size for quantitative responses to the KMO survey was as follows:

$$KMO_j = \frac{\sum_{i \neq j} R_{ij}^2}{\sum_{i \neq j} R_{ij}^2 + \sum_{i \neq j} U_{ij}^2} \quad \dots(36)$$

Where R_{ij} is the correlation matrix, and U_{ij} is the partial covariance matrix. KMO was used to measure sampling adequacy in this study.

B. Bartlett's test of sphericity

The homoscedasticity is that the dependent variables show levels of variance equal across the variable predictor. **Bartlett's test** was used as a statistical test for homoscedasticity (Hair et al., 2009). Production of unbiased correlated individual factor scores uses the Barlett method (Gie Yong and Pearce, 2013).

Bartlett's test of sphericity measures the null hypothesis that:

H_0 : The variables are orthogonal, which means the original correlation matrix was an identity matrix. Meaning the variables were unrelated and unsuitable for structure detection. A p-value < 0.05 indicates that factor analysis is worth pursuing for the data set (Shrestha, 2021).

H_1 : The variables are not orthogonal, which means the original correlation matrix was not an identity matrix. The Barlett test statistic is calculated by the following formular:

$$\chi^2 = -\left(n - 1 - \frac{2p + 5}{6}\right) \times \ln|R| \quad \dots(37)$$

Where p is the number of variables, n is the total number of sample sizes, and R is the correlation matrix. Bartlett's test measured the sphericity of the qualitative data collected in this study. Therefore, determining suitability for factor analysis of the data.

C. Average Variance Extracted (AVE) and Composite Reliability (CR)

The AVE and CR relate to the quality of a measure, where the AVE measures the amount of variance by a construct due to measurement error. AVE, in other words, measures the convergent validity. Convergent reliability measures the level of correlation between multiple indicators of the same construct in agreement. Values of AVE more than or equal to 0.5 are confirmation of the convergent validity. CR values greater than 0.6 are acceptable, and when AVE is less than 0.5, while CR is higher than 0.6, convergence

reliability is still adequate (Shrestha, 2021). The study used the following formula to calculate AVE:

$$AVE = \frac{\sum_{i=1}^n \lambda_i^2}{n} \quad \dots(38)$$

Where λ_i are the loadings, and n is the number of items.

The study used the following formula to calculate CR:

$$CR = \frac{(\sum_{i=1}^n \lambda_i)^2}{(\sum_{i=1}^n \lambda_i)^2 + \sum_{i=1}^n Var(e_i)} \quad \dots(39)$$

Where $var(e_i)$ is the variance of error terms in the i^{th} item. AVE and CR were used to measure the validity and reliability of the factors extracted through factor analysis in this study.

6.6.2 Extraction of factors (Determining the number of factors to extract)

Kaiser's (eigenvalue) criterion is a rule of thumb method that uses the eigenvalue of a factor to represent the amount of variance each factor explains. Retaining factors with eigenvalues > 1 because an eigenvalue > 1 is significant, indicating variance explained by the factor. Using this approach should be with judgment due to sampling errors (Shrestha, 2021; Hair et al., 2009). The number of factors retained is critical as too many factors may represent unwanted errors, and too few factors could omit critical common variance (Gie Yong and Pearce, 2013).

The Scree test is a graphical test for determining factors, where on the Scree plot, the magnitude on the horizontal axis is the eigenvalue number and the magnitude on the vertical axis. Factor extraction stops when there is an elbow or the plot levels (Shrestha, 2021; Hair et al., 2009). Factor loadings with values above 0.4 represent influence meeting the minimum levels to represent structure (Hair et al., 2009). The researcher used the Scree plot and Kaiser's criterion to select factors in this study.

6.6.3 Rotating factors and interpretation

Factors from the initial extraction are complicated to interpret due to significant cross-loading, where factors correlate with many variables. The orthogonal factor rotation is less complicated to explain, report, and use in a study. The Quartimax, Varimax, and

Equimax methods relate to orthogonal rotation (Shrestha, 2021). The Varimax method reduces the variables holding high loadings on each factor in section 8.9.3 and was used in this study (Shrestha, 2021; Hair et al., 2009).

6.7 Chapter summary

The study used quantitative and qualitative methods to collect and analyse data. An online survey of industry experts collected the data for the study. The data were validated and verified. The qualitative data were validated and verified using triangulation, transcript checking, constant comparison, and pre-testing. The qualitative data from the survey were validated and verified by testing the assumptions used for the analysis. The statistical assumptions were that there were no outliers in the data, the data followed a normal distribution, the data was homoscedastic and linear relationships existed.

The internal consistency of the survey was measured using Cronbach Alpha. Followed by factor analysis to determine the factors in the qualitative responses that the survey was measuring. The factor analysis also included validity and verification methods such as the KMO measure for checking sampling adequacy, Bartlett's test of sphericity for checking data suitability for factor analysis, AVE for the variance of each factor determined through factor analysis, and CR measured the internal consistency of factors.

CHAPTER 7 LIMITATIONS OF THIS STUDY

7.1 Introduction

This chapter details the limitations of this study. These limitations are from the researcher and the research tools used for collecting data, analyses, and reporting in this study. The presentation of limitations in a study shows the influence of its weaknesses (Ross and Bibler Zaidi, 2019).

7.2 Limitations due to the research approach

Delimitations are limitations to a study introduced by the researcher's conscious choice to narrow the scope of a study. In this study, the researcher designed the survey for industry experts in mining in South Africa. That limits the generalisability of the results to the select group the researcher identified. That introduced systematic bias (Ross and Bibler Zaidi, 2019). The mine chosen to conduct the research also limited the generalisability of the results as all respondents to the survey were from a single mine. The researcher chose all approaches used in this study. These were all informed choices, but data requirements and research did not eliminate the researcher's personal biases towards the selected approaches.

The researcher attempted to stay as unbiased as possible in this study, and they were aware of personal biases influencing study results.

7.3 Limitations due to the research instrument and data collection

Since the researcher collecting data can influence responses, the online nature of the survey reduced this influence, but since the researcher made participants aware of the study, this influence was still present to some extent. Another influence came from the choice of participants to participate in the survey (self-selection bias). Participants often provide biased responses because they respond to questions favourably, introducing social desirability bias that could also result from their familiarity with the researcher (Ross and Bibler Zaidi, 2019).

7.4 Limitations due to data analysis

Statistical analysis introduced limitations in this study due to factors such as purposive sampling, making it challenging to follow inferential statistical analyses. Analysis that is not specified beforehand adds limitations. Therefore, all analyses were specified

beforehand for this study (Ross and Bibler Zaidi, 2019). The basis for the choice of statistical analysis for this data was assumptions proven reasonable in some cases and unreasonable in other cases. That meant conclusions made in some instances from the result data were unsuitable for the analysis.

Another assumption used in this study was that Likert data analysed as qualitative data is appropriate, following Baran (2021) and Murray (2013), but this is not always the case, as stated in Jamieson (2004) and Batterton and Hale (2017). The researcher reduced that limitation by using non-parametric tests to accompany any parametric tests used in this study because non-parametric tests are more suitable for Likert scale results. An example was using the Chi-square hypothesis test as a supporting measurement tool to the T-test. The assumptions required by a t-test do not apply to a Chi-square test. The same applied to all AVOVA analyses and two proportion hypothesis tests (they were all supported by Chi-square tests).

Factor Analysis requires 300 participants in the survey, and surveys with 150 participants are sufficient for factor analysis if several loadings are above 0.8. This survey had 31 participants and no loadings above 0.8, making factor analysis more error-prone. Another limitation of factor analysis is the naming of factors, as they are subjective and may not accurately reflect the factors. Variables also load into multiple factors, making it difficult to interpret (split loading). Factor loading determines the contribution levels of a variable to a factor similar to weights in regression analysis. The analysis should also have a few cross-loadings (when a variable has more than 0.32 loading value in more than one factor) (Gie Yong and Pearce, 2013).

7.5 Limitations due to study results

The limitations of a study revolve around the validity of the results. Internal validity is the precision of the results, while external validity is associated with generalisable results for a larger target population (Ross and Bibler Zaidi, 2019). The limited sample used in this study and the data collected from a single mine meant that the generalisability of the data to a larger population from these results was impossible.

The time it takes to gather data introduces internal validity threats (Ross and Bibler Zaidi, 2019). The researcher collected all data within two months of each other. That meant that the threat to internal validity due to time was limited.

Measurement error is the level at which an observation does not represent the "true" value. This error is associated with sources such as measurement imprecision or the inability of respondents to respond (Hair et al., 2009). The errors in hypothesis testing are the Type I and the Type II errors. The Type I error is due to rejecting the null hypothesis while it is correct, and the Type II error is caused by accepting the null hypothesis when it is false (Wegner, 2012; Hair et al., 2009). Hypothesis testing in this study introduced the possibility of Type I and Type II errors above, meaning that conclusions based on the hypothesis testing were subject to these two error types.

7.6 Chapter summary

This study has limitations that require consideration before using any findings to generate conclusions. These limitations include the subjective approach of the researcher or bias and the research tools used. Therefore, all conclusions drawn from this study should account for the limitations. Further similar studies should consider reducing limitations.

CHAPTER 8 RESULTS

8.1 Introduction

This chapter details the results of the analysis performed on the SLR, the survey's qualitative and quantitative responses. These results are from data collected from the online survey in Appendix A and the unpublished SLR.

8.2 SLR summary findings

A systematic review of the literature was carried out as part of this study to identify fundamental gaps in the South African literature on the adoption of Industry 4.0 technology, and its preliminary findings were as follows:

- Implementing Industry 4.0 is critical for the mining industry. However, such technology comes with many risks. Therefore, mining companies require slow application of technology to small parts of the mining value chain. Optimising technology use in the selected section before transforming another part of the value chain.
- Partners with Industry 4.0 technology and technical know-how need to be involved in implementing Industry 4.0 technology. That requires acquiring new resources, which means that partnerships should include companies with established resources available.
- Leadership during technology adoption plays a pivotal role, so leaders must evolve with the changes and involve all stakeholders.
- South Africa, a developing economy, needs to use a mix of digital technology and people. These people require proper training in the changing environment, and leadership needs to change alongside. The required training should be on how to use, maintain, and continually improve the new technology. More relevant to Industry 4.0 -enabled workplaces, new leadership styles are also required.
- Mining companies need investment in research and development of Industry 4.0 methodologies and applications specific to the mining industry, as there is a lack of such research readily available, especially research focused on emerging markets such as South Africa.
- People are still hesitant about the introduction of Industry 4.0 technology. They need more information about technology and the implications for their work.

Considering people's inputs during all stages of such technology implementations is crucial, from the introduction of plans to the final steps.

- Industry 4.0 technology often fails due to a lack of planning before implementing such technology. A solution is improving the planning methods required before implementing the technology, which will determine the need for the technology and whether the technology will succeed in the organisation.
- South African literature developed roadmaps for Industry 4.0 adoption to some extent but lacks rigorous testing to prove their applicability.
- The use of simulations or pilot plants in Industry 4.0 technology can help identify opportunities and weaknesses of new technology before implementing the technology on a full scale.

The findings of the systematic literature review mention the need for rigorous testing of the implementation roadmaps available in the literature. This study developed an online survey testing these roadmaps and best practices against industry experts' ratings and views.

Note: When this dissertation was submitted for examination, the SLR was yet to be published. It was under the author's review for possible publication in the *Southern African Institute for Industrial Engineers Conference (SAIIE35)*.

8.3 Survey participant information

Table 8-1 details the number of survey participants belonging to the different demographics. The demographic data collected were gender, age groups, and experience level in the mining industry.

Table 8-2 details the type of work experience participants had in the mining industry. Some participants occupied multiple roles throughout their years of working in the mining industry.

Table 8-2: Types of work experiences for participants in the mining industry.

Type of work experience in the mining industry	Number of respondents
General work	6
Manager or supervisor	19
Engineer	7
Senior manager	3
Junior manager	2
Specialist (e.g., boiler maker)	4
Intern	1
Professional	1

8.4 Thematic analysis results for the pre-installation phase questions

The following list details the themes. Below the themes were respondents associated with each theme:

1. Theme 1: Perceived equal importance of all steps
 - Responses - 1, 2, 5, 12, 13, 14, 16, 18.
2. Theme 2: Highlighting specific steps or additions
 - Responses - 3, 7, 13, 17.
3. Theme 3: Indifference or uncertainty
 - Responses - 4, 6, 9, 8, 10, 11, 15, 19.

8.4.1 Thematic analysis report: Pre-Installation phase responses

Theme 1: Perceived equal importance of all steps

Several respondents emphasised that all the steps in the pre-installation phase were crucial. They believed that each step was vital in ensuring a successful installation. For instance, responses such as "All are equally important" (Response 1) and "They are all important" (Response 18) reflect this sentiment. This theme underscores a holistic view where the interconnectedness of all steps is acknowledged, which suggests that neglecting any part could compromise the overall process.

Theme 2: Highlighting specific steps or additions

This theme captured responses that point out specific steps or propose additional actions. Respondent 3 notes the importance of evaluating the entity's expectations and selection criteria, while Respondent 7 mentions drafting agreements and contracts. Respondent 9 emphasises the value of testing products on-site. Furthermore, Respondent 13 explained the need for Functional Design Specifications (FDS), indicating its critical role in the pre-installation phase. These responses indicated that while the overall steps in the process were necessary, some steps may require extra attention or inclusion.

Theme 3: Indifference or uncertainty

Some respondents expressed indifference or uncertainty regarding the importance of pre-installation steps. Responses such as "none" (Response 4) and "N/A" (Response 10) fall under this category. This theme suggested that not all participants see a clear significance in the steps provided. They might lack the information needed to make an informed judgment.

8.5 Thematic analysis results for the installation phase questions

The following list details the themes. Below the themes were respondents associated with each theme:

1. Theme 1: Perceived equal importance of all steps
 - Responses - 1, 5, 14, 15.
2. Theme 2: Highlighting specific steps or additions
 - Responses - 3, 7, 12, 17, 18.

3. Theme 3: Indifference or uncertainty

- Responses - 2, 4, 6, 8, 9, 10, 11, 13, 16, 19.

8.5.1 Thematic analysis report: Installation phase responses

Theme 1: Perceived equal importance of all steps

Several respondents emphasised that all the steps in the installation phase were crucial. They believe that each step is vital in ensuring a successful installation. For instance, responses such as "All are equally important" (Response 1) and "All the above steps are important and none are missing" (Response 5) reflect this sentiment. This theme underscores a holistic view where the interconnectedness of all steps is acknowledged, suggesting that neglecting any part could compromise the overall process.

Theme 2: Highlighting specific steps or additions

This theme captures responses that point out specific steps or propose additional actions. Respondent 3 highlights the importance of prototyping, system testing, continuous information gathering, documentation, and risk evaluation. Respondent 7 mentions gathering documents from the vendor, while Respondent 12 emphasises upgrading personnel for implementation. Respondent 17 discussed the importance of constant checks and effective communication to prevent issues during implementation. Additionally, Respondent 18 suggested adding safety and legal aspects to the roadmap. These responses indicated that while the overall steps in the process were necessary, some steps may require extra attention or inclusion.

Theme 3: Indifference or uncertainty

Some respondents expressed indifference or uncertainty regarding the importance of the installation steps. Responses such as "none" (Response 2) and "N/A" (Response 10) fell under this category. This theme suggested that not all participants see a clear significance in the steps provided. They might lack the information needed to make an informed judgment.

8.6 Thematic analysis results for the post-installation phase questions

The following list details the themes. Below the themes were respondents associated with each theme:

1. Theme 1: Perceived equal importance of all steps

- Responses - 1, 5, 14, 16.

2. Theme 2: Highlighting specific steps or additions

- Responses - 2, 7, 10, 13, 15, 18, 19.

3. Theme 3: Indifference or uncertainty

- Responses - 3, 4, 6, 8, 9, 11, 12, 17, 20.

8.6.1 Thematic analysis report: Post-installation phase responses

Theme 1: Perceived equal importance of all steps

Several respondents emphasised that all the steps in the post-installation phase were crucial. They believed each step was vital in ensuring the successful adoption and operation of the system. For instance, responses such as "All are equally important" (Response 1) and "All the above steps are important, especially continuous training" (Response 5) reflected this sentiment. This theme underscored a holistic view where the interconnectedness of all steps is acknowledged, suggesting that neglecting any part could compromise the overall process.

Theme 2: Highlighting specific steps or additions

This theme captured responses that point out specific steps or propose additional actions. Respondent 2 highlighted the importance of including monitoring and evaluation. Respondent 7 emphasised the need for an exit strategy. Respondent 10 suggested providing on-site assistance periodically. Respondent 13 spotlights the need for proper change management and marketing of technology to end users. Respondent 15 suggested including change management as part of the exit strategy. Respondents 18 and 19 emphasised the importance of training at all levels to ensure system success. These responses indicate that while the whole process is essential, some steps may require extra attention or inclusion.

Theme 3: Indifference or uncertainty

Some respondents expressed indifference or uncertainty regarding the importance of post-installation steps. Responses such as "none" (Response 3) and "N/A" (Response 11) fell under this category. This theme suggested that not all participants see a clear

significance in the steps provided. They might lack the information needed to make an informed judgment.

8.6.2 Additions to the roadmap

The additions that respondents suggested that were not included in the original roadmap designed at the onset of this study but respondents added were:

1. Understanding business needs
2. SWOT analyses of the proposed new technology
3. Information gathering and documentation must be continuous throughout the process
4. Communication down the line with the people who work with the new technology
5. Change management
6. Risk evaluation
7. Upgrading personnel
8. Constant checks
9. Including safety aspects
10. On-site assistance
11. Continuous training
12. Ensuring compliance through Functional Design Specifications (FDS)

8.7 Test for statistical assumption associated with multivariate analysis

8.7.1 Outliers in multivariate analysis

Results for the test for Mahalanobis distance for outliers in the survey responses are in Table 8-3, Figure 8-1 and Figure 8-2. Mahalanobis Distance measures the distance between the data point and the mean of the distribution, accounting for correlations between variables. Higher values suggest a point is further from the centre of the distribution. P-value Indicates the probability that the observed data could occur under the null hypothesis. Low p-values (< 0.05) suggest rejecting the null hypothesis, implying statistical significance. The significance column is based on the p-value, indicating the statistical significance of the result.

Table 8-3: Mahalanobis distances of the Likert scale questions, their p-values and significance.

Respondent No	Mahalanobis Distance	p-value	Significant
1	2,699	0,998	No
2	5,388	0,113	No
3	5,388	0,113	No
4	5,388	0,113	No
5	5,388	0,113	No
6	1,426	1,000	No
7	2,699	0,998	No
8	5,388	0,113	No
9	1,426	1,000	No
10	5,388	0,113	No
11	1,426	1,000	No
12	5,388	0,113	No
13	1,426	1,000	No
14	5,388	0,113	No
15	1,426	1,000	No
16	2,699	0,998	No
17	1,426	1,000	No
18	5,388	0,113	No

19	5,388	0,113	No
20	3,644	0,898	No
21	5,388	0,113	No
22	5,388	0,113	No
23	5,388	0,113	No
24	1,426	1,000	No
25	5,388	0,113	No
26	5,388	0,113	No
27	5,388	0,113	No
28	5,388	0,113	No
29	5,388	0,113	No
30	5,388	0,113	No
31	5,388	0,113	No

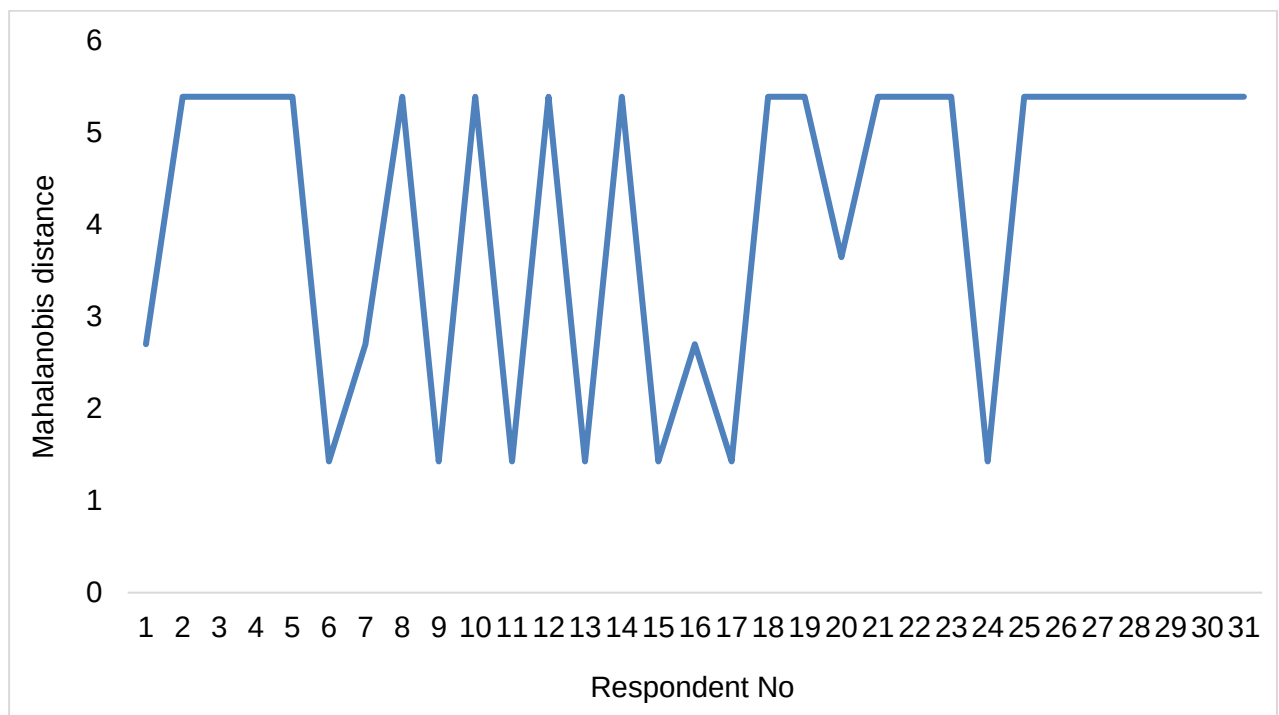


Figure 8-1: Mahalanobis distances for each respondent.

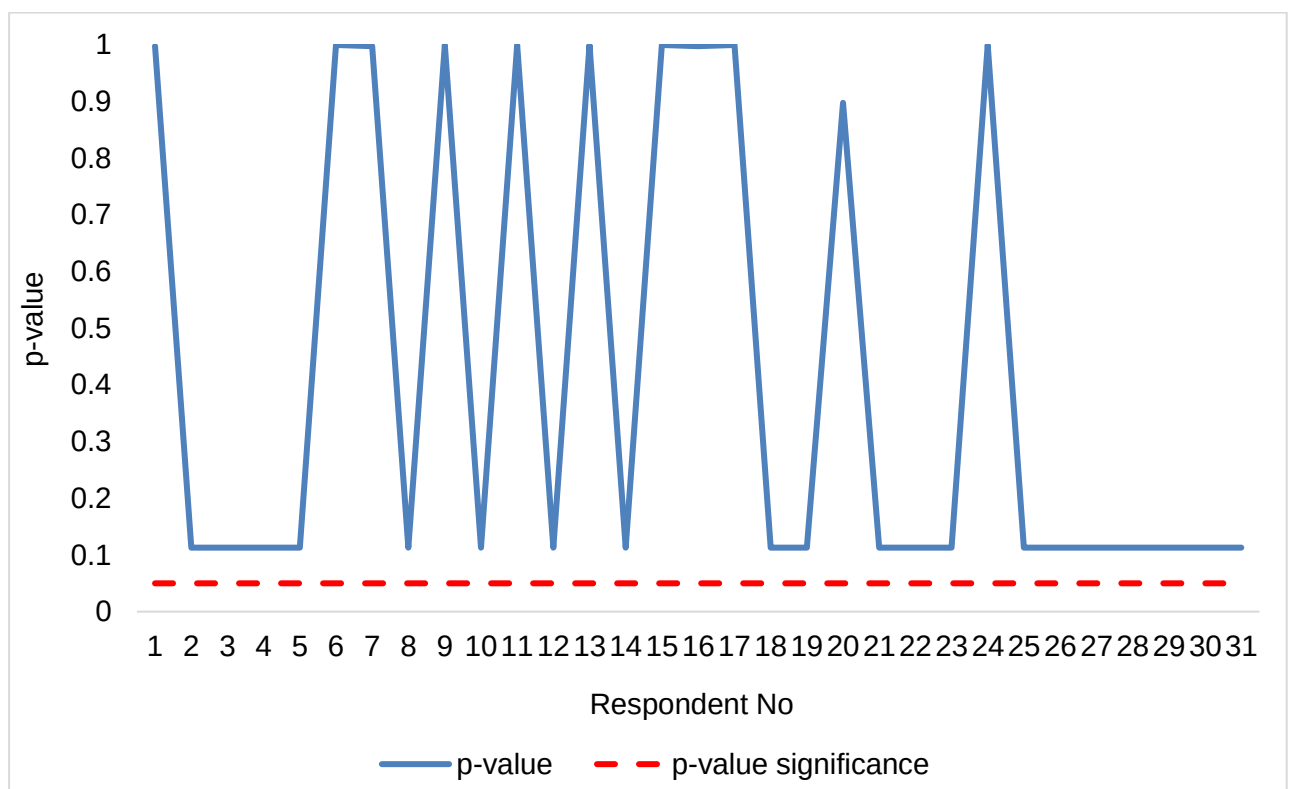


Figure 8-2: P-values for each respondent's Mahalanobis distance.

8.7.2 Normality test

Results for the normality in the survey responses are in Table 8-4, Figure 8-3 and Figure 8-4 as Kurtosis. The skewness also showed how skewed the answers were about the mean. Skewness measures the asymmetry of the distribution. A negative value indicates a left skew, while a positive value indicates a right skew.

Kurtosis measures the "tailedness" of the distribution. Negative values indicate a flatter distribution, while positive values indicate a more peaked distribution. Z-skewness is the Z-score for the skewness, indicating how many standard deviations the skewness is from zero. Z-Kurtosis is the Z-score for the kurtosis, indicating how many standard deviations the kurtosis is away from zero. Z-skewness significance shows whether the z-skewness is statistically significant (based on a threshold $p < 0.05$). Z-kurtosis significance shows whether the z-kurtosis is statistically significant.

Table 8-4: Skewness and Kurtosis of the Likert scale questions.

Question No	Skewness	Kurtosis	Z-Skewness	Z-Kurtosis	Z-Skewness significant	Z-Kurtosis significant
1	-0,364	-0,875	-0,827	-0,994	No	No
2	-0,231	-0,642	-0,525	-0,729	No	No
3	-0,355	-0,809	-0,808	-0,920	No	No
4	-0,415	-0,705	-0,943	-0,802	No	No
5	-0,438	-0,831	-0,995	-0,944	No	No
6	-0,434	-0,664	-0,987	-0,754	No	No
7	-0,706	-0,724	-1,605	-0,822	No	No
8	-0,331	-0,673	-0,752	-0,764	No	No
9	-0,129	-0,904	-0,293	-1,027	No	No

10	-0,364	-0,875	-0,827	-0,994	No	No
11	-0,434	-0,664	-0,987	-0,754	No	No
12	-0,541	-0,616	-1,230	-0,700	No	No
13	-0,434	-0,664	-0,987	-0,754	No	No
14	-0,364	-0,875	-0,827	-0,994	No	No
15	-0,364	-0,875	-0,827	-0,994	No	No
16	-1,261	2,076	-2,867	2,359	Yes	Yes
17	-1,348	2,198	-3,065	2,499	Yes	Yes
18	-0,245	-0,911	-0,557	-1,035	No	No
19	-1,149	1,273	-2,611	1,447	Yes	No
20	-0,769	-0,401	-1,748	-0,455	No	No
21	-0,331	-0,673	-0,752	-0,764	No	No

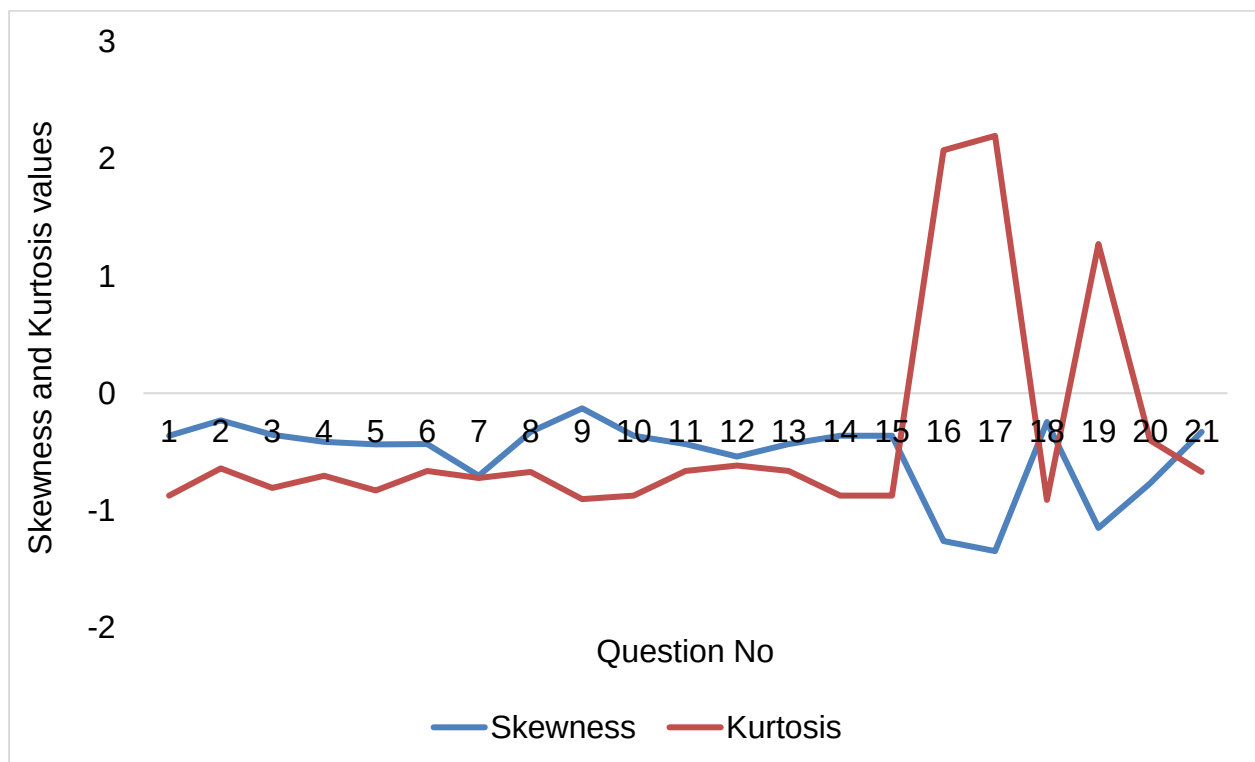


Figure 8-3: Kurtosis and Skewness values for Likert scale questions.

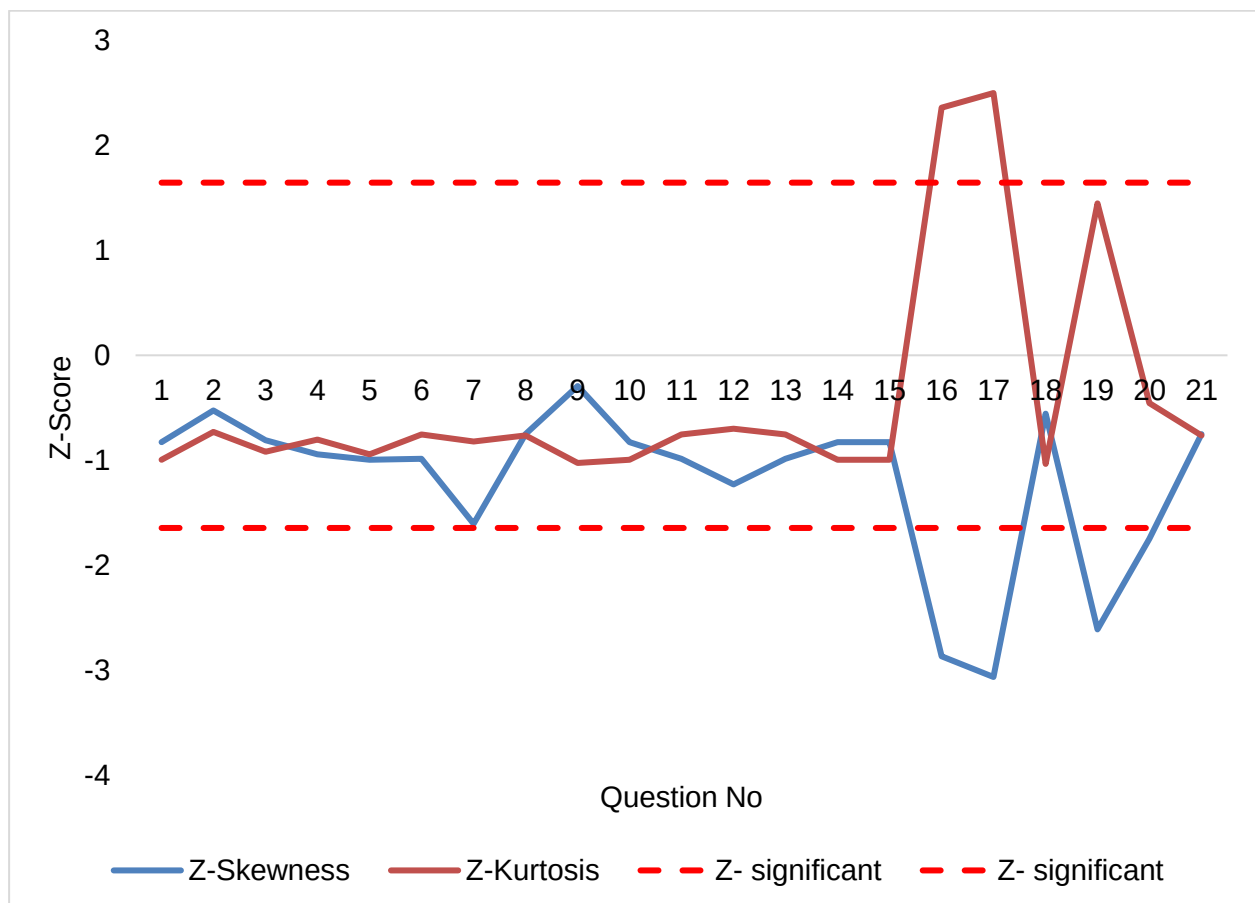


Figure 8-4: Z-value for Likert scale questions.

Results for the test for normality using the Shapiro-Wilk test of the survey Likert responses are in Table 8-5, Figure 8-5 and Figure 8-6. W-statistic show results from the test statistic for the Shapiro-Wilk test. Values closer to 1 indicate that the data is more likely to come from a normal distribution. The P-value shows the probability that the data comes from a normal distribution. A small p-value (< 0.05) suggests that the data significantly deviates from normality. The significant column shows whether the p-value indicates a statistically significant deviation from normality.

Table 8-5: Shapiro-Wilk normality test results.

Question No	W-statistic	p-value	Significant
1	0,717	2,094E-06	No
2	0,751	7,255E-06	No

3	0,787	2,943E-05	No
4	0,771	1,571E-05	No
5	0,782	2,468E-05	No
6	0,750	6,915E-06	No
7	0,752	7,565E-06	No
8	0,752	7,507E-06	No
9	0,717	2,117E-06	No
10	0,717	2,094E-06	No
11	0,750	6,915E-06	No
12	0,745	5,689E-06	No
13	0,750	6,915E-06	No
14	0,717	2,094E-06	No
15	0,717	2,094E-06	No
16	0,729	3,157E-06	No
17	0,720	2,284E-06	No
18	0,719	2,223E-06	No
19	0,756	8,628E-06	No
20	0,725	2,789E-06	No
21	0,752	7,507E-06	No

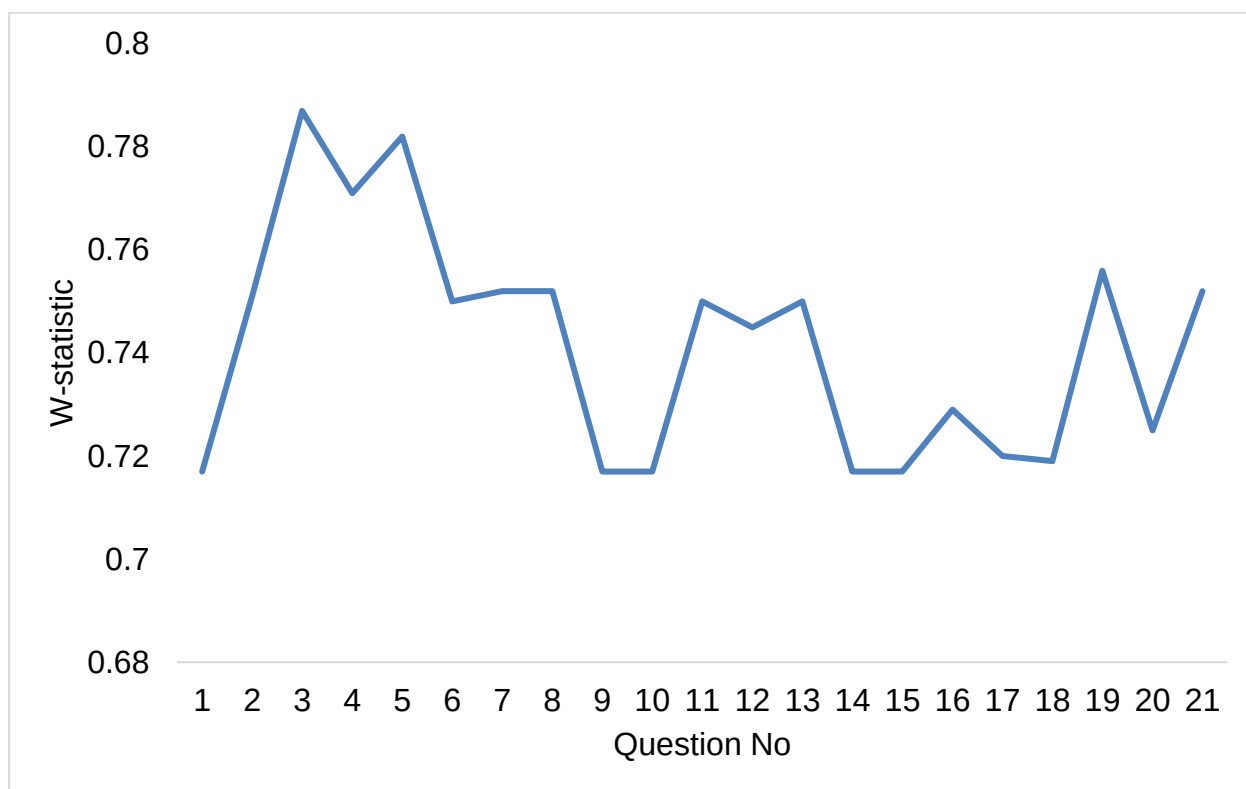


Figure 8-5: W-statistics for Likert scale question.

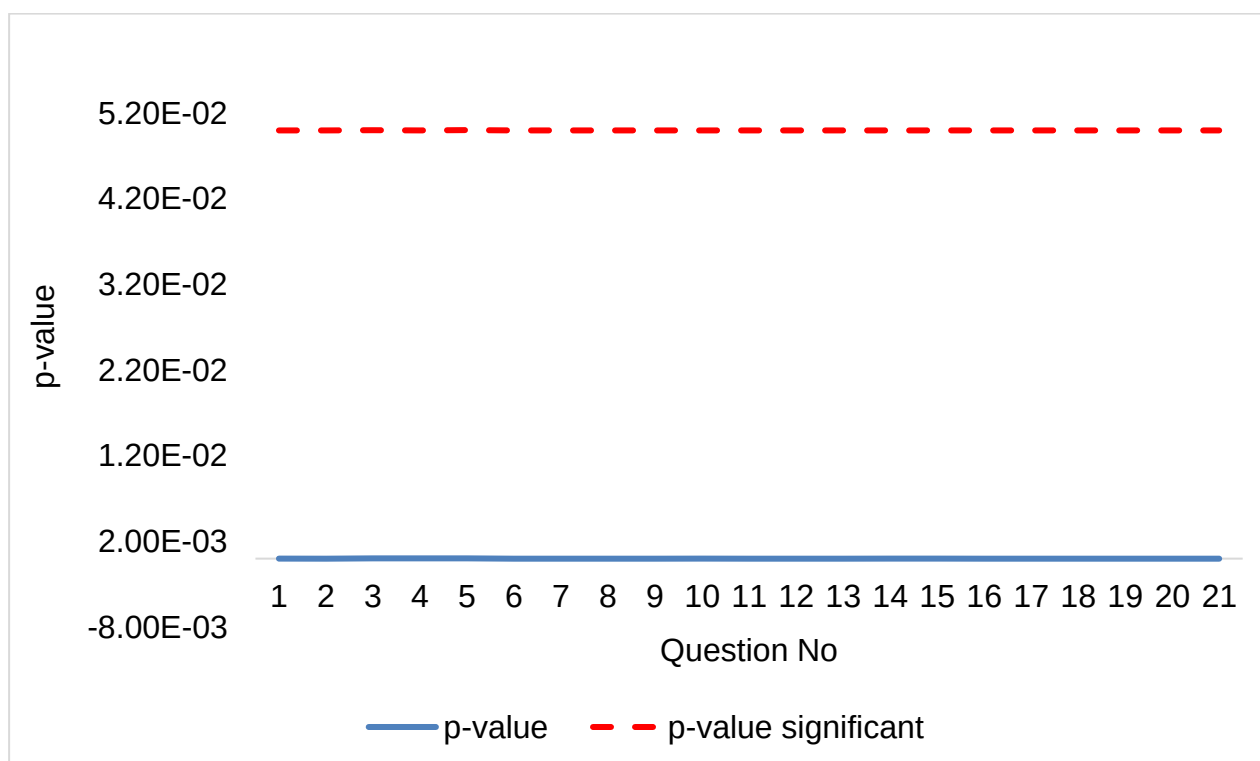


Figure 8-6: W-statistic p-values for Likert scale question.

8.7.3 Multicollinearity test

Results for the test for multicollinearity using the Variance Inflation Factor test of the survey Likert responses are in Table 8-6 and Figure 8-7. VIF measures multicollinearity in regression analysis. High VIF values indicate high multicollinearity between variables, which can affect the reliability of the regression model. Whether multicollinearity is considered significant depends on the following. A VIF of 1 means no correlation between the variable and other variables. A VIF between 1 and 5 indicates moderate multicollinearity. A VIF of more than 10 suggests high multicollinearity, which is typically a concern.

Table 8-6: Multicollinearity test using Variance Inflation Factor results.

Question No	VIF	Significant
1	674,939	Yes
2	1818,163	Yes
3	3884,889	Yes
4	2371,020	Yes
5	1829,617	Yes
6	6728,719	Yes
7	6636,553	Yes
8	675,403	Yes
9	16986,207	Yes
10	8828,327	Yes
11	2249,860	Yes
12	3466,690	Yes

13	84830,984	Yes
14	11414,973	Yes
15	3278,289	Yes
16	2399,245	Yes
17	1899,426	Yes
18	11361,201	Yes
19	1266,438	Yes
20	2252,218	Yes
21	12139,343	Yes
Determinant	4,311E-21	

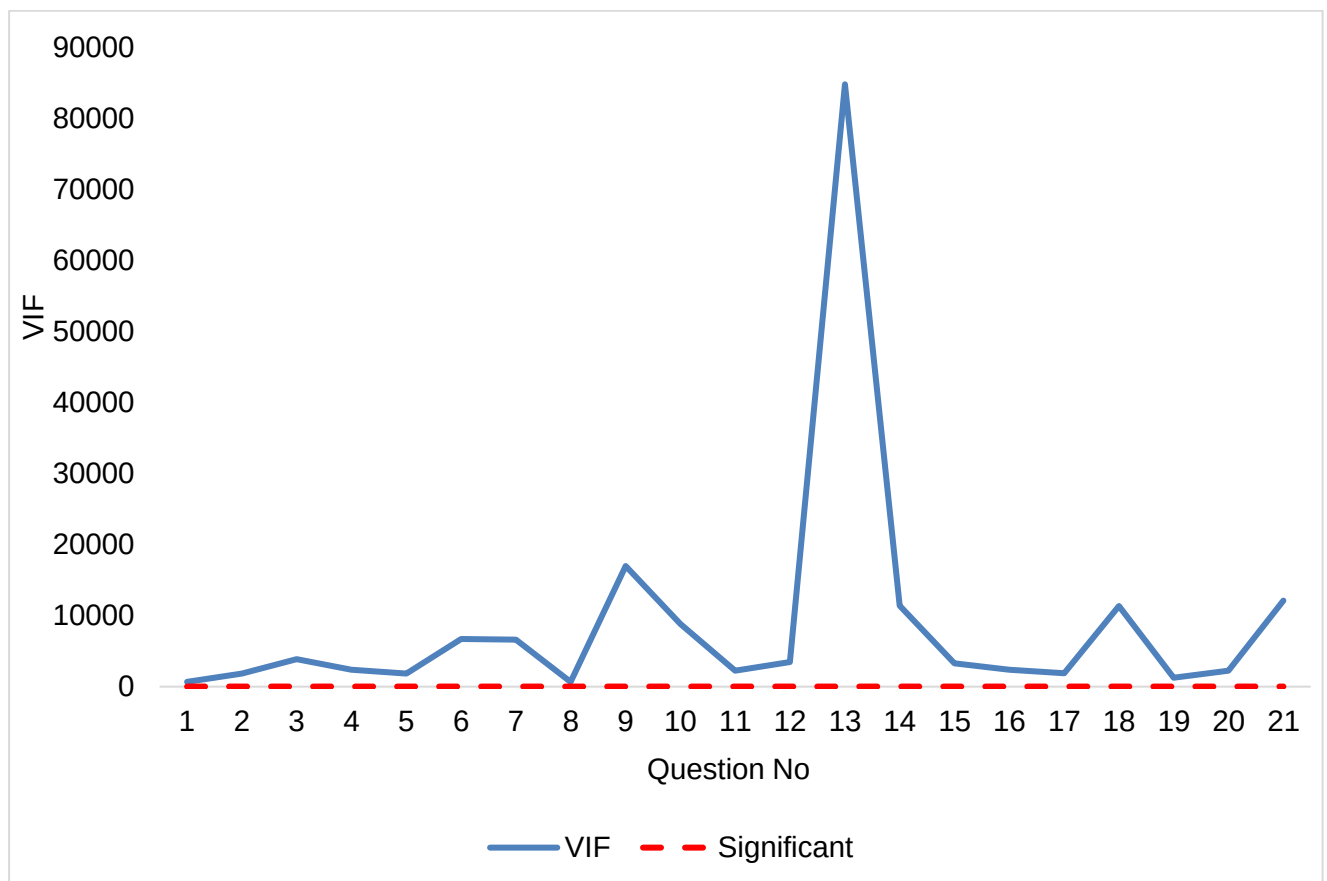


Figure 8-7: VIF values for Likert scale question.

Figure 8-8 shows the correlation between Likert scale survey responses calculated using Spearman correlation. Values close to 1 (perfect correlation) show a positive correlation between the two variables, and values close to 0 show little to no correlation. Negative values indicate a negative correlation.

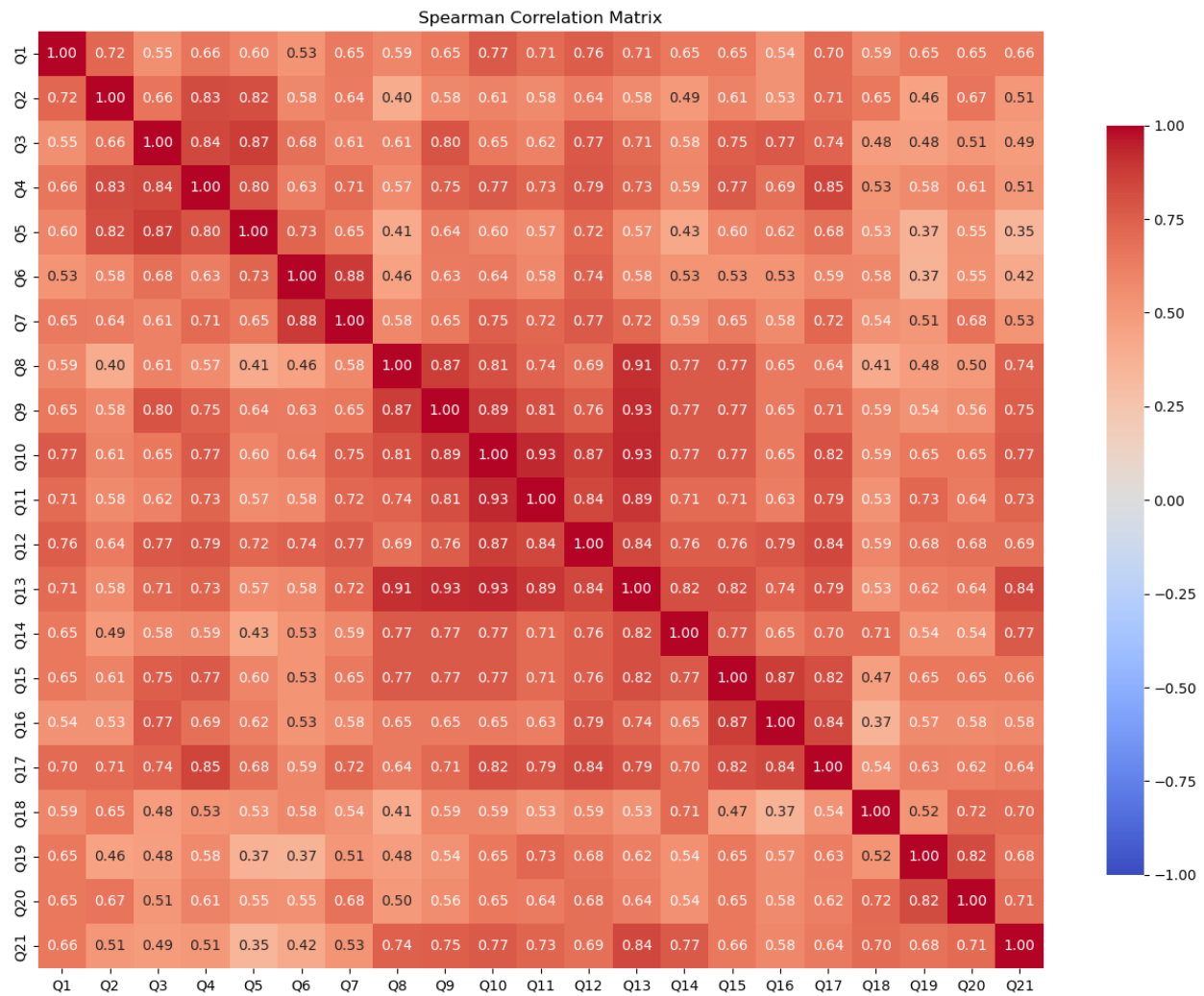


Figure 8-8: Correlation matrix for the Likert scale survey responses.

8.8 Cronbach Alpha Internal consistency test

The Cronbach Alpha values for the overall survey responses, responses relating to the pre-installation phase questions, responses relating to the installation phase questions and answers to the post-installation phase questions are in Table 8-7. The confidence interval shows that with 95% confidence, the Cronbach alpha falls within the interval. Cronbach alpha values close to 1 (perfect internal consistency) indicate reliable internal consistency.

Table 8-7: Cronbach alpha test for internal consistency of the Likert scale results.

	Cronbach Alpha	Cronbach Alpha for pre-installation questions	Cronbach Alpha for installation questions	Cronbach Alpha for post-installation questions
Alpha value	0.976	0.940	0.971	0.879
95% confidence interval for Alpha	[0.961, 0.986]	[0.900, 0.967]	[0.953, 0.984]	[0.791, 0.936]

8.9 Factor analysis

This section details the results of the factor analysis from data suitability for factor analysis, factors selected, factor loadings and variances of the factors.

8.9.1 Sampling adequacy

The Kaiser-Meyer-Olkin (KMO) value for the Likert scale question in the survey, their corresponding chi-square statistic value and P-Value are in Table 8-8. KMO model value refers to the measure of sampling adequacy. It assesses whether the data is suitable for factor analysis. A value closer to 1 means the data is well-suited for factor analysis, while values closer to 0 suggest that the data may not be ideal. The chi-square value is from Bartlett's Test of Sphericity, which tests whether the correlation matrix of the dataset is an identity matrix. In other words, it checks if there are any correlations between variables in your dataset. The Chi-Square value assesses the strength of these correlations. P-value accompanies the Chi-Square test result. It shows the probability that the observed correlations occurred by chance. A p-value less than 0.05 typically suggests significant correlations, indicating that factor analysis may be appropriate. A p-value > 0.05 means the correlations are insignificant.

Table 8-8: Bartlett's test for sphericity and sampling adequacy.

KMO model value	Chi-Square value	p-value	Significant

0,645	10,700	0,954	No

8.9.2 Scree test

The Scree plot of factor Eigenvalues is in Figure 8-9. This figure shows the eigenvalues of each survey question. The far left of the figure shows the questions with the largest eigenvalues representing the strong influence of factors on responses (factors to retain). On the right side of the figure, eigenvalues are low, representing the marginal effects of factors on responses (factors to remove). Factors with eigenvalues greater than 1 retained.

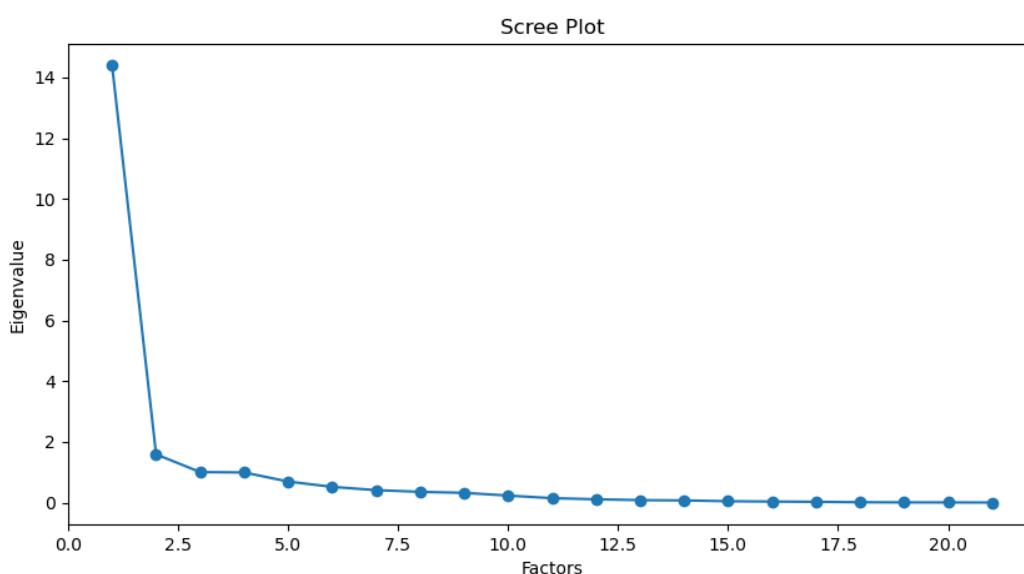


Figure 8-9: Scree plot of Eigenvalues from factor analysis.

8.9.3 Factor loadings

Factors loadings for Likert-scale responses having eigenvalues more than one (>1) are in Table 8-9 and Figure 8-10 below. The first three columns contain numerical values representing each factor's influence on each question. The last three columns indicate whether each factor affected the question (Yes or No). Loadings greater than 0.6 show influence.

Table 8-9: Factor loading values of the factors identified through factor analysis.

Question No	Factor1	Factor2	Factor3	Factor 1 affects question	Factor 2 affects question	Factor 3 affects question
1	0,419	0,397	0,582	No	No	No
2	0,699	0,148	0,510	Yes	No	No
3	0,805	0,412	0,163	Yes	No	No
4	0,768	0,344	0,379	Yes	No	No
5	0,939	0,157	0,183	Yes	No	No
6	0,627	0,291	0,248	Yes	No	No
7	0,626	0,320	0,383	Yes	No	No
8	0,210	0,887	0,227	No	Yes	No
9	0,470	0,780	0,289	No	Yes	No
10	0,419	0,672	0,497	No	Yes	No
11	0,423	0,561	0,576	No	No	No
12	0,582	0,481	0,558	No	No	No
13	0,409	0,744	0,488	No	Yes	No
14	0,252	0,678	0,496	No	Yes	No
15	0,463	0,613	0,422	No	Yes	No
16	0,532	0,403	0,462	No	No	No
17	0,584	0,364	0,572	No	No	No

18	0,353	0,287	0,570	No	No	No
19	0,184	0,348	0,635	No	No	Yes
20	0,426	0,213	0,772	No	No	Yes
21	0,151	0,571	0,721	No	No	Yes

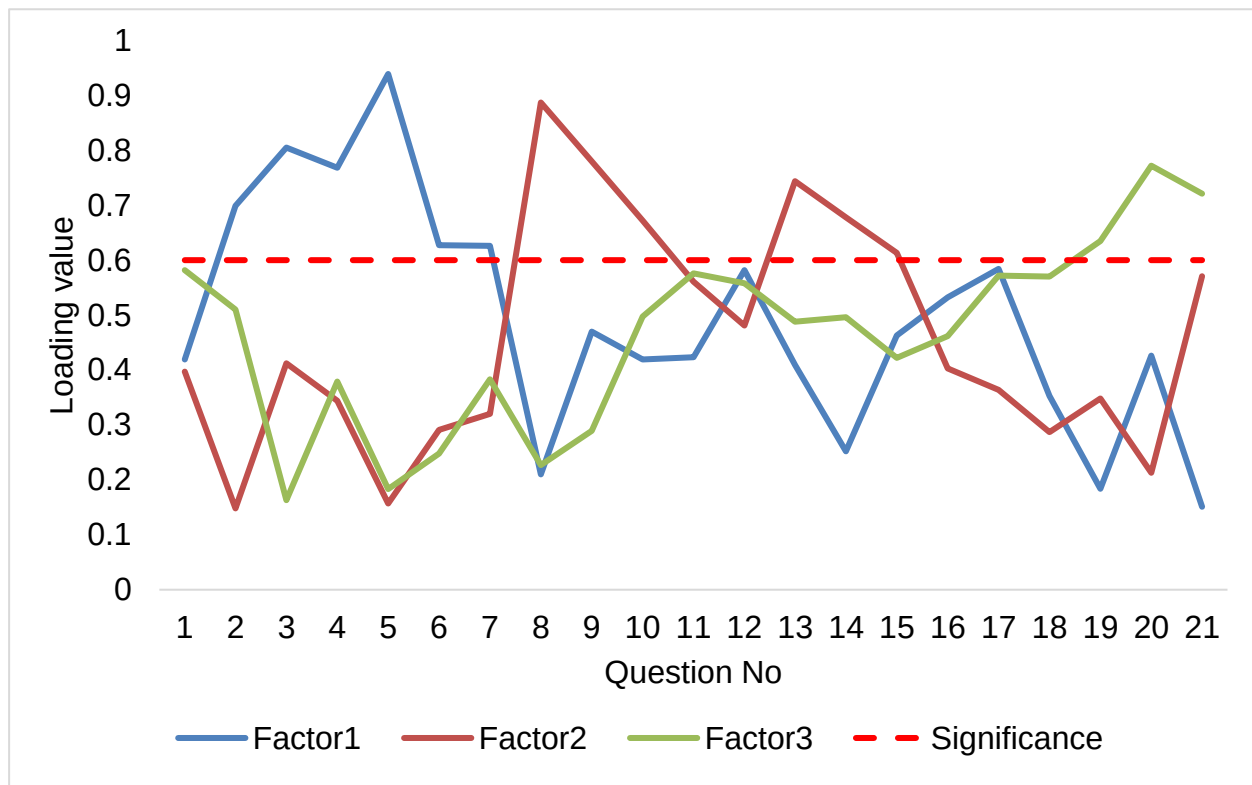


Figure 8-10: Factors and their loading values for each Likert scale question.

8.9.4 Average Variance Extracted (AVE) and Composite Reliability (CR)

Table 8-10 shows the AVE, proportional variance, CR and cumulative variance of the factors with factor loading eigenvalues more than one in the Scree plot. The three columns list the statistical measures related to the factors. AVE indicates the amount of variance captured by the factor from its indicators relative to the variance due to measurement error. Cumulative variance shows the total variance explained by the factors cumulatively. CR assesses the reliability of the factor, indicating the internal consistency of the indicators measuring the factor.

Table 8-10: Factors identified through factor loading, AVE and CR.

	Factor 1	Factor 2	Factor 3
Average Variance Extracted (AVE)	0.284	0.254	0.242
Cumulative Variance	0.284	0.538	0.780
Composite Reliability (CR)	0,563	0,535	0,523

8.10 Likert scale responses

Figure 8-11 (pre-installation phase), Figure 8-12 (installation phase) and Figure 8-13 (post-installation phase) show the respective summarised responses from the survey. These are the responses to the 5-point Likert scale questions in the survey, ranging between strongly disagree (1) and strongly agree (5). Summary statistics of the qualitative responses are in Appendix B Table B-1. The questions in the survey from Question 1 (Q1) to question 21 can be found in Appendix A.

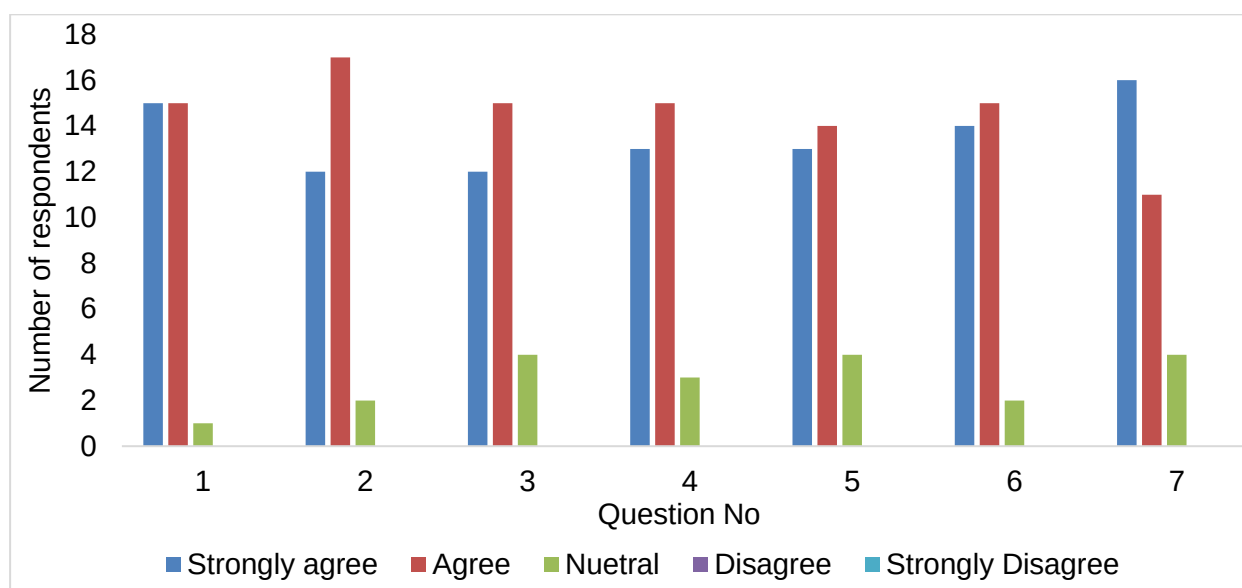


Figure 8-11: Responses to the Likert scale question in the roadmap survey (Q1 - Q7).

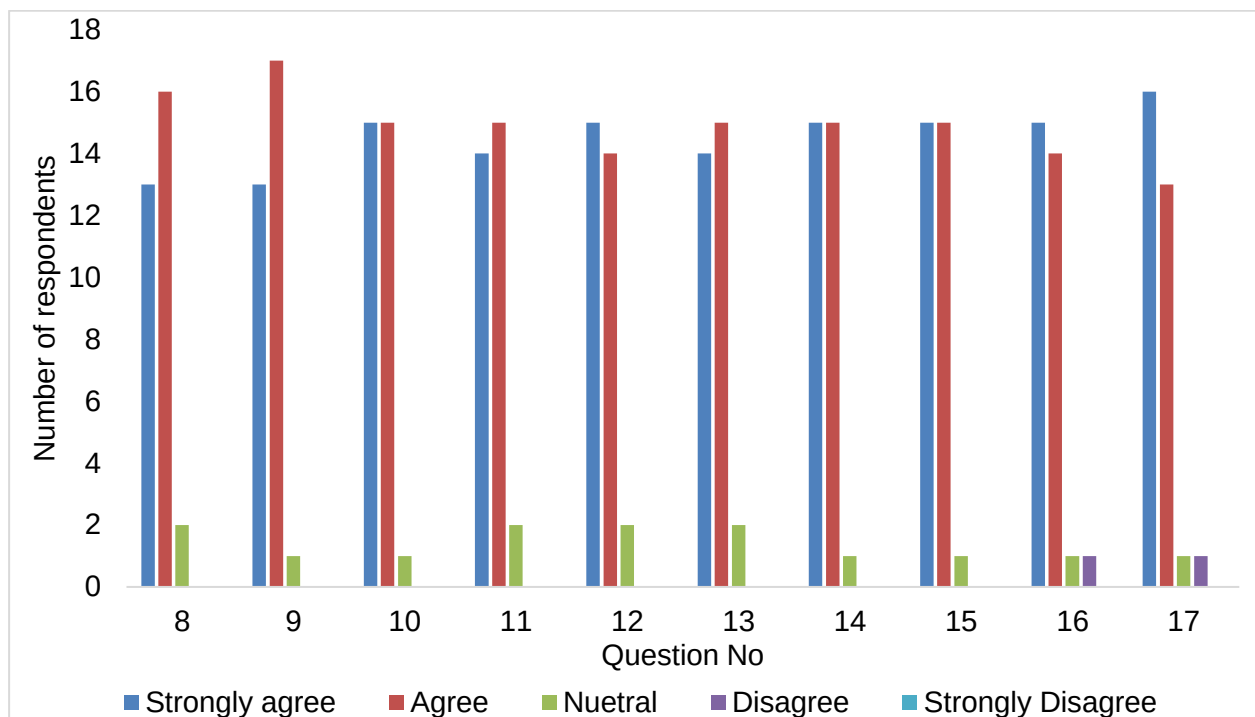


Figure 8-12: Responses to the Likert scale question in the roadmap survey (Q8 – Q17).

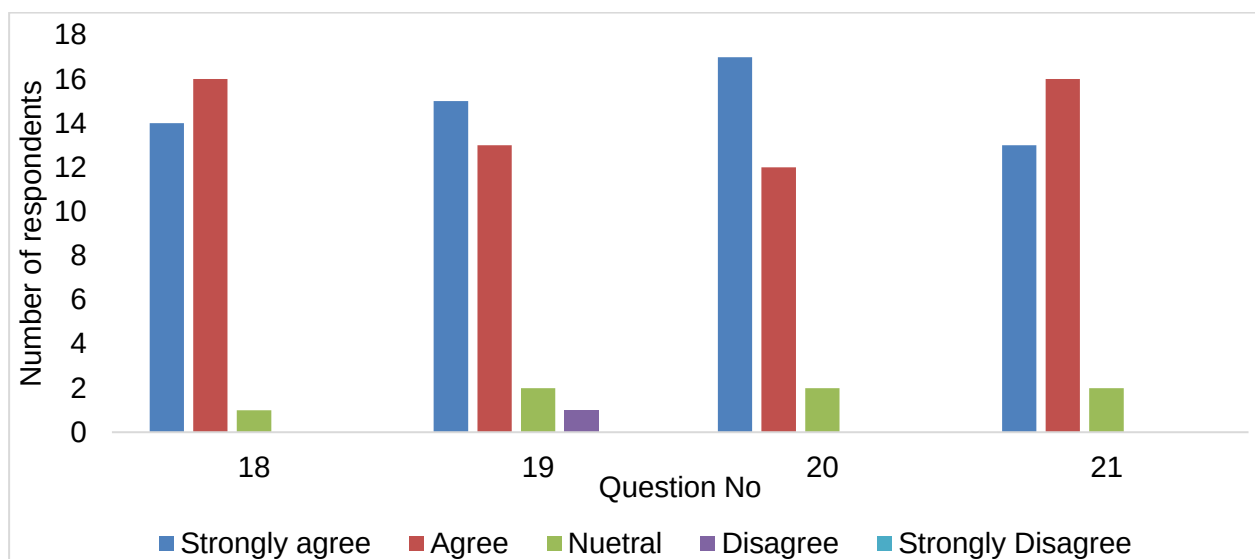


Figure 8-13: Responses to the Likert scale question in the roadmap survey (Q1 - Q7).

8.11 The two proportions hypothesis test for agreement levels

Table 8-11, Figure 8-14 and Figure 8-15 below show the results of the hypothesis test performed to prove the hypothesis made in section 4.8.3, which stated that most respondents would agree that each roadmap step was applicable and included rightfully in the roadmap. The agree count column shows the respondents who agreed with each

question. The total count column indicates the total number of respondents for each question. The proportion column represents the respondents who agreed with each question, calculated as Agree count/Total count. The P-value column contains the p-values for each question, which indicate the statistical significance of the proportion of agreement. The significant column indicates whether the result is statistically significant (Yes or No) based on the p-value. P-values less than 0.05 indicated statistically significant results.

Table 8-11: Two proportions test results of participants agreeing or disagreeing with roadmap Likert scale questions.

Question No	Agree count	Total count	proportion	p-value	Significant
1	30	31	0,968	1,490E-08	Yes
2	29	31	0,935	2,314E-07	Yes
3	27	31	0,871	1,698E-05	Yes
4	28	31	0,903	2,325E-06	Yes
5	27	31	0,871	1,698E-05	Yes
6	29	31	0,935	2,314E-07	Yes
7	27	31	0,871	1,698E-05	Yes
8	29	31	0,935	2,314E-07	Yes
9	30	31	0,968	1,490E-08	Yes
10	30	31	0,968	1,490E-08	Yes
11	29	31	0,935	2,314E-07	Yes
12	29	31	0,935	2,314E-07	Yes
13	29	31	0,935	2,314E-07	Yes

14	30	31	0,968	1,490E-08	Yes
15	30	31	0,968	1,490E-08	Yes
16	29	31	0,935	2,314E-07	Yes
17	29	31	0,935	2,314E-07	Yes
18	30	31	0,968	1,490E-08	Yes
19	28	31	0,903	2,325E-06	Yes
20	29	31	0,935	2,314E-07	Yes
21	29	31	0,935	2,314E-07	Yes

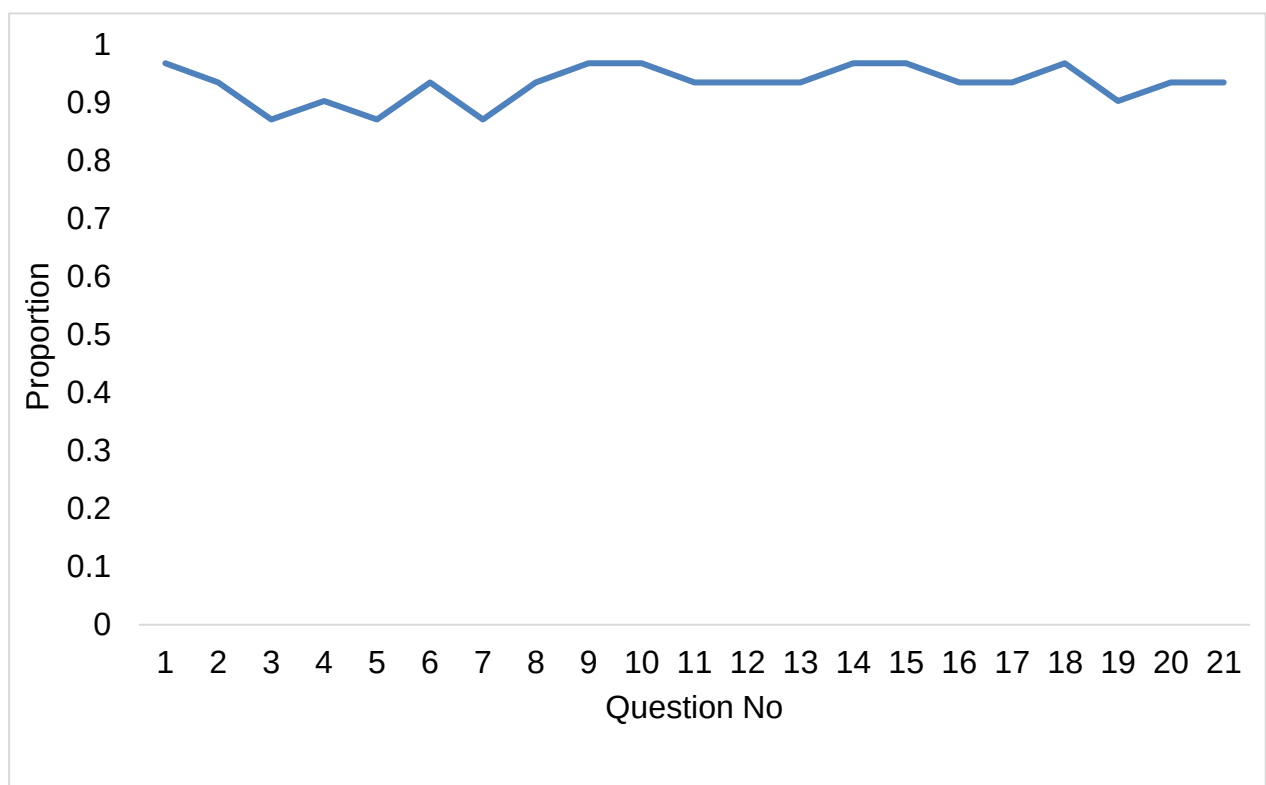


Figure 8-14: Proportion of responses that agree or strongly agree with the Likert scale questions.

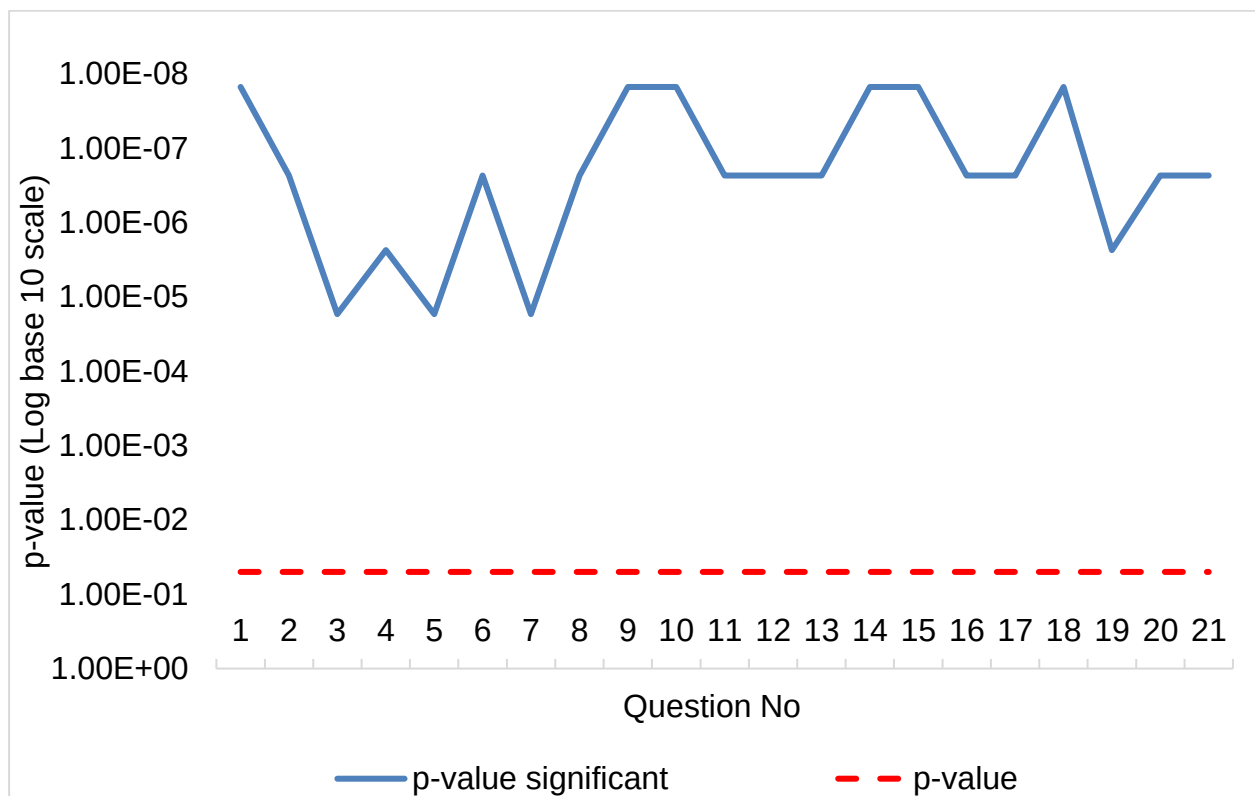


Figure 8-15: Proportion p-values of responses that agree or strongly agree with the Likert scale questions.

8.12 ANOVA analysis for the difference between ages

Table 8-12, Figure 8-16 and Figure 8-17 below show the results of the first hypothesis test performed to prove the hypothesis made in section 4.8.3, which stated there was a difference in the responses to each roadmap step due to age differences between the participants. The F-statistic column shows the F-statistic values for each question, determining if there are significant differences between groups. The P-value column contains the p-values for each question, indicating the probability that the observed results occurred by chance. The last column indicates whether the result is statistically significant (Yes or No) based on the p-value. P-values less than 0.05 indicated statistically significant results.

Table 8-12: ANOVA analysis results of participants' differences in responses due to age within the roadmap Likert scale questions.

Question No	F-Statistic	p-value	Significant

1	1,158	0,352	No
2	0,478	0,752	No
3	0,441	0,778	No
4	0,278	0,890	No
5	0,301	0,875	No
6	1,201	0,334	No
7	0,959	0,447	No
8	0,244	0,911	No
9	0,271	0,894	No
10	0,205	0,933	No
11	0,311	0,868	No
12	0,427	0,788	No
13	0,311	0,868	No
14	0,734	0,577	No
15	0,119	0,974	No
16	0,162	0,956	No
17	0,266	0,897	No
18	2,145	0,104	No
19	0,302	0,874	No
20	1,467	0,241	No

21	0,959	0,446	No

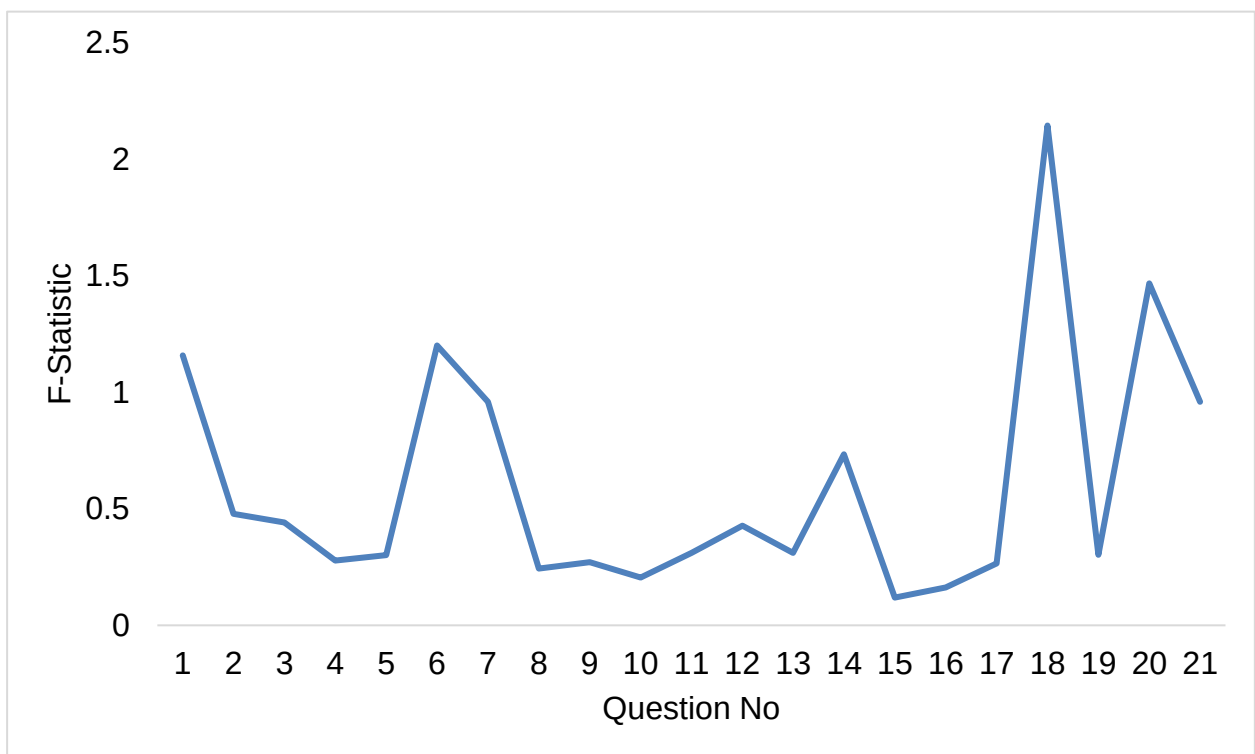


Figure 8-16: F-statistic for the difference due to age within the roadmap Likert scale questions.

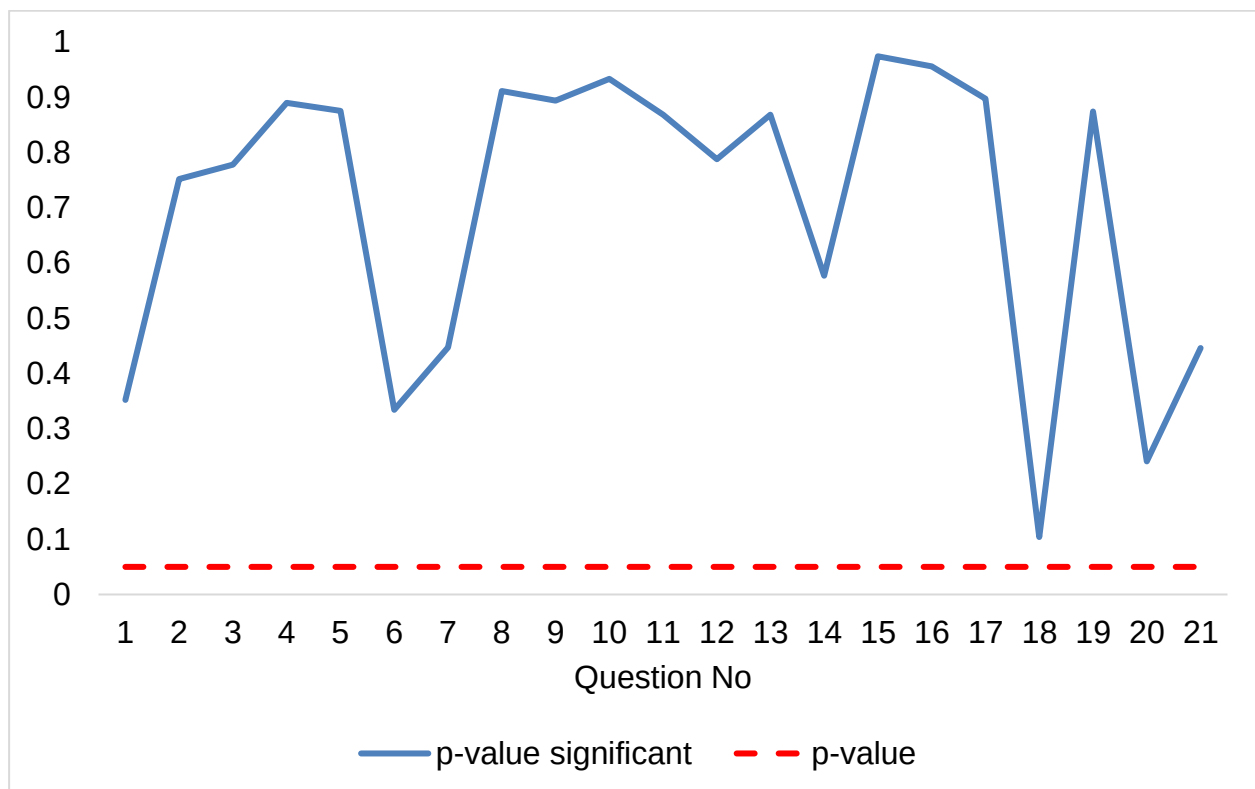


Figure 8-17: F-statistic P-value for the difference due to age within the roadmap Likert scale questions.

Table 8-13, Figure 8-18 and Figure 8-19 below show the results of the second hypothesis test performed to prove the hypothesis made in section 4.8.3, which stated there was a difference in the responses to each roadmap step due to age differences between the participants. The Chi-square column shows the Chi-squared statistic values for each question, which tests the independence of two categorical variables. The P-value column contains the p-values for each question, indicating the probability that the observed results occurred by chance. The significant column indicates whether the result is statistically significant (Yes or No) based on the p-value. P-values less than 0.05 indicated statistically significant results.

Table 8-13: Chi-square test analysis results of participants' differences in responses due to age within the roadmap Likert scale questions.

Question No	Chi-square	p-value	Significant
1	9,448	0,306	No

2	3,802	0,875	No
3	2,321	0,970	No
4	1,582	0,991	No
5	2,092	0,978	No
6	5,103	0,746	No
7	5,750	0,675	No
8	7,309	0,504	No
9	3,278	0,916	No
10	4,625	0,797	No
11	2,422	0,965	No
12	2,404	0,966	No
13	2,422	0,965	No
14	4,980	0,760	No
15	2,880	0,942	No
16	5,694	0,931	No
17	5,830	0,924	No
18	11,157	0,193	No
19	10,415	0,580	No
20	8,368	0,398	No
21	5,786	0,671	No

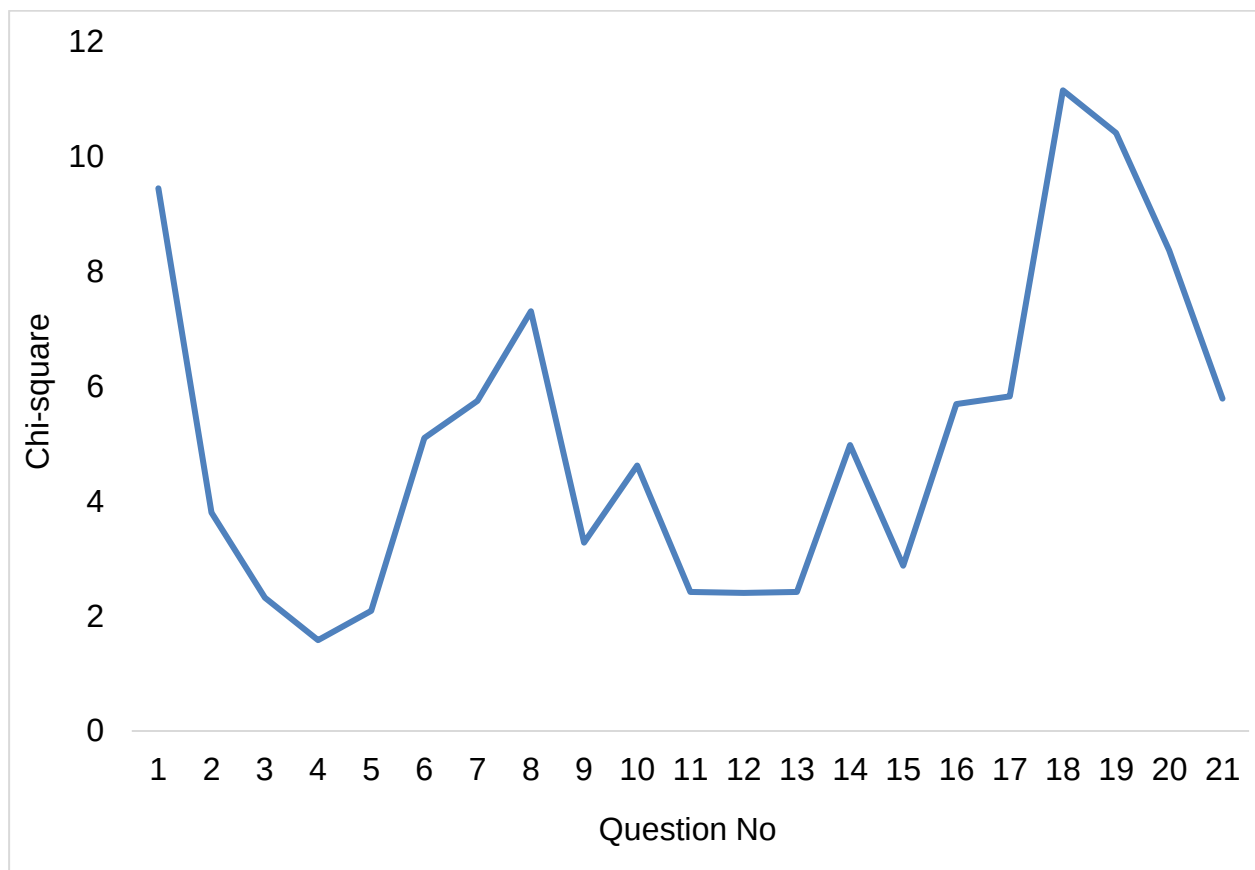


Figure 8-18: Chi-square for the difference due to age within the roadmap Likert scale questions.

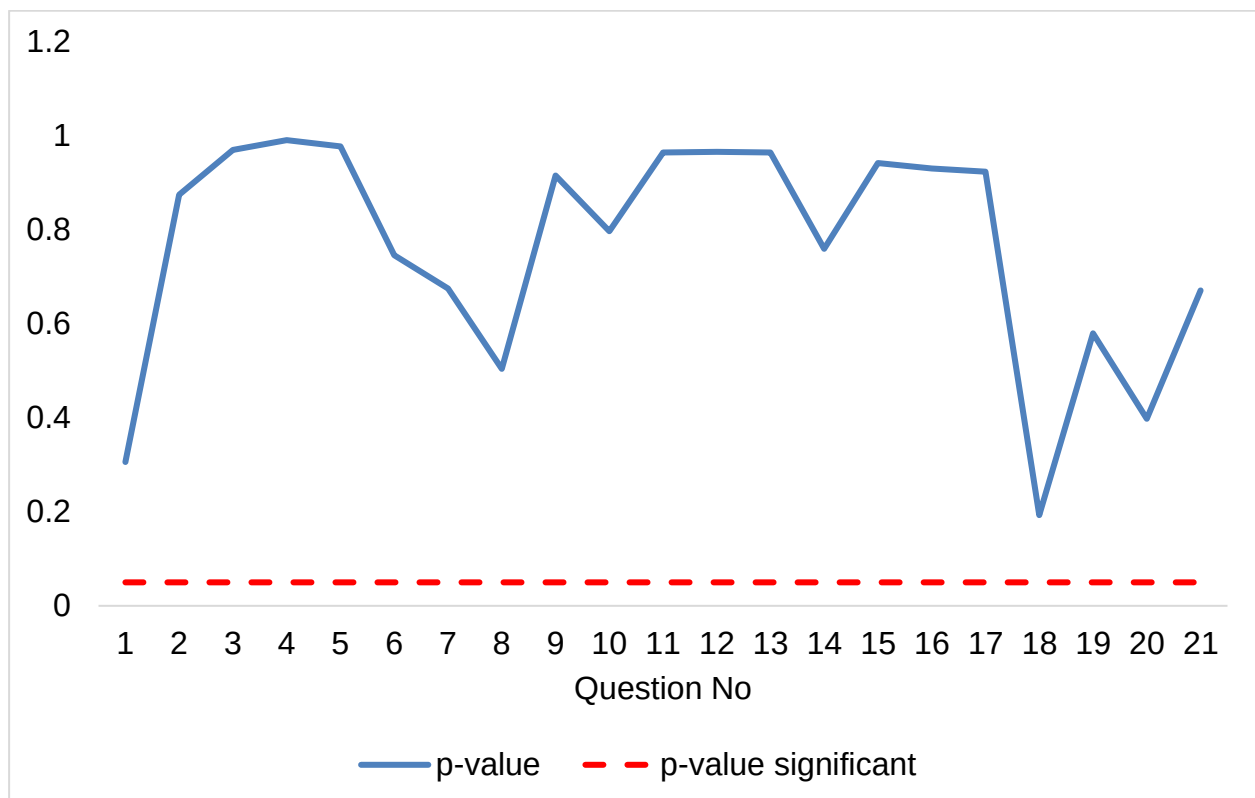


Figure 8-19: P-value for chi-square test for the difference due to age within the roadmap Likert scale questions.

8.13 ANOVA analysis for the difference due to experience

Table 8-14, Figure 8-20 and Figure 8-21 below are the results of the first hypothesis test performed to prove the hypothesis made in section 4.8.3, which stated there was a difference in the responses to each roadmap step due to experience level differences between the participants. The F-statistic column shows the F-statistic values for each question, determining if there are significant differences between groups. The P-value column contains the p-values for each question, indicating the probability that the observed results occurred by chance. The last column indicates whether the result is statistically significant (Yes or No) based on the p-value. P-values less than 0.05 indicated statistically significant results.

Table 8-14: ANOVA analysis results of participants' differences in responses due to experience within the roadmap Likert scale questions.

Question No	F-Statistic	p-value	Significant

1	1,613	0,178	No
2	1,575	0,189	No
3	0,837	0,580	No
4	1,089	0,407	No
5	0,896	0,536	No
6	0,475	0,861	No
7	0,678	0,706	No
8	0,307	0,955	No
9	0,577	0,786	No
10	1,016	0,453	No
11	1,145	0,374	No
12	0,873	0,554	No
13	0,726	0,667	No
14	0,691	0,695	No
15	1,193	0,348	No
16	0,844	0,575	No
17	1,108	0,395	No
18	0,668	0,714	No
19	2,903	0,023	Yes
20	1,086	0,408	No

21	0,764	0,637	No

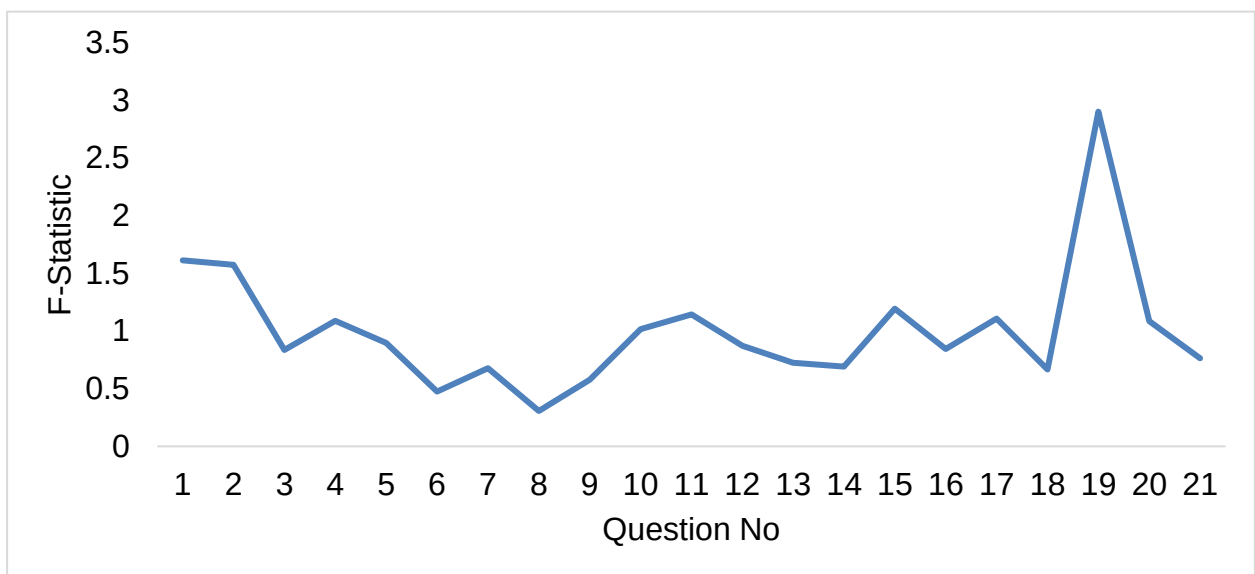


Figure 8-20: F-statistic for the difference due to experience within the roadmap Likert scale questions.

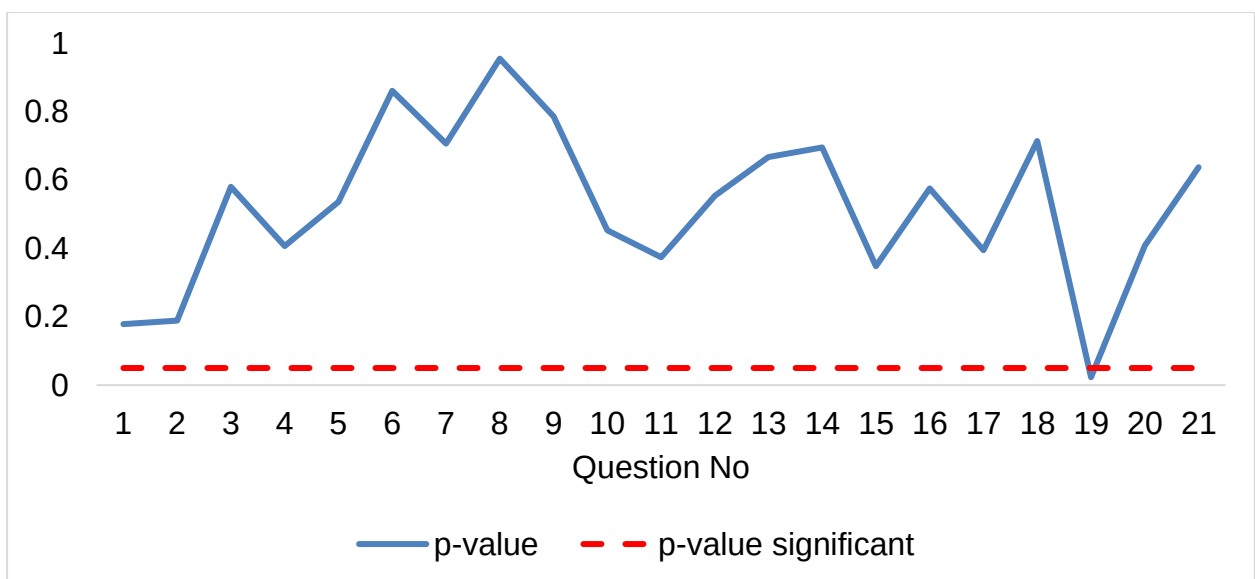


Figure 8-21: F-statistic p-value for the difference due to experience within the roadmap Likert scale questions.

Since Q19 in Table 8-14 and Figure 8-21 show significant differences in the responses, the researcher conducted a pairwise comparison using Tukey's HSD test on Q19, and the results are in Table 8-15, Figure 8-22 and Figure 8-23. The group pair column lists the pairs of groups under comparison. Group 1 column indicates the first group in each

pair. Group 2 column indicates the second group in each pair (groups in years of experience ranges). **Mean difference:** This column shows the difference in means between the two groups. The adjacent p-values column contains the p-values for the mean differences, indicating the probability that the observed differences occurred by chance. The lower CI column represents the confidence interval lower bound for the mean difference. The upper CI column represents the upper bound of the confidence interval for the mean difference. **Significant:** This column indicates whether the mean difference is statistically significant (Yes or No) based on the p-value. P-values less than 0.05 indicated statistically significant results.

Table 8-15: Pairwise comparison using Tukey's HSD test for Q19.

Group pair No	Group 1	Group 2	Mean difference	Adjacent p-values	Lower CI	Upper CI	Significant
1	0 - 2	11 - 15	-0,267	0,999	-1,654	1,121	No
2	0 - 2	16 - 20	-0,667	0,912	-2,387	1,054	No
3	0 - 2	21 - 25	0,083	1,000	-1,526	1,693	No
4	0 - 2	26 - 30	-0,667	0,878	-2,276	0,943	No
5	0 - 2	3 - 5	-0,167	1,000	-2,090	1,757	No
6	0 - 2	31 - 35	-2,667	0,025	-5,100	-0,233	Yes
7	0 - 2	36 - 40	-0,667	0,988	-3,100	1,767	No
8	0 - 2	6 - 10	0,333	0,999	-1,387	2,054	No
9	11 - 15	16 - 20	-0,400	0,983	-1,787	0,987	No
10	11 - 15	21 - 25	0,350	0,986	-0,897	1,597	No
11	11 - 15	26 - 30	-0,400	0,968	-1,647	0,847	No

12	11 - 15	3 - 5	0,100	1,000	-1,532	1,732	No
13	11 - 15	31 - 35	-2,400	0,027	-4,610	-0,190	Yes
14	11 - 15	36 - 40	-0,400	0,999	-2,610	1,810	No
15	11 - 15	6 - 10	0,600	0,852	-0,787	1,987	No
16	16 - 20	21 - 25	0,750	0,797	-0,859	2,359	No
17	16 - 20	26 - 30	0,000	1,000	-1,609	1,609	No
18	16 - 20	3 - 5	0,500	0,991	-1,424	2,424	No
19	16 - 20	31 - 35	-2,000	0,166	-4,433	0,433	No
20	16 - 20	36 - 40	0,000	1,000	-2,433	2,433	No
21	16 - 20	6 - 10	1,000	0,564	-0,721	2,721	No
22	21 - 25	26 - 30	-0,750	0,726	-2,240	0,740	No
23	21 - 25	3 - 5	-0,250	1,000	-2,075	1,575	No
24	21 - 25	31 - 35	-2,750	0,014	-5,106	-0,394	Yes
25	21 - 25	36 - 40	-0,750	0,970	-3,106	1,606	No
26	21 - 25	6 - 10	0,250	1,000	-1,359	1,859	No
27	26 - 30	3 - 5	0,500	0,988	-1,325	2,325	No
28	26 - 30	31 - 35	-2,000	0,140	-4,356	0,356	No
29	26 - 30	36 - 40	0,000	1,000	-2,356	2,356	No
30	26 - 30	6 - 10	1,000	0,480	-0,609	2,609	No
31	3 - 5	31 - 35	-2,500	0,063	-5,081	0,081	No

32	3 - 5	36 - 40	-0,500	0,999	-3,081	2,081	No
33	3 - 5	6 - 10	0,500	0,991	-1,424	2,424	No
34	31 - 35	36 - 40	2,000	0,383	-0,980	4,980	No
35	31 - 35	6 - 10	3,000	0,009	0,567	5,433	Yes
36	36 - 40	6 - 10	1,000	0,883	-1,433	3,433	No

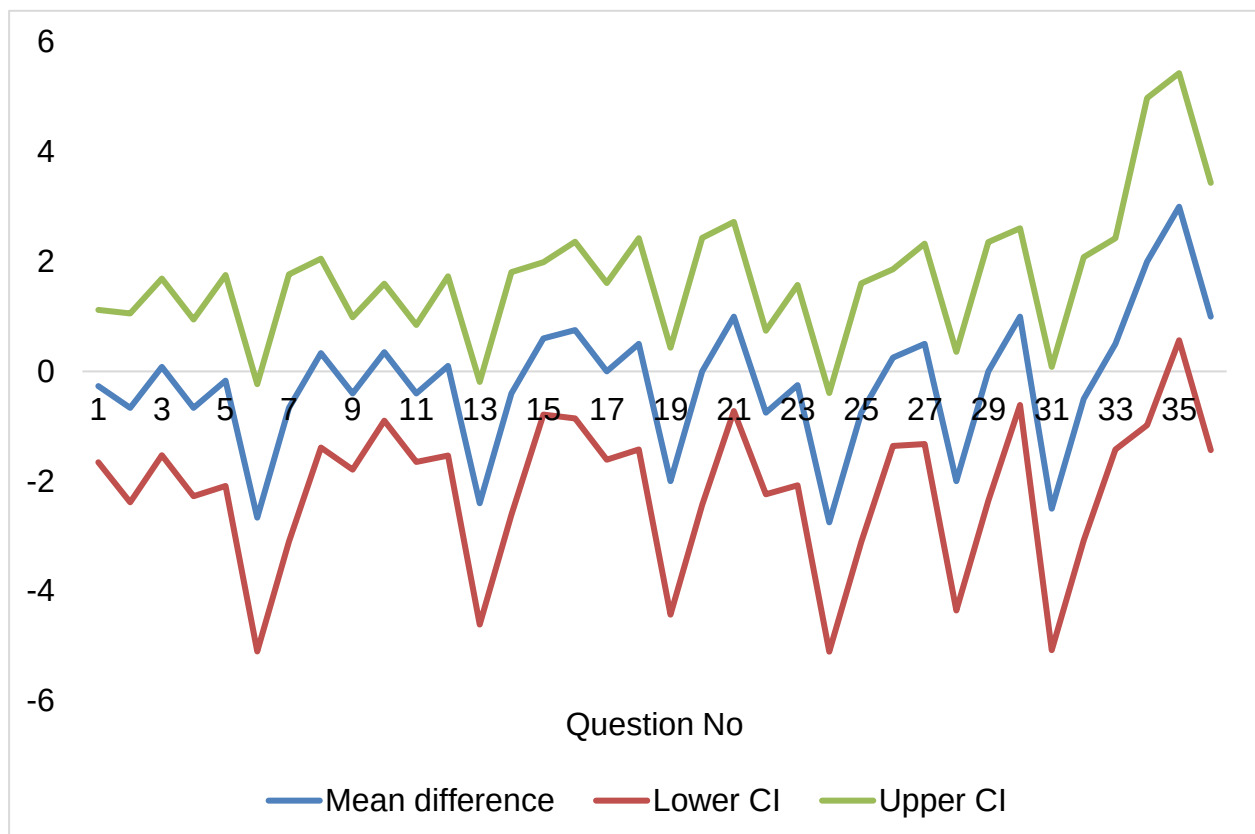


Figure 8-22: Mean difference between group pairs of experience and their Confidence intervals.

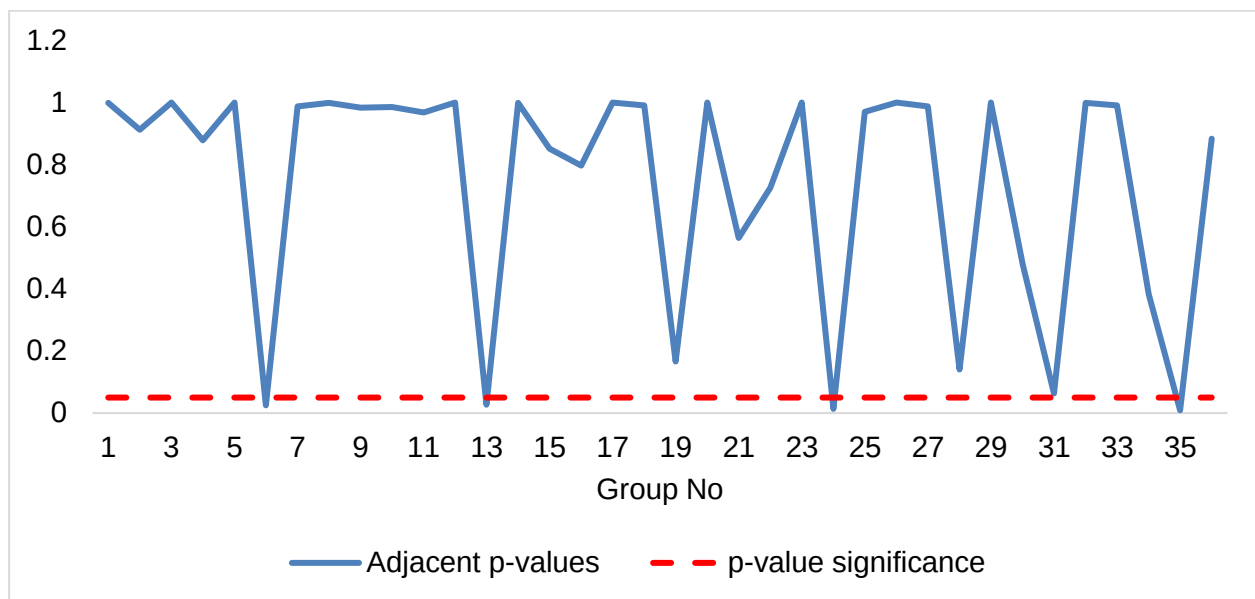


Figure 8-23: Mean difference p-values between group pairs of experience.

Table 8-16, Figure 8-24 and Figure 8-25 below show the results of the second hypothesis test (a chi-square test) performed to prove the hypothesis made in section 4.8.3, stating there was a difference in the responses to each roadmap step due to differences in experience levels between the participants, similar to Table 8-14 above. The Chi-square column shows the Chi-squared statistic values for each question, which tests the independence of two categorical variables. The P-value column contains the p-values for each question, indicating the probability that the observed results occurred by chance. The significant column indicates whether the result is statistically significant (Yes or No) based on the p-value. P-values less than 0.05 indicated statistically significant results.

Table 8-16: Chi-square test analysis results of participants' differences in responses due to experiences within the roadmap Likert scale questions.

Question No	Chi-square	p-value	Significant
1	21,631	0,156	No
2	16,630	0,410	No
3	18,178	0,314	No
4	21,059	0,176	No

5	22,293	0,134	No
6	12,304	0,723	No
7	17,150	0,376	No
8	13,883	0,607	No
9	14,401	0,569	No
10	17,636	0,346	No
11	16,265	0,435	No
12	16,265	0,435	No
13	12,127	0,735	No
14	14,880	0,533	No
15	14,811	0,539	No
16	22,118	0,572	No
17	24,678	0,423	No
18	14,969	0,527	No
19	44,925	0,006	Yes
20	13,689	0,622	No
21	13,192	0,659	No

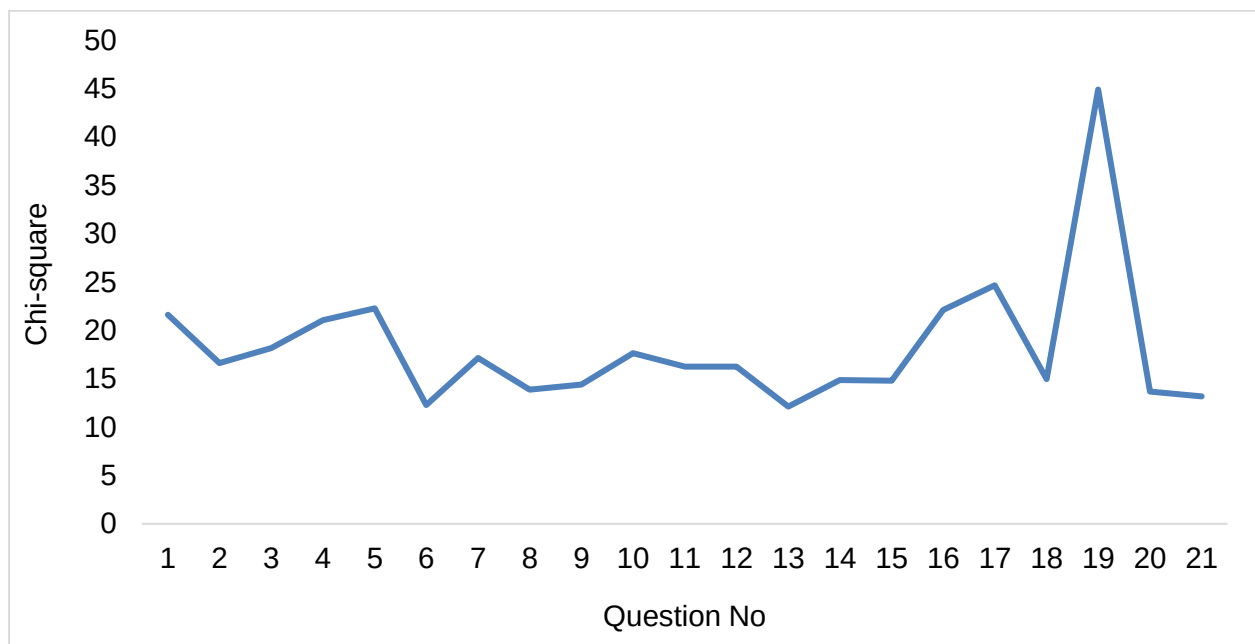


Figure 8-24: Chi-square for the difference due to experiences within the roadmap Likert scale questions.

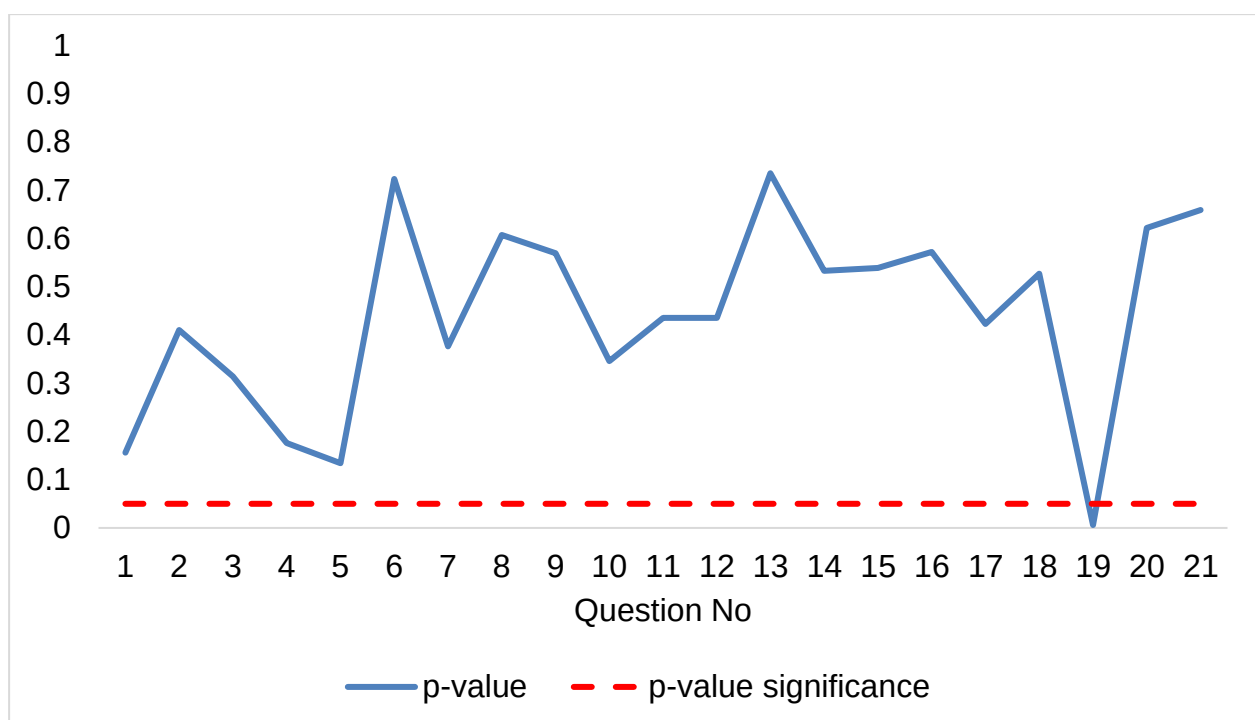


Figure 8-25: P-value for the chi-square test for the difference due to experience within the roadmap Likert scale questions.

8.14 T-test for independence between gender groups

Table 8-17, Figure 8-26 and Figure 8-27 below show the results of the hypothesis test performed to prove the hypothesis made in section 4.8.3, which stated there was a difference in the responses to each roadmap step due to gender differences between the participants. The basis for this hypothesis was on findings from Venkatesh and Morris (2000) that state gender differences in the approaches to technology implementation. The T-Statistic column shows the T-statistic values for each question, determining if there are significant differences between the means of the two groups. The P-value column contains the p-values for each question, indicating the probability that the observed results occurred by chance. The significant column indicates whether the result is statistically significant (Yes or No) based on the p-value. P-values less than 0.05 indicated statistically significant results.

Table 8-17: T-test analysis results of participants' differences in responses due to genders within the roadmap Likert scale questions.

Question No	T-Statistic	p-value	Significant
1	0,268	0,791	No
2	0,529	0,601	No
3	1,140	0,264	No
4	0,486	0,631	No
5	0,785	0,439	No
6	0,381	0,706	No
7	-0,180	0,858	No
8	1,390	0,175	No
9	1,090	0,285	No
10	0,268	0,791	No

11	0,381	0,706	No
12	0,019	0,985	No
13	0,381	0,706	No
14	0,919	0,366	No
15	0,919	0,366	No
16	-0,180	0,858	No
17	0,016	0,987	No
18	0,668	0,509	No
19	-0,357	0,724	No
20	-0,112	0,911	No
21	0,154	0,879	No

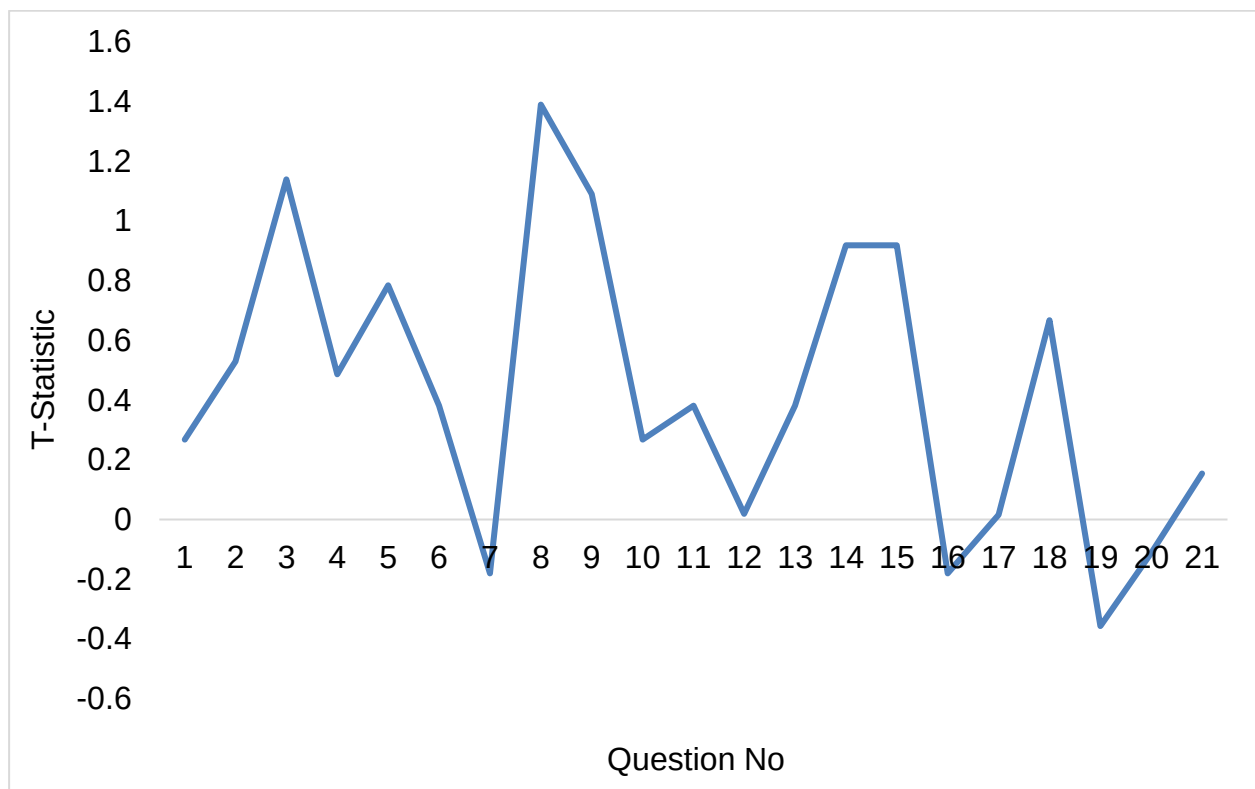


Figure 8-26: T-statistic for the difference due to gender within the roadmap Likert scale questions.

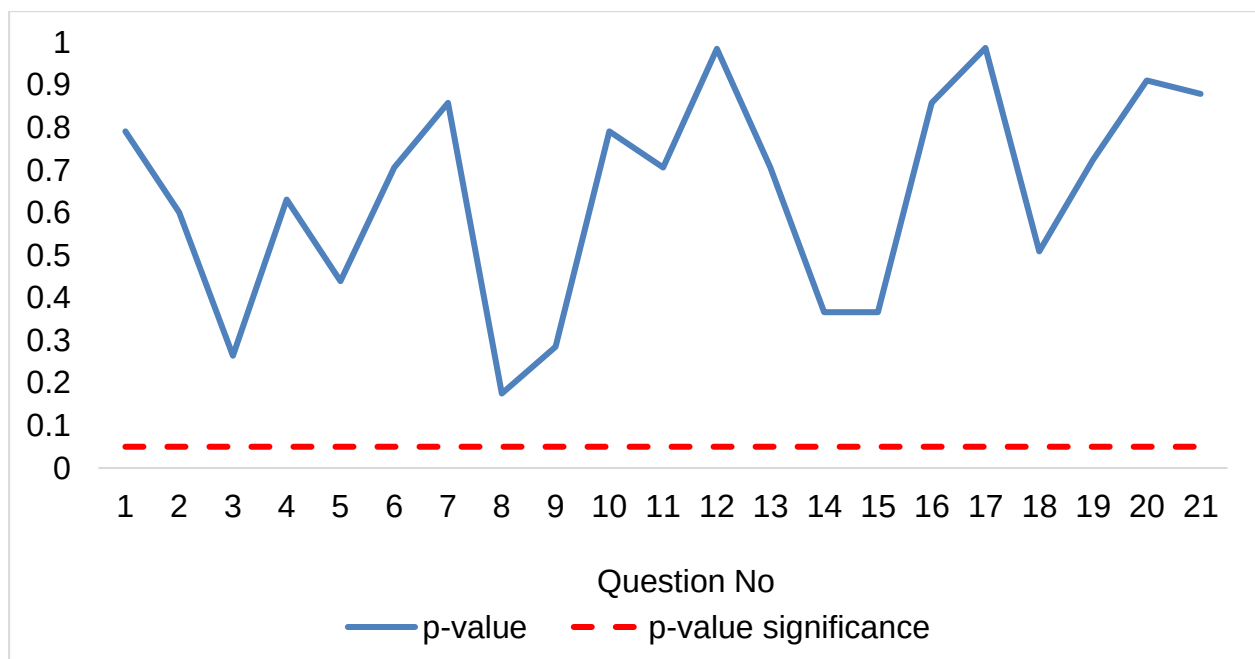


Figure 8-27: T-statistic p-value for the difference due to gender within the roadmap Likert scale questions.

Table 8-18, Figure 8-28 and Figure 8-29 below show the results of the second hypothesis test performed to prove the hypothesis made in section 4.8.3, which stated there was a difference in the responses to each roadmap step due to gender differences between the participants. The Chi-square column shows the Chi-squared statistic values for each question, which tests the independence of two categorical variables. The P-value column contains the p-values for each question, indicating the probability that the observed results occurred by chance. The significant column indicates whether the result is statistically significant (Yes or No) based on the p-value. P-values less than 0.05 indicated statistically significant results.

Table 8-18: Chi-square test analysis results of participants' differences in responses due to genders within the roadmap Likert scale questions.

Question No	Chi-square	p-value	Significant
1	1,777	0,411	No
2	0,297	0,862	No
3	1,566	0,457	No
4	0,782	0,676	No
5	0,662	0,718	No
6	0,171	0,918	No
7	0,538	0,764	No
8	3,522	0,172	No
9	1,972	0,373	No
10	1,777	0,411	No
11	0,171	0,918	No
12	0,171	0,918	No

13	0,171	0,918	No
14	1,777	0,411	No
15	1,777	0,411	No
16	2,278	0,517	No
17	2,225	0,527	No
18	1,646	0,439	No
19	0,750	0,861	No
20	0,297	0,862	No
21	0,118	0,943	No

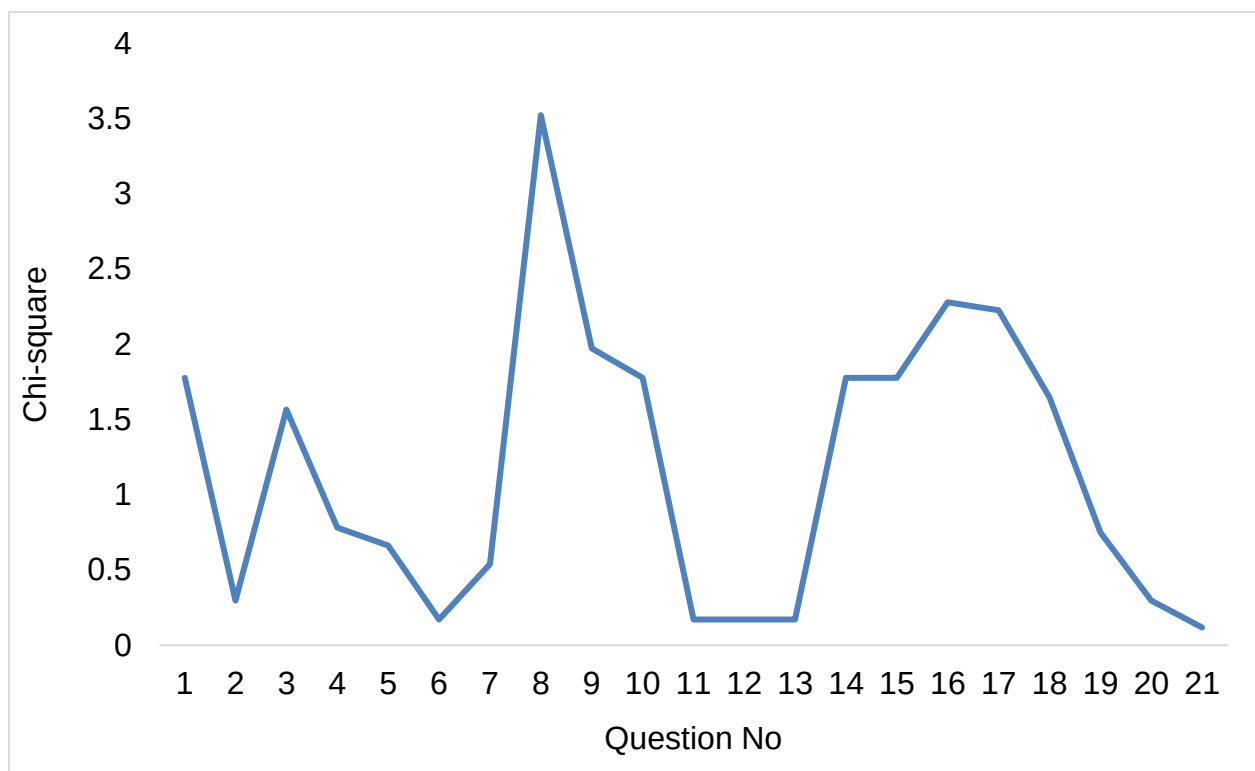


Figure 8-28: Chi-square test for the difference due to gender within the roadmap Likert scale questions.

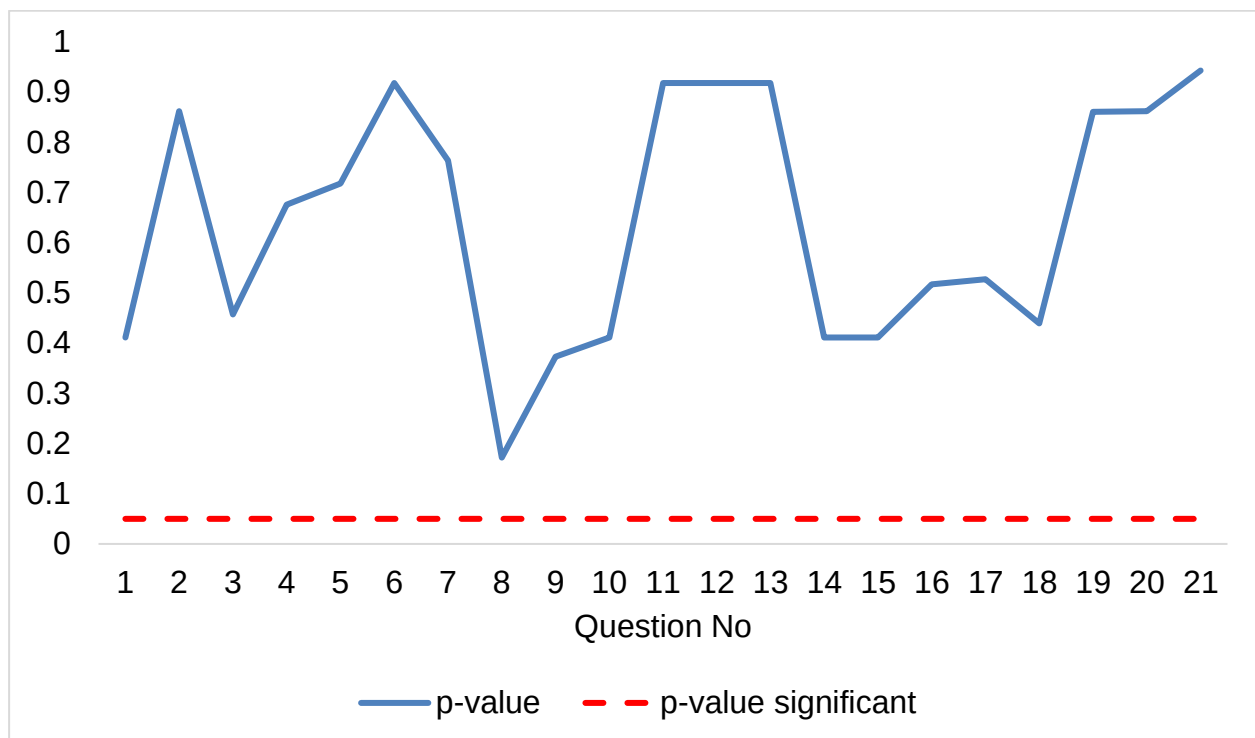


Figure 8-29: P-value for the chi-square test for the difference due to gender within the roadmap Likert scale questions.

8.15 Chapter summary

The results in this chapter include the themes found through thematic analysis of the qualitative responses to the survey. The succeeding results were from the statistical assumptions made before the analysis, namely results to test for outliers, normality, multicollinearity, and correlation. These were followed by the results for the internal consistency test through Cronbach's alpha. A summary of the qualitative responses succeeded in the factor analysis results.

The next set of results was on the hypothesis testing of the agreement level of respondents with the survey questions. The last set of results were from tests for the differences in the responses due to demographic differences such as gender, age and experience levels. The statistical tests confirmed the applicability of statistical assumptions to the analysis in this study. They validated what the survey was measuring (factor analysis). They further confirmed hypotheses about the responses to the study, providing deeper insight into what respondents thought of the roadmap to technology implementation presented to them through the survey. Further details on these tests are in the next chapter (Chapter 9).

CHAPTER 9 DISCUSSION

9.1 Introduction

This chapter details the discussion of the results from the survey's qualitative responses and quantitative responses. The basis for the discussion was the results detailed in Chapter 8.

9.2 Thematic analysis

The thematic analysis reveals a dominant perception that all pre-installation, installation and post-installation phases are crucial, with a subset of responses highlighting specific steps or suggesting additions. A notable portion of respondents also expressed indifference or uncertainty about the importance of these steps. These insights can guide further exploration and refinement of the roadmap to address all critical aspects comprehensively.

9.2.1 Defined and named themes

1. Theme 1: Perceived equal importance of all steps
 - Many respondents acknowledged that every step in the pre-installation, installation and post-installation phases was equally important.
2. Theme 2: Highlighting specific steps or additions
 - Some respondents focus on particular steps or suggest additional critical steps, like drafting agreements, testing, understanding business needs, prototyping, system testing, risk evaluation, gathering documents, upgrading personnel, constant checks, and including safety and legal aspects to the roadmap, monitoring and evaluation, exit strategy, on-site assistance, change management, continuous training and ensuring compliance through Functional Design Specifications (FDS).
3. Theme 3: Indifference or uncertainty
 - Several respondents either stated that none of the steps were crucial, or were unsure, or provided non-committal answers like "none" or "N/A". That signalled that the survey structure was unclear. Therefore, needing to be improved to clarify and get better responses. The alternative could be that

these responses indicated that the respondents did not think any more additions were necessary for the survey. Therefore, they were satisfied with the inclusions.

9.2.2 Additions to the roadmap

According to the respondents, some steps were necessary additions to the roadmap for more relevance in the mining industry's move to new technology. Some additions suggested were already in the original roadmap and, therefore, not included in the list in section 8.6.2. The new roadmap is detailed in section 9.2.2.1 below.

9.2.2.1 New roadmap with the additions suggested by the survey participants

The following is the new roadmap incorporating the recommendations from the survey participants (expert opinions on what the roadmap should include). This new roadmap requires testing with the same experts who participated in this study or a similar group of experts to test the roadmap.

- **Pre-Installation Phase**

1. Define the business problem
 - Clearly outline the challenges and objectives driving the need for technology implementation.
2. Understanding business needs
 - Stakeholder engagement gathers a comprehensive understanding of the business and operational needs addressed by the new technology.
3. Identify the commissioning entity's expectations and capacity
 - Assess the commissioning organisation's technical and financial capabilities and align expectations with its capacity.
4. Identify the technological gap
 - Analyse the existing technological infrastructure to identify gaps the technology addresses.
5. Evaluating information on the necessary technology and vendors
 - Research suitable technologies and potential vendors that can meet the identified needs.
6. Assessment and selection procedure for vendor and technology selection

- Establish clear vendor selection criteria based on technical expertise, cost, and alignment with project goals.
- 7. Risks and safety evaluation
 - Identify and evaluate risks related to the technology implementation, including safety concerns.
- 8. Communication down the line with the people who will work with the new technology
 - Ensure that all personnel, especially those operating the new technology, are well-informed of upcoming changes.
- 9. Compiling short-term, medium-term, long-term, and risk management strategies
 - Develop detailed plans that address immediate needs, medium-term adjustments, and long-term sustainability, including risk management strategies.
- 10. Drafting agreements and contracts
 - Finalise legal agreements with vendors, incorporating all project expectations, Functional Design Specifications (FDS), and Key Performance Indicators (KPIs).
- **Installation Phase**
 - 11. Design and evaluate concepts for a simulation, and create a numeric simulation of the technology scenario
 - Create and evaluate a simulation model of the technology solution to test viability in the business environment.
 - 12. Evaluate the numeric simulation against expectations
 - Compare the simulation results with predefined expectations to validate or adjust the approach.
 - 13. SWOT analyses of the proposed new technology
 - Perform a detailed SWOT analysis to assess the strengths, weaknesses, opportunities, and threats associated with the proposed technology.
 - 14. Prepare prototype designs for possible implementation based on simulation separated from normal operations

- Develop prototype designs based on the simulation, ensuring separation from normal business operations for initial testing.
- 15. Validate the prototype against simulation expectations, choosing optimal (if the results of the prototype are unfavourable, terminate the project)
 - Test the prototype and validate it against simulation results. If outcomes are unfavourable, revise or terminate the project.
- 16. Gathering system requirement documents from the vendor
 - Collect detailed system requirements from the selected vendor, ensuring alignment with business needs.
- 17. Gathering system requirements for infrastructure upgrade
 - Assess the infrastructure upgrades needed to support the new technology.
- 18. Ensure implementation of legal agreements
 - Oversee the implementation of all legal aspects, ensuring compliance with contracts and agreements.
- 19. Implement budget control measures
 - Set up financial controls to ensure the project remains within the budget.
- 20. Constant checks of design and quality of civil works
 - Regularly inspect the design and quality of any infrastructure or civil work involved in the implementation.
- 21. Provide support and cooperation (communication)
 - Maintain open communication between all parties to ensure smooth implementation and problem-solving.
- **Post-Adoption Phase**
 - 22. System calibration, testing, and integration
 - Fine-tune the system to ensure it meets performance requirements and integrate it into the existing infrastructure.
 - 23. Providing training services
 - Offer comprehensive training to personnel at all levels to ensure smooth operation and understanding of the new system.
 - 24. Upgrading personnel
 - Continuously enhance the skills of the staff involved in maintaining and operating the new technology.

- 25. Ensuring compliance with the new system through Functional Design Specifications (FDS)
 - Verify that the system operates according to the agreed FDS and ensure all parties align with the system's functionalities.
- 26. Activities required to maintain continuous system functionality
 - Implement regular maintenance, monitoring, and updates to ensure the system remains operational and up-to-date.
- 27. On-site assistance, if necessary
 - Provide on-site support after the technology goes live to address issues and ensure smooth operation.
- 28. Exit strategy
 - Develop and execute an exit strategy that includes a handover of responsibilities and post-implementation support to maintain long-term system viability.

According to the survey respondents, the steps in the roadmap should not be once-off events but iterative if necessary. The steps in the roadmap have two levels. The highest technology adoption tiers were pre-installation, installation, and post-installation. The second tier is the steps that subdivide the highest tier, for example, Defining the business problem and Understanding business needs, which are subsets of the pre-installation phase.

The second tier of the roadmap remains a high-level description of the steps in the roadmap, and a lower third tier of steps is required to further subdivide the steps in the second tier of the roadmap. Figure 2-21, Figure 2-22, and Figure 2-23 are examples of the third tier to add to the roadmap. This additional tier would require a similar investigation to this study, sending the detailed third-tier steps to experts for their opinions on whether they agree or disagree with the third-tier steps.

This roadmap offers a comprehensive, phased approach to technology implementation. It covers the pre-installation, installation, and post-adoption phases, ensuring thorough planning, execution, and sustainability.

The new technology implementation roadmap was developed by integrating a list of phases (Pre-Installation, Installation, Post-Adoption) with the original roadmap structure.

9.2.2.2 The approach for developing the roadmap

Understanding the Core Objective

The goal was to create a clear and structured roadmap for a developing country to implement new technology. The input from the original roadmap and survey expert participants, which detailed specific steps for the Pre-Installation, Installation, and Post-Adoption phases, provided an outline for these stages. However, the aim was to ensure the comprehensiveness of the roadmap, which was logical and easy to follow. The original roadmap, broken into three phases, already outlined key actions like planning, testing, training, and post-implementation support.

Analysis of Steps from the original roadmap and expert input

The steps included essential tasks such as defining business problems, conducting risk assessments, performing SWOT analyses, and validating prototypes. While some steps were specific (e.g., gathering system requirements from vendors), others were broader and focused on ongoing processes (e.g., constant checks of design and quality).

To create the final roadmap, the following was done:

- Grouped related activities: This helped to streamline steps that naturally align with each other (e.g., vendor selection and gathering system requirements).
- Organised phases logically: Following a clear progression from initial assessment (pre-installation) to installation and testing (installation phase) and finally to post-adoption activities like training and system maintenance, to ensure each phase built on the previous one.

Combining with the Original Roadmap

The original roadmap focused on a broader, strategic view of technology implementation in a developing country. It outlined actions such as needs assessment, vendor selection, prototyping, and training. The expert opinions offered more detailed, practical steps fitting within these broader categories. Here's how the combining came about:

- Phase 1: Pre-Installation: The integrated focus on business problem definition, understanding business needs, vendor selection, and risk management, along with steps like strategic planning and stakeholder engagement, created a comprehensive plan for the preparation phase.

- Phase 2: Installation: Detailed steps, such as simulations, SWOT analysis, and prototype validation, naturally fit into the installation phase. These were combined with existing concepts like prototyping and testing to cover the practical and strategic aspects of installation.
- Phase 3: Post-Adoption: Emphasis was on system calibration, training, compliance with Functional Design Specifications (FDS), and exit strategy was crucial. The researcher integrated the steps suggested by the survey participants with the original roadmap's focus on monitoring, evaluation, and sustainability to form a well-rounded post-adoption phase.

Avoiding Redundancies

Since the expert opinions and the original roadmap covered similar areas, they were carefully removed redundancies while retaining critical elements. For example:

- Similar steps were merged, such as vendor selection and gathering system requirements, into one logical action to avoid duplication.
- Steps like risk management and continuous system checks were addressed once within their relevant phases to streamline the process.

Adding Detail and Flow

Lastly, each phase logically flowed from the previous one, giving the roadmap coherence. The detailed steps helped flesh out each stage, particularly in technical areas like system calibration and prototype validation.

9.3 Statistical assumption associated with multivariate analysis

9.3.1 Outliers in multivariate analysis

Table 8-3, Figure 8-1 and Figure 8-2 show the Mahalanobis distances of each response from each participant to the survey Likert scale questions. All the respondents were above the threshold for outliers in the analysis because none resulted in a p-value less than 0.005, as required for the threshold for outliers. This means the researcher excluded none of the responses from the analysis because they were outliers.

9.3.2 Tests for data suitability

9.3.2.1 Normality test results

Skewness and Kurtosis were tests used as normality tests of the Likert scale responses in the survey. Summarised in Table 8-4, Figure 8-3 and Figure 8-4 are the interpretations of the results. The table shows that the only question responses that did not follow a normal distribution were 16 and 17, with 19 showing a moderate deviation from normality. Questions 7, 12, and 20 skewed moderately, while 16, 17, and 19 were highly skewed.

Table 9-1: Normality interpretation for the Likert scale responses.

Question No	Interpretation
1	Skewness is approximately symmetric (insignificant at $p < 0.05$), and Kurtosis indicates an approximately normal distribution (insignificant at $p < 0.05$).
2	Skewness is approximately symmetric (insignificant at $p < 0.05$), and Kurtosis indicates an approximately normal distribution (insignificant at $p < 0.05$).
3	Skewness is approximately symmetric (insignificant at $p < 0.05$), and Kurtosis indicates an approximately normal distribution (insignificant at $p < 0.05$).
4	Skewness is approximately symmetric (insignificant at $p < 0.05$), and Kurtosis indicates an approximately normal distribution (insignificant at $p < 0.05$).
5	Skewness is approximately symmetric (insignificant at $p < 0.05$), and Kurtosis indicates an approximately normal distribution (insignificant at $p < 0.05$).
6	Skewness is approximately symmetric (insignificant at $p < 0.05$), and Kurtosis indicates an approximately normal distribution (insignificant at $p < 0.05$).

7	Skewness is moderately skewed (insignificant at $p < 0.05$), and Kurtosis indicates approximately normal distribution (insignificant at $p < 0.05$).
8	Skewness is approximately symmetric (insignificant at $p < 0.05$), and Kurtosis indicates an approximately normal distribution (insignificant at $p < 0.05$).
9	Skewness is approximately symmetric (insignificant at $p < 0.05$), and Kurtosis indicates an approximately normal distribution (insignificant at $p < 0.05$).
10	Skewness is approximately symmetric (insignificant at $p < 0.05$), and Kurtosis indicates an approximately normal distribution (insignificant at $p < 0.05$).
11	Skewness is approximately symmetric (insignificant at $p < 0.05$), and Kurtosis indicates an approximately normal distribution (insignificant at $p < 0.05$).
12	Skewness is moderately skewed (insignificant at $p < 0.05$), and Kurtosis indicates approximately normal distribution (insignificant at $p < 0.05$).
13	Skewness is approximately symmetric (insignificant at $p < 0.05$), and Kurtosis indicates an approximately normal distribution (insignificant at $p < 0.05$).
14	Skewness is approximately symmetric (insignificant at $p < 0.05$), and Kurtosis indicates an approximately normal distribution (insignificant at $p < 0.05$).
15	Skewness is approximately symmetric (insignificant at $p < 0.05$), and Kurtosis indicates an approximately normal distribution (insignificant at $p < 0.05$).

16	Skewness is highly skewed (significant at $p < 0.05$), and Kurtosis indicates high deviation from normality (significant at $p < 0.05$).
17	Skewness is highly skewed (significant at $p < 0.05$), and Kurtosis indicates high deviation from normality (significant at $p < 0.05$).
18	Skewness is approximately symmetric (insignificant at $p < 0.05$), and Kurtosis indicates an approximately normal distribution (insignificant at $p < 0.05$).
19	Skewness is highly skewed (significant at $p < 0.05$), and Kurtosis indicates moderate deviation from normality (insignificant at $p < 0.05$).
20	Skewness is moderately skewed (not significant at $p < 0.05$), and Kurtosis indicates approximately normal distribution (insignificant at $p < 0.05$).
21	Skewness is approximately symmetric (insignificant at $p < 0.05$), and Kurtosis indicates an approximately normal distribution (insignificant at $p < 0.05$).

The researcher conducted a Shapiro-Wilk test as a second normality test, which results in Table 8-5, Figure 8-5 and Figure 8-6 showing results yielded W-statistics ranging from 0,717 to 0,787 (close to 1, values close to 1 approximate a normal distribution). Their corresponding p-values were much less than 0.05 (the significance level chosen for this study), meaning that the p-values showed no normal distribution for the data according to this second measure of normality.

9.3.2.2 Multicollinearity test results

The researcher performed a multicollinearity test using the Variance Inflation Factor, and the results are in Table 8-6 and Figure 8-7. The VIF statistics in the table were all greater than 10, which showed that the data had multicollinearity for each question in the 21 Likert scale questions. In Figure 8-8, the Spearman correlation matrix shows a strong positive relationship between many pairs of questions, indicating the potential presence of underlying factors that similarly influence multiple questions. That also indicates that

some of the questions or steps in the roadmap measure the same thing. Some roadmap steps can combine to form an improved roadmap with fewer steps and encompass the steps more concisely and meaningfully.

9.4 Cronbach Alpha internal consistency test

The researcher completed a test for the internal consistency of the survey using Cronbach's Alpha. The details are in Table 8-7. The overall Alpha value was 0.976, meaning the survey responses were highly internally consistent. That was followed by calculating subsequent internal consistency alphas for each survey section. The first section (the pre-installation phase questions) had an alpha value of 0.940, the second section (the installation phase questions) had an alpha value of 0.971, and the last section (the post-installation phase) had an alpha value of 0.879. That also meant that the sections of the survey Likert scale questions were also internally consistent.

9.5 Statistical summaries of responses

Appendix B, Table B-1 shows the summary statistics of the survey Likert responses. The 25th percentile for all questions was 4 (agree), indicating that 25% of responses are below 4. The 50th percentile (Median) was generally 4, except for Q7, Q17, and Q20, which are 5 (strongly agree). The 75th percentile for all questions was 5, indicating that 75% of responses are below 5. The mean (average) response ranges from 4.258 (Q3) to 4.484 (Q20), showing a tendency towards agreement or strong agreement with the roadmap steps. In the ranges of Standard Error from 0.100 (Q9) to 0.136 (Q19), the low values indicate a high precision of the mean estimate for the sample.

The most frequent response (mode) is either 4 (agree) or 5 (strongly agree), depending on the question. The standard deviation ranges from 0.558 (Q9) to 0.755 (Q19), showing moderate response variability. Sample Variance ranges from 0.312 (Q9) to 0.570 (Q19). Most questions have a range of 2, with Q16, Q17, and Q19 having a range of 3, indicating a few possible outliers. Minimum responses are mostly 3, with Q16, Q17, and Q19 having a minimum of 2. Maximum responses are consistently 5 (strongly agree) throughout the questions. Confidence Level ranges from 0.205 (Q9) to 0.277 (Q19), indicating the interval within which the true mean lies with 95% confidence.

The median, mean, and mode suggest that most participants agreed with the statements (scores of 4 and 5). Moderate variability was indicated by the standard deviation and

range, with some questions (Q16, Q17, Q19) showing slightly more variability. Narrow confidence intervals demonstrate that the sample means are precise estimates of the population means.

Questions like Q7, Q17, and Q20 show slightly higher median and mode values, suggesting strong agreement or positive responses. Questions Q16, Q17, and Q19 have higher standard deviations and ranges, indicating more diverse opinions or possible outliers. The overall consistent responses across questions (mean around 4.3 to 4.5) reflect a generally agreeable or positive sentiment among participants regarding the steps in the roadmap.

9.6 Factor analysis

9.6.1 Sampling adequacy

KMO measured sample adequacy and suitability of the data for factor analysis, and the results were in Table 8-8. The KMO value was 0.645, meaning the sample was adequate and suitable for factor analysis to a limited extent.

In Table 8-8, the p-value was 0.954, much higher than 0.05, indicating that the test results were insignificant. Which meant the correlations between variables were insufficient to justify factor analysis. In summary, while the KMO value suggests that the data was marginally suitable for factor analysis, Bartlett's Test results of Sphericity indicated a potential issue with the intercorrelations among variables. The homoscedasticity assumption holds.

9.6.2 Scree test

A Scree plot was completed and was detailed in Figure 8-9. The Scree plot showed the three factors that met the threshold of eigenvalues equal to or above 1. That meant three factors were associated with the responses to the Likert scale questions.

9.6.3 Factor loadings

For each question's factor loadings in Table 8-9 and Figure 8-10, below are the dominant factors with the highest loading and the questions the factor applies to (factor loadings with values above 0.6 represent influence considered to meet the minimum levels to represent structure in this study):

- **Factor 1:** Questions 2, 3, 4, 5, 6, 7

- **Factor 2:** Questions 8, 9, 10, 13, 14, 15
- **Factor 3:** Questions 1, 11, 12, 17, 18, 19, 20, 21

Interpretation of Factors

- **Factor 1:** High loadings on questions related to the pre-installation phase and some installation phase tasks. This factor appeared to represent tasks related to **planning and evaluation**. It involved defining the problem, identifying gaps, assessing and selecting vendors, drafting agreements, and preparing system requirements.
- **Factor 2:** High loadings on questions primarily related to the installation phase. This factor seemed to represent **implementation and control**. It included designing and evaluating simulations, validating prototypes, ensuring legal agreements, and budget control measures.
- **Factor 3:** High loadings on questions, primarily from the post-adoption phase and some from the installation phase. This factor likely represented **testing, integration, and support**. It included system calibration, training services, maintaining system functionality, and having an exit strategy.

The factor analysis revealed three distinct factors based on the survey questions:

- **Factor 1: Planning and Evaluation** - Dominated by tasks from the pre-installation phase.
- **Factor 2: Implementation and Control** - Focused on the installation phase tasks.
- **Factor 3: Testing, Integration, and Support** - Centred around post-adoption and, to a lesser extent, installation tasks.

9.6.4 Average Variance Extracted (AVE) and Composite Reliability (CR)

9.6.4.1 Average Variance Extracted (AVE)

AVE values were calculated and detailed in Table 8-10. The AVE values for each factor were 0.284, 0.254 and 0.242, respectively. In this study, an AVE of 0.5 or higher was acceptable, indicating that more than half of the variance of the observed variables a factor captures. In this study, all AVE values were below 0.5, suggesting that each factor

explains less than half of the variance in the observed variables, indicating room for improvement in the factor model.

9.6.4.2 Cumulative Variance

Cumulative variance values were calculated and detailed in Table 8-10. The cumulative variance value for all three factors identified by factor analysis was 0.780. Cumulative variance represents the total amount of variance explained by the factors combined. The cumulative variance indicates how much of the total variance is in the data when adding more factors. In this case, the combined three factors explained 78% of the total variance, which indicates that the factor model captures a substantial portion of the variance in the data.

9.6.4.3 Composite Reliability (CR)

CR values were calculated and are detailed in Table 8-10. The CR values for each factor were 0.563, 0.535 and 0.523, respectively. In this study, CR values above 0.6 were considered acceptable. The CR values here are close to the threshold but lower, suggesting weak internal consistency and reliability of factors.

9.7 The two proportions hypothesis test for agreement levels

Table 8-11, Figure 8-14 and Figure 8-15 detailed the two proportion hypothesis test results for the responses to the survey Likert questions. All questions are marked as significant because their p-values were very low (much lower than 0.05), indicating that the mean proportions for all questions were statistically significantly different from expectations under the null hypothesis. All p-values were extremely low, providing strong evidence against the null hypothesis and suggesting that the responses to these questions differed significantly from random or expected values. The mean proportion values were very high for all questions, ranging from 0.871 to 0.968. That meant that most respondents agreed with each of the Likert items.

The mean proportion values indicate high agreement among respondents for all the survey questions, with proportions ranging from 87.1% to 96.8%. The extremely low p-values and high mean proportions provided strong evidence that the agreement levels were statistically significant and not due to chance. Respondents strongly agree with the Likert scale questions for gathering and evaluating information, developing a detailed

project plan, and system calibration, testing, and integration phases, as indicated by the significant results and high mean proportions.

9.8 ANOVA analysis for the difference between age groups

Table 8-12, Figure 8-16 and Figure 8-17 detailed the ANOVA analysis of differences in the different age groups. None of the questions were marked as significant because all their p-values were higher than 0.05, indicating that the differences observed in the data were not statistically significant. That implies, any response differences were likely chance occurrences and not due to any meaningful differences between the age groups. The F-statistic values were low across all questions, suggesting little to no variation between the age groups relative to the variation within the age groups. That implied there were not enough observed differences to reject the null hypothesis. All p-values were much higher than the 0.05 threshold, indicating weak evidence against the null hypothesis. That meant that any observed differences in the data were likely due to random chance rather than actual differences between age groups.

Table 8-13, Figure 8-18 and Figure 8-19 detailed the Chi-square analysis of differences in the different age groups. None of the questions were marked as significant because all their p-values were higher than 0.05, indicating that the differences observed in the data were not statistically significant. The Chi-square values were relatively low across all questions, suggesting little to no deviation from expectations under the null hypothesis. That implied that the observed differences do not support rejecting the null hypothesis. All p-values were much higher than the 0.05 threshold, indicating weak evidence against the null hypothesis. That meant that any observed differences in the data were likely due to random chance rather than actual differences between age groups. For all the survey questions, the evidence does not support rejecting the null hypothesis, implying that any differences in responses are likely due to chance and not any meaningful differences between the age groups.

9.9 ANOVA analysis for the difference between experience groups

Table 8-14, Figure 8-20 and Figure 8-21 detailed the ANOVA analysis of differences in the different experience groups. Most questions were marked as insignificant because their p-values were higher than 0.05, indicating that the differences observed in the data were not statistically significant. Question 19 was marked with yes on the significant

column because its p-value (0.023) was less than 0.05, indicating that the differences observed for this question were statistically significant. The F-statistic values vary across the questions, with some questions having slightly higher values, but only Q19 had an F-statistic (2.903, noticeably higher than the rest) alongside a p-value below 0.05.

All p-values, except for Q19, were much higher than the 0.05 threshold, indicating weak evidence against the null hypothesis. That meant any observed differences in the data for these questions were likely due to random chance rather than actual differences between groups. The p-value for Q19 was 0.023, below the 0.05 threshold, indicating a statistically significant difference. Rejecting the null hypothesis for most survey questions was impossible, implying that response differences were likely due to chance. However, for Q19, the null hypothesis was rejected, suggesting a significant difference in responses to this question.

Table 8-15, Figure 8-22 and Figure 8-23 detailed the pairwise comparison analysis of differences in the different experience groups for responses to Q19, which showed significance in Table 8-14. Comparison between "0 - 2 years" and "31 - 35 years" shows a significant mean difference of -2.667 with an adjacent p-value of 0.025 and a confidence interval ranging from -5.100 to -0.233. Therefore, the null hypothesis was rejected. Comparison between "11 - 15 years" and "31 - 35 years" showed a significant mean difference of -2.400 with an adjacent p-value of 0.027 and a confidence interval ranging from -4.610 to -0.190. The null hypothesis was rejected. Comparison between "21 - 25 years" and "31 - 35 years" showed a significant mean difference of -2.750 with an adjacent p-value of 0.014 and a confidence interval ranging from -5.106 to -0.394. The null hypothesis was rejected. **Pair 35:** Comparison between "31 - 35 years" and "6 - 10 years" showed a significant mean difference of 3.000 with an adjacent p-value of 0.009 and a confidence interval ranging from 0.567 to 5.433. The null hypothesis was rejected in this case as well. For most group pairs, the mean differences were not statistically significant, as indicated by the adjacent p-values greater than 0.05 and the "Significant" column marked as "No". That suggests observed differences are likely due to random variation rather than group differences in these cases. People with 31 - 35 years of experience answer differently from a few other experience groups. That might signify their disagreement with question 19 compared to the alternative responses.

Table 8-16, Figure 8-24 and Figure 8-25 detailed the Chi-square analysis of differences in the different experience groups. For most questions (Q1 to Q18 and Q20), the p-values were above 0.05, indicating that the Chi-squared tests did not find any statistically significant differences between the observed and expected frequencies, failing to reject the null hypothesis for most questions. Q19 has a p-value of 0.006, below the 0.05 threshold, suggesting significance and rejecting the null hypothesis for Q19. In conclusion, most of the questions show no statistically significant results, meaning there was no sufficient evidence to suggest differences in the observed responses for most of the questions compared to expectation under the null hypothesis except for Q19, showing a significant difference in responses only to this question.

9.10 T-test for independence for the difference between gender groups

Table 8-17, Figure 8-26 and Figure 8-27 detailed the t-test analysis of differences in the different gender groups. For all questions (Q1 to Q21), the p-values were above 0.05, indicating that the t-tests yielded no statistically significant differences between the sample means and population means for any question. Therefore, the null hypothesis for all questions is accepted. In conclusion, none of the questions showed statistically significant results, meaning there was no noteworthy evidence to suggest differences in the responses due to gender differences for any of the questions compared to expectations under the null hypothesis.

Table 8-18, Figure 8-28 and Figure 8-29 detailed the Chi-square analysis of differences in the different gender groups. For all questions (Q1 to Q21), the p-values are above 0.05, indicating that the Chi-square tests did not find any statistically significant differences between the observed and expected frequencies for any question. Therefore, we fail to reject the null hypothesis for all questions. In conclusion, none of the questions show statistically significant results based on the Chi-square tests, meaning there is no remarkable evidence to suggest differences in the responses for any of the questions compared to expectations under the null hypothesis due to gender differences.

9.11 Chapter summary

This study used quantitative and quantitative methods to collect and analyse data. An online survey of industry experts collected the data for the study. This chapter details the discussion of results obtained through the survey used in this study. The thematic

analysis of the qualitative responses revealed three themes associated with the responses. The themes were:

1. The perceived equal importance of all steps in the roadmap
2. Highlighting specific steps or additions
3. Indifference or uncertainty in responses theme. This either signalled agreement with the existing steps or a lack of understanding of the question asked of the respondents.

Based on the roadmap's survey responses, the researcher developed a new roadmap with the additions suggested by the experts. This new roadmap requires confirmation by similar experts to gauge its applicability in the South African mining industry.

The analysis of the qualitative responses began with statistical tests of statistical assumptions about the data. The first test was for outliers using Mahalanobis distance. It revealed that the data had no outliers to consider when analysing the data. Two tests for normality, namely, Kurtosis and Shapiro-Wilk, were conducted. The results show that when using Kurtosis as a test for normality, most of the data was approximately normal, but when using the alternative Shapiro-Wilk test, none of the results showed significance for the data to be classified as normally distributed. Multicollinearity tests performed showed there were linear relationships between responses to all questions. The Likert responses were internally consistent, with an alpha of 0.976.

The summary statistics of the responses show that most respondents either agreed or strongly agreed with the steps in the roadmap presented to them through the survey. That was further confirmed by the statistical tests for significance (two proportion hypothesis test in this case) that showed that a large proportion of responses agree or strongly agree with the survey questions, and their responses were statistically significant, meaning they were not random chance. The last statistical tests for significance performed were to test the differences among deferring demographics. The demographics tested were differences between age groups, genders and experience levels. The tests assessing differences in demographics were the T-test for independence hypothesis tests (for differences between genders) and ANOVA (for differences between experience levels and age). A secondary test using the Chi-square hypothesis test confirmed the results. There were no significant differences in responses due to differences in gender or age.

The experience levels also showed no differences in responses to the Likert questions except for one question (Q19), where experience levels influence answers between groups.

CHAPTER 10 CONCLUSIONS AND RECOMMENDATIONS

This chapter details the conclusions and recommendations of the study. These conclusions and recommendations were from the qualitative and quantitative responses to the survey used in this study. This section describes the conclusions drawn from the analysis of the qualitative and quantitative responses to the survey on technology implementation steps.

10.1 Responses

10.1.1 Qualitative survey responses

The qualitative portion of the study used thematic analysis to analyse written responses to the survey. The questions asked respondents to either add to the steps already included in the study's survey or modify the steps if they thought they were insufficient in the roadmap presented. Some of the 31 respondents added written responses. The themes identified were:

1. The respondents said the steps were equally important.
2. The respondents said the survey needed additional steps added.
3. The respondents were either uncertain or they were indifferent about the survey questions.

The respondents agreed with most of the steps in the roadmap, and only a minority of respondents made suggestions for changes. Some long-sentence responses suggested that the questioning might be confusing and need more clarity if used on different respondents. The changes to develop a new roadmap and this roadmap also require similar testing to the one done through the survey in this study.

The two tiers of the roadmap are still higher-level tiers. They require subdivisions or further breakdown. That will allow for clarification of the higher-level steps through the lower-level steps. This subdivision would result in more clearly defined roles and responsibilities in the roadmap.

The study developed a comprehensive technology implementation roadmap by combining the strategic focus of the original roadmap with the practical steps. This approach ensures that each phase, starting from pre-installation planning to post-

adoption support, is well-structured and aligned with the goal of sustainable technology implementation in a developing country.

10.1.2 Quantitative survey responses

As part of the investigation, the researcher made assumptions for data analysis of the data collected. These assumptions were that:

- The responses to the Likert scale data had no outliers.
- The responses to the Likert scale data followed a normal distribution.
- There was no multicollinearity between the responses to the Likert scale data.

The first assumption test was for the assumption of no outliers in the data, which used the Mahalanobis distance. None of the results met the threshold to be considered outliers. Therefore, no outliers were in the data, meaning the assumption was reasonable for the data. Kurtosis was used to measure the normality assumption for responses to the survey questions. Most of the question's responses were approximately normal according to this test. Questions 16, 17 and 19 deviated from normal. The researcher used a second test for normality using the Shapiro-Wilk test, and the W-statistics showed approximately normally distributed data. On the other hand, the p-values were less than 0.05, showing that the null hypothesis stating that survey response data followed a normal distribution was rejected.

The test for multicollinearity assumption used the VIF test, and the results showed that all the responses to questions show multicollinearity with each other. A Spearman correlation matrix was computed and used as a second test for multicollinearity. The test results showed that there was a positive linear relationship between all of the questions.

The survey was tested for internal consistency using Cronbach Alpha. The test results showed internal consistency in the survey, with an alpha value of 0.976.

The researcher performed factor analysis on the Likert responses. To determine sampling adequacy for factor analysis, the researcher calculated a KMO value. The KMO value was 0.645, which meant the sample was adequate and suitable for factor analysis. However, the corresponding p-values suggested that the data may not be fit for factor analysis.

The researcher used a Scree plot of eigenvalues to identify significant factors. It yielded three factors with eigenvalues greater than 1, meaning three factors were noteworthy. These factors were subsequently named Planning and Evaluation, Implementation and Control and Testing, Integration, and Support based on their respective factor loadings. The three factors accounted for 78% of the cumulative variance. Which meant they accounted for a vast majority of the variance in the factors. The study calculated a Composite Reliability for the three factors, and their values showed weak internal consistency and reliability.

The researcher used a hypothesis test to evaluate the level of satisfaction respondents had with each step in the roadmap. The hypothesis stated that most respondents would agree or strongly agree with the steps. The theorises hypothesis was proven true, with all the mean proportions for the questions having highly significant p-values (p-values were all less than 0.05) and the proportions values being close to 1, suggesting strong agreement. To further test differences in the responses between demographics, ANOVA analysis tested the differences between age groups, ANOVA analysis again to test differences between levels of experience, and a T-test for independence to test the differences between genders in the study. A secondary chi-square test was used as a triangulation measure to support the first tests in each case. The results of these tests showed that there were no significant differences between age groups and gender groups. That was the case for the ANOVA (the test used for age groups), T-test (the test used for gender groups), and their supporting chi-square tests.

The only demographic that showed a significant difference was the experience level. That was the case for Q19 in the survey. But all the other questions were not significant. Further investigations of the significance of differences in Q19 responses caused by differences in experience levels took place using a pairwise comparison analysis. This test showed that Q19 responses were different between experience groups. The noteworthy differences in responses to question 19 were confirmed further by the chi-square test, which also showed significance.

10.2 Recommendation for future work

The results from the respondents suggest that the roadmap in the survey is satisfactory for the most part. The respondents recommended minor adjustments to the roadmap to improve its clarity and robustness.

- The roadmap is mostly sufficient as it is currently. If there are changes to the roadmap, the researcher should implement minor changes according to the responses to the survey.
- The changes and additions to the new roadmap incorporating the suggestions should be tested with similar experts to this study to determine if indeed people also agree with it as they do the roadmap in the survey used in this study.
- The steps in the roadmap are still high level and they should be further subdivided to provide better clarity on the roles and responsibilities of each step in the roadmap. These must be tested in a similar manner applied in this study to gauge their applicability according to the experts.
- The demographics considered in this study show little to no differences between them. Therefore, no consideration is necessary for demographic differences when improving the roadmap.
- This study used a small sample from a single mining company population. The generalisability of the findings can be improved by including more mines across South Africa for future research with a larger sample.
- Not all the statistical assumptions made for the analysis were suitable. Future studies should use larger samples to improve the assumptions test results, or other statistical tests under different assumptions must be used to raise the validity and reliability of the results.
- Some of the short sentences that the respondents provided as answers to the questions that required them to add or remove steps in the roadmap showed a misunderstanding that might exist in the survey due to misinterpretation of the question. The survey questions need to be improved when using a similar question set in the future.
- Since ARM has already purchased new technologies but struggled with implementation, future research should include reviewing the acquisition strategies

from ARM's history against best practices established in the SLR to gain insight into better implementation strategies.

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A. APPENDIX A: SURVEY DESIGN

The following survey questions were used to collect data from survey participants. The three sections subdivided the survey: pre-installation, installation, and post-installation phase questions. These phases had subsets of steps that the respondents rated regarding their applicability in the South African mining industry. The survey was made of 21 5-point Likert scale questions, allowing responses from strongly agree, agree, neutral, disagree, and strongly disagree. Additionally, follow-up questions on the opinions on improvements to the roadmap were asked after each of the three sections. The questions were as follows.

- Pre-installation phase (gathering and evaluating implementing entity's capacity and potential partners)
 1. Define the business problem
 2. Identify the technological gap
 3. Identify the commissioning entity's expectations and capacity
 4. Evaluating information on the necessary technology and vendors
 5. Assessment and selection procedure for vendor and technology selection
 6. Compiling short-term, medium-term, long-term and risk management strategies
 7. Drafting agreements and contracts
- a. Do you agree with the listed checklist items and their order for gathering and evaluating the information above?
- Installation phase questions
 8. Design and evaluate concepts for a simulation, create a numeric simulation of the technology scenario
 9. Evaluate the numeric simulation against expectations
 10. Prepare prototype designs for possible implementation based on simulation separated from normal operations
 11. Validate the prototype against simulation expectations, choosing optimal (if the results of the prototype are unfavourable terminate the project)
 12. Gathering system requirement documents from the vendor
 13. Gathering system requirements for infrastructure upgrade

14. Ensure implementation of legal agreements
 15. Implement budget control measures
 16. Constant checks of design and quality of civil works
 17. Provide support and cooperation (communication)
- b. Do you agree with the listed checklist items for developing a detailed project plan above?
- Post-adoption phase (System calibration, testing, integration and after-sale service) questions
18. System calibration, testing and integration
 19. Providing training services
 20. Activities required to maintain continuous system functionality
 21. Exit strategy
- c. Do you agree with the listed checklist items for system calibration, testing and integration above?

B. APPENDIX B: SUMMARY STATISTICS OF QUALITATIVE RESPONSES

Table B-1 below shows the summary statistics of the survey Likert responses.

Table B-1: Survey Likert responses summary statistics.

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18	Q19	Q20	Q21
count	31	31	31	31	31	31	31	31	31	31	31	31	31	31	31	31	31	31	31	31	31
25%	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
50% (Median)	4	4	4	4	4	4	5	4	4	4	4	4	4	4	4	4	5	4	4	5	4
75%	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
Mean	4,452	4,323	4,258	4,323	4,290	4,387	4,387	4,355	4,387	4,452	4,387	4,419	4,387	4,452	4,452	4,387	4,419	4,419	4,355	4,484	4,355
Standard Error	0,102	0,108	0,122	0,117	0,124	0,110	0,128	0,109	0,100	0,102	0,110	0,111	0,110	0,102	0,102	0,128	0,129	0,101	0,136	0,112	0,109
Mode	5	4	4	4	4	4	5	4	4	5	4	5	4	5	5	5	5	4	5	5	4
Standard Deviation	0,568	0,599	0,682	0,653	0,693	0,615	0,715	0,608	0,558	0,568	0,615	0,620	0,615	0,568	0,568	0,715	0,720	0,564	0,755	0,626	0,608
Sample Variance	0,323	0,359	0,465	0,426	0,480	0,378	0,512	0,370	0,312	0,323	0,378	0,385	0,378	0,323	0,323	0,512	0,518	0,318	0,570	0,391	0,370
Range	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	3	3	2	3	2	2
Minimum	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	2	2	3	2	3	3
Maximum	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
Sum	138	134	132	134	133	136	136	135	136	138	136	137	136	138	138	136	137	137	135	139	135
Confidence Level (95,0%)	0,208	0,220	0,250	0,239	0,254	0,226	0,262	0,223	0,205	0,208	0,226	0,228	0,226	0,208	0,208	0,262	0,264	0,207	0,277	0,229	0,223

C. APPENDIX C: PUBLICATION FROM THIS STUDY

This appendix details the publication (Baloyi et al., 2024), submitted that as part of this dissertation.

SOUTH AFRICA'S MINING INDUSTRY EXPERT'S OPINION ON TECHNOLOGY IMPLEMENTATION STEPS

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ABSTRACT

SA's mining industry is moving towards implementing Industry 4.0 technology. As a developing country, circumstances surrounding the implementation of this technology need to account for the unique circumstances of developing countries. While also learning relevant lessons from developed countries. Considerations required for developing countries are how the move to Industry 4.0 technology will affect people, including addressing workers' concerns and the broad communities the mines affect. Concerns include job security, worker safety and the environmental impact of mining. This study used a survey to solicit responses from SA's mining industry experts on a technology implementation roadmap. SA's mining industry was the basis for the roadmap development. The survey measured the experts' satisfaction levels with the roadmap. Results reinforced inclusions on the roadmap that experts agree with. While also shedding light on topics the experts disagreed with. Experts also provided additional areas the roadmap needed to cover.

Keywords: technology implementation, mining, South Africa, roadmap

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INTRODUCTION

The mining industry is increasingly embracing technology, which offers benefits such as money-saving, time-saving and reduced risks. Adopting technological innovations minimises waste and provides a competitive edge, as noted by [1]. Despite these benefits, there has been limited research on the challenges and facilitators of technology adoption in mining, highlighting the importance of such studies.

According to [2], there has been a rapid increase in digital twin technology use, which is transforming business operations to cut costs. A 2019 survey found that 75% of companies using the Internet of Things (IoT) have adopted digital twin technology [3]. Additionally, 13% were implementing this technology already, and 62% planned to do so within a year. Digital twin technology can simulate every product, process, or service aspect, enabling faster decision-making against traditional methods.

Developing countries like South Africa are seeking the benefits of implementing these new technologies in the mining industry. This paper used a survey on the steps necessary for applying these new technologies in the South African mining context. The survey questions were from the literature from other countries with similar experiences and those leading in this pursuit.

The study aims to develop a roadmap that South African mining companies can use when introducing new technologies, accounting for the unique circumstances specific to the country.

1 LITERATURE REVIEW

1.1 Pakistan's implementation

1.1.1 *Awareness of Autonomous Mining Systems*

Awareness of autonomous mining systems in Pakistan primarily comes from social networks, word of mouth, and academia [4].

1.1.2 *Stakeholder preparedness*

Pakistan's mining industry supports semi-autonomous and fully autonomous systems due to safety improvements, productivity, and cost reductions. However, concerns about knowledge gaps and unemployment persist. Many feel prepared for autonomous systems employment, though some do not. Most are willing to undergo training, but it is currently unavailable in Pakistan [4].

1.1.3 *Impact of implementing autonomous mining systems*

The main concern is unemployment. Proponents believe the government will support new technology due to its positive effects on GDP and productivity. Sceptics cite potential unemployment, political risks, labour unrest, and health and safety concerns [4].

1.2 India's implementation

The study, based on [5], identified several themes for technology adoption in India's mining industry:

1. Technology adoption must be an organisational initiative.
2. Reliable emerging technology providers are crucial.
3. Mining companies seek partnerships with proven technology providers.
4. The initial step is the digitalisation of mining data.
5. Public sector companies are slow to adopt technology due to job creation goals.
6. Strategies for long-term goals and technology implementation are misaligned.
7. Difficult geographical and geological conditions hinder technology adoption.
8. A shortage of skilled employees is a barrier.
9. Improved legal environments could expedite technology adoption.

[47]-2

10. Natural factors limit economies of scale in the Indian mining industry.
11. Bureaucracy and legal restrictions impede new technology implementation.
12. Data analytics and cloud computing are the most feasible technologies.
13. Solutions from developed countries often do not suit India, requiring unique solutions.
14. Managers prefer extracting total value from current technology before upgrading.
15. New technology affects the entire organisation.
16. New technology requires significant initial investments.
17. New technology must enable mining activities.
18. Technology providers must understand the economic context of mining companies.
19. Providers need to comprehend the geological and geographical conditions of mining.
20. The benefits of new technology are often unclear and need a better definition.
21. Organisational culture plays a critical role in technology adoption.
22. Mining managers often lack awareness of emerging technologies.
23. If new technologies solve current problems, adoption will increase.
24. Benefits like cost reduction, faster delivery, and better quality enhance adoption likelihood.

1.3 South Africa's implementation

Key factors enabling technology implementation in South Africa include powerful political will, supportive culture, adequate funding, effective Intellectual Property Laws (IPL), robust partnership networks, market competition, high market demand, substantial R&D capacity, solid engineering capacity and access to natural resources. The absence of these factors hinders implementation [6].

1.4 Technology implementation roadmaps

Technology road mapping is identified as a well-known technique yet infrequently applied [7]. Technology implementation roadmaps are visual tools that align an organisation's technology strategy with its business strategy [8]. Successful implementation of these roadmaps requires setting clear, organisation-specific objectives that align with the company's culture [8]. The development process has three phases: Initial, Development, and Integration.

1. **Initial phase:** This phase involves gathering information for subsequent stages. Key stakeholders form a team to develop the organisation's technology implementation roadmap. Measure success by stakeholder acceptance of the customised roadmap.
2. **Development phase:** Data from internal and external sources is collected and analysed by stakeholders, who then present it in a roadmap format. This phase often requires multiple iterations. Measure success by the quality of roadmap content and the expertise contributed by stakeholders.
3. **Integration phase:** The roadmap integrates with business operations. Success measure is the roadmap's alignment with the business strategy, quality, and ongoing development.

Technology road mapping helps build consensus on technological needs, forecast technology developments, and plan future technology implementations [9]. A roadmap for Industry 4.0 technology in manufacturing with seven phases as follows [10]:

1. **DEFINE:** Identify problems and resource limitations. Develop a scope for Industry 4.0. Involve stakeholders and develop a transition team. Create detailed project plans and identify long-term, mid-term, and short-term strategies. Define skills and training needs and establish a change management strategy. Adapt the supply chain and legal framework to the new technology, including risk management strategies.
2. **MEASURE:** Gather data to understand and address the company's requirements using Quality Function Deployment (QFD) and Measurement System Analysis (MSA) to capture realistic views of process variations.

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3. **EVALUATE:** Benchmark the readiness for Industry 4.0 technology, compare quality processes with market leaders, and develop new concepts using methods like FMEA and TRIZ. Use the Pugh matrix to identify the best design.
4. **OPTIMISE:** Build a detailed design using performance analysis software such as Anylogic and CAD tools like Autodesk.
5. **DEVELOP:** Build a prototype, evaluate hardware and software needs, and develop the prototype based on previous simulations without disrupting the production line.
6. **VALIDATE:** Test the prototype against the simulation model to mitigate risks and confirm expectations. Gather stakeholder feedback and conduct risk assessments.
7. **IMPLEMENT:** Implement the system, making adjustments where necessary. Focus on cost-saving, standardise processes and create a training plan for users. Continuously improve the system.

1.4.1 Roadmap of technology implementation in a generic industry

[11] developed a generic roadmap for technology adoption and divided it into three phases: analysis, goal setting, and implementation, which split further into six steps addressing production, purchasing, intralogistics, human resources, and sales.

1. Create Awareness: Involve employees and conduct a SWOT analysis.
2. Gather Data: Assess the company's capabilities to implement Industry 4.0 technologies.
3. Define Target States: Use techniques like morphological analysis and brainstorming with industry experts.
4. Draw Documents and Measure Evaluation: Evaluate differences between expectations and results, rating efforts and benefits.
5. Define Objectives: Establish the relevance and impact of objectives on the organisation.
6. Connect Projects with Budgets: Use pilot projects to gain experience and address early issues before full-scale implementation.

1.4.2 South African roadmap for Industry 4.0 implementation

[12] developed a roadmap for technology implementation in South African mines through a case study at the Wits Mining Institute (WMI). The roadmap's three phases with various challenges are as follows:

1. Pre-installation Challenges:
 - Identifying and selecting appropriate technologies
 - Budget overspending
2. Installation Phase Challenges:
 - Overspending
 - Delays in civil works
 - Poor system compatibility
 - System malfunctions
 - Unreliable communication systems
 - Faulty hardware design
 - Remote access restrictions
 - System integration issues
3. Post-installation Phase Challenges:
 - Poor after-sales support
 - Inadequate maintenance and upgradability provisions

The literature review covers technology implementation in Pakistan, India, and South Africa's mining sectors, with technology road mapping for Industry 4.0. Pakistanis and Indians show support for autonomous systems but face challenges like training availability and bureaucratic hurdles, respectively. South Africa benefits from political will and strong R&D, but some regions lack these advantages. Highlighted as critical was technology road mapping for aligning

strategies and engaging stakeholders. Challenges include complex implementation phases and issues like budget overspending and system compatibility. Overall, the review stresses adapting global solutions to local contexts and continuous alignment with business strategies to maximise technology adoption benefits.

From the literature review on Industry 4.0 technology implementation and roadmaps, the researcher compiled a survey to be assessed by participants. The participants had experience with approaches suitable for South African mines. Therefore, they quantified whether the new roadmap would succeed in this context. A Appendix A: Survey questions shows the survey, and the methods used for designing this study's survey are in subsection 2.1 below.

2 METHODOLOGY

2.1 Survey design

Why surveys? Over the past 50 years, online surveys have become the most popular method for data collection in research, aligning with the rise of the internet [13]. This method is more convenient for gathering information, especially when surveyors and respondents are geographically distant. Online surveys allow respondents to participate at their convenience. This study used Google Forms for the survey, which stores responses in real-time, is free, and allows easy data export [14] - [17].

Surveys collect primary data through direct questions to respondents, measuring attitudinal data such as opinions, preferences, awareness, perceptions, and motivations. E-surveys are popular due to their autonomous data collection, low cost, wider reach, and current data [18]. They eliminate interviewer bias, give respondents more time, and ensure anonymity, resulting in more honest answers [15]; [16]; [18].

However, e-surveys have drawbacks, such as the lack of personal communication between respondents and researchers, no control over the collection procedure, low response rates, and no provision for clarity for respondents. Surveys must be simple and short, limiting the amount of data collected. There's also no control over who the final respondent is, increasing bias, and no opportunity for further probing [18]. Surveys need thorough testing before use. Researchers must ask only relevant questions, carefully considering the form, wording, and sequence of questions [13]. This study included Likert scale questions to assess respondents' views on a topic [19]. The survey was on a roadmap developed through the literature on adopting Industry 4.0 technology in the mining industry. The researcher aimed to test whether this new roadmap was sufficient for the South African mining industry. Google Forms online decimated the survey. Appendix

A Appendix A: Survey questions shows the questions in the survey. Based on the literature, the recurring subdivisions were three phases in the technology implementation. The three phases were pre-installation, installation, and post-installation. These three phases also had their subdivisions that the survey roadmap was quantifying. The survey amalgamated all the roadmaps in the literature survey and redesigned them into the new roadmap.

2.2 Sampling

The study used purposive sampling, a non-random (or non-probability) sampling method based on experience, common sense, expertise, and researcher intention [20]. The study used purposive sampling because it allows the extraction of information from a particular group of individuals, in this case, people familiar with technology implementation in the mining industry.

2.2.1 Type of purposive sampling

The study employed expert sampling, which gathers data from individuals with specific expertise. This sampling is helpful in situations involving high uncertainty [20]. Participants were experts familiar with implementing new mining industry technology (all respondents worked at a single mine). The experts chosen in this study varied in professions, from plant

[47]-5

engineers, mining engineers, managers, artisans, supervisors, superintendents and health and safety officers. Their experience ranged from 0 to more than 40 years of experience. Additional information on the participant's demographic information, such as gender, age groups, years of experience in the mining sector and type of position held, can be found in B Appendix B: Respondents demographics information.

2.2.2 Snowball sampling

Snowball sampling supplemented the purposive sampling. This study applied the s-stage k-name Snowball sampling method by asking individuals identified in the purposive sample to name k additional individuals with the necessary expertise (technology implementation in mining). This process continued in stages until an adequate sample size was reached [21].

2.3 Strategies for survey validation and verification

Emphasising validity, generalisability, and reliability ensures that observed effects honestly reflect the causes. Valid results accurately represent the phenomenon under study, reliable results remain consistent across different contexts, and generalisable results hold across various conditions [22].

2.3.1 Survey pre-testing

Environmental triangulation involves testing findings across different settings to establish validity [23]. A pilot study pre-tested the survey with a smaller participant set [19]. The pre-test confirmed the survey's clarity, readability, and consistency. It also identified grammatical or punctuation errors [24]. Five participants unfamiliar with the study were used in the pre-testing to ensure the survey's validity and reliability [15]; [17]; [25].

2.3.2 Identifying outliers in multivariate analysis

The Mahalanobis measure calculates the distance from the mean centre of the overall observations in a multidimensional space used to identify outliers in the data [26]. The levels of significance chosen were 0.05 (5%). For small samples, the $\frac{D^2}{df}$ value should be 2.5, while for larger samples, it should be between 3 and 4 [26].

2.3.3 Statistical assumptions in multivariate analysis

In multivariate analysis, the crucial assumption is normality, which compares the distribution shape to the normal distribution [26]. Examining graphed plots and statistical normality tests, namely Kurtosis and skewness, were conducted. The $Z_{skewness}$ statistic calculation follows the formula:

$$Z_{skewness} = \frac{skewness}{\sqrt{\frac{6}{N}}} , \quad (1)$$

The used $z_{critical}$ values are ± 1.96 for a 0.05 significance level. Similarly, $z_{kurtosis}$ is determined by:

$$Z_{kurtosis} = \frac{kurtosis}{\sqrt{\frac{24}{N}}} , \quad (2)$$

Homoskedasticity assumes equal variance levels across predictor variables [26]. Linearity, assessed with scatter plots, is essential for correlation-based measures.

2.3.4 Measuring internal consistency: The Cronbach Alpha

Cronbach's alpha measures internal consistency in multi-item scales [27]. The alpha calculation follows the formula:

$$\alpha = \frac{N}{N-1} \left(\frac{\sigma_X^2 - \sum_{i=1}^N \sigma_{Y_i}^2}{\sigma_X^2} \right) , \quad (3)$$

[47]-6

where N is the number of surveys in the scale, σ_x^2 is the variance of the observed total scores and σ_{yi}^2 is the variance of items i for person y [27].

2.4 Factor analysis

Assumptions that go along with factor analysis include linearity, no outliers in the data, no multicollinearity, homoscedastic data, interval data and correlation between variables [26]; [28].

2.4.1 Determining the number of factors to extract

In Kaiser's Criterion, the eigenvalue of a factor indicates the amount of variance it explains. The study retained factors with eigenvalues greater than one as they signified a more common variance than the factors' variance. This method requires careful judgment due to potential sampling errors [26]; [28]. Factor loadings with values above 0.4 represent influence considered to meet the minimum levels to represent structure [26]. The Scree test graphically determines factors, with eigenvalues on the vertical axis and factor numbers on the horizontal. Factor extraction stops where the plot levels off or forms an elbow [26]; [28]. Rotating Factors and Interpretation Initial factor extraction is often complex due to cross-loading. Orthogonal rotation simplifies interpretation. Varimax reduces the number of variables with high loadings on each factor [26]; [28].

2.4.2 Factor analysis

Factor analysis extracts critical factors from a large set of variables. Confirmatory Factor Analysis (CFA) and Exploratory Factor Analysis (EFA) are the main factor analysis methods. EFA, used in early research stages, examines the interrelationships among variables [26]; [28]. Steps include assessing data suitability, extracting factors, and rotating factors for interpretation. Measures like the Kaiser-Meyer-Olkin (KMO) test and Bartlett's test for sphericity evaluate data adequacy for factor analysis [28].

$$KMO_j = \frac{\sum_{i \neq j} R_{ij}^2}{\sum_{i \neq j} R_{ij}^2 + \sum_{i \neq j} U_{ij}^2}, \quad (4)$$

where R_{ij} is the correlation matrix and U_{ij} is the partial covariance matrix.

$$\chi^2 = -\left(n - 1 - \frac{2p+5}{6}\right) \times \ln|R|, \quad (5)$$

where p is the number of variables, n is the total number of sample sizes, and R is the correlation matrix.

2.4.3 Average Variance Extracted (AVE) and Composite Reliability (CR)

AVE measures the variance a construct explains versus measurement error, indicating convergent validity. CR assesses the correlation between multiple indicators of the same construct. AVE values ≥ 0.5 confirm convergent validity, and CR values > 0.6 are acceptable. If AVE < 0.5 but CR > 0.6 , convergent reliability remains adequate [28].

$$AVE = \frac{\sum_{i=1}^n \lambda_i^2}{n}, \quad (6)$$

where λ_i are the loadings, and n is the number of items.

$$CR = \frac{(\sum_{i=1}^n \lambda_i)^2}{(\sum_{i=1}^n \lambda_i)^2 + \sum_{i=1}^n \text{Var}(e_i)}, \quad (7)$$

where $\text{var}(e_i)$ is the variance of error terms in the i^{th} item.

3 RESULTS

3.1 Likert scale responses

Figure 3-1 - Figure 3-3 show the respective summarised responses from the survey.

[47]-7

Pre-installation phase (gathering and evaluating implementing entity's capacity and potential partners)

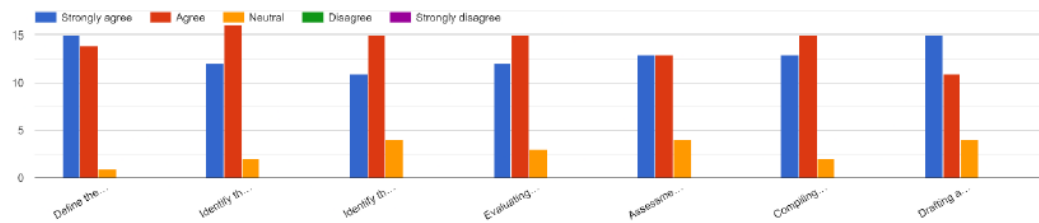


Figure 3-1: Responses to questions on the pre-installation phase.

Installation phase

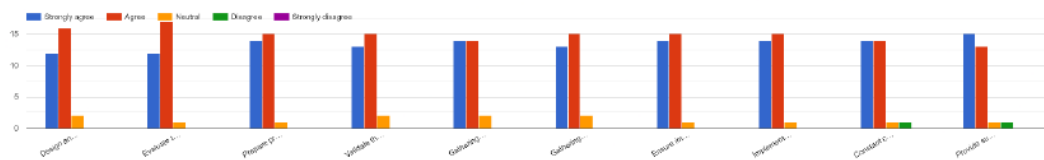


Figure 3-2: Responses to questions on the installation phase.

Post-adoption phase (System calibration, testing, integration and after-sale service)

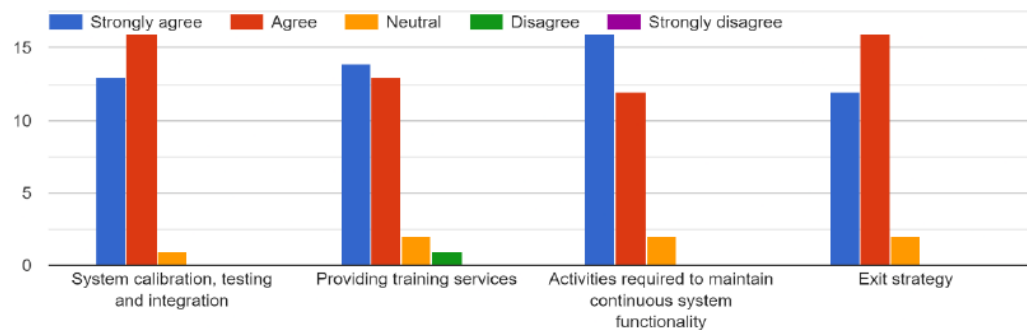


Figure 3-3: Responses to questions on the post-installation phase.

3.2 Identifying outliers in multivariate analysis

Results for the test for outliers in the survey responses are detailed in Figure 3-4 and Figure 3-5.

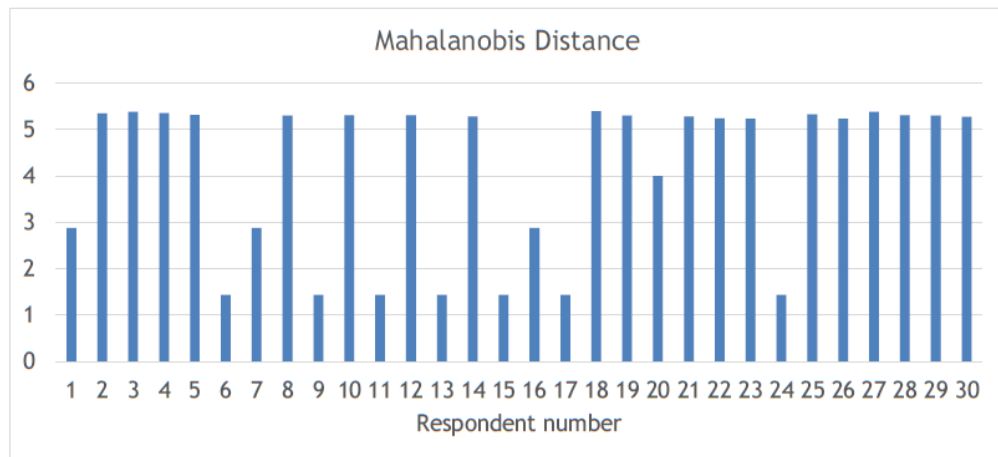


Figure 3-4: Mahalanobis Distance test for outliers.

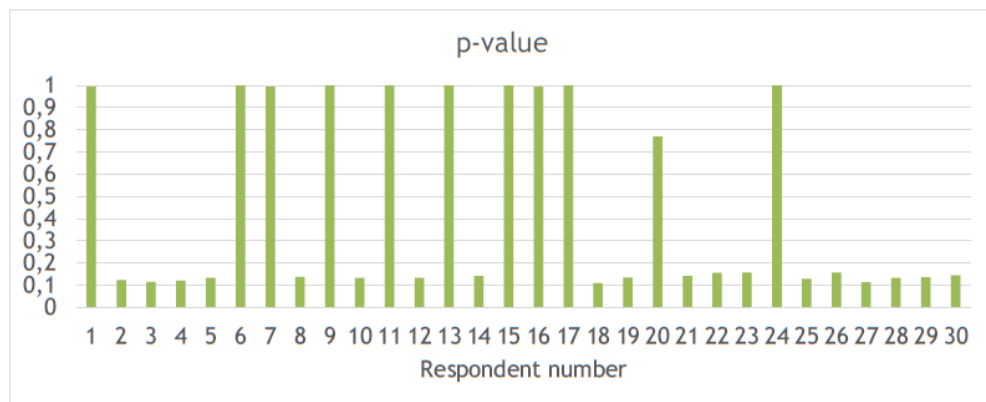


Figure 3-5: Corresponding P-values of respondents Mahalanobis Distance

Figure 3-4 and Figure 3-5 illustrate the Mahalanobis Distance and p-values of the respondents, respectively. All p-values were > 0.05 , so the null hypothesis was false for all respondents.

3.3 Measuring internal consistency: The Cronbach Alpha

Table 1 lists the Cronbach Alpha values for the overall survey responses, responses relating to the pre-installation phase questions, responses relating to the installation phase questions and answers to the post-installation phase questions, respectively. The table details the confidence interval of Cronbach Alpha values at $\alpha = 0.05$.

Table 1: Cronbach alpha test for internal consistency of survey.

	Cronbach Alpha	Cronbach Alpha for pre-installation questions	Cronbach Alpha for installation questions	Cronbach Alpha for post-installation questions
Alpha value	0.976	0.944	0.970	0.874

Confidence interval	[0.961, 0.987]	[0.907, 0.970]	[0.951, 0.984]	[0.781, 0.934]

3.4 Factor analysis

3.4.1 Skewness, Kurtosis, Spearman Average correlation, Mean and Standard deviation.

Table 2 details the results for the normality in the survey responses as Kurtosis. The skewness also shows how skewed the answers were around the mean. The average correlation details the average Spearman correlation coefficients between the Likert scale question responses.

Table 2: Summary statistics for all survey question results.

Question No	Skewness	Kurtosis	Z-Skewness	Z-Kurtosis	Average correlation	Mean	Standard deviation	Variance
1	-0.433	-0.822	-0.968	-0.920	0.709	4.467	0.571	0.326
2	-0.280	-0.656	-0.625	-0.734	0.663	4.333	0.606	0.368
3	-0.307	-0.800	-0.686	-0.895	0.670	4.233	0.679	0.461
4	-0.366	-0.706	-0.818	-0.789	0.708	4.300	0.651	0.424
5	-0.474	-0.851	-1.060	-0.951	0.653	4.300	0.702	0.493
6	-0.383	-0.670	-0.857	-0.749	0.600	4.367	0.615	0.378
7	-0.657	-0.781	-1.468	-0.873	0.668	4.367	0.718	0.516
8	-0.280	-0.656	-0.625	-0.734	0.641	4.333	0.606	0.368
9	-0.070	-0.863	-0.156	-0.965	0.727	4.367	0.556	0.309
10	-0.309	-0.882	-0.691	-0.986	0.755	4.433	0.568	0.323
11	-0.383	-0.670	-0.857	-0.749	0.722	4.367	0.615	0.378
12	-0.491	-0.643	-1.098	-0.719	0.761	4.400	0.621	0.386
13	-0.383	-0.670	-0.857	-0.749	0.757	4.367	0.615	0.378
14	-0.309	-0.882	-0.691	-0.986	0.669	4.433	0.568	0.323
15	-0.309	-0.882	-0.691	-0.986	0.713	4.433	0.568	0.323
16	-1.224	2.004	-2.738	2.241	0.654	4.367	0.718	0.516
17	-1.309	2.102	-2.926	2.351	0.732	4.400	0.724	0.524
18	-0.188	-0.896	-0.421	-1.002	0.573	4.400	0.563	0.317
19	-1.109	1.200	-2.480	1.342	0.590	4.433	0.758	0.575

20	-0.720	-0.463	-1.609	-0.518	0.641	4.467	0.629	0.395
21	-0.280	-0.656	-0.625	-0.734	0.649	4.433	0.606	0.368

3.4.2 Linearity of the data

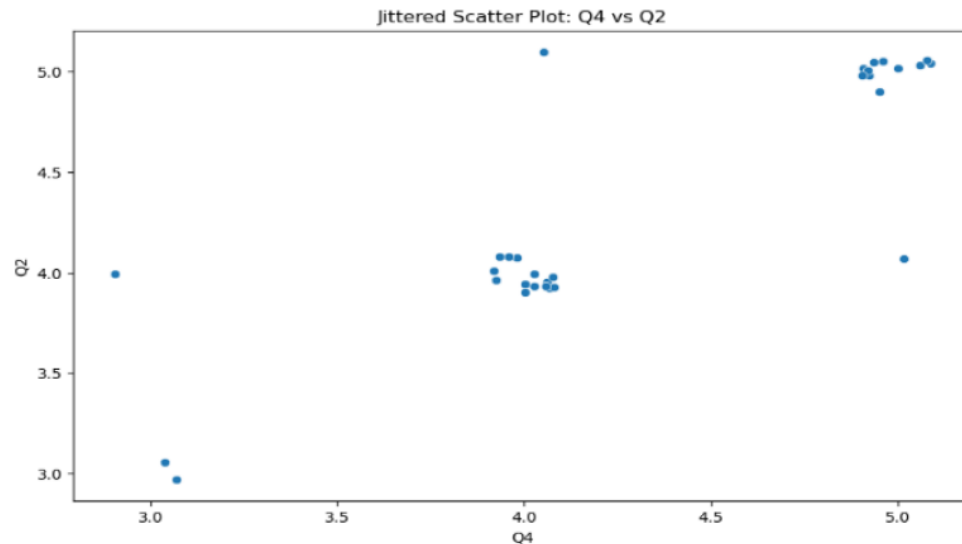


Figure 3-6: Jittered scatter plot for Q2 vs Q4.

Figure 3-6 above shows the Jitters scatter plot of Question 2 against Question 4 of the Likert survey responses. Many other plots similar to the above are available (not included because of space constraints), and the plots displayed above were selected randomly for analysis.

3.5 Factor analysis

3.5.1 KMO measure of sampling adequacy and Barlett test for sphericity

The Kaiser-Meyer-Olkin (KMO) value for the Likert scale questions in the survey, their corresponding chi-square statistic value and their p-value are in Table 3.

Table 3: KMO value for the model and significance.

KMO model value	Chi-Square value	p-value	Is p-value < 0.05
0,716	696.110	2.060x10 ⁻⁵³	Yes

3.5.2 Scree Test for Eigenvalues

The Scree plot of Eigenvalues of all factors is in Figure 3-7. This figure shows eigenvalues for each question, with questions having eigenvalues greater than 1 being influential factors.

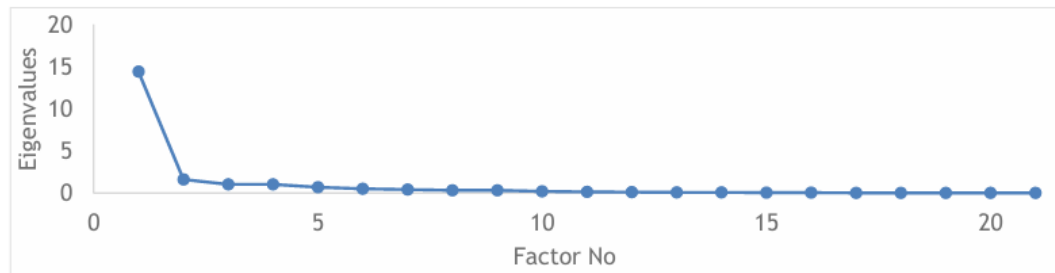


Figure 3-7: Scree plot of Eigenvalues of all factors.

3.5.3 Factor loadings

The factors loadings for Likert-scale responses having eigenvalues of more than one (>1) are detailed in Table 4 below.

Table 4: Factors, their corresponding loadings and influence on each question.

Question No	Factor1	Factor2	Factor3	Factor4	Factor 1 affects question	Factor 2 affects question	Factor 3 affects question	Factor 4 affects question
1	0.365	0.478	0.409	0.496	Yes	Yes	Yes	Yes
2	0.650	0.186	0.394	0.443	No	Yes	Yes	Yes
3	0.799	0.358	0.285	0.049	Yes	No	No	Yes
4	0.739	0.304	0.447	0.177	Yes	No	No	No
5	0.918	0.172	0.200	0.204	Yes	No	Yes	No
6	0.655	0.281	0.002	0.413	Yes	No	No	No
7	0.613	0.310	0.252	0.347	Yes	No	No	Yes
8	0.207	0.879	0.225	0.090	Yes	No	No	No
9	0.462	0.787	0.186	0.263	No	Yes	No	No
10	0.387	0.684	0.350	0.379	Yes	Yes	No	No
11	0.379	0.552	0.526	0.310	No	Yes	No	No
12	0.539	0.464	0.516	0.326	No	Yes	Yes	No
13	0.377	0.736	0.480	0.227	Yes	Yes	Yes	No
14	0.214	0.688	0.305	0.424	No	Yes	Yes	No
15	0.430	0.592	0.454	0.179	No	Yes	No	Yes
16	0.497	0.345	0.679	0.029	Yes	Yes	Yes	No

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17	0.532	0.317	0.692	0.188	Yes	No	Yes	No
18	0.291	0.277	0.180	0.787	Yes	No	Yes	No
19	0.108	0.320	0.675	0.242	No	No	No	Yes
20	0.355	0.213	0.576	0.553	No	No	Yes	No
21	0.092	0.575	0.535	0.483	No	No	Yes	Yes

3.5.4 Average Variance Extracted (AVE) and Composite Reliability (CR)

Table 5 shows the variance, proportional variance, CR and cumulative variance of the factors with factor loading eigenvalues of more than one in the Scree plot.

Table 5: Factors, their variance and composite reliability.

	Factor 1	Factor 2	Factor 3	Factor 4
Variance	5.361	5.207	4.034	2.749
Proportional Variance	0.255	0.248	0.192	0.131
Cumulative Variance	0.255	0.503	0.695	0.826
Composite Reliability (CR)	4.397	4.397	4.397	4.397

4 DISCUSSION

4.1 Identifying outliers in multivariate analysis

None of the respondents were outliers because the Mahalanobis distances P-values (significance values) were all > 0.005. That meant all responses were suitable for use in the analysis. The Mahalanobis distances divided by the degree of freedom ranged between 0.068 and 0.257. That is lower than the threshold of 2.5 used to determine outliers for small samples [26].

4.2 Measuring Internal Consistency: The Cronbach Alpha

The overall Cronbach Alpha value for this study was 0.976. That meant the Likert scale questions responses internal consistency in the survey were internally consistent. In addition to the internal consistency of the overall Likert questions, the three sections, namely pre-installation, installation and post-installation, were also checked for internal consistency. Their Alpha values were 0.944, 0.970 and 0.874, respectively and were considered internally consistent.

4.3 Linearity of the data

One of the assumptions made for the factor analysis was a linear relationship between the Likert scale results. This assumption was tested by visually comparing the Jitter plots of the different questions. For example, in Figure 3-6, most of the answers were the same in Q2 and Q4, with only two exceptions where a respondent gave a 4 for Q2 and a 5 for Q4 and vice versa, leading to the assumption that a linear relationship existed between the two questions. Similar Jitter plots of a combination of questions all indicated linear relationships. It was, therefore, concluded that the Likert question in the survey had a linear relationship.

4.4 Factor analysis

4.4.1 Normality of the data

The following is a summary of the results for the normality and skewness test of the Likert scale questions in the survey. Testing was at significance values at $p < 0.05$.

- Q1 - Q6, Q8 - Q 15, Q18, Q21: Approximately symmetric. Kurtosis indicates approximately normal.
- Q7, Q20: Moderately skewed. Kurtosis indicates approximately normal.
- Q16 - Q17, Q19: Highly skewed. Kurtosis indicates a high deviation from normality.

That confirms normality for all the questions except Qs 16, 17 and 19. These questions also showed high skewness. It is safe to assume that the data follows a normal distribution.

4.4.2 KMO measure of sampling adequacy and Barlett test for sphericity

The KMO value calculated was 0.716, meaning the survey responses had adequate sampling [26]; [28]. Since the p-value corresponding to Bartlett's Test of Sphericity in Table 3 was less than 0.05, confirming Homoskedasticity, factor analysis was worth pursuing [26];[28].

4.4.3 Scree Test for eigenvalues

From Figure 3-7, only four factors had Eigenvalues > 1 . That meant these four factors affected Likert scale responses significantly. Subsubsection 4.4.4 below lists the four factors.

4.4.4 Factor loadings

In factor analysis, appropriate names should reflect the underlying theme or concept that groups the questions. Based on the questions and their associated factors, the following four were the names of the factors chosen:

- Strategic Planning and Management;
- Technological Assessment and Implementation;
- Stakeholder and Expectation Management; and
- Legal and Contractual Compliance.

The reasoning behind these names is based on Table 4 factor loadings:

- **Strategic Planning and Management:** This factor encompasses questions affecting the overall planning and management processes required to ensure the project's success. The tasks involve high-level strategic decisions, risk management, and continuous oversight of the project.
- **Technological Assessment and Implementation:** This factor includes questions focusing on the technical aspects of the project, such as identifying technological needs, evaluating technical options, and implementing technology solutions.
- **Stakeholder and Expectation Management:** This factor is centred around understanding and managing the expectations and needs of various stakeholders, ensuring their requirements are met, and maintaining effective communication and support throughout the project.
- **Legal and Contractual Compliance:** This factor pertains to the legal and contractual obligations fulfilled throughout the project. It involves drafting agreements, ensuring compliance with legal requirements, and managing contracts.

These names succinctly captured the essence of the grouped questions, making it easier to understand the focus areas of each factor in the factor analysis.

4.4.5 Average Variance Extracted (AVE) and Composite Reliability (CR)

The four factors listed in the factor analysis above, accounted for 82,6% of the variance in responses.

The AVE values were 0.255, 0.248, 0.192 and 0.131 respectively. Their respective CR values were 4.397, 4.397, 4.397 and 4.397. Since all the AVE values for the factors were < 0.5 , but their respective CR values were > 0.6 , convergent reliability was adequate.

4.5 Likert scale responses

From Figure 3-1, Figure 3-2 and Figure 3-3, the respondents mostly agreed or strongly agreed with the implementation steps outlined on the survey's new proposed roadmap. That is also confirmed by Table 2 where the means for responses to each question range from 4.300 to 4.467, which are between agree (4) and strongly agree (5) on a Likert scale. The standard deviations also had a low range between 0.556 and 0.758 (less than a standard deviation from the mean). The variance ranged from 0.309 to 0.575, confirming the Homoskedasticity assumption.

The study conducted a rigorous analysis of data related to technology implementation in the mining sector, covering various aspects such as outlier identification, internal consistency, data linearity, and factor analysis. The Mahalanobis distances confirmed no outliers, ensuring the robustness of the dataset. High Cronbach Alpha values (0.976 overall and ranging from 0.874 to 0.970 across the three phases of Likert scale questions) indicated internal consistency among Likert scale questions. Visual inspections and statistical tests affirmed the linearity of Likert questions, supporting the assumption of a linear relationship. Factor analysis revealed four significant factors—Strategic Planning and Management, Technological Assessment and Implementation, Stakeholder and Expectation Management, and Legal and Contractual Compliance, explaining 82.6% of variance with good reliability. Most respondents agreed or strongly agreed with the implementation steps outlined, backed by low standard deviations and variance, suggesting consistent perceptions among respondents. These findings underscore the reliability and comprehensiveness of the study's data analysis methods in assessing technology adoption in the mining industry.

4.6 Limitations of the study

- A small sample size from a single mine was used for the analysis, limiting the generalisability of the findings across South African mines.
- The high Cronbach Alpha values suggest internal consistency, but they do not account for the possibility of overly homogeneous responses that might not truly reflect the diverse views of the population.
- Confirming the linearity assumption was through visual inspection of Jitter plots. However, visual inspection can be subjective and may not be as reliable as more rigorous statistical tests for linearity.
- While most questions showed approximately normal distributions, questions 16, 17, and 19 exhibited high skewness and Kurtosis deviations from normality. That indicates that the assumption of normality might not hold for all data points, potentially affecting the validity of factor analysis results.
- The study does not delve into demographic differences that could influence responses, such as gender, age, years of experience, and type of mining experience, limiting the generalisability of the findings across different demographic groups within the mining industry.
- The study relies heavily on self-reported data from survey respondents. This data type can be subject to biases such as social desirability bias, where respondents may answer in a manner they believe is more socially acceptable or favourable rather than providing their actual opinions or experiences. That can potentially skew the results and affect the accuracy and reliability of the findings [29].

5 CONCLUSION AND RECOMMENDATIONS

5.1 Conclusions

The study utilised quantitative methods for data collection and analysis. The survey consisted of questions based on the literature on roadmaps for technology implementation in the mining

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or similar industry. An online Google Form collected data. The participants purposively sampled with expertise in implementing technology in the mining industry. To ensure data validity and reliability, triangulation, pre-testing, and constant comparisons were pursued through the data collection. The researcher tested statistical assumptions made for analysis, such as linearity, normality, no outliers and correlation between the data. Statistical testing and visual inspections confirmed all assumptions. Internal consistency was measured using Cronbach's alpha. Factor analysis was employed to refine survey questions and ensure the robustness of the findings. The factor analysis yielded four factors which each question in the survey fell under, namely:

- Strategic Planning and Management
- Technological Assessment and Implementation
- Stakeholder and Expectation Management
- Legal and Contractual Compliance

These factors accounted for a majority of the variance. The actual means of the Likert scale responses ranged from 4.300 to 4.467 (four on the Likert scale meant the participant agreed with the step in the survey roadmap, and five on the Likert scale meant they strongly agreed with the step).

5.2 Recommendations

- Develop a new roadmap that includes the four identified factors (Strategic Planning and Management, Technological Assessment and Implementation, Stakeholder and Expectation Management, and Legal and Contractual Compliance). Highlight critical elements within each factor and integrate qualitative responses from experts to include necessary additional steps.
- Analyse demographic data collected from the survey, including gender, age, years of experience, and type of mining experience. Check for differences in these demographics not included in this initial study.
- Expand the participant pool to include representatives from multiple mining companies in South Africa. Ensure that the new data collection supplements the existing dataset and aims to generalise the study's conclusions to the entire South African mining industry.

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A APPENDIX A: SURVEY QUESTIONS

The following was the survey used for data collection for this study. The three sections that subdivided the survey were pre-installation, installation, and post-installation phase questions. These phases had steps that the respondents quantified by the survey respondents in terms of their applicability in the South African mining industry context. The survey consisted of 5-point Likert scales with responses allowed from strongly agree, agree, neutral, disagree, and strongly disagree. The questions were as follows.

- **Pre-installation phase (gathering and evaluating implementing entity's capacity and potential partners) questions**

1. Define the business problem
2. Identify the technological gap
3. Identify the commissioning entity's expectations and capacity
4. Evaluating information on the necessary technology and vendors
5. Assessment and selection procedure for vendor and technology selection
6. Compiling short-term, medium-term, long-term and risk management strategies
7. Drafting agreements and contracts

Do you agree with the listed checklist items and their order for gathering and evaluating the information above?

- **Installation phase questions**

8. Design and evaluate concepts for a simulation, create a numeric simulation of the technology scenario
9. Evaluate the numeric simulation against expectations
10. Prepare prototype designs for possible implementation based on simulation separated from normal operations

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11. Validate the prototype against simulation expectations, choosing optimal (if the results of the prototype are unfavourable terminate the project)
12. Gathering system requirement documents from the vendor
13. Gathering system requirements for infrastructure upgrade
14. Ensure implementation of legal agreements
15. Implement budget control measures
16. Constant checks of design and quality of civil works
17. Provide support and cooperation (communication)

Do you agree with the listed checklist items for developing a detailed project plan above?

- **Post-adoption phase (System calibration, testing, integration and after-sale service) questions**

18. System calibration, testing and integration
19. Providing training services
20. Activities required to maintain continuous system functionality
21. Exit strategy

Do you agree with the listed checklist items for system calibration, testing and integration above?

B APPENDIX B: RESPONDENTS DEMOGRAPHICS INFORMATION

There were multiple different age groups, experience levels and gender. Table 6 shows these differences among the participants.

Table 6: Sample characteristics table (demographics)

Female		Male		Gen der												
		Age group				Experience level										
0	18 - 20 years	0	18 - 20 years													
1	20 - 29 years	2	20 - 29 years													
7	30 - 39 years	9	30 - 39 years													
2	40 - 49 years	3	40 - 49 years													
2	50 - 59 years	3	50 - 59 years													
0	60 years or older	2	60 years or older													
1	0 - 2 years	2	0 - 2 years													
1	3 - 5 years	1	3 - 5 years													
2	6 - 10 years	1	6 - 10 years													
5	11 - 15 years	5	11 - 15 years													
2	16 - 20 years	1	16 - 20 years													
1	21 - 25 years	3	21 - 25 years													
0	26 - 30 years	4	26 - 30 years													
0	31 - 35 years	1	31 - 35 years													
0	36 - 40 years	1	36 - 40 years													
0	More than 40 years	0	More than 40 years													

Table 7 below shows the different types of work the participants had undertaken in the mining industry.

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Table 7: Sample characteristics table (types of work experiences)

Type of work experience in the mining industry	Number of respondents
General work	6
Manager or supervisor	19
Engineer	7
Senior manager	3
Junior manager	2
Specialist (e.g., boiler maker)	4
Intern	1
Professional	1