



**Cultural factors hindering mining technology
adoption in South Africa**

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DECLARATION

I, Tshidiso Mokgatla, declare that this research report entitled 'Cultural factors hindering mining technology adoption in South Africa' is my own unaided work. I have acknowledged, attributed and referenced all ideas sourced elsewhere. I am hereby submitting it in partial fulfilment of the requirements for the degree of Master of Business Administration at the University of the Witwatersrand, Johannesburg. I have not submitted this report before for any other degree or examination to any other institution.

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ABSTRACT

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The performance of South Africa's mining industry shows a downward trend, with traditional mining practices not suitable to produce minerals economically. The current conditions require technological innovations to safely mine the ore reserves efficiently and cost-effectively.

This quantitative cross-sectional study explored possible cultural factors to determine whether they can explain the variance in the behavioural intentions of users to adopt technology in the context of South Africa's mining industry and to assist the adopters of technology to increase the rate of adoption.

The study explored the research hypotheses to determine whether the additional variables can further explain the variance in the behavioural intentions to adopt technological innovations.

A random sampling technique was utilised for the study; research respondents consisted of both males and females working across organisational structures in the South African mining industry.

The data were analysed using SPSS and applied descriptive statistics to test a proposed model for accepting technology in the South African mining industry. The study provides recommendations and the results of the study add to the body of knowledge in the field of technology acceptance.

TABLE OF CONTENTS

DECLARATION	ii
ABSTRACT	iv
TABLE OF CONTENTS.....	v
LIST OF TABLES	viii
LIST OF FIGURES	ix
LIST OF TABLES IN THE APPENDICES	x
ACKNOWLEDGEMENTS	xi
DEFINITION OF KEY TERMS AND CONCEPTS.....	xii
1 INTRODUCTION TO THE RESEARCH.....	1
1.1 Background and context	1
1.2 The mining industry in South Africa.....	1
1.3 An introduction to formative evaluation	2
1.4 Research conceptualisation	2
1.4.1 The research problem statement.....	2
1.4.2 The research purpose (aim and objectives) statement	4
1.4.3 The research questions and, where applicable, accompanying research hypotheses or research propositions	5
1.5 Delimitations and assumptions of the research study.....	7
1.6 Significance of the research study	8
1.7 Preface to the research report	10
2 LITERATURE REVIEW	11
2.1 Research problem analysis – cultural factors influencing mining technology adoption in South Africa.....	11
2.2 Research knowledge gap analysis – methods, data, findings and conclusions of studies on and investigations of technology adoption	23
2.3 Qualitative attributes or quantitative variables key to the research	26

2.4	Framework for interpreting research findings – established frameworks for technology acceptance	28
2.5	Summary and conclusion.....	31
2.5.1	Summary of literature reviewed	31
2.5.2	Proposed research strategy, design, procedure and methods arising from the literature review.....	32
3	RESEARCH STRATEGY, DESIGN, PROCEDURE AND METHODS.....	35
3.1	Research strategy.....	35
3.2	Research design.....	36
3.3	Research procedure and methods	37
3.3.1	Research data and information collection instruments.....	38
3.3.2	Research instrument	39
3.3.3	Measurement scales	40
3.3.4	Research target population and selection of respondents.....	42
3.3.5	Ethical considerations when collecting research data	43
3.3.6	Research data and information collection process.....	44
3.4	Research data and information processing and analysis	46
3.4.1	Research data and information processing.....	46
3.4.2	Research data and information analysis.....	46
3.4.3	Description of the research respondents	49
3.5	Research strengths – reliability and validity measures applied.....	49
3.6	Research weaknesses – technical and administrative limitations.....	55
4	PRESENTATION OF RESEARCH RESULTS	56
4.1	Perceived use does not inform the behavioural intention to adopt technological innovation in the South African mining industry	57
4.2	Perceived ease of use does not inform the behavioural intention to adopt technological innovation in the South African mining industry	57
4.3	Relative attitude does not inform the behavioural intention to adopt technological innovation in the South African mining industry	58

4.4	Potential to reduce costs does not inform the behavioural intention to adopt technological innovation in the South African mining industry	58
4.5	Potential to improve safety does not inform the behavioural intention to adopt technological innovation in the South African mining industry	59
4.6	Perceived threat to job security does not inform the behavioural intention to adopt technological innovation in the South African mining industry	59
4.7	The hypothesised model.....	60
5	REPORT AND DISCUSSION OF RESEARCH FINDINGS	63
5.1	Introduction.....	63
5.2	Report and discussion of research findings.....	63
6	SUMMARY, CONCLUSIONS, LIMITATIONS AND RECOMMENDATIONS	66
6.1	Summary	66
6.2	Conclusions	67
6.3	Limitations	68
6.4	Recommendations.....	69
	REFERENCES	71
	APPENDICES	75
	Appendix 1.1: Data Collection Instrument(s).....	76
	Appendix 1.2: Reliability Test.....	78
	Appendix 1.3: Convergent Validity Test	81
	Appendix 1.4: Multiple Regression.....	85
	Appendix 2.1: Bio of the Researcher Including Declaration of Interest in the Research	87
	Appendix 2.2.1: Ethics Documentation	88
	Appendix 2.2.2: Ethics Documentation	89
	Appendix 3.1: Dully Filled in Data Collection Instrument(s)	90

LIST OF TABLES

Table 3.3.2.1 Summary of the survey responses.....	40
Table 3.5.1 Convergent validity.....	52
Table 3.5.2 Discriminant validity	54
Table 4.1 Summary of individual predictors with their p-values	56
Table 4.2 Descriptive statistics.....	60

LIST OF FIGURES

Figure 2.4.1 The original technology acceptance model (TAM)	28
Figure 2.5.2.1 The proposed technology acceptance model	34
Figure 4.7.1 Proposed model path coefficients	60

LIST OF TABLES IN THE APPENDICES

Table 1.2.1 Reliability statistics	78
Table 1.2.2 Item-Total Statistics.....	78
Table 1.3.1 Correlation matrix used for convergent validity test.....	82
Table 1.3.2 KMO statistic	84
Table 1.4.1 Variables in the regression model	85
Table 1.4.2 Model Summary	85
Table 1.4.3 Analysis of variances	85
Table 1.4.4 Coefficients and p-values.....	86

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DEFINITION OF KEY TERMS AND CONCEPTS

Several terminologies used in the study were obtained from Ali and Miraz (2015, p. 115).

Innovators can be defined as “people like novelty and are commonly risk takers, innovative themselves, need little convincing, and are the easiest to target” (Ali & Miraz, 2015, p. 115).

Early adopters can be referred to as “strategic leaders and are acutely aware of the need to change, very amenable to adopting innovative changes and technologies, and they require little information to adopt innovation” (Ali & Miraz, 2015, p. 115).

Early majority can be referred to as “non-leaders who like to embrace innovation and need to be presented with clear evidence of the benefit of adopting the innovative product or idea” (Ali & Miraz, 2015, p. 115).

Late majority refers to the “sceptics of the population, who will only take on the innovation after the majority, and need to be convinced about how the others have successfully embraced the innovation before them and have clearly benefitted from it and continue to do so” (Ali & Miraz, 2015, p. 115).

Laggards can be thought of as “traditionalists, sceptics and conservatives, who are resistant to change and are hardest to convince, and need to be presented with statistics, peer pressure from the other groups and even ‘fear appeals’” (Ali & Miraz, 2015, p. 115).

Relative advantage is defined as “the extent to which the innovation is seen to offer an advantage over the contemporaneous instrument it is replacing” (Ali & Miraz, 2015, p. 115).

The study further used terminology applied to the technology acceptance model by Davis (1985).

Behavioural intention – “an individual's subjective probability that he or she will perform a specified behaviour” (Davis, 1985, p. 16).

Perceived usefulness is “the degree to which an individual believes that using a particular system would enhance his or her job performance” (Davis, 1985, p. 26).

Perceived ease of use is “the degree to which an individual believes that using a particular system would be free of physical and mental effort” (Davis, 1985, p. 26).

Attitude is “an individual's degree of evaluative affect toward the target behaviour” (Davis, 1985, p. 16).

Technological innovation is described as “a tool which can be used by the adopting society to perform tasks more efficiently or to perform new tasks” (Mugodi & Fleming, 2003, p. 505).

Productivity is described as “a measure of production efficiency, and is the rate at which input resources are effectively translated into outputs” (Neingo & Cawood, 2011, p. 181).

1 INTRODUCTION TO THE RESEARCH

1.1 Background and context

This research investigated the possible cultural factors that impact technology adoption in the South African mining industry. However, before addressing the research conceptualisation (Section 1.4), the terms and concepts that were used in conceptualising this research were briefly, generally and broadly introduced in the Definition of Key Terms and Concepts section. Chapter 2 presents a more specific and detailed discussion of the research context as a prelude to and foregrounding of the literature review.

The research conceptualisation section provides the research problem statement, the purpose of this research, and the research questions. The delimitations and assumptions of the research study are set out in Section 1.5 and the significance of the research study is discussed in Section 1.6. A preface to the research report is provided in Section 1.7.

1.2 The mining industry in South Africa

The South African mining industry commenced in early 1860 after the first diamond was discovered on the southern bank of the Orange River (Antin, 2013). In the period preceding current mining practices, vast demand for labour characterised most of the industry's activities (Corrigan, 2019). South Africa is rich in minerals, estimated at around US\$2.5 trillion. The mining industry contributes 5 per cent of the country's employment and roughly a third of its exports (Corrigan, 2019). To realise the economic potential of the untapped mineral resources, companies exploiting these minerals are likely to require a shift to contemporary systems employing technology to extract these minerals efficiently and safely (Lane, Guzek, & Van Antwerpen, 2015; Rupprecht, 2016; Hermanus, 2017; Rupprecht, 2017).

Rogers (2010a) argues that the adoption of technological innovation requires either of two conditions. First, there must be an alignment between

technological innovation and cultural norms. Second, the culture has to change before adoption can take place. These conditions imply that a shift from historically labour-intensive conventional systems to new technological innovations will require a mindset change to ensure successful technology implementation and adoption.

Technology implementation requires a review of the process to understand the organisation's readiness from a culture and capability perspective (Richard, 2004). This implies that the industry requires a change in organisational processes that can lead to employees reconsidering old attitudes towards technological innovations and abandoning outdated perceptions that act as a hindrance to technology adoption. The South African mining industry with its embedded history of a labour-intensive mindset and unskilled labour set-up is likely to experience a significant turnaround if technology were to be successfully incorporated into an integrated system of mining (Leeuw & Mtegha, 2018).

1.3 An introduction to formative evaluation

Research gathers momentum when an intense literature review process is undertaken (Matthee, Henneke, & Johnson, 2014). The literature review process introduced this study to technology acceptance frameworks for interpretation and guidance. The critical task of this study is to contribute to the body of knowledge by identifying the knowledge gaps in the existing technology acceptance models. Sourcing the right questionnaires appropriate for this study was a crucial part of the study. The literature review of previous similar research was used extensively to inform the appropriate research strategies, designs and methods this study used.

1.4 Research conceptualisation

1.4.1 The research problem statement

The current technology acceptance model by Davis (1989) does not entirely explain the variance in the acceptance of technology in South Africa's mining industry. This model only examines perceived usefulness (PU) and perceived

ease of use (PEU) as the attributes influencing technological innovations (Karahanna, Straub, & Chervany, 1999). It does not incorporate the contextual circumstances that may have divergent impacts on the innovation-decision process.

The South African mining industry is facing escalating costs and labour availability and utilisation challenges (Neingo & Tholana, 2016); it is characterised by labour-intensive operations in some areas (Leeuw & Mtegha, 2018), low literacy levels and challenging government policies (Lane et al., 2015). These aspects contribute to putting the survival and competitiveness of the industry under pressure. Lane et al. (2015) further posit that to achieve their goals and aspirations, mining companies need to make choices that include technological innovations.

Current technological innovations have been shown to yield positive results on the health and safety aspect of the business (Hermanus, 2017). Several authors, including Hermanus (2017), confirm that the industry is yet to increase the rate of technology adoption (Leeuw & Mtegha, 2018) to realise the associated efficiency improvements (Matthee et al., 2014; Carr, 2020). Companies with higher technology intensity realise more revenue from their assets (Westerman, Bonnet, & McAfee, 2014), however, culture-related human factors influence the rate of technology adoption in organisations (Singh, Gaur, & Ramakrishnan, 2017).

Technology can contribute to the sustainability of businesses in the future world of volatility, uncertainty, complexity and ambiguity (VUCA) (Carr, 2020), as recently demonstrated for several industries during the COVID-19 crisis. Even though technology can make a big difference in overall efficiencies and profits, organisational culture affects its rate of adoption (Ali & Miraz, 2015). Possible factors that may affect the rate at which technological innovation is adopted exist. This literature implies that derivation of benefits from technology critically depends on its adoption processes and use. The South African mining industry can benefit from a technology adoption model suited to its unique challenges to advance technology innovations and unlock value (Antin, 2013).

Several authors, including Lane et al. (2015), Neingo and Tholana (2016) and Hermanus (2017), highlight that the South African mining industry has its own unique challenges. This implies that most of the research work undertaken around technology adoption and the development of models used as frameworks for technology acceptance were based in other countries with different labour dynamics, which makes the results of these particular studies difficult to generalise to the mining industry in South Africa.

Numerous studies conducted in the field of technology adoption and its infusion rate reveal that culture-related human behaviour influences the adoption rate of technology in organisations (Lee, Hsieh, & Chen, 2013; Singh et al., 2017). These studies have led to the development of theoretical models that centred around human behavioural beliefs about and behavioural intention (BI) towards technology adoption, culminating in the technology acceptance model (TAM) developed by Davis (1989).

TAM premises on PU and PEU as being the determinants of technology acceptance. They are seen to be the key antecedents of the BI to use information technology (IT). Some theories attempted to integrate the internet of things (IoT) with TAM to produce an IoT-TAM theoretical framework (Singh et al., 2017), which is about consciously intended behaviour being determined by a person's attitude (AT) and subjective norm (SN).

1.4.2 The research purpose (aim and objectives) statement

This study looked at the mining industry in South Africa to understand innovation diffusion patterns across diverse technological innovations. It contributes to the existing body of knowledge in understanding the diffusion process required for the acceptance of technological innovations in the South African mining industry as different settings are likely to imply very different adoption dynamics.

The purpose of this research was to determine the possible factors that could explain the variance in the adoption of technological innovations by pursuing six related research questions to establish the possible variables that explain the variance in the BI to adopt mining technology in South Africa. It determined

the possible cultural factors that could increase the explanatory power of the current technology acceptance models and reduce the unexplained variance in the BI to adopt the technology.

To adequately respond to the research questions and their hypotheses, this study applied TAM as a theoretical framework to interpret the research results.

This research was designed to determine whether there were additional cultural factors responsible for the acceptance of technological innovations in South Africa's mining industry. It also proposed a suitable adoption model that might be unique to the dynamics that exist in this research setting.

1.4.3 The research questions and, where applicable, accompanying research hypotheses or research propositions

The research questions and explored hypotheses for this study were formulated by conducting a research knowledge gap analysis on previous similar studies (Lee et al., 2013; Matthee et al., 2014; Ali & Miraz, 2015; Carr, 2020; Porto, 2020). The research knowledge gap analysis resulted in a questionnaire that was used as a tool to collect data for the study.

1.4.3.1 Question 1: Does perceived use inform the adoption of technology in the South African mining industry?

Null hypothesis: Perceived use does not inform the adoption of technology in the South African mining industry

Research hypothesis (directional or non-directional): Perceived use informs the adoption of technology in the South African mining industry

1.4.3.2 Question 2: Is the perceived ease of use important in determining the behavioural intention to adopt technology?

Null hypothesis: Attitude is not important in determining the behavioural intention to adopt technology

Research hypothesis (directional or non-directional): Attitude is important in determining the behavioural intention to adopt technology

1.4.3.3 Question 3: Is relative attitude important in determining the behavioural intention to adopt technology

Null hypothesis: Relative attitude is not important in determining the behavioural intention to adopt technology

Research hypothesis (directional or non-directional): Relative attitude is important in determining the behavioural intention to adopt technology

1.4.3.4 Question 4: Do perceptions of technological innovations as having the potential to reduce cost determine the behavioural intention to adopt technology?

Null hypothesis: The beliefs that technological innovations have the potential to reduce costs are not important in determining the behavioural intention to adopt technology

Research hypothesis (directional or non-directional): The beliefs that technological innovations have the potential to reduce costs are important in determining the behavioural intention to adopt technology

1.4.3.5 Question 5: Do perceptions of technological innovations as having the potential to improve safety determine the behavioural intention to adopt technology?

Null hypothesis: The beliefs that technological innovations have the potential to improve safety are not important in determining the behavioural intention to adopt technology

Research hypothesis (directional or non-directional): The beliefs that technological innovations have the potential to improve safety are important in determining the behavioural intention to adopt technology

1.4.3.6 Question 6: Do perceptions of technological innovations as being a threat to job security determine the behavioural intention to adopt technology?

Null hypothesis: The beliefs that technological innovations threaten job security are not important in determining the behavioural intention to adopt technology

Research hypothesis (directional or non-directional): The beliefs that technological innovations threaten job security are important in determining the behavioural intention to adopt technology

1.5 Delimitations and assumptions of the research study

The slow pace of technology adoption in the mining industry (Antin, 2013) is due to various causes including unreliable connectivity, the shortage of employees with digital skills, the ineffective collection and management of data (Carr, 2020), a culture that is not conducive, ergonomics, ownership of technology design, inadequate change management, political interference (Macfarlane, 2001) and relative advantage, compatibility, complexity, trialability, and observability (Ali & Miraz, 2015).

Culture and change management plays a major role in the success of innovation in organisations. As Ali and Miraz (2015) assert, culture affects the permeation of technology in world society. This research explores the literature review to identify the potential additional variables that are likely to influence technology adoption in the South African mining industry. Numerous examples in the literature highlight that the current technology acceptance models, i.e. TAM and IoT-TAM, account for less than 60 per cent of the variance in explaining the rate of technology adoption in organisations (Lee et al., 2013; Singh et al., 2017).

Rogers and Williams (1983) divide technology adopters into five categories which indicate the level of readiness to adopt technology and stress that these have not received equal attention from scholars. Based on time constraints and the need to contain the report within the required length, this study neither

quantifies the relative impact of cultural attributes nor compares the relative impact of these cultural attributes on the adoption of technology. Furthermore, the study does not attempt to classify technology adopters.

Three fundamental assumptions are made in this research. First, the participants, and not their delegates, responded to the survey instrument. Second, potential users are aware of the technology existing in their workplace. Lastly, if potential adopters accept technology, the adoption rate of technological innovations will increase.

1.6 Significance of the research study

The adoption of technology in the mining industry has historically been slow, although mining companies are driving its implementation to increase efficiencies (Rogers et al., 2019). The possible root causes include unreliable connectivity, a shortage of employees with digital skills, the ineffective collection and management of data, a culture not conducive and inadequate change management (Carr, 2020). The significance of this study is to assist in pointing out possible additional variables describing the variance in human behaviour that determine a user's acceptance of technological innovations.

This research utilised cultural factors to address the research problem, by determining their impact on the acceptance of mining technology and the rate of adoption of technological innovations in South Africa. It utilised a literature review to identify research knowledge gaps and formulate the research questions and hypotheses. The knowledge gaps include the understanding of how people's perceptions of technology improve safety, reduce costs and threaten job security, impacting the BI to accept technology.

The literature review reveals that resistant business culture is largely responsible for the slow adoption of technology (Ali & Miraz, 2015). Similar past and present research have pointed out that culture is a key determinant of technology adoption and influences its infusion rate (Lee et al., 2013). This threatens to leave the industry with low efficiencies, makes it difficult for companies to fight increasing costs and results in negative economic impact.

The study conducted by Carr (2020) indicated that 36 per cent of mining industry executives found culture among the barriers to technology adoption. This research points out some of these culture-related variables that need attention from company executives to unlock the potential value associated with the adoption of technology to increase efficiencies. Westerman et al. (2014) assert that companies with higher technology intensity realise more revenue from their assets. This implies that companies which fail to adopt technology are likely to end up with high costs of doing business and subsequently lose their market share.

Klintonberg, Wallin, and Azimoh (2014) points out that people are critical to the successful development, transfer and implementation of technology. Heightened empirical research in the area of the adoption of technological innovations is required to assist the industry, with recent developments showing a move in that direction (Rogers et al., 2019). Rupprecht (2017) stresses that there is a need for collaboration and coordinated empirical research to assist South Africa's mining industry in its efforts to implement technology that will enhance occupational health and safety, as well as improve operational efficiencies.

Other authors advise that the effectiveness of technology depends on the user's uptake and/or acceptance of the intended technological innovations (Ghebrihiwet, 2019). They further point out that acquiring knowledge on barriers to adapting to new behaviour patterns can be utilised as a strategy to assess the appropriateness of basic assumptions and opinions among persons. The associated benefits of technological innovations in the mining industry are related to improved safety and increased efficiencies (Rogers et al., 2019).

If they can successfully implement technology, mining companies in South Africa are likely to address future uncertainties related to declining resource quantity and grade. Meanwhile, future trends indicate an increased demand for minerals (Franks, Cohen, McLellan, & Brereton, 2010). This implies that for the South African mining industry to enhance conditions for a viable industry,

the adoption of technological innovations must experience minimal or no barriers.

1.7 Preface to the research report

This research report consists of six chapters. Building on Chapter 1, the introductory chapter, Chapter 2 provides a literature review covering the problem, past studies, explanatory framework and conceptual framework. Chapter 3 discusses the research strategy, design, procedures, reliability and validity measures as well as limitations. Chapter 4 and Chapter 5 present and discuss the findings to interrogate the research questions, respectively, and Chapter 6 summarises and concludes the research.

2 LITERATURE REVIEW

This chapter has three broad objectives: to understand the research problem, to identify the knowledge gap and to develop a framework for interpreting the research findings. Specifically, in Section 2.1, the research problem is detailed. In Section 2.2, the literature on past studies that have attempted a similar study or research is reviewed. The information arising from Section 2.2 enables the identification and detailing of quantitative variables that are key to this research in Section 2.3. The theoretical framework that will be used to interpret the research findings is revealed in Section 2.4.

2.1 Research problem analysis – cultural factors influencing mining technology adoption in South Africa

This section starts by providing a general overview of the South African mining industry. The subsequent paragraphs discuss in detail, the challenges facing the mining industry. First, the increasing cost of labour and its associated impact on the mining industry is detailed. Second, the capital investment required to stay in business is discussed. Third, the industry contribution to the country's gross domestic product (GDP) is discussed to illustrate the need for change. Fourth, declining production is discussed to highlight the unsustainability of the current approach to mining practices.

The conventional nature of the South African mining industry, highlighting its inappropriateness in current conditions, is the fifth aspect discussed. Sixth, technological innovations are discussed to highlight the potential associated gains. Seventh, the difficult mining conditions are discussed to highlight the occupational health and safety challenges presented by the current conventional systems. Eighth, the industry's declining productivity resulting from unsuitable mining practices is discussed.

The prevailing geotechnical complexities presenting safety risks and unsustainable mining are discussed in ninth place. Tenth, the reduced time spent at work face and associated declining productivity are discussed to highlight the need for a change from current labour-intensive practices. Lastly,

the potential job losses associated with the likely closure of the industry as a result of these challenges are discussed.

The mining industry in South Africa has dominated the world globally (Neingo & Tholana, 2016). According to Leeuw and Mtegha (2016), South Africa is rich in mineral resources, which makes the mining industry one of the crucial pillars of economic development in the country. Based on the claims of these authors, the mining industry in South Africa has a comparative advantage over mineral resources and is an important player in the production of these minerals for economic use globally.

This view is echoed by Matthee et al. (2014) who state that the contribution made by the mining industry to South African economic development is significant. O'Connor (2019) affirms this view by stating that South Africa is the world's richest country with its mineral reserves estimated at US\$2.5 trillion. However, according to (Lane et al., 2015), the mining industry in South Africa is facing the challenges of difficult situations that include tough operating conditions, a complex socio-political environment and financial performance that is under pressure.

Neingo and Tholana (2016) add that the South African mining industry is facing challenges that are unique to the country and threaten the survival and competitiveness of the industry. This implies that the industry needs to find solutions that are suitable to these challenges and unique to its context. These challenges require the mining industry in South Africa to find interventions that can bring about change to improve the situation.

South Africa's mining operating costs are escalating and are the highest in the world, with costs of labour being in the top five cost drivers (Rupprecht, 2017). The South African mining industry has historically been characterised as labour-intensive (Leeuw & Mtegha, 2018), with labour costs constituting a high percentage of mining costs. Over decades of mining in South Africa, the costs of labour have become expensive (Neingo & Tholana, 2016) and remain a major cost driver for the industry.

Labour costs have increased by 11 per cent, from 36 to 47 per cent, in the period from 2010 to 2018 (Corrigan, 2019). The escalating operating costs contribute to putting current operating models under pressure (Hermanus, 2017), severely impacting the South African mining industry's competitiveness on the global stage (Rupprecht, 2017). Neingo and Tholana (2016) assert that rising costs and decreasing commodity prices reduce the industry's profit margins, while intermittent labour unrest greatly affects labour productivity.

Labour costs account for 50 to 60 per cent of mining costs (Rupprecht, 2016). In some sectors of the industry, such as platinum, mining input costs have nearly doubled, characterised by employee earnings increase of around 193 per cent over 12 years (Rupprecht, 2017). From the literature review (Lane et al., 2015; Hermanus, 2017; Rupprecht, 2017), it can be seen that South Africa's mining costs are increasing unsustainably, mainly due to the escalating cost of labour. This is likely to have a negative impact on the long-term survival of the industry and its ability to continue playing a significant role, not only in the country but also globally (Lane et al., 2015).

Based on the current mining technology drive by the industry to improve efficiencies (Hermanus, 2017), it can be hypothesised that if technology is perceived to have the potential of reducing costs, then its rate of adoption is likely to increase. According to the literature review, studies on autonomous systems show that mines could reduce the cost of fuel in hauling activities by 14.8 per cent (Cosbey et al., 2016).

Capital investment in exploration to find new deposits has been declining (Lane et al., 2015; Hermanus, 2017). Investment in new mining methods has also been sluggish (Lane et al., 2015). Hermanus (2017) indicates that the mining industry in South Africa has shrunk by both size and value. Corrigan (2019) points out that the South African mining industry's spend on exploration has been the lowest among leading mining companies. He states that the industry's share of global exploration spending has worsened from 1.6 to 1.1 per cent, against a target of 10 per cent, over the period from 2009 to 2017.

Current identified mechanisation methods require substantial capital requirements (Rupprecht, 2017), making such investment unattractive and undesirable for most South African mining companies. The declining investment in exploration could be an indication of the concern over unfavourable operating costs associated with mining in South Africa's mining industry (Lane et al., 2015). This highlights the need for new ways of mining, ways that can drive down the input costs.

The implication is that potential efficiency improvement associated with technology implementation could result in an industry appetite to invest capital in expansion as well as exploration projects. Rupprecht (2016) asserts that research is required to identify suitable mining methods to survive current prevailing conditions, with some company executives confirming that conventional mining systems are no longer the future of mining in South Africa (Rupprecht, 2016, 2017).

The South African mining industry's contribution to the country's GDP has been on a general decline for over a decade now (Antin, 2013), particularly in the gold mining sector (Neingo & Tholana, 2016). Production volumes, revenue generated, as well as job losses, characterised the declining South African mining industry contribution to GDP (Antin, 2013). The diminishing contribution to GDP is signified by the industry's marked decline in production volumes from over 6 million tons in 2006 to just over 4 million tons in 2014 (Neingo & Tholana, 2016). This being the case, the country's economy has fallen in uncertain times (Corrigan, 2019).

This is further highlighted by the situation in the platinum mining sector, where 70 per cent of the mines in this sector are operating at a loss (Rupprecht, 2017). Employment has also been on a general decline in the South African mining industry, with the industry shedding some 25,000 jobs since 2012 (Rupprecht, 2017). The literature review indicates that current technology methods are likely to improve the mining industry's GDP contribution, as indicated in the article by Rupprecht (2017), which reflects the potential upswing that might be associated with the introduction of technology. The

adoption of these technologies is crucial, more so the rate at which they are adopted.

The production volume output for the South African mining industry shows a steady decline, particularly in the gold mining sector (Matthee et al., 2014; Lane et al., 2015; Leeuw & Mtegha, 2016; Rupprecht, 2016, 2017; Leeuw & Mtegha, 2018). The industry has lost its number-one spot concerning the average annual contribution of minerals to all exports (Neingo & Tholana, 2016). This declining trend has continued for several decades (Matthee et al., 2014), even though South Africa is well endowed with minerals of economic value within its borders (Leeuw & Mtegha, 2016).

The literature suggests that a decline in South African mining is to be expected over a long-term period, from both relative and absolute numbers perspectives (Rupprecht, 2016, 2017). Between 1990 and 2015, South Africa's gold mining contribution declined from 40 to 4 per cent of the world's gold mining industry (Corrigan, 2019). Platinum group metal (PGM) production remains relatively constant (Rupprecht, 2017), while conventional methods of mining are characterised by declining productivity (Rupprecht, 2016).

Some proponents of technology hypothesise that some technology adoption is likely to result in a 15 to 20 per cent increase in output (Cosbey et al., 2016). The implication is that companies can expand their operations, increase efficiencies or improve productivity. However, the situation suggests that the current mining methods are unable to deliver these improvements (Rupprecht, 2016, 2017). This suggests that there is a need for fundamental change in mining methods to bring improvement in efficiencies or volumes to take advantage of the mining industry's comparative advantage. Technology adoption can lead to more efficient mining methods that can improve mining output in the South African mining industry.

The South African mining industry is a conventional system which relies heavily on labour (Neingo & Cawood, 2011; Leeuw & Mtegha, 2018). Amid a changing landscape that is characterised by the introduction of technology to replace conventional systems, this practice has become less efficient

(Rupprecht, 2016, 2017). The lack of technology adoption means that mining operations remain conventional and labour-intensive (Rupprecht, 2016). This phenomenon could explain the downward trends in output for the gold mining sector.

From the literature review, the downward trends in mining exports culminated in a position where mining export value per capita for South Africa has worsened when compared to other mineral commodity producers (Antin, 2013). Those mines that employ the use of technology in their mining practices show a 14 per cent improvement in productivity and a 13 per cent decrease in mining costs (Cosbey et al., 2016). Conventional mining systems are proving to be inefficient and not suitable for current and future mining (Rupprecht, 2016, 2017).

Advances in technology that will exploit minerals are necessary to improve mining efficiencies in South Africa, make the industry competitive and allow the industry to continue mining into the future. Even though the literature shows evidence of proven technology that results in an improvement in efficiencies, the rate of adoption of such technology seems sluggish (Cosbey et al., 2016). This implies that research into the adoption of technology in the mining industry is worth the effort to ensure the long-term survival of the mining industry in South Africa.

Technology adoption can lead to the mining of ultra-deep gold deposits (Rupprecht, 2017; Corrigan, 2019), enable 24/7 operation (Rupprecht, 2017), make it possible to economically mine gold grades in the region of 3 g/t (Rupprecht, 2016) and result in a 17 per cent increase in economically viable ore reserves (Macfarlane, 2001). In the main, these authors seem to suggest that technology adoption can result in current uneconomical low-grade gold reserves being mined economically, enable the mining of ultra-deep gold ore reserves and increase current economically mineable gold ore reserves.

If technology can make all this possible, the question is why is there no rush by mining companies to adopt this technology and abandon old conventional uneconomical mining systems. From the literature, the answer likely involves

technological innovations to bring a step change in mining performance (Leeuw & Mtegha, 2016; Neingo & Tholana, 2016; Rupprecht, 2016, 2017; Leeuw & Mtegha, 2018). Other views point to focusing on the ability of mine management and close monitoring of effective utilisation of people, materials, and money (Neingo & Cawood, 2011). The answers to this question could provide a way forward that might assist the mining industry in South Africa to change its fortunes and claim back its spot in world rankings.

Mining in South Africa is characterised by deep underground deposits in hot, narrow reefs and seismically risky conditions that make current conventional labour-driven extractions difficult (Leeuw & Mtegha, 2016; Neingo & Tholana, 2016; Leeuw & Mtegha, 2018). Temperatures over 60°C are experienced in South Africa's mines, requiring expensive ventilation and sophisticated refrigeration systems to keep the working environments cool (Neingo & Tholana, 2016).

Ore quality is declining and the structure of the economy is evolving (Corrigan, 2019). Hard rock mining of narrow reefs are associated with the risk of fall of ground, geotechnical challenges and fires (Rupprecht, 2016, 2017). Further, the mining industry in South Africa is facing potential mine closure difficulties related to economic factors and statutory constraints (Rupprecht, 2016). The highlighted difficult conditions characterising South Africa's mining industry further lay bare the problems facing the industry.

What is evident is the inappropriateness of the conventional systems that have become unsuitable for these prevailing conditions (Neingo & Tholana, 2016; Rupprecht, 2016, 2017). The industry must find alternative means to remain competitive on the global stage and survive for at least two decades. Breakthroughs in technological innovations to navigate these difficulties are inevitable to bring sustainability in South Africa's mining at its current position on the cost curve and minimise exposure of personnel to occupational health and safety risk (Antin, 2013).

South Africa's mining industry productivity in general has been a challenge (Rupprecht, 2017), showing a downward trend over the period from 2000 to

2013 (Rupprecht, 2016). The productivity levels are unsustainable under prevailing conditions where South Africa's mineral production from current mine designs and methods that are cyclic is almost at capacity (Leeuw & Mtegha, 2016; Neingo & Tholana, 2016; Rupprecht, 2017; Leeuw & Mtegha, 2018). The implication is that the industry requires interventions that offer alternatives to current approaches. Productivity improvements can be achieved by taking a closer look at the value chain to exploit the concept of shared value creation as well as technology adoption that can lead to the realisation of some associated benefits (Cosbey et al., 2016).

The literature indicates that the introduction of suitable technologies has the potential to offer better alternatives, exemplified by around 250 per cent productivity improvements elsewhere in the mining industry (Rupprecht, 2016). This further highlights the need for South Africa's mining industry to intensify its efforts in identifying suitable technological innovations that can create value.

South Africa's challenging geotechnical conditions (Rupprecht, 2016, 2017; Leeuw & Mtegha, 2018), narrow reefs and deep ore bodies result in an environment that presents a risk to occupational health and safety (Hermanus, 2017). Based on this literature, these conditions are likely to result in unsafe mining conditions that are characterised by intolerable temperatures, seismic events and high costs. The unsafe conditions result in ore losses of 110 000 t/m due to worse potholing than anticipated (Rupprecht, 2016).

Compared to other mining countries, South Africa holds the record for the world's deepest underground mines at depths of around 4 km (around 90 per cent of gold production) and which are characterised by temperatures in the region of 60°C, particularly in the gold mines (Neingo & Tholana, 2016). Rupprecht (2016) emphasises that South Africa's mining industry consists of operating environments that entail wet bulb temperatures over 29°C at 90% humidity, conditions that might require the application of technology as a necessary intervention while acknowledging that some work might be required to counter resistance to change.

South Africa's mining deposit characteristics (Lane et al., 2015; Leeuw & Mtegha, 2018) paint a bleak picture of the industry that was once the pillar of the economy of the country (Neingo & Tholana, 2016). Key challenges are evident from the literature and, in particular, current operating conditions are unsustainable from occupational health and safety perspective, necessitating the need to adopt technological innovations (Rupprecht, 2016, 2017; Leeuw & Mtegha, 2018). It can therefore be hypothesised that the perceived safety improvements associated with technology can lead to an increase in the rate of technology adoption.

Time spent at the workplace, which is negatively impacted by human elements such as behaviour, skills level and mining culture, is one of the major contributors to low productivity in South Africa's mining industry (Rupprecht, 2016). The industry's pace of modernisation and innovation needs to increase to alleviate the situation and bring improvements (Leeuw & Mtegha, 2018).

Looking at the situation in which the mining industry finds itself (Hermanus, 2017), where productivity is low, technology is available and the pace of adopting technological innovations is sluggish, fundamental factors appear to be hampering the adoption of these technological innovations. A deeper understanding of these factors will assist South Africa's mining industry to identify the contributing circumstances and build strategies that could lead to a faster pace of adoption.

Lane et al. (2015) assert that for the South African mining industry to remain competitive on the global stage, it needs to implement new methods and technologies. The implication is that the successful implementation of these innovations is crucial to ensure the long-term survival of the industry. Nonetheless, most mines, at the management level, appear to be unaware of the imperative for a paradigm shift from labour-intensive systems to new methods and technology (Rupprecht, 2017). Rupprecht (2016) contends that labour accounts for between 50 and 60 per cent of the mining costs, while productivity continues to decline.

The labour-intensive nature of the mining industry is likely to contribute to societal challenges facing the economy of South Africa. On the one hand, the mining industry has the responsibility of providing much-needed employment to address societal needs (Lane et al., 2015), while on the other hand, the industry has to find ways that make their business more efficient and profitable (Neingo & Tholana, 2016; Leeuw & Mtegha, 2018).

To address this dilemma and in the name of the creation of shared value, the industry has to conduct a comprehensive analysis of the value chain to identify new opportunities associated with innovations (Rupprecht, 2016, 2017). This implies that in adopting technological innovations, the industry must consider the potential job losses associated with such adoption and produce ways to minimise the impact. If technological innovations are perceived as a threat to job security in the mining industry, the rate of technology adoption is likely to be affected negatively (Cosbey et al., 2016). This hypothesis is worth testing to see if it can explain the BI to adopt the technology.

This has been evident from the declining contribution of minerals to all exports (Neingo & Cawood, 2011), falling levels of direct employment (Matthee et al., 2014) and falling profit margins (Lane et al., 2015). Between 1985 and 1995, there has been a decline in the average contribution of minerals to all exports, falling from 66.7 to 48 per cent, particularly gold falling by 2.91 per cent from 1984 to 1995 (Vermaak, 1997). The challenges in the gold mining sector are contributing to escalation costs and low-profit margins, leading to reduced taxation (Neingo & Tholana, 2016). The declining tax revenues in mining are likely to result in government innovating approaches and dictating to companies the level of returns that should be received (Cosbey et al., 2016).

Other authors anticipate that South African mining industry employment and minerals output will be a fraction of the current volumes in 15 to 20 years (Rupprecht, 2017). As a developing country, South Africa needs revenue from taxes generated by the mining industry (Leeuw & Mtegha, 2016). Due to this industry experiencing a decline in relative contribution to the economy, squeezed profit margins (Lane et al., 2015; Neingo & Tholana, 2016) and a

reduction in employment (Rupprecht, 2017), the expected tax income is diminishing.

This implies that, first, the other income sources must carry the burden and start contributing at unaffordable levels. Second, the associated loss of jobs is destroying the created shared value. Third, the associated societal needs remain unresolved. Lastly, the South African government is forced to review current concession agreement models for the generation of tax revenue. The latter submission might mean that work needs to be done to establish the value proposition that can lead to an increase in the relative economic contribution of the mining industry.

There have been job losses associated with difficulties in the mining industry (Rupprecht, 2017), with the gold mining sector being among the hardest hit (Leeuw & Mtegha, 2016). This trend is likely to continue if the current conventional and cyclical methods are not replaced with new and more efficient ways of mining (Rupprecht, 2016). Most of the operating mines are currently marginal (Rupprecht, 2016, 2017) and their operating costs far exceed those of other mines elsewhere in the world.

Corrigan (2019) states that, in the period from 1990 to 2018, the employment drop experienced by South Africa in the mining industry was from 692 900 to 451 638, with employment in the gold mining sector falling from 160 064 to 111 795 between 2007 and 2017. Rupprecht (2016) confirms that the South African gold mining sector's contribution to the industry's employment fell from 60 per cent in the 1980s to just over 20 per cent currently, with the industry employment falling from 800 000 in the 1980s to 495 000 in 2014.

Contrarily, new ways of work that employ technological innovation are likely to reduce additional jobs created by potential growth in mining, rather than resulting in a net reduction in employment (Cosbey et al., 2016). This view is supported by (Macfarlane, 2001) who states that, instead of destroying jobs, technology is likely to create jobs. Additionally, industry analysts suggest that a further 200 000 jobs could be lost by 2025 in the South African mining industry (Rupprecht, 2017).

The situation highlights the potential job losses in South Africa's mining space which could harm the economy of the country significantly. Around 70% of the mines in the platinum sector that was already in a loss-making operational state (Rupprecht, 2017) saw their survival coming mainly from both recent commodity price increases and the weakening rand against the dollar. The captains of that industry might need to look at the areas where they have control to do something about the situation. The country itself cannot afford job losses as the downstream impact could have devastating consequences. Already Rupprecht (2017) is estimating that 2 000 000 people could be indirectly affected negatively by 200 000 job losses.

South Africa's mineral industry is headed for the closure of most mines if the current extraction methods are not replaced with new methods and technological innovations (Rupprecht, 2016, 2017). Most of the mines are closing down or put on care and maintenance and the future of those that are operational seems unsustainable (Lane et al., 2015). In the main, the industry needs a fundamental shift in the way that it runs mining operations to remain globally competitive (Matthee et al., 2014; Lane et al., 2015; Hermanus, 2017; Rupprecht, 2017; Leeuw & Mtegha, 2018; Ghebrihiwet, 2019; Carr, 2020).

Corrigan (2019) highlights that many of the mines in South Africa are coming to the end of their life of mine (LOM) in a country that boasts approximately US\$2.5 trillion in ore reserves (some of which are inaccessible). Modernisation of the operations in the gold mining sector could potentially extend the LOM and ultimately save jobs (Leeuw & Mtegha, 2018). In this sector, the industry needs to innovate its current extraction strategies to ensure long-term viability and remain globally competitive (Neingo & Tholana, 2016). Rupprecht (2016) adds that significant changes in mining methods are inevitable if the industry is to avoid the extinction of mining.

The platinum mining sector is facing similar challenges, with trends showing that by 2030, tonnage coming from traditional extraction methods is likely to be depleted (Rupprecht, 2017). The declining mineral production accompanied by a decreasing LOM for several deposits in South Africa's mining industry paints an uncertain picture of the country's economy (Lane et al., 2015).

The literature shows that significant amounts of proven ore reserves are likely to be disposed of under the current mining systems (Antin, 2013; Lane et al., 2015; Neingo & Tholana, 2016; Leeuw & Mtegha, 2018). This implies that unless the industry innovates current conventional extraction methods, the long-term viability of mining is uncertain and the associated jobs are at risk. Rupprecht (2017) contents that automation in the platinum mining sector could potentially extend LOM beyond 2050. This implies that South Africa's mining industry must invest in the modernisation of its mining methods by, among others, bringing technological innovations to ensure the long-term survival and global competitiveness of the industry. A wholistic approach that incorporates all the elements that impact the adoption of such technological innovation is a likely enabler in this regard (Rupprecht, 2016).

2.2 Research knowledge gap analysis – methods, data, findings and conclusions of studies on and investigations of technology adoption

The literature review was conducted in previous similar studies with aims and objectives that involved applying TAM to determine the possible cultural effects on technology adoption (Lee et al., 2013; Singh et al., 2017; Porto, 2020). These involved environments where communication was achieved through electronic means (Matthee et al., 2014). The context is dissimilar in that the studies were conducted in different settings. The concept is applied in the adoption of an electronic learning environment (Lee et al., 2013; Porto, 2020), as well as in the adoption of an electronic information communication environment (Singh et al., 2017). This implies that the adoption of technology requires an understanding of the underlying factors that affect its acceptance, the rate of its adoption, as well as the rate of infusion.

The interpretive frameworks used for these similar studies include the TAM by Davis (1989), which is a commonly used interpretive framework to determine the possible factors that are important for technology adoption (Porto, 2020). A new model that builds on TAM was proposed to incorporate the IoT (Singh et al., 2017). These established theoretical models have identified the main factors important for the adoption of technological innovations (Davis, 1989).

It will be interesting to see the results of these models when they are applied to South Africa's mining industry setting, with its unique dynamics (Lane et al., 2015; Leeuw & Mtegha, 2016; Neingo & Tholana, 2016) and labour-intensive operations (Leeuw & Mtegha, 2018).

From the research design perspective, similar previous studies employed a variety of designs from descriptive-correlational (Porto, 2020), cross-sectional (Lee et al., 2013) to exploratory (Singh et al., 2017). Additional factors have been found to further explain BI in technology adoption and its infusion rate among adopters (Singh et al., 2017). What has been learned from the literature review is that the current variables explaining the variance in BIs towards technology adoption, namely PEU and A, do not account for 100% of the variance. This implies that there are still factors that are yet to be identified to explain technology acceptance and adoption.

The instrument utilised by similar studies (Lee et al., 2013; Singh et al., 2017) entails a questionnaire survey to collect data. To suit the research, the questionnaires were adopted from previous similar studies (Lee et al., 2013; Singh et al., 2017; Porto, 2020). This implies that the instrument needs to be suitable for the context and setting. For the incumbent study, the uniqueness of South Africa's mining industry should be incorporated to achieve valid results concerning what explains the BI towards technology adoption in such a context and setting.

Diverse approaches to measuring consistency and demonstrating the rigour and trustworthiness of studies were observed during the literature review. Confirmatory factor analysis (CFA) is utilised to assess reliability and validity (Lee et al., 2013). Other studies utilised the first-generation multivariate method of multiple regression to evaluate the constructs and their relationships (Singh et al., 2017). The incumbent study utilised the Statistical Package for Social Sciences (SPSS) program to analyse data. It followed these techniques to improve the consistency as well as the external and internal validity of the research.

Key empirical results from previous similar studies show that culture affects technology infusion, with PU, PEU and AT having a significant positive effect towards the adoption of technological innovations (Lee et al., 2013; Singh et al., 2017; Porto, 2020). From the literature review, AT affects the adoption of technology (Porto, 2020). External factors such as organisational support (OS), computer self-efficacy (CSE), prior experience (PED) and task equivocality (TE) affect PU and PEU (Lee et al., 2013).

Some authors found that factors such as external and internal variables of the organisation have a positive correlation with behavioural intent to adopt technological innovation (Singh et al., 2017). Since BI seems to drive technology adoption, it is thus necessary (Mugodi & Fleming, 2003) for companies intending to introduce technological innovations to conduct groundwork in understanding the interventions required for successful adoption.

Key research findings from previous similar studies (Ali & Miraz, 2015) confirm that culture plays a major role in the adoption of technology. Organisational readiness and support could play a major role in the adoption of technology. Management support (Porto, 2020), management maturity level and investment in IT applications (Lee et al., 2013) were identified as additional factors in ensuring the successful adoption of technology. Based on these findings (Lee et al., 2013; Singh et al., 2017; Porto, 2020), about 40% of the variance in BI to adopt technology is still unexplained. This implies that research is required to identify possible factors that can further explain the acceptance of technology in adopting technological innovations.

Most previous similar studies documented a non-random sampling technique (Lee et al., 2013; Singh et al., 2017) and self-reported measurements (Lee et al., 2013) as limitations of the studies. In addition to the lack of randomised sampling, cross-cultural validation, more variables and the snapshot nature of the result, the results lack generalisation for the study (Lee et al., 2013). The implication is that the areas where research was conducted for technology adoption have different contexts and sampling procedures, paving a way for the incumbent study to research the apparent gaps.

In terms of the unstated limitations of previous similar studies, research was conducted by (Porto, 2020) on a target population that appeared to be conversant with the use of technology. The studies by (Lee et al., 2013; Singh et al., 2017; Porto, 2020) were conducted in different industries and countries.

2.3 Qualitative attributes or quantitative variables key to the research

Research work by Fishbein and Ajzen (1975) on the theory of reasoned action (TRA) and by Davis, Bagozzi, and Warshaw (1989) on TAM, provided the body of knowledge with key quantitative variables that are applicable in the framework for appropriate technology adoption models.

Davis (1989) suggests that PU and PEU are the two main variables that lead to the BI to adopt technology. In a literature review of the study concerned with explaining variables that cause people to accept or reject IT in field and lab settings, PU is described as "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989, p. 320). In a study on the theoretical extension of TAM to explain interrelated social forces influencing an individual to adopt or reject a new system, PU is described as "the extent to which a person believes that using the system will enhance his or her job performance" (Venkatesh & Davis, 2000, p. 187).

In an article about a study that examines factors that were believed to influence employees' acceptance of e-learning systems in an organisational setting, PU is further described as "the degree to which an individual believes that a particular system would enhance job performance within an organisational context" (Lee et al., 2013, p. 175). In an article about organisational culture influences on the adoption of technology, as well as AT and behaviour as predictors of the actual adoption of e-learning technologies in an educational setting, PU is described as "the degree to which a person believes that using a particular system would enhance his or her job performance" (Porto, 2020, p. 3).

Most authors describe PU in terms of one's belief in whether a system can enhance the performance of a job. Minor differences in the definitions are related to the context within which the perception is measured. An awareness

of the adopter's beliefs about the use of the system is crucial to managing the perceptions, thus, ensuring the success of a system.

In a journal explaining variables that cause people to accept or reject IT, PEU is described as "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989, p. 320). In another journal on the theoretical extension of TAM to explain interrelated social forces on an individual adopting or rejecting a new system in a setting spanning various industries, PEU is described as "the extent to which a person believes that using the system will be free of effort" (Venkatesh & Davis, 2000, p. 187).

From a study examining factors influencing employees' acceptance of e-learning systems in an organisational setting, PEU is described as "the degree to which an individual believes that using a particular system would be free of effort" (Lee et al., 2013, p. 175; Porto, 2020, p. 3). The authors' descriptions refer to the adopter's perception of the effortlessness of using a system. There seems to be no divergence in the description of PEU by the various authors. What can be inferred from the definitions is that the adopter is likely to increase the use of a system if he or she holds a belief that there is no effort required to use the system.

In an article concerning the theory of planned behaviour as a useful conceptual framework for explaining the complexities of human social behaviour, BI is described as "indications of how hard people are willing to try, of how much of an effort they are planning to exert, to perform the behaviour" (Ajzen, 1991, p. 181). In a book on the evaluation of TRA, BI is described as "a function of one's attitude toward performing the behaviour and one's SN related to performing the behaviour" (Hale, Householder, & Greene, 2002, p. 260).

Further, in a book about the development of an instrument designed to measure the various perceptions that an individual may have of adopting an IT innovation, BI is described as "a person's motivation in the sense of her or his conscious plan or decision to exert effort to perform the behaviour" (Conner & Sparks, 2020, p. 10). The definitions of BI commonly refer to a person's intentional act to display a certain behaviour. The differences in the definitions

are in whether the intention is from the person's willingness, attitude or motivation. Implied in the definitions is the need for identifying and understanding the drivers of a person's intention to perform the desired behaviour.

According to the TAM of Davis (1989), both PU and the additional variable, AT, determine the BI, which leads to actual use. User behaviour is directly influenced by AT and BI, which are two core psychological variables (Lee et al., 2013). AT is described as “the degree of a person’s positive or negative feelings about performing the target behaviour” (Lee et al., 2013, p. 4). Belief strength (the behavioural belief that performing the behaviour leads to some consequence) and belief evaluation are the determinants of AT. The implication from the preceding definitions is that BI emanates from the effect of both an individual influence and a normative influence.

2.4 Framework for interpreting research findings – established frameworks for technology acceptance

Numerous empirical and quantitative models involved in the adoption of technological innovations, with a specific focus on the cognitive behaviour models, are utilised to explain the variance in the use of technology (Lee et al., 2013; Miraz, Excell, & Ali, 2016; Singh et al., 2017; Porto, 2020). Without necessarily implying the list is exhaustive, the relevant model or theoretical framework to be used in this study is TAM (Davis, 1985). Figure 2.4.1 shows the original TAM.

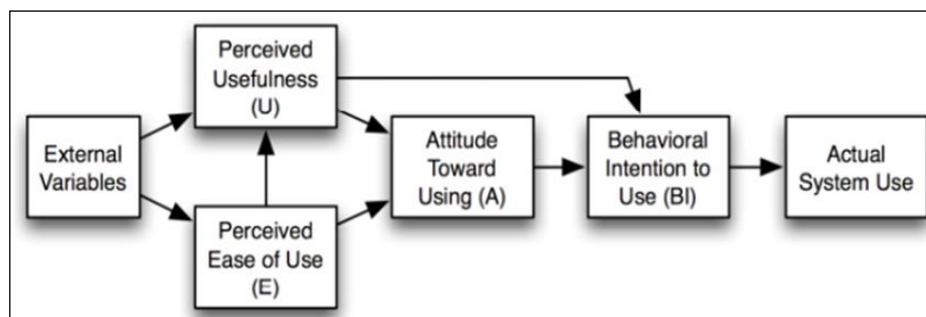


Figure 2.4.1 The original technology acceptance model (TAM)

Source: Singh et al. (2017)

According to Mugodi and Fleming (2003), the introduction of information systems and technology in organisations to improve work was the main event that led to the need to understand the factors that influence successful implementation and use. Several events that led to the development of TAM include the need to understand the factors that influence the successful development and implementation of computer-based systems (Davis, 1985), the diffusion of IT and what determines its adoption (Adams, Nelson, & Todd, 1992; Scherer, Siddiq, & Tondeur, 2019) and the need to measure and analyse user satisfaction (Legris, Ingham, & Colletette, 2003).

In sum, the introduction of information systems and technology as essential tools in organisations and the need to understand the criteria for their successful use presented the events that led to the development of TAM (Lane et al., 2015).

TAM was developed as an adaptation of TRA to establish the factors that help organisations understand an individual's behaviour towards the acceptance and use of computer-based systems (Fishbein & Ajzen, 1975). It is the basis for tracing how external factors impact internal beliefs, attitudes and intentions (Adams et al., 1992). It can be a guide for implementation and the use of new technology (Lucas Jr & Spitler, 1999), reasons for user acceptance or rejection of IT (Legris et al., 2003) or intended behaviour towards the actual use of technology (Scherer et al., 2019).

Further, TAM is seen as a tool to predict an individual's use and acceptance of information systems and technology (Sana'a, 2016). According to Davis et al. (1989), TRA forms a theoretical framework upon which TAM is developed (Davis et al., 1989). These authors also assert that TAM is used first by researchers to determine the factors that will influence the acceptance and use of new technology and second by organisations to develop strategies that will enhance the adoption of new technology.

Davis et al. (1989) point out that TAM describes the external variables that influence user behaviour. It describes motivational processes mediating the characteristics of the system and the behaviour of the user (Davis, 1985), a

set of external variables influencing intended use (Lucas Jr & Spitler, 1999), the acceptance of the information system by an individual (Y. Lee, Kozar, & Larsen, 2003) and explains the computer acceptance determinants that explain the behaviour of the user (Adams et al., 1992). The original TAM, proposed by Davis (1985), was developed to assess the effect of internal factors, namely, PEU, PU, and AT, towards the use of BI to use technology.

This model theorises that the BI of the user is the key predictor for using technology (Davis, 1985). The BI is itself determined by two variables, which are AT towards the use and PU. Davis (1985) further theorised that PEU and PU determine the AT towards the use, while PEU influences PU. According to Huang (2017), TAM has become one of the most widely used models in the adoption of technological innovations. In the main, TAM describes the external variables that influence the BI of the user (Renaud & Van Biljon, 2008).

The advantages or usefulness of TAM include providing valuable information for designers and implementers of new information systems and technology (Davis, 1985; Adams et al., 1992; Lucas Jr & Spitler, 1999). It is useful in predicting factors that facilitate the integration of information systems into business (Legris et al., 2003), easily transferable to various contexts and samples, has the potential to explain variance in the use of technology and is one of the influential models to determine the rate of adoption of information systems (Sana'a, 2016).

According to Davis (1985), TAM is advantageous in guiding the acceptance and adoption of new information systems and technology. The author further asserts that TAM provides input for designers to develop information systems and technology that will be easily accepted by users and valuable information for implementors to develop strategies that can enhance the rate of adoption of new information systems and technology.

TAM has its limitations in that the study context and setting could be different and the study was cross-sectional in design (Karahanna et al., 1999). The two constructs of TAM are likely to vary with time and experience for any given application (Adams et al., 1992). Another limitation is that TAM does not

account for social factors (Renaud & Van Biljon, 2008). In the main, the limitation of TAM is that the results are unlikely to be representative of most of the settings where information systems and technology are applied, as these settings might not be similar (Davis et al., 1989).

2.5 Summary and conclusion

2.5.1 Summary of literature reviewed

The mining industry in South Africa, like other industries, operates in a volatile and uncertain environment (Carr, 2020) which necessitates that organisations adapt their ways of operating through technological innovations that are likely to create efficient and sustainable business throughout the industry. It has a history of labour-intensive and conventional mining practices (Neingo & Tholana, 2016) which might require some effort to bring a mindset of technology adoption (Lane et al., 2015).

The literature review has revealed a declining production profile (Leeuw & Mtegha, 2016; Neingo & Tholana, 2016; Leeuw & Mtegha, 2018) consequent to difficult mining conditions that require a technology approach to continue mining efficiently and safely (Lane et al., 2015; Leeuw & Mtegha, 2018). More literature indicates some benefits of technological innovation in certain areas such as safety (Carr, 2020) but indicates that more work is required to unlock the potential yet to be realised by changing the culture of the mining industry to increase the pace of adoption (Cosbey et al., 2016; Rupprecht, 2016, 2017; Corrigan, 2019).

The literature review process has brought to light numerous studies conducted on the cultural influences on the adoption of technological innovations (Lee et al., 2013; Matthee et al., 2014; Singh et al., 2017; Porto, 2020). These empirical studies on cultural influences on technology adoption were conducted outside of South Africa and in different industries, which is a different setting to the one of the incumbent study. The literature indicates that past similar studies resulted in around 60 per cent of the variance being explained by the current models that were developed to assist in the adoption of technological innovations, with specific reference to cultural influences

(Davis, 1985). Moreover, the literature review of past similar studies has highlighted research gaps in ecological validity and external validity that are likely to be explored by the incumbent study (Singh et al., 2017).

Previous similar research has resulted in the proliferation of both qualitative attributes and quantitative variables that will assist the incumbent study to identify the possible cultural impact as well as the related behaviours that might be influencing the rate of adoption among the technology adopters in the South African mining industry (Rogers & Williams, 1983). The literature review identifies external and internal factors with variables and the constructs that were used to explain the BI to adopt and use technological innovation (Lee et al., 2013; Singh et al., 2017). The identified attributes and variables are clearly described using previous studies to explain the causal links (Davis, 1985, 1989).

In addition, the literature review process highlighted the established frameworks that are useful for interpreting culture and technology acceptance (Lee et al., 2013; Singh et al., 2017; Porto, 2020). Most of these frameworks focus on cognitive behaviour and internal factors and are utilised to explain the variance in the use of technology (Davis, 1985, 1989). From the literature review process, the process through which technology permeates among the adopters is outlined and was useful for the incumbent study (Rogers, 2003). According to the literature review of past similar studies, a widely used system in the permeation process follows the categorisation of adopters of technology that informs strategies to be followed in influencing the adoption rate of technological innovations (Ali & Miraz, 2015; Miraz et al., 2016).

2.5.2 Proposed research strategy, design, procedure and methods arising from the literature review

This research applies information obtained from previous similar research on the acceptance of technology and the adoption of technological innovations (Lee et al., 2013; Singh et al., 2017; Porto, 2020). Similar research employed a quantitative research approach to study the cultural effects on technological innovations. Following the literature review on previous similar empirical

research, numerous researchers used this strategy in their studies (Lee et al., 2013; Singh et al., 2017; Porto, 2020).

The literature review pointed to a research design that employed descriptive statistics from previous similar studies (Hernández-Mogollon, Cepeda-Carrión, Cegarra-Navarro, & Leal-Millán, 2010). The SPSS was used as the software to compute descriptive and inferential statistics from the data collected for the study. These previous similar studies conducted structure equation modelling (SEM) to test research hypotheses (Lee et al., 2013).

Previous similar studies (Singh et al., 2017; Porto, 2020) involved the distribution of survey questionnaires to the target population. The 'culture barriers' scale and proper items of this construct were identified from the literature review.

Most of the previous similar studies consisted of survey questionnaires adapted from previous similar research on cross-cultural aspects of technology diffusion and adoption trends (Lee et al., 2013; Singh et al., 2017; Porto, 2020) as well as a technology acceptance questionnaire from Davis (1989), among others. The surveys for these were distributed through the web, focus groups, one-to-one, structured and unstructured interviews to the targeted population using measurements on a 5-point Likert scale (Lee et al., 2013; Singh et al., 2017). The measures consisted of a total of ten variables that were mostly adjusted from studies (Lee et al., 2013).

For reliability and validity assessment, previous similar studies made use of a first-generation multivariate method of multiple regressions used by Singh et al. (2017). For ethical considerations, most studies ensured that a letter of consent accompanied the survey instrument that was sent to the respondents requesting their voluntary participation in the research.

This study draws on the factors identified from the literature review to determine whether these factors are important in the BI to adopt mining technology in the South African mining industry. The identified factors include PU, PEU, relative AT, perceived reduced cost (PRC), perceived improved safety (PIS) and perceived threat to job security (PTJS). From the literature

review, these factors stand out as key to ensuring the future of the South African mining industry. This implies that the rate at which mining technology is adopted in the South African mining industry is likely to be influenced by how the adopters relate to these factors. Figure 2.5.2.1 is a diagrammatic representation of the potential influence of the identified factors on BIs regarding the adoption of mining technology in the South African mining industry.

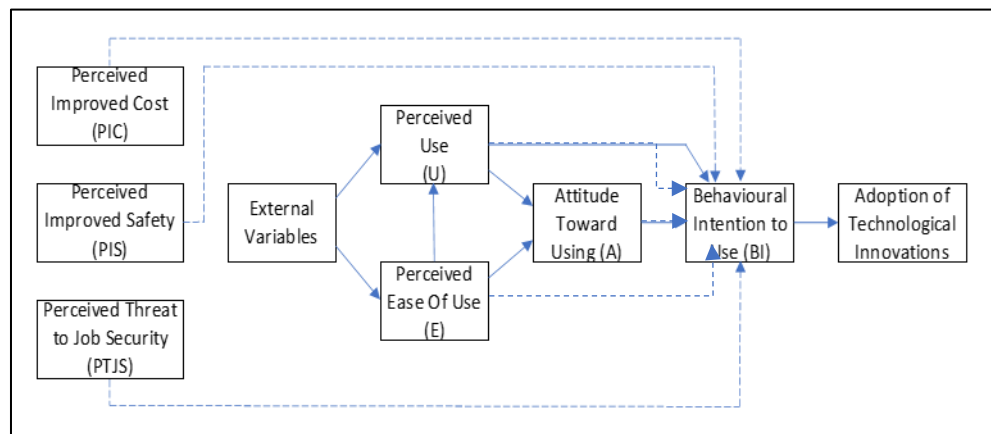


Figure 2.5.2.1 The proposed technology acceptance model

In Figure 2.5.2.1, the factors are connected to the BI to show the hypothesised proposed model for mining technology acceptance in the South African mining industry. The dotted lines represent the hypothesised TAM. The solid lines represent the existing TAM (Singh et al., 2017) used to represent technology adoption.

This study explores the hypothesised links to determine the relationships between the identified factors and the BI to adopt mining technology in the South African mining industry. The literature review conducted for this study forms the basis of the proposed TAM, hypothesised to be influential in increasing the rate of mining technology adoption in the South African mining industry. The literature review highlighted the need for technological interventions to ensure the sustainability of the mining industry in South Africa (Cosbey et al., 2016; Rupprecht, 2016, 2017; Corrigan, 2019).

3 RESEARCH STRATEGY, DESIGN, PROCEDURE AND METHODS

Section 1.4.3 posed the three questions that this research report intends to answer: 'Do perceptions of technological innovations as having the potential to reduce cost inform the adoption of technology in the South African mining industry?', 'Do perceptions of technological innovations as having the potential to improve safety determine the behavioural intention to adopt technology in the South African mining industry?' and 'Do perceptions of technological innovations as being a threat to job security determine the behavioural intention to adopt technology in the South African mining industry?'. The reviewed literature and the developed interpretative, as well as conceptual, framework guided the choice of techniques that were utilised.

This chapter identifies and describes the research approach and design, as well as the procedure and methods that were employed by this research to collect, process and analyse empirical evidence. Broadly, it has the following objectives: to identify and describe the research strategy (Section 3.1), the research design (Section 3.2), the procedure and methods (Section 3.3), the research data and information processing and analysis (Section 3.4). The chapter also describes the reliability and validity measures that this research applied to make it credible (Section 3.5) as well as the technical and administrative limitations of the choices made (Section 3.6).

3.1 Research strategy

A research strategy is about providing the main outline defining the researcher's approach to the advancement of knowledge. From the main research strategies – qualitative, quantitative and mixed methods – and informed by previous similar research, this study adopted a quantitative strategy.

The quantitative strategy entails the primary use of previous positivist claims for developing knowledge and also employs data collection to produce

statistical data for analysis (Roberts & Priest, 2006). It involves the utilisation and analysis of numerical data using specific statistical techniques to answer research questions and test hypotheses (Apuke, 2017). The incumbent study adopted this strategy to test the research hypotheses, as well as to determine and describe the characteristics of the variables of importance for this research.

From the literature review of past similar research, Porto (2020) employed a quantitative research strategy in a study that involved determining the relationship between organisational culture and technology acceptance in technology infusion for a university setting. This strategy was selected to determine and describe the characteristics of the variables of importance in a setting. In Porto's research, the hypotheses were successfully tested and inferences were made from the results. Similarly, the incumbent study took this approach and benefitted from it.

3.2 Research design

Research design can be described as the development of a plan or structure for conducting a study that reduces bias, distortion and random error (Kumar, 2019). It fundamentally outlines the way a researcher collects data. It can be defined as "a framework or blueprint for a business research project in an efficient manner" (Sreejesh, Anusree, & Mohapatra, 2013, p. 27).

Several comprehensive classifications of research designs entail cross-sectional, longitudinal, case study, comparative and experimental designs. From the literature review, numerous previous similar empirical research used a cross-sectional research design. The incumbent research, therefore, utilised a cross-sectional research design to conduct this study.

This research design entails the use of a survey methodology to provide data at one point in time and is best suited to finding out the prevalence by taking a cross-section of the population (Kumar, 2019). It is employed under time and resource constraints to provide a snapshot of a situation.

In empirical research, to determine the factors that influence human behaviours towards the adoption of technology, Lee et al. (2013) and Singh et al. (2017) utilised a cross-sectional research design. These authors elected to use this design due to the lack of a reliable sampling frame and time. However, it provided them with a snapshot of human perceptions and intentions to use technology. The benefit of a cross-sectional design to the incumbent study is that it measures the perceptions and intentions to use technology towards the introduction of new working practices as this is the challenge currently faced by the industry. It was also a suitable design for the constrained conditions under which the incumbent study was conducted.

The study employed the cross-sectional research design to achieve the research objective of determining the possible factors that can explain the variance in the acceptance of technology and influence the adoption rate of technological innovations. According to Spector (2019), a cross-sectional design is suitable to determine if the variables of interest are related and assists in ruling out a myriad of potential alternative explanations for why two variables are related.

The variables that the study explored are perceived BI to use technology, PU of technology, PEU of technology, AT towards using technology, perceived potential of technology to improve safety (PIS), perceived potential of technology to reduce cost (PRC) of mining and perceived potential of technology as a threat to job security (PTJS).

3.3 Research procedure and methods

This section documents the actual procedure and methods employed in this research to collect, collate, process and analyse empirical evidence. Broadly, it details the data and information collection instruments (Section 3.3.1), the research instrument (Section 3.3.2), the measurement scales (Section 3.3.3) the target population and sampling of respondents (Section 3.3.4), the ethical considerations during the research process (Section 3.3.5 and the data and information collection process and storage (Section 3.3.6).

3.3.1 Research data and information collection instruments

A research data collection instrument is a means, in the form of a questionnaire, a researcher uses to collect data that will be used to answer the research questions established to address the research problem (Bryman, 2016). Some of the instrument types used by researchers include observation schedules and interview schedules.

Based on similar past empirical research conducted by various researchers, this study used a questionnaire to collect data. A questionnaire entails posing questions that will be answered by respondents to shed light on and answer one or more research questions (Kumar, 2019). This study employed this instrument type because it is inexpensive to administer, needs very little or no training to develop and can be easily and quickly analysed once completed.

A research data collection instrument structure happens when research instruments are designed to implement what is being studied, after the process of establishing a general form of what the study is attempting to find out. Such structures include a structured interview, unstructured interview, semi-structured interview and fully structured interview.

Structured observation entails an approach that uses pre-prepared questionnaires where the same questions are posed to all respondents (Kumar, 2019). The decision to commit to this structure was to create conditions for minimal interaction with respondents and keep questions standard.

From the literature review, a journal article by Porto (2020), in a cross-sectional study to determine the relationship between organisational culture and technology acceptance in technology infusion in a university setting, captures the application of a standardised questionnaire. This procedure resulted in all the respondents answering the same questions with minimal interaction with the researcher. For the incumbent study, the structured interview revealed what factors influence the adopters in a South African mining industry setting with its unique historical background.

The incumbent study sourced the questions from various previous similar research conducted by, among others, Lee et al. (2013), Porto (2020) and Singh et al. (2017). Obtaining questions from previous similar research was planned to assist the study to create questions suitable for the study, as well as contribute towards the content validity of the study.

The previous similar studies included mostly participants who were likely to be conversant with and knowledgeable about the use of technology. Sampling techniques from most of these previous studies were not randomised and convenience sampling was predominantly employed (Lee et al., 2013; Singh et al., 2017; Porto, 2020). However, some studies employed probability sampling to choose the respondents (Porto, 2020). Such a non-randomised technique could have potentially resulted in results being unreliable, implying that different results can be produced if a different sampling technique is employed. The setting of the incumbent study entails a legacy of labour-intensive conventional systems and different mindsets, which could lead to different results for the study.

3.3.2 Research instrument

The survey instrument for exploring the six research hypotheses used a 5-point Likert scale as the measurement scale to ascertain the participants' collective BI towards accepting technology and increasing the adoption rate of technological innovations. The questionnaires used for the study were mostly an adaptation from previous similar studies (Lee et al., 2013; Singh et al., 2017; Porto, 2020).

Most studies go through a process of approval, addressing ethical considerations and clearly explaining the purpose of the study to ensure the process of data gathering is accurate. The questionnaire was distributed to 576 participants over 3 weeks, to achieve a minimum of 325 responses. The actual number of responses achieved was 310, yielding a response rate of 53,8 per cent. These results are summarised in Table 3.3.2.1.

Table 3.3.2.1 Summary of the survey responses

Items	Social	Email	Total
Surveys administered	400	176	576
Number of responses	243	67	310
Percentage contribution	61%	38%	100%

The response rate of 310 participants represents 95.4 per cent of the study target of 325 responses, the details of which are discussed later in the data sample section. Both cases compare favourably with most similar studies encountered in the literature.

3.3.3 Measurement scales

For the incumbent research, the questionnaire items were categorised as an interval scale to allow for the items to be combined to generate a composite score, as affirmed by Joshi, Kale, Chandel, and Pal (2015). The responses were assigned the numerical codes 1, 2, 3, 4 and 5 as they are comparable across different questions (Joshi et al., 2015). Literature on previous similar research was the main source of multi-item measurement scales such as for BI, PU, PEU and AT. These were adapted from previous similar research (Appendix 1.1). Adapting constructs from previous research served as the validation of items for the study.

The measurement scales for the PIS, PRC and PTJS were validated using literature on technological innovation. First, Rogers (2010a) theorised that potential users will generally consider technological innovation further if there is a perceived relative advantage in the innovation. All three variables of interest, PIS, PRC and PTJS, seem to represent potential relative advantages/disadvantages likely to be offered by technological innovations for South Africa's mining industry.

Second, Kline and Rosenberg (2010) theorised that successful innovation requires balancing the need to maintain an organisation that can continue to support all its activities effectively. Essentially, for the mining industry in South Africa, these include safe operations, cost-effectiveness and creating much-needed jobs for societies. Kline and Rosenberg (2010) definition that successful technological innovation is a simultaneous coupling of technical and economic factors that bring substantial benefits to consumer needs and desires was key in developing the multi-item scales on the constructs, including improved safety, improved costs and threat to job security.

Lastly, in the interest of ecological validity, the target sample was carefully selected to form equitable representation by taking into consideration the role of each participant category in the sample and the environmental setting. For example, the equipment operator category makes up a larger sample size due to their relatively higher involvement with technological innovation and, therefore, they form a larger sample (61,5 per cent) for the study.

The participants were selected from the mining companies in South Africa. These included more than ten mining companies, technology companies and the South African Department of Mineral Resources (DMR) inspectors. The preceding procedure was followed to ensure ecological validity and improve the generalisability of the study. This procedure was also followed by a recommendation by Brunswik (1943) who recommended that studies should consider “situations of the investigation and replace proper sampling of participants with a representative sampling of situations or tasks” to ensure the ecological validity of a study.

It is worth noting that the study used self-reported measurement, implying that there could potentially be differences between the participants' responses and their actual actions. To improve result reliability, the study employed a tactic of ensuring the multi-item scale consisted of a balance of both positive and negative items to minimise the bias in responses. The TAM scales of PU, PEU and BI were measured using items adapted from Davis (1989) and Davis et al. (1989).

3.3.4 Research target population and selection of respondents

3.3.4.1 Research target population

A target population can be described as a group of subjects identified to take part in a study. The research target population entails first-line supervisors involved in production, professional office employees working in business improvements and technology as well as managers.

The instrument was distributed to senior executives, senior and middle management as well as equipment operators as planned. The sample sites spanned a range of companies, organisational contexts and functional areas as the study sought to utilise a representative sample which would improve the generalisability of the results. The literature review provided the theoretical foundation from which the information that was used to generate the initial set of items for the incumbent research was sourced. This was in line with the plan to ensure the content validity of the scales as contemplated in an article by Hinkin (1998), among others.

The actual questionnaire measured user perceptions of technological innovation's impact on costs, safety and job security using a 5-item scale. This study's theoretical model posits that the perceptions, such as costs, safety and job security, of technological innovations as giving relative advantage on key aspects of the business determine the BI to adopt the technology. A questionnaire was administered to South African mine technology users across job categories at different companies through various distribution channels.

The literature review revealed that Matthee et al. (2014) had conducted a case study research to gain an understanding of e-learning adoption in the mining industry and selected the target population to consider different perceptions. That study obtained information from diversified sections of the organisation. This approach benefitted the incumbent study to gain a wider perspective of the variables of interest.

3.3.4.2 Sampling or selecting respondents from the target population

Sampling is the process of selecting a subset of the population (Kumar, 2019) so that a representative of the larger population can be used to conduct research. Some of the sampling techniques encountered during the literature review included random, purposive, quota, convenience and snowball sampling (Kumar, 2019).

Based on the literature review of previous similar empirical research, such as that of Singh et al. (2017), this study planned to utilise random sampling, in particular stratified random sampling, to collect information. According to Gray (2013), stratified random sampling entails the selection of a sample from various subgroups of the population with an equal chance of being a selected member. This method of sampling increases the chances of a sample being representative (Gray, 2013).

From the literature review of past similar research, a journal by Hernández-Mogollon et al. (2010) about a study of cultural barriers and how they relate to open-mindedness and organisational innovation in 133 small and medium-sized enterprises revealed that random sampling was selected as the population was relatively similar concerning operating conditions and would participate fairly on research questions that were pursued. This study employed a similar method to collect data from participants who were expected to engage with technology in the mining industry of South Africa. The target population was relatively homogenous concerning participating in the research questions being pursued, a move planned to improve the generalisability of the results of this study.

3.3.5 Ethical considerations when collecting research data

Ethics in research deals with how appropriately the research is conducted and the behaviour of the researcher relative to the research subjects (Bryman, 2016). Concerning ethical considerations for the incumbent research, the survey instrument was accompanied by a consent form which outlined the purpose of the research and gave a commitment to ensuring the protection and anonymity of the respondents. Previous similar research is characterised

by a letter of consent that accompanies the survey to request voluntary participation (Porto, 2020). Other studies prefer to work through a central point such as a human resources department (Lee et al., 2013).

The incumbent study followed these established best practices for the research to ensure ethical considerations. To assure participants, the instrument contained the contact numbers where participants could call in and raise any concerns about their rights.

3.3.6 Research data and information collection process

Research data collection refers to the gathering of data from the sample of the target population to answer the research questions (Bryman, 2016). Some of the commonly used modes for the delivery and collection of research questionnaires include participant observation or ethnography, interviews (face-to-face, telephone or internet-based), focus group discussion and documents.

Numerical data was collected to pave the way for the subsequent utilisation of specific statistical techniques to answer the research questions and test the hypothesised model. This section deals with an account of how the research was conducted to achieve the objectives of the study and add to the body of knowledge.

The distribution targeted participants from mining companies in South Africa. The research tool was distributed through social media and emails to the target sample which included equipment operators, managers and senior executives in South African mining companies. This was done by pinpointing the participants through company email distribution lists, LinkedIn and WhatsApp groups.

Previous similar studies collected data through questionnaires mostly on 5-point Likert scales (Lee et al., 2013; Singh et al., 2017; Porto, 2020). The surveys were distributed to the target population via electronic means, mostly web-based and by mail. Data must then undergo refinement to ensure correctness before analysis takes place. The incentivised respondent

approach adopted by Lee et al. (2013) was quite a unique and differentiating approach that likely resulted in encouraging participation in the survey. Looking at the scale of the research and the practicality of reaching the target population, distribution through electronic means became the suitable option for the incumbent study. This study aligned with a 5-point Likert scale adopted by similar studies to make it easier to compare the study results.

A journal article by Lee et al. (2013) about employees' adoption of technology, in research aimed at examining the factors that influence employees' use of e-learning systems, demonstrated the application of internet-based questionnaires as a mode of data collection in similar research to reach significant parts of the targeted population for a reliable sample. Similarly, the incumbent research benefitted from this mode as it made it easier to collect data for the study.

From 171 emails that were administered to the target sample, only 67 responses were received, which shows a yield of 39.2 per cent. This appears to compare favourably with many mail surveys reported in the literature. It was difficult to reach the operator category through emails, hence social media platforms, particularly WhatsApp, were the best means to solicit responses from this group of participants. For this group of participants, the study relied on referrals, which partly explains the high number of responses from the anonymous link.

Ultimately, through social media and anonymous links, a total of 243 responses were received from 400 surveys that were administered for the study. This translates into a 60.8 per cent response rate from social media. Due to the strict control measures to curb the COVID-19 pandemic, the planned face-to-face interviews through a facilitated process utilising clickers for collecting data could not be carried out. The expectation for the study was that this procedure would have increased the chance of higher participation in the operator category of the target audience. Nevertheless, social media was used as the main channel to distribute the survey. Frontline supervisors were utilised to assist in making sure the survey link reached as many participants

as possible through work WhatsApp groups. The resulting questionnaire item is included in Appendix 1.1.

The storage of raw data was protected to ensure that the responses and confidentiality of identity were strictly safeguarded. Data storage means such as 'cloud storage' and a portable drive, with passwords created to restrict access, were utilised.

3.4 Research data and information processing and analysis

This section broadly deals with the actual procedure and the methods employed in this study to process the research data and information (Section 3.4.1), analyse the research data and information (Section 3.4.2) and describe the research respondents (Section 3.4.3).

3.4.1 Research data and information processing

Data coding is concerned with describing data by allocating a number to it, enabling the grouping of data into categories (Kumar, 2019). As seen in Lee et al. (2013), this study operationalised data coding by separating data into different measurement categories. Data entry into the computer entailed 'cleaning' the data, planning and implementing the actual input of the data and dealing with missing data. To deal with missing data, the study excluded incomplete responses, as seen from the literature review of past empirical research conducted by Karahanna et al. (1999) and Lee et al. (2013) in similar studies.

Data cleaning deals with accurately entering data into a computer. For the incumbent study, the survey was refined and protected from manipulation and tedious responses by applying the procedure followed by Singh et al. (2017) in similar past research.

3.4.2 Research data and information analysis

This section deals with how the variables of interest were quantified and analysed to get the research results. The research data and information analysis entail the management and interpretation of the data, as well as the

application of statistical techniques applied to the collected data to derive or infer meaning (Bryman, 2016). This study utilised descriptive statistics, regression analysis and inferential statistics. From the literature review, several past similar empirical studies utilised descriptive statistics and regression analysis. This study utilised all three methods: descriptive statistics, regression analysis and inferential statistics.

Descriptive statistics uses graphical analysis to describe the basic features of a study by providing the potential for the communication of data through the creation of a summary picture of a population in terms of key variables in the research (Leedy & Ormrod, 2014).

Inferential statistics entails formulating the research hypotheses, specifying the significance level, identifying the probability distribution, defining the region of rejection, selecting appropriate statistical tests, calculating the test statistic and accepting or rejecting the hypotheses. For inferential statistics, this study utilised correlation and linear regression for the analysis.

In a journal article (Porto, 2020) which involved determining the relationship between organisational culture and technology acceptance in technology infusion in a university setting, descriptive and inferential statistics were used to analyse the research data. This design was selected to determine and describe the characteristics, i.e. relationships and associations, of the variables of importance in a setting. In that research, the characteristics of the variables, as well as the relationship between relevant variables, were determined and discussed. Similarly, this approach benefitted the incumbent study to identify the characteristics of the relevant variables and the associations between them.

The relationship between the variables and BI for this study was examined utilising first-generation multiple regression, adopted from research statistical methods used by Singh et al. (2017) and Stevens (2012) to evaluate the constructs and the relationships between individual constructs.

From the 310 responses received, the final sample for the study was 299 after dropping several observations because of missing data. Where possible, the

individual participants were contacted directly or through their supervisors to provide information on the job category. The results show that there was a lack of responses mostly from senior executives, the technology department and operator categories, all accounting for the shortfall in the actual sample size obtained for the study. The results are summarised in Table 3.4.2.1. However, the yields compare favourably with most of the yields from previous similar research conducted by Karahanna et al. (1999). Another sample characteristic required by this study was age range; the age demographic was given a range to make participants comfortable to indicate their age. The results are also summarised in Table 3.4.2.1.

Table 3.4.2.1 Summary of population age range characteristic

Participant	Age range	Responses	Target	% yield	% of sample
Senior staff	40–55	17	30	56,7	5,7
Technology	40–50	25	45	55,6	8,4
Manager	35–50	124	50	248,0	41,5
Operator	30–55	120	200	60,0	40,1
Other		13	0		4,3
Total		299	325	92,0	100

When the sample was categorised according to the required age range, senior executives showed 17 out of the expected 30 responses with a yield of 56.7 per cent; the technology department showed 25 out of the required 45 responses with a yield of 55,6 per cent ; the management category showed 124 out of required 50 responses with a yield of 248.0 per cent; the operator category showed 120 out of required 200 responses with a yield of 60.0 per cent. The results of this exercise produced a total sample size of 299 against the planned 325 responses, showing a response rate of 92.0 per cent. This

outcome compared favourably with a similar study conducted by Karahanna et al. (1999) which had a sample size of 230 responses.

3.4.3 Description of the research respondents

The incumbent study derived data from both male and female research respondents, with an age range from 30 to 55 years old. The research respondents included 30 senior management personnel with an age range from 40 to 55 years, 45 personnel from the technology portfolio with an age range between 40 and 50, 50 managers at the middle level aged between 35 and 50 years, two hundred equipment operators aged between 30 and 55 years. The research focused on respondents that had more than 3 years of working experience.

According to Ali and Miraz (2015) taking the characteristics of the target population into account enhances the effective adoption of innovation. The study focused on encouraging participation in the equipment operator category. The study achieved this by utilising social networks and prominent individuals.

3.5 Research strengths – reliability and validity measures applied

This section deals with the procedure followed to ensure the research strengths, measured by reliability and validity. Broadly explained, reliability and validity generally describe ways of indicating and interacting with the rigour of the research process and the dependability of research findings (Maher, Hadfield, Hutchings, & de Eyto, 2018). These are important to ensure that those reading the research are not misled by its contents.

According to Leedy and Ormrod (2014), reliability and validity influence the extent to which a phenomenon can be learned through a study, the probability of data analysis obtaining statistical significance and the extent to which meaningful conclusions can be drawn from the data. Research reliability is an indication of a study producing consistent results even if the same instrument was applied in two instances of the same instrument being overseen by two different individuals (Leedy & Ormrod, 2014). To ensure the reliability of the

results, the incumbent study made use of the instruments used in past similar research.

The study instrument was subjected to relevant tests to determine its reliability. The results of the reliability tests produced Cronbach's alpha @.801 for the instrument reliability, as indicated in Table 1.2.1 in Appendix 1.2. The highest value of Cronbach's alpha if an item was deleted was @.805, as indicated in Table 1.2.2 from Appendix 1.2. No item was deleted from the scale, as the study's Cronbach's alpha was considered satisfactory @.801. Appendix 1.2 shows the tables produced by SPSS which were used to analyse the instrument for reliability.

In a journal article by Lee et al. (2013) about employees' adoption of technology in research aimed at examining the factors that influence employees' use of e-learning systems, the authors used questionnaires from previous similar studies to ensure the instruments measured what the study claimed, resulting in their study reaching satisfactory levels of reliability and validity. The incumbent research employed this strategy as one of its approaches to improve its reliability.

Research validity refers to making sure that the questions contained in a research instrument measure what a study intends to measure (Leedy & Ormrod, 2014). At its basic level, and since this study is quantitative, validity refers to measurement validity, internal validity, external validity and ecological validity.

Since this research employed a quantitative strategy, several applicable validity measures were applied. First, measurement validity, which entails accurately naming and manipulating research studies, was achieved by obtaining data from previous similar empirical studies and making relevant adjustments to the data to suit the incumbent study.

Second, internal validity, which entails the cause-and-effect relationship between variables of interest, as well as the extent to which causal inferences can be drawn, was achieved by putting measures in place to prevent participants from reassigning themselves, making sure the selection of groups

was representative, as well as conducting checks through multiple regression, particularly Cronbach's alpha coefficient, to determine reliability.

Third, external validity, which entails the extent to which the results of a study can be generalised from the data to a larger population or setting, was achieved by conducting random sampling, in particular, the stratified random sampling technique. Also, the data was collected from multiple companies within the mining industry.

Lastly, ecological validity, which refers to the relationship between real-life phenomena and the study of these phenomena in experimental settings, was addressed for this study. It involves "maintaining the integrity of the real-life situation in the experimental context while remaining faithful to the larger social and cultural context" (Schmuckler, 2001, p. 421). This research achieved ecological validity by conducting the study within the environment where the phenomena of concern were being measured.

In a journal article by Hernández-Mogollon et al. (2010) – revealed in the literature review – on the role of cultural barriers in the relationship between open-mindedness and organisational innovation, their research utilised measurement validity described above for the reasons of making accurate inferences. For content validity, this study utilised previous similar studies to ensure the elements of the assessment instrument were relevant to and representative of the targeted construct for this study. According to the journal by Hernández-Mogollon et al. (2010), a definitive sample produced from valid questionnaires and multiple regression resulted in a favourable Cronbach's alpha coefficient, indicating satisfactory internal validity.

Validity

The accuracy of the measurement scale for the study was tested by determining both convergent validity and discriminant validity in SPSS.

Construct validity

Construct validity and discriminant validity of SEM were determined using the correlation matrix approach to test how close the indicator variables measured the latent variables and how many latent variables deviated from each other. The within-factor correlations were found to be significantly different than zero, hence convergent validity was supported for the study, indicating that the items measure the construct. All the p-values, other than the p-value for PEU, were .000, while the p-value for PEU was found to be .037.

Factor analysis statistics are summarised in Table 1.3.1 of Appendix 1.3, which shows that the Kaiser-Meyer-Olkin measure of sampling adequacy (KMO) was found to be highly statistically significant @ .815, which shows the sample size was adequate for the study.

The standardised loadings, composite reliability and average variance extracted are summarised in Table 3.5.1 and were used to estimate the convergent validity of the scale items (Fornell & Larcker, 1981). All the items of the seven constructs were analysed in SPSS to determine the values against the minimum criteria.

Table 3.5.1 Convergent validity

Constructs/ Factors	Indicators	Standardised loadings (>0.5)	Composite reliability (>0.7)	Average variance extracted (>0.5)
Behavioural intention (BI)	BI	1,000	0,862	0,682
	BI.0	0,755		
	BI.1	0,690		
Perceived use (PU)	PU	1,000	0,825	0,443
	PU.0	0,705		
	PU.1	0,589		
	PU.2	0,609		

Constructs/ Factors	Indicators	Standardised loadings (>0.5)	Composite reliability (>0.7)	Average variance extracted (>0.5)
Perceived ease of use (PEU)	PEU	1,000	0,750	0,625
	PEU.0	0,499		
Attitude (AT)	AT	1,000	0,790	0,668
	AT.0	0,579		
Perceived improved safety (PIS)	PIS	1,000	0,830	0,718
	PIS.0	0,66		
Perceived reduced cost (PRC)	PRC	1,000	0,770	0,646
	PRC.0	0,540		
Perceived threat to job security (PTJS)	PTJS	1,000	0,892	0,737
	PTJS.0	0,801		
	PTJS.1	0,754		

The constructs of PU, PEU, AT, PIS and PRC had one item each dropped due to their standardised loadings being less than the minimum threshold of 0.50. The results show the composite reliabilities and average variance-extracted values for all constructs, other than the average variance-extracted value for the PEU construct, which exceeded the minimum recommended loading criteria of 0.70 and 0.50, respectively (Fornell & Larcker, 1981). However, this study considered the average variance-extracted value for PEU to be acceptable, as previous similar studies found the value of average variance-extracted below 0.50 to be useful (Jiang, Klein, & Carr, 2002). Therefore, this test confirmed the convergent validity of the study.

Discriminant validity

To determine discriminant validity, the correlation matrix in Table 1.3.1 in Appendix 1.3 was examined to compare factor item loadings with item loadings of other factors. The item correlation values of PU, PEU, PIS and PRC were observed to be lower when compared with correlations with items of other constructs. This meant that a violation of discriminant validity had occurred. The number of potential comparisons was 436, while the number of total violations was 31. However, when applying the procedure recommended by Campbell and Fiske (1959), discriminant validity was supported. This procedure requires that the number of violations should be less than 50 per cent of the potential number of comparisons. In this case, 50 per cent of potential comparisons translates to 218 (0.5×436), which is greater than 31.

Discriminant validity was further tested by comparing the correlations between factors with the average variance extracted from the individual factors (Fornell & Larcker, 1981).

The results, as summarised in Table 3.5.2, indicated that the correlations between factors were less than the average variance extracted from the individual factors, when comparing both horizontally and vertically, confirming that the study's discriminant validity was supported.

Table 3.5.2 Discriminant validity

Construct	BI	PU	PEU	AT	PIS	PRC	PTJS
BI	0,826						
PU	0,045	0,666					
PEU	0,011	0,228	0,790				
AT	0,027	0,087	0,422	0,817			
PIS	0,005	0,509	0,332	0,213	0,847		
PRC	0,033	0,401	0,297	0,283	0,455	0,804	
PTJS	-0,042	0,080	0,133	0,310	0,157	0,250	0,858

3.6 Research weaknesses – technical and administrative limitations

Quantitative research strategy has several sources of technical limitations which include the complexity of multivariate research methods, multivariate normality, large sample sizes dictated by this strategy and difficulty in understanding and interpreting the results (Benbasat, Goldstein, & Mead, 1987). This might make it difficult to get participation from companies, given the current pressures of recovering from production slowdown potentially affecting the sample size. There was insufficient time to pilot test the instruments and administration procedures for validation. CFA could not be done for this study due to logistical constraints created by the imposed COVID-19 restrictions.

4 PRESENTATION OF RESEARCH RESULTS

This research study investigated the cultural factors that could explain the adoption of technology for the mining industry in South Africa. It proposed a model which was tested through seven research questions and hypotheses, which concerned BI, PEU, AT, safety, mining costs and job security.

The presentation of the empirical research results showed how BI to use technology is affected by PEU, AT, PRC, PIS and PTJS in the South African mining industry. This research then determined if these possible factors could explain the variance in the adoption of technological innovations for South Africa's mining industry. It attempted to determine, through three research questions, the cultural factors that could increase the explanatory power of the current technology acceptance models and reduce the unexplained variance in the BI to adopt technology.

Data in Table 4.1 show the linear regression of the study variables to the adoption of technology.

Table 4.1 Summary of individual predictors with their p-values

Coefficients					
Model	Unstandardised Coefficients		Standardised Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	4.203	.381		11.022	.000
Mean PU	.062	.085	.051	.737	.462
Mean PEU	-.010	.067	-.010	-.149	.882
Mean AT	.033	.051	.043	.640	.522
Mean PIS	-.029	.067	-.032	-.440	.660
Mean PRC	.029	.063	.033	.465	.642
Mean PTJS	-.030	.031	-.062	-.986	.325

a. Dependent Variable: Mean BI

The data reveal that all six endogenous variables tested in the model are not significant in explaining, with PU ($\beta = 0.051$, $p > 0.05$), PEU ($\beta = - 0.020$, $p > 0.05$), AT ($\beta = 0.043$, $p > 0.05$), PIS ($\beta = - 0.032$, $p > 0.05$), PRC ($\beta = 0.033$, $p > 0.05$) and PTJS ($\beta = - 0.062$, $p > 0.05$).

4.1 Perceived use does not inform the behavioural intention to adopt technological innovation in the South African mining industry

The first research question seeks to determine whether PU informs the BI to adopt technological innovation in the South African mining industry.

The outcome of the study shown in Table 4.1 indicates that PU is not important in determining BI to adopt mining technology in the South African mining industry. According to the results of this study, the link between PU and BI is positive and weak with a 0.051 coefficient, which is insignificant at a 0.462 significance level.

This implies that there is no sufficient evidence to suggest that PU is significant in determining the BI to adopt mining technology in the South African industry. The result indicates that there is no sufficient evidence to support the research hypothesis. The null hypothesis is therefore supported for this study.

4.2 Perceived ease of use does not inform the behavioural intention to adopt technological innovation in the South African mining industry

The second research question seeks to determine whether PEU is important in determining the BI to adopt technology in the South African mining industry.

This study established that PEU is not significant in determining the BI to adopt mining technology in the South African industry. The multiple regression analysis results in Table 4.1 established that there is a weak negative link between PEU and BI with a -0.010 coefficient, which is insignificant at a 0.882 significance level. The result implies that there is no sufficient evidence to support the research hypothesis. Therefore, the null hypothesis is supported.

4.3 Relative attitude does not inform the behavioural intention to adopt technological innovation in the South African mining industry

The third research question is concerned with determining whether relative AT is important in determining the BI to adopt technology.

Similarly to the outcome of the first two variables, AT was found not to be significant in determining the BI to adopt mining technology in the South African mining industry. Multiple regression results show that there is a positive and weak link between AT and BI with a.043 coefficient, which is insignificant at a.522 significance level.

The results shown in Table 4.1 indicate that there is no sufficient evidence to support the research hypothesis. Therefore, the null hypothesis is supported by this study.

4.4 Potential to reduce costs does not inform the behavioural intention to adopt technological innovation in the South African mining industry

The fourth research question determines whether perceptions of technological innovations as having PRC determine the BI to adopt technology in the South African mining industry.

This study revealed that PRC is not an important factor in adopting mining technology in the South African industry. The result of the regression analysis in Table 4.1 indicates a weak positive link between PRC and BI with a.033 coefficient, which is insignificant at a.642 significance level.

This result implies that there is no sufficient evidence to support the research hypothesis. Therefore, the null hypothesis is supported.

4.5 Potential to improve safety does not inform the behavioural intention to adopt technological innovation in the South African mining industry

The fifth research question is concerned with determining whether perceptions of technological innovations as having PIS determine the BI to adopt technology in the South African mining industry.

This study established that PIS is not important in determining BI to adopt mining technology in the South African mining industry. The result of the regression analysis shown in Table 4.1 indicates a weak negative link between PIS and BI with a .032 coefficient, which is insignificant at a .660 significance level. This result implies that there is insufficient evidence to support the research hypothesis. Therefore, the null hypothesis is supported.

4.6 Perceived threat to job security does not inform the behavioural intention to adopt technological innovation in the South African mining industry

The sixth research question seeks to determine whether perceptions of technological innovations as being PTJS are important in the BI to adopt technology in the South African mining industry.

This study found that PTJS is not significant in determining the BI to adopt mining technology in the South African mining industry. The result of the regression analysis shown in Table 4.1 indicates that there is a negative weak link between PTJS and BI with a $-.062$ coefficient, which is insignificant at a .325 significance level. This result implies that there is no sufficient evidence to support the research hypothesis. Therefore, the null hypothesis is supported.

Table 4.2 displays the mean and standard deviations for all constructs of the study.

Table 4.2 Descriptive statistics

	Mean	Std. Deviation	N
BI	1,51	0,632	298
PU	1,40	0,522	298
PEU	2,30	0,575	298
AT	4,01	0,839	298
PIS	2,25	0,564	298
PRC	2,22	0,561	298
PTJS	2,94	1,281	298

Results in Table 4.2 reveal the mean and standard deviation of the variables. Study results show that, for relative AT towards technology, respondents mostly showed that the AT towards the adoption of technology is highly likely to influence technology acceptance.

4.7 The hypothesised model

The resulting path coefficients of the proposed research model are depicted in Figure 4.7.1. All the coefficients have p-values greater than 0.05.

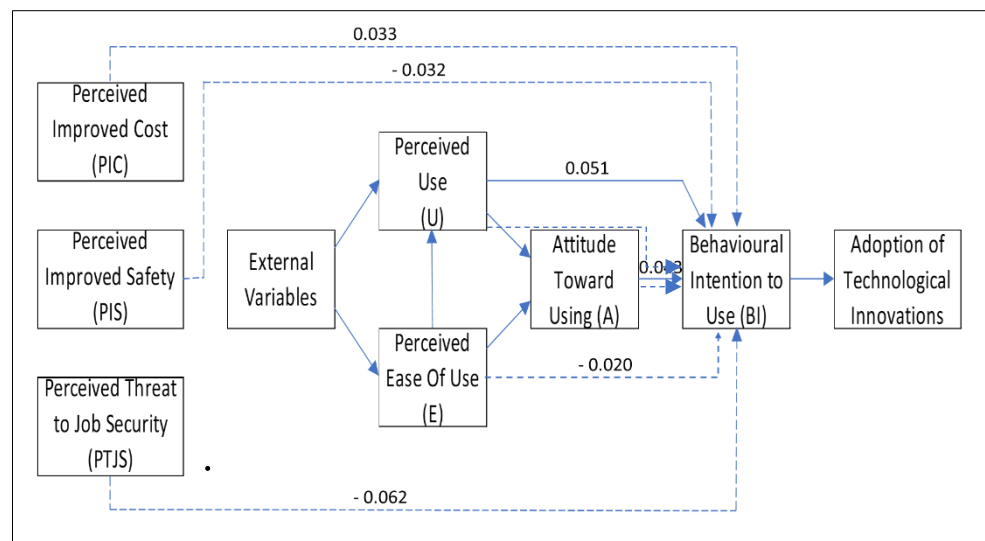


Figure 4.7.1 Proposed model path coefficients

*p < 0.05; **p < 0.01.

The dotted lines represent the resulting path coefficients of the proposed research model, while the original TAM is represented by solid lines.

H1: Perceived use is important in determining the behavioural intention to adopt technology in South Africa's mining industry.

H2: Perceived ease of use is important in determining the behavioural intention to adopt technological innovations in South Africa's mining industry.

H3: Attitude is important in determining the behavioural intention to adopt technological innovations in South Africa's mining industry.

H4: The perceptions that technology has the potential to reduce costs are important in determining the behavioural intention to adopt technological innovations in South Africa's mining industry.

H5: The perceptions that technology has the potential to improve safety are important in determining the behavioural intention to adopt technological innovations in South Africa's mining industry.

H6: The perceptions that technology has the potential to threaten job security are important in determining the behavioural intention to adopt technological innovations in South Africa's mining industry.

The results of multiple regression indicated that all the predictors are not significant in describing the BIs of the South African mining industry population to accept technology and increase its rate of adoption. Overall, all the study hypotheses are not supported by the data.

The results of the study for PEU are consistent with the original TAM, which found no significant relationship between PEU and BI. This construct has been confirmed by previous similar studies as having an indirect influence on BI (Lee et al., 2013). However, Singh et al. (2017) found a direct relationship between PEU and BI. This construct is likely influenced by organisational and upper-management support (Lee et al., 2013). The participation from upper managers was sluggish in this study, which could mean the need for

organisations to demonstrate a determination to use new technology to strengthen employees' confidence and determination.

The new variables introduced in this study, that is, PIS, PRC and PTJS, did not show any significant relationship with BI. There is no sufficient evidence for the study to support a direct relationship between these variables and BI. However, these variables are likely to be the formative indicators or external variables in the original TAM for constructs of PU, PEU and AT, therefore, influencing BI via these constructs. Constructs of PIS, PRC and PTJS have a low mean between 2.25, 2.22 and 2.94, respectively. Consistent with Rogers (2010a) theory, this could imply that the respondents do not perceive these constructs as having a relative advantage in innovation.

5 REPORT AND DISCUSSION OF RESEARCH FINDINGS

5.1 Introduction

The results of the research imply that none of the six research variables affects the BI to adopt technology. They established whether the research does validate the TAM as one of the most accepted theories (Porto, 2020) for explaining the adoption. This is signified by the results showing a weak relationship between the PU, PEU and AT variables.

5.2 Report and discussion of research findings

The study results for PU and AT, are inconsistent with the original TAM by Davis (1989) and the results from previous studies conducted by (Lee et al., 2013) in that both PU and AT were found to be significant in determining BI in those studies. The inconsistency may suggest that the population has not yet reached a critical mass to overcome initial inertia in adopting technological innovations.

However, the results of this study for AT, are consistent with the findings of the results from previous studies conducted by Karahanna et al. (1999) who found that AT was not significant in determining BI for potential adopters. This could mean that the underlying formative indicators of AT did not influence AT for the sample population. It does seem like, for this population, a change in one belief does not necessarily influence changes in other beliefs. Another factor may be how supportive the frontline supervisors are towards employees adopting technology. Previous similar studies highlighted that supervisor support mediates job satisfaction (Naidoo, 2018).

The result implies that the model does not fit the theory for the study. The analysis of first-generation multiple regression is indicated in Appendix 1.4. The results in the model summary table (Table 1.4.2) show that R square, which is the proportion of variance in the dependent variable that can be predicted from the independent variables, is 0.007, with a significance level

above 0.05. In sum, the overall regression model was insignificant, $f(6,292)=0,336$, $p>0.05$, $R^2=0.007$.

The result of AT from descriptive statistics, shown in Table 4.6.2 is likely talking to the South African context, a country burdened by societal challenges such as unemployment, where users might be viewing technology as leading to job losses. This could mean that the respondents can develop an AT that can influence their BIs to either accept or reject technology. This observation is consistent with the studies of (Jan, Lu, & Chou, 2012), who posited that actors' ATs towards technology adoption depend on a collection of implicit rules imposed on and upheld by the actors.

A look at the constructs of the TAM, PU and PEU showed them to be less likely to influence the respondents' BIs towards technology adoption, contrary to results of previous similar studies. The fundamental difference between this study and previous similar studies is the technological differences. Most of the previous studies were on computer-based technologies. This behaviour can be similarly explained by the studies of (Jan et al., 2012) who posited that actors' behaviours of technology adoption depend on a collection of implicit rules imposed on and upheld by the actors.

On the variables introduced by the study, that is, PRC, PIS and PTJS, the respondents showed a moderate likely influence of technology adoption, with PTJS showing above the moderate influence. For this study, these can be considered as the shared beliefs of the respondents. It can be inferred from the results that the respondents' beliefs about PRC and PIS are close to moderate when it comes to the potential of technology to reduce costs and improve safety.

More than moderately, the respondents seem to hold a belief that technology is a likely threat to job security. In a society such as that in South Africa where unemployment, poverty and inequality are the main societal challenges, the potential of reducing costs and improving safety are likely to be less likely imposed and upheld beliefs, while the threat to job security is a more likely imposed and upheld belief by a critical mass of respondents. This

phenomenon is consistent with the studies of (Jan et al., 2012) which suggest that the actors' beliefs are a function of society's collection of implicit rules. The result shows the influence of the participants' composition which was dominated by black or African participants and 31 per cent of total participants in the low-income bracket, most of whom are likely to be impacted by the country's societal challenges of unemployment, poverty and inequality.

6 SUMMARY, CONCLUSIONS, LIMITATIONS AND RECOMMENDATIONS

6.1 Summary

The study has three major research questions for this research which focus on the population of South Africa's mining industry. First, the study established whether the perceptions of technology as having the potential to improve safety are important in explaining BI to use technology and increasing the adoption rate of technological innovation. Second, the study established whether the perception of technology as having the potential to reduce the cost of mining is important in explaining BI to use technology and increase the rate of technological innovation. Third, the study established whether perceptions of technology as having the potential to threaten job security in mines is an important factor in determining BI to accept technology and increase the rate of technological innovation.

The survey data were utilised to test the hypotheses and attempted to answer the research questions for the study regarding the potential factors explaining the variance in technology acceptance and influencing the rate of adoption of technological innovations.

First, the measurement instrument for this study was found to be consistent and the multi-item scales on the measurement were reliable in measuring what the study intended to measure, implying the measurement scale passed the reliability test. The results of the analysis are shown in tables in Appendix 1.2, which shows the reliability statistics table for the value of Cronbach's alpha and the items-total statistics table for reading Cronbach's alpha value if the item were deleted. Second, the instrument reliability and validity were supported for the study with two different statistical approaches confirming convergent and discriminant validity.

Third, the regression analysis produced an R square of 0.007 which showed that the six variables can only explain 0.7 per cent of the variance in the

dependent variable BI. With a p-value above 0.05, this result shows that when the six predictors are put together as a group they cannot predict the BI of the respondents to use technology and increase the adoption of technological innovation. Therefore, the null hypothesis is supported, and the alternative hypothesis is rejected for this study.

In sum, there is not enough evidence to suggest that the six predictors can explain the variance in the BI of the population working in South Africa to accept technology and increase the rate of technological innovation.

6.2 Conclusions

The mining industry in South Africa continuously implements new technologies in the hope of increasing productivity and improving the safety of operations (Cosbey et al., 2016; Corrigan, 2019; Carr, 2020). However, gaining user acceptance and system adoption remains a challenge to the mining industry, resulting in organisations facing difficulties during the initial stage of design and implementation.

The results of this study indicate that there was not enough evidence to support the proposed model for the acceptance of technology in a South African setting. The mining industry in South Africa is yet to find strategies to influence the workforce to accept technology and increase the adoption rate of technological innovations. The three variables introduced by this study could potentially be the external variables of PU, PEU and AT.

From the results of this research, it can be concluded that for the study population, multi-item scales from previous similar studies did not produce the same results. The implication is that a different setting is likely to require a different approach unique to the circumstances of that particular setting. This view is confirmed by Lee et al. (2013) who suggest that the role of antecedent variables should be cautiously investigated due to their association with user acceptance behaviours.

As asserted by Singh et al. (2017), a blueprint for technology implementation is based on different intrinsic factors experienced in an organisation to ensure

the acceptance of every introduction, design and implementation of new technology to improve its rate of adoption.

6.3 Limitations

The sample size of 325 participants required for this study presented a serious challenge for three categories: senior management, the technology department and equipment operators. The sample sizes required for these categories were larger compared to other categories due to these categories being considered more likely to interface with technology far more intensely than other categories.

The study age range requirement was a challenge, both from restricting sample size and its justification point of view. This significantly reduced the sample size from the operator category. Most of the subjects utilised in the study, particularly in the operator category, came from one mining company, which could potentially limit the generalisability of the results.

The multi-items that were used to measure the variables of interest such as PRC, PIS and PTJS, were not sourced or adjusted from similar previous studies. These were validated by making inferences from the principle of relative advantage theorised by Rogers (2010b).

Data collection for the target population posed a serious challenge for the study. The study aimed to utilise the clickers method in a facilitated setting, which could have resulted in higher participation for this category. The study multi-item scales required to undertake the exploratory factor analysis process to improve the measurement scale and hence improve the results of the study could not be undertaken.

The study took place in an environment with acute socio-economic challenges when compared with most of the settings where previous similar studies had been conducted. This is likely to have a material impact on the outcome of the study results. The unique challenges of the South African setting will likely result in the need for a different TAM to address the peculiar circumstances faced by the study population. These socio-economic challenges may

influence how each category, ethical group and income bracket responds to the survey questionnaire.

Exploratory factor analysis could come in handy to establish the underlying factors that could be utilised on the multi-item scale of the measurement. Time constraints and restrictions related to the COVID-19 pandemic made it difficult for the study to establish an optimum foundation. Further, what constitutes the right composition of the study population is not supported by any empirical data to ensure equitable representation of the participant groups that could produce a representative result.

The setting for this study is fundamentally different from the settings of the previous similar studies, necessitating multi-item scales different from those utilised by other similar studies. This study made extensive use of social media platforms to distribute the survey questionnaire. This presents a risk of participants passing on the survey to other people to complete the survey on their behalf and, therefore, making the responses not reliable.

6.4 Recommendations

The study determined the relations between the variables of interest, to show their impact on the BI to use technology and subsequently increase the adoption rate of technological innovations. It is recommended that a study be undertaken that would determine the relationship between the PIS, PRC, PTJS and other variables of TAM to determine if these variables may have a mediating effect.

To increase the generalisability of the results, a study that includes all relevant subjects' categories from a representative sample of mining companies in South Africa is recommended. The measurement scales on the three variables of interest, that is, PIC, PIS and PTJS, were derived from the literature review process. It is recommended that these be validated through relevant literature to further improve the results of this research.

It is also recommended that a study be undertaken to understand the impact of population demographics on exogenous variables such as PIS, PRC and

PTJS. A further study is recommended to determine the relationships among the independent variables in this study to establish the possible mediating relationships among the variables. The mining industry in South Africa needs to understand the level of maturity of its employees concerning technology. It is therefore recommended that a study to establish the maturity curve for a setting be conducted before a technology acceptance study is undertaken. This should assist in designing a measurement scale that is fit for purpose.

Lastly, this was a cross-sectional study, a longitudinal study might be required to assess the changing patterns as technology is being rolled out and a critical mass of the population size has experienced the associated benefits and or costs of technological innovation. Exploratory factor analysis is also recommended to ensure the adequacy of the measurement scales in incorporating the relevant aspects of research.

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APPENDICES

Appendix 1.1: Data Collection Instrument(s)

Appendix A: Questionnaire Items (Adoption)

Note:

Items designated with * are adopted from Lee et al. (2013).

Items designated with ** are adopted from Rogers et al. (2019)

Items designated with *** are adopted from Hyder, Siau, and Nah (2019)

- **Behavioural Intentions**

1. I intend to adopt new technology in my job within the next six months*
2. During the next six months, I plan to experiment with or regularly use new technology in my work*
3. I will strongly recommend others to use it*

- **Perceived usefulness (PU)**

1. If I were to adopt technology, it would enable me to accomplish my tasks more quickly.*
2. If I were to adopt technology, the quality of my work would improve.*
3. If I were to adopt technology, it would enhance my effectiveness on the job.*
4. If I were to adopt technology, it would make my job easier.*
5. How would you rate technology adoption as being extremely useful in your organisation?

- **Ease of Use (EOU)**

1. Learning to operate new technology would be easy for me.*
2. If I were to adopt new technology, it would be to use.*
3. If I were to adopt technology, it would be difficult to use.

- **Attitude (AT)**

All things considered, adopting technology in my job within the next six months would be

1. I believe that working with technology is very difficult.*
2. I believe that working with technology is very complicated.*
3. I believe that working with technology let me feel psychological stress very greatly.*

- **Improved safety (IS)**

1. If I were to adopt technology, it would improve safety**
 2. Technology offers relatively high potential safety improvements**
 3. If I were to adopt technology, it would not improve safety
- **Improved costs (IC)**
 1. Technology provides economic benefits to the mining industry through cost reduction***
 2. Technology offers relatively high potential cost improvements***
 3. Adopting technology in the mining will not reduce costs
 - **Threatened job security (TJS)**
 1. Adopting technology at work takes jobs away from people in the mine
 2. Technology threatens job security at workplace of a mine in South Africa
 3. Accepting technology and adopting it in the workplace reduces the chances of people finding jobs in South African mines

Appendix 1.2: Reliability Test

Table 1.2.1 Reliability statistics

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardised Items	N of Items
.801	.822	23

Table 1.2.2 Item-Total Statistics

Item-Total Statistics					
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
BI recoding	90.55	89.636	.159	.674	.801
BI.0 recoding	90.64	90.245	.074	.637	.805
BI.1 recoding	90.54	89.859	.143	.543	.802
PU recoding	90.36	87.031	.419	.567	.793
PU.0 recoding	90.41	86.532	.403	.646	.793
PU.1 recoding	90.40	87.083	.411	.578	.793
PU.2 recoding	90.43	87.101	.392	.617	.793
PU.3 recoding	90.72	85.702	.392	.344	.792
PEU recoding	90.58	88.413	.251	.312	.798
PEU.0 recoding	90.79	87.718	.274	.386	.797

If I were to adopt new technology, it would be difficult to use	91.40	82.120	.330	.277	.797
I believe that working with technology is very difficult	90.97	83.073	.411	.432	.790
I believe that working with technology is very complicated	91.14	84.602	.448	.478	.790
I believe that working with technology let me feel psychological stress very greatly	91.05	82.398	.370	.357	.793
PIS recoding	90.55	85.434	.437	.541	.791
PIS.0 recoding	90.50	86.379	.405	.531	.792
If I were to adopt technology, it would not improve safety	91.24	81.825	.339	.283	.796
PRC recoding	90.60	86.220	.391	.434	.793
PRC.0 recoding	90.64	86.904	.323	.393	.795
Adopting technology in mining will not reduce costs	91.52	79.233	.442	.353	.789
Adopting technology at work takes jobs away from people in the mine	92.16	79.940	.435	.707	.789
Technology threatens job security at workplace of a mine in South Africa	92.20	79.133	.441	.720	.789

Accepting technology and adopting it in the workplace reduces the chances of people finding jobs in South African mines	92.02	77.909	.472	.669	.786
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Appendix 1.3: Convergent Validity Test

Table 1.3.1 Correlation matrix used for convergent validity test

Correlation Matrix^a

	BI recoding	BI.0 recoding	BI.1 recoding	PU recoding	PU.0 recoding	PU.1 recoding	PU.2 recoding	PU.3 recoding	PEOU recoding	PEOU.0 recoding	If I were to adopt new technology, it would be difficult to use	I believe that working with technology is very difficult	I believe that working with technology is very complicated	I believe that working with technology let me feel psychological stress very greatly	PIS recoding	PIS.0 recoding	If I were to adopt technology, it would not improve safety	PRC recoding	PRC.0 recoding	Adopting technology in mining will not reduce costs	Adopting technology at work takes jobs away from people in the mine	Technology threatens job security at workplace of a mine in South Africa	Accepting technology and adopting it in the workplace reduces the chances of people finding jobs in South African mines
Correlation	1.000	.755	.690	.120	.081	.070	.036	-.001	.001	-.034	-.011	.100	-.004	-.013	.058	.098	-.023	.075	.074	-.004	-.031	-.021	.024
	.755	1.000	.644	.028	-.003	-.020	-.024	.010	.088	.032	-.009	.064	-.060	-.026	.013	.027	-.024	.018	.035	-.017	-.071	-.078	-.049
	.690	.644	1.000	.085	.044	.079	.045	.038	.074	-.033	.020	.090	-.009	.059	.027	.049	-.048	.087	.065	.001	-.073	-.003	-.016
	.120	.028	.085	1.000	.705	.589	.609	.390	.204	.292	.065	.076	.069	.019	.399	.377	.148	.327	.281	.102	.041	.047	.110
	.081	-.003	.044	.705	1.000	.653	.679	.409	.168	.273	.013	.041	.023	.018	.492	.423	.184	.371	.277	.134	.023	-.001	.065
	.070	-.020	.079	.589	.653	1.000	.659	.358	.160	.214	-.022	.083	.054	.025	.512	.488	.179	.337	.316	.124	.035	.051	.096
	.036	-.024	.045	.609	.679	.659	1.000	.480	.201	.325	-.004	.063	.028	-.002	.472	.466	.135	.404	.314	.124	.006	.006	-.003
	-.001	.010	.038	.390	.409	.358	.480	1.000	.158	.213	.057	.063	.094	.150	.421	.396	.096	.359	.300	.155	.115	.117	.116
	.001	.088	.074	.204	.168	.160	.201	.158	1.000	.499	.104	.130	.108	.008	.228	.140	.107	.212	.196	.064	.008	.037	.035
	-.034	.032	-.033	.292	.273	.214	.325	.213	.499	1.000	.081	.144	.221	.123	.281	.266	.052	.260	.192	.192	.047	-.024	-.009
	-.011	-.009	.020	.065	.013	-.022	-.004	.057	.104	.065	1.000	.392	.369	.332	.090	.068	.289	.040	-.004	.313	.182	.153	.166
	.100	.064	.090	.076	.041	.083	.063	.063	.130	.144	.392	1.000	.579	.429	.071	.034	.181	.040	.077	.317	.147	.197	.221
	-.004	-.060	-.009	.069	.023	.054	.028	.094	.108	.221	.369	.579	1.000	.497	.112	.110	.201	.051	.147	.311	.231	.263	.253
	-.013	-.026	.059	.019	.018	.025	-.002	.150	.008	.123	.332	.429	.497	1.000	.070	.059	.176	.001	.019	.261	.240	.241	.292
	.058	.013	.027	.399	.492	.512	.472	.421	.228	.281	.090	.071	.112	.070	1.000	.660	.197	.399	.379	.113	.071	.057	.074
	.098	.027	.049	.377	.423	.488	.466	.396	.140	.266	.068	.034	.110	.059	.660	1.000	.166	.403	.418	.184	.034	-.001	.021
	-.023	-.024	-.048	.148	.184	.179	.135	.096	.107	.052	.289	.181	.201	.176	.197	.166	1.000	.065	-.046	.426	.178	.160	.176
	.075	.018	.087	.327	.371	.337	.404	.358	.212	.260	.040	.040	.051	.001	.399	.403	.065	1.000	.540	.261	.099	.101	.101
	.074	.035	.065	.281	.277	.316	.314	.300	.196	.192	-.004	.077	.147	.019	.379	.418	-.046	.540	1.000	.125	.074	.066	.108
	-.004	-.017	.001	.102	.134	.124	.124	.155	.064	.047	.313	.317	.311	.261	.113	.184	.426	.261	.125	1.000	.241	.238	.266
	-.031	-.071	-.073	.041	.023	.035	.006	.115	.008	-.024	.182	.147	.231	.240	.071	.034	.178	.099	.074	.241	1.000	.801	.754
	.021	-.078	-.003	.047	-.001	.051	.006	.117	.037	-.017	.153	.197	.263	.241	.057	-.001	.160	.101	.066	.238	.801	1.000	.765
	.024	-.049	-.016	.110	.065	.096	-.003	.116	.035	-.009	.166	.221	.253	.292	.074	.021	.176	.101	.108	.266	.754	.765	1.000
Sig. (1-tailed)		.000	.000	.019	.081	.114	.270	.491	.496	.280	.428	.042	.474	.412	.161	.046	.346	.098	.103	.470	.298	.360	.340
	.000		.000	.313	.478	.362	.342	.430	.065	.293	.438	.137	.153	.325	.411	.324	.341	.377	.276	.386	.111	.091	.201
	.000	.000		.071	.225	.086	.219	.442	.257	.102	.285	.061	.219	.155	.323	.202	.206	.067	.130	.495	.105	.478	.394
	.019	.313	.071		.000	.000	.000	.000	.000	.000	.133	.095	.118	.370	.000	.000	.005	.000	.000	.040	.243	.207	.029
	.081	.478	.225	.000		.000	.000	.000	.002	.000	.414	.241	.346	.379	.000	.000	.001	.000	.000	.010	.347	.491	.132
	.114	.362	.086	.000	.000		.000	.000	.083	.000	.355	.077	.177	.335	.000	.000	.001	.000	.000	.016	.276	.189	.049
	.270	.342	.219	.000	.000	.000		.000	.000	.000	.474	.139	.316	.484	.000	.000	.010	.000	.000	.016	.461	.457	.477
	.491	.430	.257	.000	.000	.000	.000		.003	.000	.161	.139	.052	.005	.000	.000	.049	.000	.004	.024	.022	.022	.023
	.496	.065	.102	.000	.002	.003	.000	.003		.000	.037	.012	.032	.442	.000	.008	.032	.000	.000	.136	.446	.260	.272
	.280	.293	.285	.000	.000	.000	.000	.000	.000		.081	.006	.000	.017	.000	.000	.187	.000	.000	.211	.341	.383	.438
	.428	.438	.366	.133	.414	.355	.474	.161	.037	.081		.000	.000	.000	.060	.120	.000	.245	.471	.000	.001	.004	.002
	.042	.137	.061	.095	.241	.077	.139	.139	.012	.006	.000		.000	.000	.111	.282	.001	.247	.093	.000	.006	.000	.000
	.474	.153	.442	.118	.346	.177	.316	.052	.032	.000	.000	.000		.000	.027	.029	.000	.189	.006	.000	.000	.000	.000
	.412	.325	.155	.370	.379	.335	.484	.005	.442	.017	.000	.000	.000		.114	.154	.001	.496	.370	.000	.000	.000	.000
	.161	.411	.323	.000	.000	.000	.000	.000	.000	.000	.060	.111	.027	.114		.000	.000	.000	.000	.026	.111	.163	.102
	.046	.324	.202	.000	.000	.000	.000	.000	.008	.000	.120	.282	.029	.154	.000		.002	.000	.000	.001	.277	.492	.362
	.346	.341	.206	.005	.001	.001	.010	.049	.032	.187	.000	.001	.000	.001	.000	.002		.133	.216	.000	.001	.003	.001
	.098	.377	.067	.000	.000	.000	.000	.000	.000	.000	.245	.247	.189	.496	.000	.000	.133		.000	.000	.044	.042	.042
	.103	.276	.130	.000	.000	.000	.000	.000	.000	.000	.471	.093	.006	.370	.000	.000	.216	.000		.016	.100	.128	.032
	.470	.386	.495	.040	.010	.016	.016	.004	.136	.211	.000	.000	.000	.000	.026	.001	.000	.000	.016		.000	.000	.000
	.298	.111	.105	.243	.347	.276	.461	.024	.446	.341	.001	.006	.000	.000	.111	.277	.001	.044	.100	.000		.000	.000
	.360	.091	.478	.207	.491	.189	.457	.022	.260	.383	.004	.000	.000	.000	.163	.492	.003	.042	.128	.000	.000		.000
	.340	.201	.394	.029	.132	.049	.477	.023	.272	.438	.002	.000	.000	.000	.102	.362	.001	.042	.032	.000	.000		.000

a. Determinant = 2.610E-5

Table 1.3.2 KMO statistic

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.815
Bartlett's Test of Sphericity	Approx. Chi-Square	3044.760
	df	253
	Sig.	.000

Appendix 1.4: Multiple Regression

Table 1.4.1 Variables in the regression model

Variables Entered/Removed^a			
Model	Variables Entered	Variables Removed	Method
1	Mean PTJS, Mean PU, Mean PEU, Mean PRC, Mean AT, Mean PIS ^b		Enter

a. Dependent variable: Mean BI

b. All requested variables entered

Table 1.4.2 Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.083 ^a	.007	-.014	.637

a. Predictors: (Constant), Mean PTJS, Mean PU, Mean PEU, Mean PRC, Mean AT, Mean PIS

Table 1.4.3 Analysis of variances

ANOVA^a						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.819	6	.137	.336	.917 ^b
	Residual	118.627	292	.406		
	Total	119.446	298			

a. Dependent Variable: Mean BI

b. Predictors: (Constant), Mean PTJS, Mean PU, Mean PEU, Mean PRC, Mean AT, Mean PIS

Table 1.4.4 Coefficients and p-values

Coefficients^a						
Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	4.203	.381		11.022	.000
	Mean PU	.062	.085	.051	.737	.462
	Mean PEU	-.010	.067	-.010	-.149	.882
	Mean AT	.033	.051	.043	.640	.522
	Mean PIS	-.029	.067	-.032	-.440	.660
	Mean PRC	.029	.063	.033	.465	.642
	Mean PTJS	-.030	.031	-.062	-.986	.325

a. Dependent Variable: Mean BI

Appendix 2.1: Bio of the Researcher Including Declaration of Interest in the Research

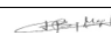
I am a professional qualified in mining engineering degree from the university of the Witwatersrand. I have a wealth of knowledge in various methods of mining, spanning over 20 years, gained from the most reputable mining houses in South Africa, in which I headed mining operations and technology implementation. As a mining professional engaged in efficiency improvement projects as well as technology implementation roll out within my organisation, my interests in this research include understanding of the factors that influence technology adoption in the workplace. Therefore, I have a keen interest in understanding the factors that drive technology adopters to accept or not accept technological innovations.

Appendix 2.2.1: Ethics Documentation

MBA Project Proposal Review – Research Article

Note: this form is to be used for Research Articles only. Separate forms must be used for Consultancy Projects, Business Venture Proposals and Social Entrepreneurship Projects.

Student name: Tshidiso Mokgatla	Proposed title: Investigating possible factors that explain the variance for technology adoption in South African mining industry.
Student number: 9404983x	
Criterion	Comment and / or Specific Recommendations / Improvements Required
Academic journal has been nominated; structure, headings and style consistent with the nominated journal	OK.
Appropriate research problem and sub-problems, include a verb at or near the beginning and align with each other	OK.
Integrated literature review based on problem and sub-problems, citing a minimum of 20 peer-reviewed academic journal articles	OK.
Hypotheses, propositions or research questions arise directly from the literature review, clearly related to the applicable sub-problem and stated at end of the relevant literature section	OK.
Research methodology section detailing research design, population and sample, participants, research instrument (survey, interview guideline, etc.) and method of analysis	OK.
APA 6 th referencing including in-text citations, reference list and alignment between the two	OK.
Appropriate academic style including level of formality, formatting, grammar and spelling; figures and tables clearly legible and in the style of the nominated journal	OK.
Additional comments and instructions: Ethics clearance application approved:	-The research proposal is approved. -The ethics clearance application form is approved.

Decision	X	Panel Chair	Panel member	Panel member	Panel member
Proceed with Supervisor	X	Name: Dr Jenika Gobind	Dr Manamela	Peter Mmari	Chantal Banga
Revise and re-submit		Signature: J	M	P	

Note: this form is to be returned to the student immediately after the panel session.

Proposed Internal examiner[†]:	
Supervisor name: Patrick Zhuwao	Panel Date: 11 November 2020

[†] For completion by the research office only.

APPENDIX 2.2.2: ETHICS DOCUMENTATION



**SCHOOL OF GRADUATE SCHOOL OF BUSINESS ADMINISTRATION ETHICS COMMITTEE
CONSTITUTED UNDER THE UNIVERSITY HUMAN RESEARCH ETHICS COMMITTEE (NON-MEDICAL)**

CLEARANCE CERTIFICATE

PROTOCOL NUMBER WBS/FI9404983x/571

PROJECT TITLE

Investigating possible factors that explain the variance for technology adoption in South African mining industry

INVESTIGATOR

Mr Tshidiso Mokgata

SCHOOL/DEPARTMENT OF INVESTIGATOR

MBA (Research Article)

DATE CONSIDERED

24 November 2020

DECISION OF THE COMMITTEE

Approved unconditionally

RISK LEVEL


LOW RISK

EXPIRY DATE

30 JUNE 2021

ISSUE DATE OF CERTIFICATE 15 December 2020

CHAIRPERSON _____


(Dr MDJ Matshabaphala)

cc: Supervisor: Mr Zhuwao

--

DECLARATION OF INVESTIGATOR

To be completed in duplicate and **ONE COPY** returned to the Chairperson of the School/Department ethics committee.

I fully understand the conditions under which I am authorized to carry out the abovementioned research and I guarantee to ensure compliance with these conditions. Should any departure to be contemplated from the research procedure as approved I/we undertake to resubmit the protocol to the Committee.

Signature

Date

PLEASE QUOTE THE PROTOCOL NUMBER ON ALL ENQUIRIES

Appendix 3.1: Dully Filled in Data Collection Instrument(s)

Participant Information Sheet

Dear Sir / Madam

My name is Tshidiso Mokgatla and I am a Masters student in Business Administration at the University of the Witwatersrand in Johannesburg. As part of my studies, I have to undertake a research project, and I am investigating the possible factors that explain the variance for technology adoption in South African mining industry. The aim of this research project is to develop a technology acceptance model that will assist companies to improve the rate of adoption of technological innovations in their respective workplaces.

As part of this project, I would like to invite you to take part in anonymous survey. This activity will involve an electronic device and will take around 5 - 7 minutes.

You will not receive any direct benefits from participating in this research, and there are no disadvantages or penalties for not participating. You may withdraw at any time or not answer any question if you do not want to. The survey will be completely confidential and anonymous as I will not be asking for your name or any identifying information, and the information you give to me will be held securely and not disclosed to anyone else.

If you have any questions during or afterwards about this research, feel free to contact me on the details listed below. This study will be written up as a research report which will be available online through the university library website. If you have any concerns or complaints regarding the ethical procedures of this study, you are welcome to contact the University Human Research Ethics Committee (Non-Medical), telephone +27(0) 11 717 1408, email hrec-medical.researchoffice@wits.ac.za

*Yours sincerely,
Tshidiso Mokgatla*

*Researcher:
Tshidiso Mokgatla, 9404983x@students.wits.ac.za, +2763 6997147*

*Supervisor:
Patrick Zhurwao, 331780@students.wits.ac.za, +2762 3062312*

I agree that my participation will remain anonymous

- Yes
 No

I agree that the researcher may use anonymous quotes in his / her research report

- Yes
 No

I,, agree to participate in this research project. The research has been explained to me and I understand what my participation will involve. I agree to the following:

(Please circle the relevant options below).

Rosinah Mmopi

BI. I intend to adopt new technology in my job within the next six months

- Describes me extremely well
- Describes me very well
- Describes me moderately well
- Describes me slightly well
- Does not describe me

BI. During the next six months, I plan to experiment with or regularly use new technology in my work

- Describes me extremely well
- Describes me very well
- Describes me moderately well
- Describes me slightly well
- Does not describe me

BI. I will strongly recommend others to use it

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

PU. If I were to adopt technology, it would enable me to accomplish my tasks more quickly

- Strongly agree

- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

PU. If I were to adopt technology, the quality of my work would improve

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

PU. If I were to adopt technology, it would enhance my effectiveness on the job

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

PU. If I were to adopt technology, it would make my job easier

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

PU. How would you rate technology adoption as being extremely useful in your organisation?

- Extremely useful
- Very useful
- Moderately useful
- Slightly useful
- Not at all useful

PEOU. Learning to operate new technology would be easy for me

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

PEOU. If I were to adopt new technology, it would be to use

- Extremely easy
- Somewhat easy
- Neither easy nor difficult
- Somewhat difficult
- Extremely difficult

PEOU. If I were to adopt new technology, it would be difficult to use

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

AT. I believe that working with technology is very difficult

- A great deal
- A lot
- A moderate amount
- A little
- None at all

AT. I believe that working with technology is very complicated

- Always
- Most of the time
- About half the time
- Sometimes
- Never

AT. I believe that working with technology let me feel psychological stress very greatly

- A great deal
- A lot
- A moderate amount
- A little
- None at all

PIS. If I were to adopt technology, it would improve safety

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

PIS. Technology offers relatively high potential safety improvements

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

PIS. If I were to adopt technology, it would not improve safety

- Extremely likely
- Somewhat likely
- Neither likely nor unlikely
- Somewhat unlikely
- Extremely unlikely

PRC. Technology provides economic benefits to the mining industry through cost reduction

- Extremely likely
- Somewhat likely
- Neither likely nor unlikely
- Somewhat unlikely
- Extremely unlikely

PRC. Technology offers relatively high potential cost improvement

- Extremely likely
- Somewhat likely
- Neither likely nor unlikely
- Somewhat unlikely
- Extremely unlikely

PRC. Adopting technology in mining will not reduce costs

- Extremely likely
- Somewhat likely
- Neither likely nor unlikely
- Somewhat unlikely
- Extremely unlikely

PTJS. Adopting technology at work takes jobs away from people in the mine

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

PTJS. Technology threatens job security at workplace of a mine in South Africa

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

PTJS. Accepting technology and adopting it in the workplace reduces the chances of people finding jobs in South African mines

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

AGE. What is your age?

- Under 18
- 18 - 24
- 25 - 34
- 35 - 44
- 45 - 54
- 55 - 64
- 65 - 74
- 75 - 84
- 85 or older

GENDER. What is your gender?

- Male
- Female
- Non-binary / third gender
- Prefer not to say

INCOME. What is your net salary per month?

- Less than R15,000
- R15,000 - R19,999
- R20,000 - R29,999
- R30,000 - R39,999
- R40,000 - R49,999
- R50,000 - R59,999
- R60,000 - R69,999
- R70,000 - R79,999
- R80,000 - R89,999
- R90,000 - R99,999
- R100,000 - R149,999
- More than R150,000

ETHNICITY. Which race/ethnicity best describes you? (Please choose only one.)

- Black or African
- White
- Coloured
- Indian

JOB. What job are your employed to do in your company?

operator

Scoring Results

Score

Mean Score:	31.00
Weighted Mean of Items:	3.44
Weighted Standard Deviation of Items:	0.73
Items:	9.00