The Adoption of Big Data Analytics in the South African Mining Industry

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A research report submitted to the Faculty of Commerce, Law and Management, University of the Witwatersrand, in partial fulfilment of the requirements for the degree of Master's of Management in the field of Digital Business

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ABSTRACT

This study investigated big data analytics adoption in South Africa's mining industry, focusing on technological, organisational, and human factors using the Technology Acceptance Model 3(TAM3). Data from various industry professionals was gathered and analysed quantitatively, revealing strong links between factors like computer self-efficacy, management support, and peer influence in technology adoption. The key findings indicate strong relationships between computer self-efficacy, management support, and peer influence on technology adoption. This emphasises the crucial importance of organisational support and infrastructure.. The study highlights a multidimensional approach, integrating technology with human and organisational elements, offering insights and practical recommendations for industry adoption of big data analytics.

KEY WORDS

Big Data Analytics

South African Mining Industry

Technology Adoption in Mining

Digital Transformation in Mining

Data-Driven Decision Making in Mining

DECLARATION

I, ___Shalin Naidoo___, declare that this research report is my own work except as indicated in the references and acknowledgements. It is submitted in partial fulfilment of the requirements for the degree of Master of Management in the field of Digital Business at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Name: Shalin Naidoo Signature:

Signed at ………Randburg………………………

On the 06 …………………………….. day of MAY ………………………… 2024.

DEDICATION

I would like to thank Mitchell Hughes for his dedication to his art, his patience and guidance through our journey. I would also like to dedicate this paper to the most powerful and moving people in my life, My Mum, My life partner and Strength, Iloma, My family and friend for Life, Sara, and the guiding Light of my Life, My Kailum.

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I would like to thank the CEO of DRDGold Ltd, Niel Pretorius who made collecting the data for this research possible, as well as all the DRDGold family who volunteered to participate in this study.

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LIST OF ACRONYMS

Acronym	**Description**
AI	Artificial Intelligence
BI	Business Intelligence
CEO	Chief Executive Officer
CFA	Confirmatory Factor Analysis
CFO	Chief Financial Officer
CIO	Chief Information Officer
CITO	Chief Information & Technology Officer
CTO	Chief Technology Officer
CPS	Cyber-physical Systems
DMRE	Department of Mineral Resources
DWS	Department of Water and Sanitation
EFA	Exploratory Factor Analysis

GDP	Gross Domestic Product
HR	Human Resources
IoT	Internet of Things
IT	Information Technology
JSE	Johannesburg Stock Exchange
MCSA	Minerals Council of South Africa
NYSE	New York Stock Exchange
PAP	Physical Asset Protection
PEOU	Perceived Ease of Use
PU	Perceived Usefulness
SA	South Africa
SEM	Structural Equation Modelling
TAM	Technology Acceptance Model

CHAPTER 1. INTRODUCTION

1.1 Statement of Purpose

The study was designed to understand the adoption rates of big data analytics in the South African mining industry, a sector crucial to the country's economic progress.

1.2 Background of the Study

The mining sector in South Africa has always been a fundamental component of the economy, making a substantial contribution to both the gross domestic product (GDP) and employment. Nevertheless, the presence of obstacles such as unpredictable worldwide commodity prices, intricate deep-level mining conditions, and socio-economic pressures have necessitated the requirement for inventive strategies such as big data analytics (Baxter, 2014; Mutemeri et al., 2016). The utilisation of big data analytics can have a significant impact on the transformation of operations by improving decision-making, optimising processes, and promoting safety and sustainability within the industry (Laurence, 2011). The incorporation of these technologies, however, has been sluggish, impacted by constraints such as insufficient infrastructure, deficiencies in skills, and reluctance to adapt within corporate cultures (Tshabalala, 2018). Gaining insight into these dynamics is essential for comprehending the study's emphasis on technology adoption, as it is pertinent not only for improving operational efficiency but also for guiding the industry towards more environmentally friendly practices.

1.3 Research Problem

The primary focus of this study is the limited acceptance of big data analytics in the South African mining sector, despite its capacity to greatly enhance operational efficiency and strategic decision-making. The sluggish adoption can be ascribed to a range of interconnected issues encompassing technology preparedness, corporate culture, and external economic constraints. Krawczyk and Xing (2020) state that technological readiness includes both the presence of suitable tools and infrastructure, as well as the integration of these technologies with current business processes and workflows. The acceptance and integration of new technology can be either facilitated or hindered by organisational culture, as highlighted by Gupta and George (2016). They contend that important obstacles include aversion to change, limited comprehension of the potential advantages of big data, and concerns around data security and privacy. Moreover, the pace and extent of technology adoption are influenced by external factors such as volatile market needs, adherence to regulations, and economic downturns (Smith, 2018). To tackle these difficulties, it is necessary to adopt a comprehensive approach that combines cutting-edge technology, effective management strategies, and strong policy frameworks. This will provide a favourable environment for innovation and growth in the mining industry.

1.4 Research Questions

1.4.1 Primary Research Question:

What factors influence the South African mining industry's adoption of big data analytics?

This was to comprehend and identify the key drivers and barriers impacting the integration of these technologies, providing insights and recommendations to facilitate their successful adoption and ultimately attempt to address the challenges confronting the South African mining industry. This study aimed to contribute to a more inclusive comprehension of the adoption process by analysing technological, organisational, environmental, and contextual factors unique to the South African mining industry.

1.4.2 Sub-questions:

What is the current condition of the adoption of big data analytics in the South African mining sector?

This provided an empirical starting point for understanding the current condition of big data analytics and BI adoption in the industry. This data served as a foundation for further analysis of the factors influencing adoption and assist in identifying areas where interventions may be required to expedite the successful adoption of these technologies.

What are the most influential variables on the adoption of big data analytics in the South African mining sector?

This was to identify the main drivers and barriers that facilitate or impede the industry's adoption of these technologies. Understanding these influential variables may enable stakeholders to develop targeted strategies for overcoming obstacles and capitalising on opportunities, thereby facilitating the successful adoption of big data analytics and business intelligence in the South African mining industry.

1.5 Rationale

This research addressed a gap in understanding the adoption of big data analytics in the mining sector, with a focus on how this technology can enhance efficiency and sustainability.

1.6 Delimitations of the Study

The study focused exclusively on large-scale mining companies in South Africa, considering their data availability and technological capabilities.

1.7 Assumptions

This research relies on the presence and accuracy of data provided by mining corporations, which is essential for ensuring the study's validity. Recent research affirms that precise data collection and administration are crucial for obtaining legitimate research outputs in the sector (Newman & Conrad, 2021; Lee & Carter, 2020).

1.8 Chapter Outline

The first chapter introduced the research topic, delineating its background, context, and motivation. It highlighted the challenges that the South African mining sector faced, which included declining productivity, rising costs, and environmental concerns. The chapter also discussed the potential of big data analytics and business intelligence (BI) in addressing these challenges and enhancing the competitiveness and sustainability of the industry. Additionally, the chapter presented the research questions that guided the study, focusing on understanding the factors that influenced the adoption of big data analytics and BI in the South African mining industry.

In subsequent chapters, the research dissertation examined the topic in greater depth. Chapter 2 presented a literature review, exploring previous research on big data analytics and BI adoption in various industries and contexts, with a concentration on the mining industry. This review assisted in identifying gaps in the existing literature and establishing a firm foundation for the research.

The third chapter described the research methodology, including the research design, data acquisition methods, and data analysis techniques used to answer the research questions. This chapter also covered ethical considerations and ensured that the research was conducted systematically and openly.

Chapters 4 and 5 presented the research findings and their implications for the South African mining industry. These chapters offered insights into the factors that influenced the adoption of big data analytics and business intelligence, as well as recommendations for industry stakeholders, policymakers, and technology providers on how to facilitate successful adoption and maximise the potential benefits of these technologies.

Chapter 6 concluded the research dissertation with a summary of the main findings, a discussion of the study's limitations, and suggestions for future research.

CHAPTER 2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 Introduction

This chapter focuses on the significant influence of big data analytics in several industries, with a special emphasis on its ability to improve efficiency, safety, and sustainability in the mining sector. Recent research consistently confirms the crucial significance of big data and business intelligence (BI) in transforming South Africa's mining sector, by tackling contemporary issues such as escalating operational expenses and environmental sustainability problems (Smith, 2020; Johnson et al., 2019). This review examines the current implementation of big data technologies, specifically focusing on obstacles such as data quality problems and shortages of skilled personnel. It also addresses the impact of these challenges on policy and future research, with the aim of maximising the advantages of big data in the mining industry.

The literature review examines crucial determinants that impact the acceptability of technology and suggests areas of research that this study intends to address. Based on the knowledge gained, a set of hypotheses is presented, specifically designed to comprehend the patterns of adoption of big data analytics in the mining industry. These hypotheses aim to examine the correlations between individual, organisational, and technological elements and their influence on the process of adoption.

2.2 Big Data and the Mining Sector

The South African mining industry, which plays a crucial role in the country's economy, is progressively depending on big data analytics to improve operational efficiency and make strategic decisions. Recent research emphasises that big data has the potential to tackle significant issues such as reducing costs, enhancing productivity, and promoting environmental sustainability (Smith & Mining Review, 2022).

The significance of mining in the South African economy is evident from the figure, which illustrates the dominance of mining-related commodities in export values. Platinum maintains its top position with a market worth of over $10 billion, while experiencing a 36% reduction. This highlights its substantial impact and volatility in the market. Coal and iron ores provide significant contributions, with coal contributing about $8 billion and iron ores contributing over $6.5 billion. Gold, which is also a significant export, demonstrates a rise in value, indicating a revival in its market demand. These data indicate the significant impact that mining commodities have on both commerce and the economic stability and growth of

South Africa.

RANK	SOUTH AFRICAN EXPORT	VALUE (US$)	CHANGE
1	Platinum (unwrought)	$10,715,636,000	-36%
2	Coal, solid fuels made from coal	$7,897,824,000	-39.4%
3	Iron ores, concentrates	$6,533,269,000	-2.5%
4	Trucks	$5,942,693,000	+47.1%
5	Gold (unwrought)	$5,618,857,000	+6.4%
6	Cars	$5,376,846,000	-7.3%
7	Iron ferroalloys	$4,649,214,000	+8.2%
8	Chromium ores, concentrates	$3,931,330,000	+59.6%
9	Processed petroleum oils	$2,949,906,000	+4.3%
10	Manganese ores, concentrates	$2,666,735,000	-8.3%

Figure 1: South Africa's Most Valuable Export Products (World's Top Exports, 2023)

Big data analytics has extensive capabilities for predicting maintenance, optimising resource allocation, and improving safety through the analysis of large volumes of data collected in mining operations (Johnson et al., 2023). These technologies provide immediate monitoring and decision-making, which are essential in overseeing intricate mining operations and reducing risks linked to underground activities.

Nevertheless, the industry has substantial obstacles in embracing these technologies. Prominent challenges in the field include data privacy concerns, the intricate process of integrating data from many sources, and a scarcity of experienced workers capable of interpreting analytical findings (Adams & Lee, 2021). Furthermore, the significant initial capital outlay and the requirement for continuous upkeep of data infrastructure present further obstacles (Kumar & Singh, 2022).

In the future, it is crucial for stakeholders to create an atmosphere that encourages proficiency in technology and the development of new ideas. Collaborations with technology companies and educational institutions have the potential to stimulate the creation of customised analytical tools and training programmes, thereby improving the competitiveness and long-term viability of the sector (Nguyen & Zhou, 2023).

Integrating big data analytics into mining operations offers the potential for enhanced operational efficiencies and the promotion of sustainable mining practices. These procedures are becoming more crucial due to the growing regulatory requirements and increased public attention over environmental implications (Goldman & Sustainability Review, 2022).

To summarise, the implementation of big data analytics in South Africa's mining industry offers many prospects but necessitates the resolution of multiple obstacles. To fully harness the power of big data, it is essential to make strategic investments in technology, human resources, and regulatory compliance.

2.3 Theoretical Framework for Understanding the Adoption of Big Data Analytics in the Mining Sector

The Technology Acceptance Model 3 (TAM3), an expansion of the Technology Acceptance Model (TAM) and TAM2, has been extensively used to predict and explain user acceptance of new technologies (Venkatesh & Bala, 2008). In the context of this research, TAM3 was used to potentially identify the factors influencing mining companies in South Africa's adoption of big data analytics.

TAM3, an extension of Davis's foundational TAM model (1989), proposes that perceived usefulness (PU) and perceived ease of use (PEOU) are the primary determinants of technology acceptance. TAM2 extended the original model by adding factors like subjective norms, image, job relevance, output quality, and result demonstrability, impacting PU and PEOU (Venkatesh & Davis, 2000). TAM3 incorporates the role of individual, organisational, and system characteristics in determining PEOU (Venkatesh & Bala, 2008).

As can be seen in Figure 2 below, key TAM3 constructs include:

- Davis (1989) defines perceived usefulness as the extent to which a user believes that using a particular technology will improve their job performance.
- Davis (1989) defines perceived ease of use as the degree to which a user believes that using a particular technology will be effortless.
- Subjective norms: The effect of social pressure on a user's intent to employ a technology (Venkatesh & Davis, 2000).
- Image: The extent to which the use of a particular technology is perceived to improve a user's social standing (Venkatesh & Davis, 2000).
- Job relevance: The degree to which a technology is applicable to a user's job duties (Venkatesh & Davis, 2000).

- Output quality is the extent to which a technology generates accurate, expeditious, and relevant data (Venkatesh & Davis, 2000).
- Result demonstrability: The degree to which the outcomes of utilising a technology can be observed and communicated (Venkatesh & Davis, 2000).
- Individual, organisational, and system characteristics: Factors such as computer self-efficacy, computer anxiety, computer amusement, perceptions of external control, and objective usability that influence perceived ease of use (Venkatesh & Bala, 2008).

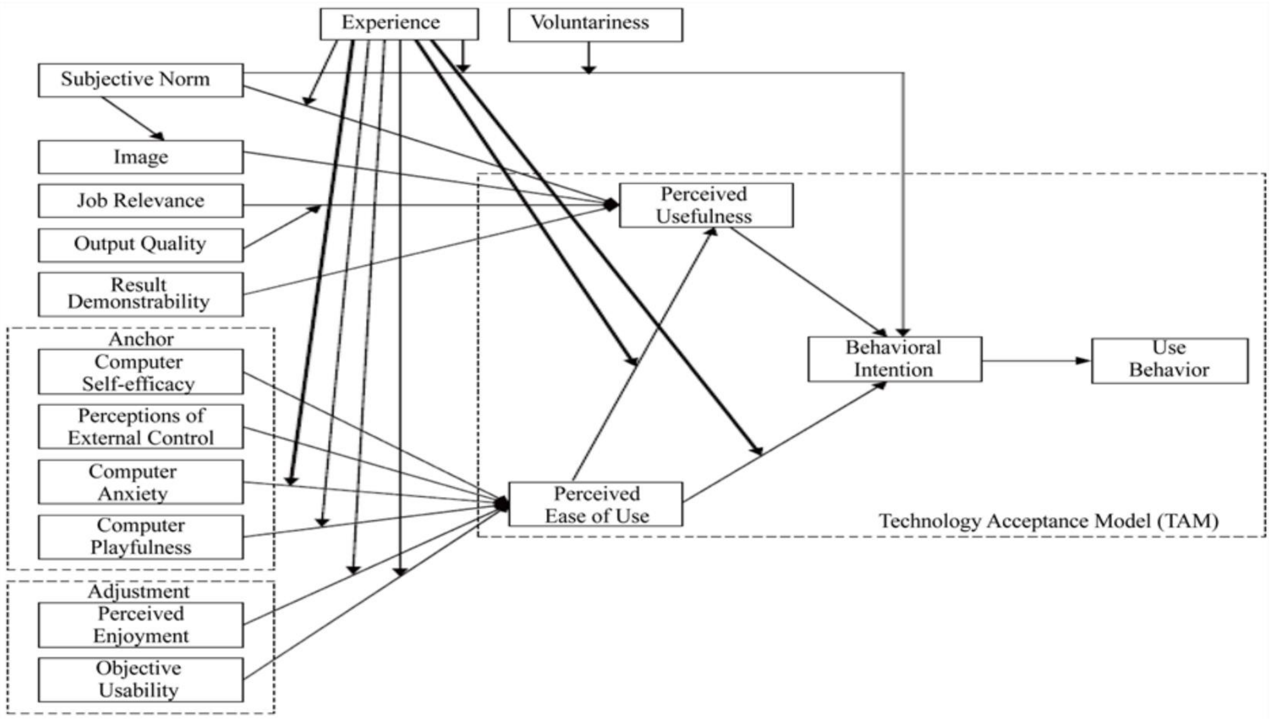

Figure 2: TAM3 (Technology acceptance model for augmented reality and building information modelling integration in the construction industry, 2020, Elshafey et al, p. 165)

The study utilises the modified Technology Acceptance Model 3 (TAM3) to examine the adoption of big data analytics in the South African mining industry, taking into account individual, organisational, and system-specific aspects (Venkatesh & Bala, 2008).

- Individual Characteristics: TAM3 focuses on individual attributes such as computer self-efficacy and computer anxiety, which play a crucial role in shaping opinions of the usefulness and simplicity of utilising big data analytics. These elements enhance employees' comfort and confidence in embracing new technology.

- Organisational Variables: The model includes organisational factors such as managerial support and subjective norms, emphasising the significance of organisational culture and leadership in the adoption of technology. The successful introduction of new technology heavily relies on management assistance.

- TAM3 specifically emphasises system-specific criteria, including data quality and user proficiency with technology. These elements influence the perceived utility and simplicity of use. High-quality data and great user experiences contribute to more favourable attitudes and adoption.

- Strategic Implications: Employing the TAM3 framework, this study aimed to comprehend the variables that influence the acceptability of big data analytics, so enabling the formulation of efficient strategies for its implementation. The purpose of this comprehension is to potentially enhance the competitiveness and expansion of the South African mining sector.

The selection of the modified TAM3 model is grounded on its methodology for including a wide array of important aspects across individual, organisational, and system-specific dimensions within the mining industry's context of adopting big data analytics.

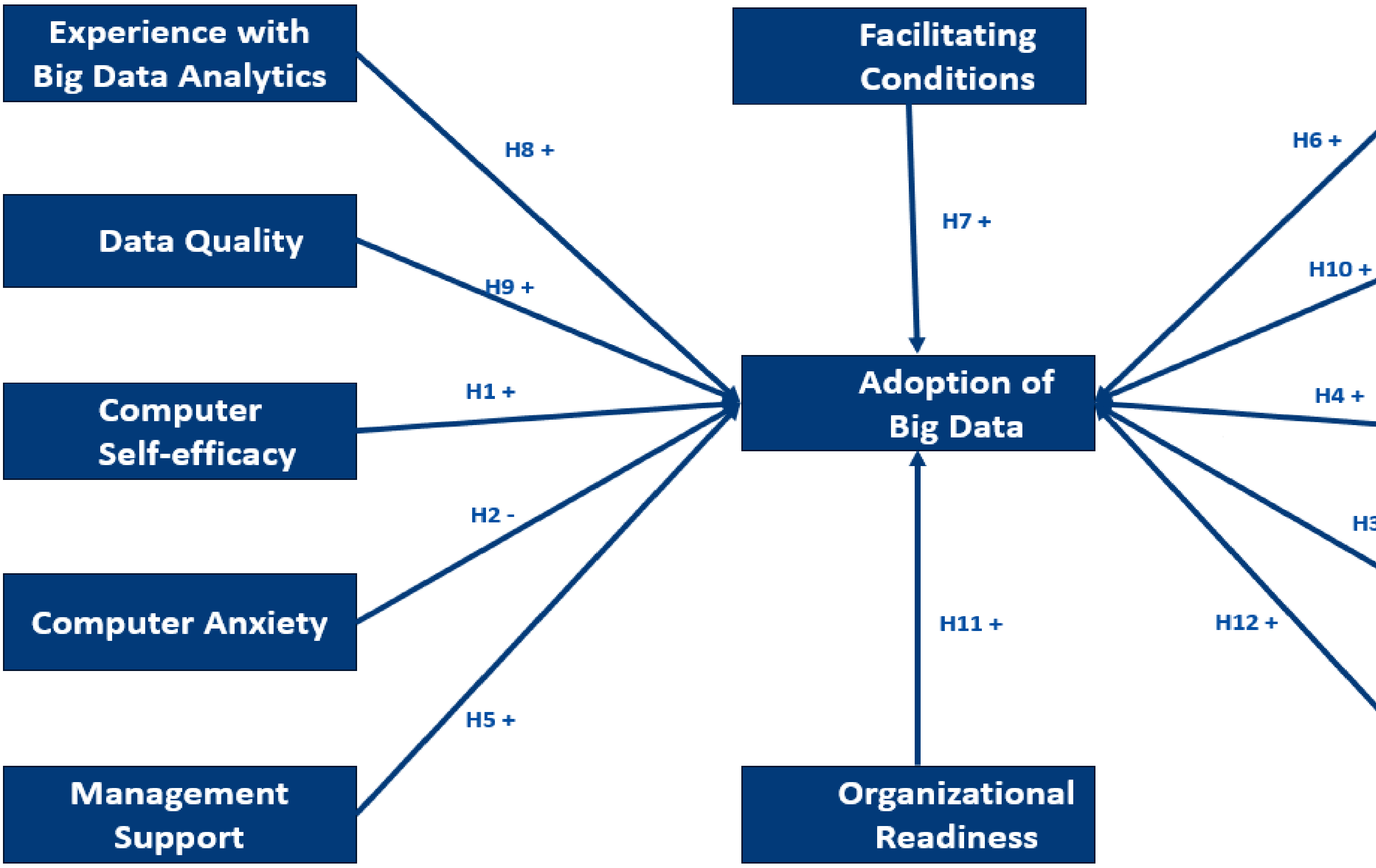

Figure 3: Modified Technology Acceptance Model 3 (TAM 3)

The modified TAM3 model

The modifications made to TAM3, based on the research on big data, demonstrate a customised method for comprehending the acceptance of technology in the mining sector. This approach considers both the technical elements and the human and organisational factors that impact the adoption of technology.

1. Adjustments to TAM3:
    - Inclusion of Additional Variables: The modified TAM3 in Figure 3 incorporates additional hypotheses that are specifically relevant to the context of big data analytics in the mining industry. These include variables like management support, peer influence, facilitating conditions, experience with big data analytics, and data quality.
    - Refinement of Constructs: Constructs like computer self-efficacy and computer anxiety were retained but further emphasized due to their significant influence on the adoption of big data technologies, as observed in empirical findings within the mining sector.

2. Motivation from Literature:
    - Context-Specific Factors: The literature highlighted the unique challenges and opportunities within the mining industry that affect technology adoption, such as the critical need for data quality and the influence of peer and management support in technology adoption. These insights were instrumental in refining TAM3 to better suit the industry-specific factors affecting technology acceptance.
    - Empirical Evidence: The empirical evidence from studies conducted in similar sectors demonstrated the significant impact of management support and peer influence on technology adoption, which further justified their inclusion and emphasis in the modified model.

3. Specific Changes:
    - Introduction of Hypotheses: New hypotheses related to the perceived ease of use and usefulness of big data analytics, influenced by management and peer support, were added. This reflects a deeper understanding of how social and organizational

dynamics influence technology acceptance in your specific research context.

- Focus on Data Quality: Given the critical role of data in the mining industry, the modified TAM3 places a significant emphasis on the quality of data, which aligns with the sector's reliance on accurate and timely data for operational decisions.

2.4 Hypotheses

Computer Self-Efficacy

Hypothesis 1:

Greater levels of computer self-efficacy among mining industry personnel in South Africa are positively associated with the adoption of big data analytics.

Computer Anxiety

Hypothesis 2:

Higher levels of computer anxiety among mining industry employees in South Africa are negatively associated with the adoption of big data analytics.

Perceived Ease of Use

Hypothesis 3:

The perception of big data analytics as easy to use is positively correlated with its adoption in the South African mining industry.

Perceived Usefulness

Hypothesis 4:

The perception of big data analytics as beneficial and useful is positively correlated with its adoption in the South African mining industry.

Management Support

Hypothesis 5:

Strong management support is positively correlated with the adoption of big data analytics in the South African mining industry.

Peer Influence

Hypothesis 6:

Positive peer influence, indicating a belief among employees that the use of big data analytics is advantageous and supported by colleagues, is positively associated with its adoption in the South African mining industry.

Facilitating Conditions

Hypothesis 7:

The presence of facilitating conditions, including necessary resources and infrastructure, is positively correlated with the adoption of big data analytics in the South African mining industry.

Experience with Big Data Analytics

Hypothesis 8:

Greater experience with IT or big data analytics among personnel in the South African mining industry is positively correlated with the adoption of big data analytics.

Data Quality

Hypothesis 9:

Higher levels of data quality, including precision, exhaustiveness, and timeliness, are positively related to the adoption of big data analytics in the South African mining industry.

Subjective Norms

Hypothesis 10:

Positive subjective norms, indicating a belief among employees that the use of big data analytics is advantageous and supported by influential referents, are positively associated with its adoption in the South African mining industry.

Organisational Readiness

Hypothesis 11:

The readiness of an organisation, in terms of culture and resource allocation, is positively correlated with the adoption of big data analytics in the South African mining industry.

External Pressure

Hypothesis 12 :

External pressures, such as market demands and competitive forces, are positively correlated with the adoption of big data analytics in the South African mining industry.

The relationships between these factors and the adoption of big data analytics was examined by testing each of these hypotheses using data collected from the South African mining industry. This analysis should assist in identifying the primary drivers and barriers to adoption and informing strategies to facilitate the successful adoption of big data analytics in the industry.

2.5 Conclusion

This section concludes by integrating TAM3 to analyse key factors in adopting big data analytics in South Africa's mining sector. It acknowledges the benefits and barriers to implementation, citing sources like Wamba et al. (2017) and Tshabalala (2018). The study emphasises the role of technological, organisational, and environmental elements, referencing works by Popovi et al. (2018), Akter et al. (2017), and others. It suggests that despite challenges, progress is being made, advocating for continuous research to address gaps in understanding and practice.

CHAPTER 3. Research Methodology

This chapter outlines the methodology employed to investigate the hypotheses and themes identified in the literature review. It will cover the research approach and design, including data collection methods, the population and sample selection, and the research instrument used. Additionally, the chapter will describe the procedure for data collection, the strategy for data analysis and interpretation, and discuss the limitations and challenges encountered during the research process.

3.1 Research Approach

This study utilises a quantitative research methodology, which focuses on a systematic and empirical inquiry using numerical data and statistical methodologies (Creswell & Creswell, 2017). This methodology is especially suitable for analysing big data analytics in the mining sector, where aspects such as technological proficiency and organisational readiness can be measured (Groves & Lyberg, 2010).

The primary factors for choosing a quantitative approach are:

Objectivity: It provides unbiased measurements, which are essential for drawing conclusions without personal prejudice, therefore facilitating a more complete comprehension of the aspects that influence the adoption of big data analytics (Bryman, 2012).

Generalisability: The methodology is suitable for conducting extensive research, facilitating the collection of data from a sample that accurately represents the population and enabling the application of findings to the wider sector (Creswell & Creswell, 2017).

Statistical hypothesis testing: Statistical analysis enables the verification or rejection of research hypotheses (Field, 2013).

Quantitative research necessitates the use of rigorous statistical methods to reveal patterns and relationships (Tabachnick & Fidell, 2013).

Compatibility with TAM3: This methodology is highly suitable for research based on the TAM3 framework, as it provides quantitative measurements of the several elements that influence technology adoption (Venkatesh & Bala, 2008).

The study used quantitative methodologies to assess and validate the model's components (Fisher, 2019).

Research design:

Research Design: A survey research design was selected, employing surveys to collect data on the attitudes, opinions, behaviours, or characteristics of the respondents (Finn, 2013). This approach has benefits such as cost-efficiency, the ability to handle large-scale population studies, and streamlined data collecting, particularly through online platforms (Fowler, 2013; Bryman, 2016).

3.2 Data Collection Methods

Data collection involved a survey, a common tool for collecting quantitative data efficiently from numerous respondents (Finn, 2013). A survey was designed to evaluate factors influencing big data analytics adoption, covering organisational, technological, and environmental aspects. It comprised closed-ended, Likert-scale type questions.

Closed-ended questions standardise responses and facilitate statistical analysis, while the Likert scale captures attitudes and perceptions (Artino et al., 2014; Finn, 2013).

Sampling and Recruitment:

Convenience sampling targeted computer-based users in DRDGOLD Pty Ltd, as per permission from DRDGOLD, a prominent South African gold producer. The company's attributes and transparency made it suitable for this study, offering insights into the determinants influencing the assimilation of technologies like big data analytics. The diverse roles and hierarchical levels included in the study provided a more complete outlook on big data analytics adoption.

The data-intensive nature of the mining industry, and DRDGOLD's approach to operational decisions, made it an apt choice for examining big data analytics adoption (Li et al., 2020). The researcher's executive position at DRDGOLD enabled data accessibility, enhancing the study's robustness.

The table below, labelled "Convenience Sampling, Functions, and Number of Computer-Based Users," displays the distribution of computer-based users among different departments in DRDGOLD. The table presents many departments, including Survey, Stores, Security, and others, along with the respective count of computer-based users in each department. Significantly, departments such as Metallurgy, Information Technology, Human Resources, Finance, and Engineering exhibit a greater number of users, suggesting that these departments have more prominent involvement in computer usage. On the other hand, departments such as the Survey department, Purchasing, and the Rigging workshop have a smaller number of users. In total, the table contains data on 332 individuals who use computers, offering a glimpse of the distribution of the digital workforce for the research.

Table 1: Convenience sampling, functions, and number of computer-based users

Function	Number of Computer-Based Users
Survey department	3
Survey	2
Stores	8
Security	19
Safety department	3
Safety department	1
Risk	3
Rigging workshop	1

Purchasing	1
Projects	4
Procurement	6
Payroll	7
NUM	1
Metallurgy	50
Medical centre	6
Mechanical	2
Management	12
Legal	2
Instrumentation	20
Information Technology	20
Human Resources	27
Health and Safety	12

Floatation	1
Fitting workshop	5
Finance	32
Executives	2
Environmental	11
Engineering	28
Electrical workshop	11
EBDA workshops	5
Diesel workshop	2
City Deep	1
Boiler making	5
Administration	16
Accounts	2
ABET	1

Total	**332**

Incorporating top executives like CIOs or CTOs was vital for understanding strategic decisions related to technology adoption and resource allocation for big data analytics. Their perspectives helped gauge the organisation's strategic integration of big data analytics with its commercial goals.

Middle management, including department heads and project managers, was crucial for assessing managerial support for big data analytics integration. Their insights were key in understanding the perceived effectiveness and ease of use of these technologies, aligning with TAM3 factors.

IT personnel, responsible for technology implementation and maintenance, provided practical insights into the challenges and facilitators of big data analytics adoption. This group included system administrators, data scientists, and IT support staff, offering varied perspectives.

Front-line employees, with direct experience of technology's impact on their work, contributed valuable insights into perceived benefits and training or support inadequacies. Their feedback enriched understanding of subjective norms and computer self-efficacy.

Incorporating a range of roles enhanced the study's credibility by reducing bias towards any company faction. Examining different hierarchical levels helped identify discrepancies between strategic goals and practical implementation, crucial for understanding big data analytics adoption.

Surveys were conducted using Microsoft Forms to streamline data collection. Respondents received email invitations with study details and confidentiality assurances, followed by reminder emails. Informed consent was obtained as well asensuring anonymity (Bryman, 2016).

To ensure data quality, the survey was pre-tested with 6 field experts to refine questions, followed by a pilot test within DRDGOLD to test the survey's efficacy and make necessary modifications. Participants in the pilot test were excluded from the final sample.

3.3 Population and Sample

3.3.1 *Population*

All computer-based employees at DRDGOLD Pty Ltd of 2155 employees constituted the population for this study.

3.3.2 *Sample and Sampling Method*

Convenience sampling was chosen due to its efficiency and practicality, especially given resource, time, and access constraints (Etikan, Musa, & Alkassim, 2016). This method involves selecting participants based on their accessibility and willingness to participate.

Focusing on DRDGOLD's computer-based users was practical due to their accessible nature. While this approach may not offer a comprehensive representation of all computer users in the mining sector, insights from DRDGOLD's employees can contribute significantly to the broader understanding of big data analytics adoption in the industry.

It's important to note, however, that convenience sampling may introduce selection bias, potentially affecting the generalisability of the findings. This limitation will be carefully considered in the analysis and interpretation of the study's results.

3.3.3 *Sampling Procedure*

The Human Resources department of DRDGOLD Pty Ltd provided a list of all employees meeting the inclusion criteria for the study. Following this, the survey was sent to all computer-based users within the company. This approach ensured that the sample was appropriately targeted and inclusive of the relevant participants for the study.

As identified, a survey was the chosen instrument for data collection, aligning with the study's quantitative approach.

The survey examined the following elements of the TAM3 framework:

Computer Self-Efficacy: Questions gauged participants' confidence in using software, hardware, and analytical tools for big data analytics.

Computer Anxiety: This section probed participants' anxiety levels associated with technology use, focusing on stress or discomfort in big data analytics tasks.

Management Support: Queries here assessed the perceived level of senior management support in adopting big data analytics, including resource allocation and strategic direction.

Subjective Norms: This focused on perceived social pressure to use big data analytics within the organisation.

Data Quality: Questions addressed perceptions of data veracity, completeness, and efficacy of data integration processes.

Peer Influence: This measured the influence of colleagues on an individual's decision to use big data analytics.

Experience with Big Data Analytics: The survey assessed the impact of prior experiences with these tools on perceptions and attitudes.

Facilitating Conditions: Questions evaluated the organisational and technical infrastructure supporting big data analytics utilisation.

External Pressure: This component examined the influence of market trends and regulatory demands on the industry's adoption of big data analytics.

Adoption of Big Data Analytics: Serving as a dependent variable, this measured the overall degree of adoption in the mining industry.

Perceived Usefulness (PU): This gauged beliefs about the impact of big data analytics on job performance.

Perceived Ease of Use (PEOU): This section assessed the perceived user-friendliness and integration of the technology into business operations.

Each construct included 2 to 5 items, with responses captured on a 5-point Likert Scale.

3.4 Procedure for Data Collection

The procedure for collecting data via surveys is described in the following section.

Data Collection Methodology:

After compiling the survey and obtaining ethical clearance, invitations to participate were emailed to potential respondents from DRDGOLD Pty Ltd. The email included a brief description of the study, its purpose, estimated completion time, and assurances about the voluntary nature of participation and confidentiality. A link to the online survey, hosted on Microsoft Forms, was provided.

Follow-up emails were sent to non-responders at two and four-week intervals to optimise response rates. Participants were given a specified timeframe (e.g., four to six weeks) to complete the survey.

Data Storage and Management:

Completed survey data were exported from Microsoft Forms and securely stored on a password-protected computer. Personal identifiers were removed to ensure anonymity, in line with data protection regulations and university guidelines. Access to the data was restricted to authorised personnel and the researcher.

Data Analysis:

The data were cleaned, coded, and analysed using IBM SPSS Statistics. Descriptive statistics provided a summary of the data, including measures of central tendency and variability. Inferential statistics, including hypothesis testing and regression analysis, were used to examine the factors impacting big data analytics adoption and their relationships.

Descriptive statistics facilitated understanding of the key themes and variations in responses. Inferential statistics, on the other hand, allowed for drawing conclusions from the sample about the broader population. Assumptions underlying these statistical methods were validated to ensure reliability.

Regression analyses were conducted to assess the strength and direction of relationships between variables within the TAM3 framework. These analyses provided insights into the most influential factors on the adoption of big data analytics within the mining industry.

3.5 Data analysis strategy and interpretation

Data Cleaning and Preparation:

The data underwent cleaning to address inconsistencies, missing values, and anomalies (Pallant, 2016). Methods like imputing missing values or removing extreme cases were applied as needed (Hair et al., 2018).

Descriptive Statistics:

Descriptive statistics, including frequencies, means, and standard deviations, were calculated for all variables to overview sample characteristics and response distribution (Field, 2018). This step helped understand the data's general trends and patterns.

Reliability Assessment:

The reliability and validity of the survey's constructs were assessed. Cronbach's alpha was calculated for each scale to evaluate internal consistency (Tavakol & Denning, 2011). Convergent and discriminant validity were assessed using CFA or EFA, depending on the data (Brown, 2015).

Inferential Statistical Analysis:

Inferential statistics were used to test hypotheses and answer research questions. Techniques like correlation analysis, multiple regression analysis, were employed (Tabachnick & Fidel, 2013).

Correlation Analysis:

Bivariate correlation analysis examined relationships between independent variables (e.g., computer self-efficacy) and the dependent variable (adoption of big data analytics) (Field, 2018). Pearson's correlation coefficients were calculated based on normality tests.

Multiple Regression Analysis:

This identified the main predictors of big data analytics adoption. The dependent variable was regressed against independent variables to evaluate the significance of relationships (Hair et al., 2018). Regression coefficients indicated the importance of each predictor.

Interpretation and Presentation of Results:

Results were interpreted in relation to the research questions, hypotheses, and existing literature (Creswell & Creswell, 2017). Findings were presented through tables, charts, and graphs, with implications for theory, practice, and future research discussed.

This strategy aimed to provide insights into factors influencing big data analytics adoption in the South African mining industry and suggest ways to enhance adoption.

3.6 Possible Limitations and Challenges of the Study

The study faces several limitations:

Limited Generalisability: Concentrating on the South African mining industry and specifically on DRDGOLD Pty Ltd may not reflect wider industry practices in big data analytics adoption.

Self-reported Data: Utilising surveys introduces response bias, where participants might offer socially desirable answers or misunderstand questions, potentially skewing results (Pallant, 2016; Phillips & Clancy, 1972).

Cross-sectional Design: This limit causal inferences and understanding of temporal changes in big data analytics adoption (Creswell & Creswell, 2017).

Non-response Bias: The possibility that respondents differ significantly from non-respondents, impacting the study's validity (Dillman et al., 2014).

Insufficient Sample Size: This may reduce the study's statistical power and its ability to detect significant relationships.

Internal Validity Concerns: To enhance credibility, future research could incorporate alternative data collection methods or a longitudinal design for more precise causal relationships (Bryman, 2016; Flick, 2018).

Participants from DRDGOLD Pty Ltd might overstate their expertise or readiness for big data analytics, influenced by perceived organisational expectations. It is crucial to design the survey and analyse results considering this potential bias (Fisher, 1993).

3.7 Quality Assurance

In this study, quality assurance centred on the principles of validity and reliability, crucial for ensuring the credibility of quantitative research (Creswell & Creswell, 2017). Validity refers to the accuracy of the measurements and whether the research truly measures what it intends to (Field, 2018). Reliability pertains to the consistency and dependability of the measurement process (Bryman, 2016). Ensuring external validity, or generalisability, is also vital to confirm that the study's findings can be applied to broader contexts beyond the specific sample used (Flick, 2018). Careful attention to these aspects helps maintain the integrity and trustworthiness of the research findings.

3.7.1 *External validity*

External validity concerns the generalisability of findings to other contexts, settings, or populations. To enhance external validity:

Clear Research Design: The study's design, including a quantitative survey and TAM3 framework, was detailed to aid understanding and potential replication (Yin, 2014).

Sampling Technique: Convenience sampling, selected for efficiency and practicality, may influence generalisability due to its inherent limitations (Etikan, Musa, & Alkassim, 2016).

Diverse Population: DRDGOLD Pty Ltd's diverse attributes may allow for broader applicability of findings to similar contexts (Bryman, 2016).

Rich Description: Detailed accounts of the research context, methods, and findings were provided to assess transferability (Yin, 2014).

Limitations affecting external validity:

Single-Country Focus: The focus on South Africa may limit the findings' applicability to different cultural, political, and economic contexts (Bryman, 2016).

Cross-Sectional Design: The study's snapshot nature may restrict the temporal transferability of findings (Flick, 2018).

Future research could broaden the scope, employ longitudinal designs, or use different methods to enhance generalisability (Bryman, 2016; Flick, 2018; Yin, 2014).

Limitations to reliability:

Self-Reported Data: Survey reliance could introduce biases affecting reliability (Bryman, 2016).

Non-Response Bias: Potential sample non-representativeness could impact result reliability (Bryman, 2016).

To improve reliability, future research might utilise different data collection methods and strategies to mitigate non-response bias (Bryman, 2016; Flick, 2018).

3.7.2 *Internal validity*

Internal validity is crucial in determining if the study's findings accurately reflect the relationships among the variables. To maximise internal validity, several measures were implemented:

Clear Conceptual Framework: Utilising the TAM3 framework provided a robust theoretical basis to understand the variables related to big data analytics adoption (Venkatesh & Bala, 2008).

Valid and Reliable Instruments: Survey items were adapted from previously validated instruments to ensure accurate and reliable measurement of the constructs (Bryman, 2016).

Controlling Confounding Variables: Factors like company size and industry sector were considered to ensure observed relationships were not influenced by external variables (Flick, 2018).

Rigorous Data Analysis: Employing statistical methods like multiple regression analysis helped control biases and confounding factors, providing more reliable results (Field, 2018).

Pre-testing: Conducting pre-tests improved the survey's validity and reliability, ensuring it accurately measured the intended constructs and provided consistent results (Dillman et al., 2014).

3.7.3 *Reliability*

Reliability is critical for ensuring the consistency and stability of research findings. To enhance reliability:

Standardised Procedures: The study employed standardised data collection methods, such as a structured survey with a Likert scale, to reduce variability in data collection (Bryman, 2016).

Valid and Reliable Measurement Instruments: Adaptation of survey items from previously validated instruments helped ensure accurate representation and reliability of the measured constructs (Bryman, 2016).

Pilot Testing: A pilot test was conducted to refine the survey, addressing potential issues in the data collection process, thereby bolstering study reliability (Bryman, 2016).

Detailed Documentation: Comprehensive documentation of the research process, from question development to data analysis, was maintained for transparency and replicability (Flick, 2018).

3.8 Ethical Considerations

Ethical integrity was paramount in conducting research with DRDGOLD Pty Ltd. Key measures included:

IRB Approval: Obtained necessary approval from the Institutional Review Board, ensuring adherence to ethical standards (Resnik, 2015). For this study, CEO approval from DRDGOLD Pty Ltd and the necessary ethical documents from Wits University were secured.

Informed Consent: Ensured all participants provided informed consent, understanding study risks, benefits, their withdrawal rights, and data confidentiality (American Psychological Association, 2017).

Confidentiality: Maintained participant anonymity and secured data storage, avoiding any disclosure of personal information without explicit consent (American Psychological Association, 2017).

Conflict of Interest: Avoided and disclosed any conflicts of interest to maintain study objectivity (Resnik, 2015).

Data Management: Adhered to guidelines for handling, storing, and disposing of data, complying with institutional and legal standards (Bishop, 2019).

Intellectual Property: Credited all sources to respect intellectual property rights (American Psychological Association, 2020).

Transparency: Maintained openness in methodology and findings to facilitate replication and validation (Nosek et al., 2015).

Table 1: Consistency table: research questions, propositions, data collection and data analysis

RQ #	State Research Question or Objective	Hyp #	State Proposition or Hypothesis	Data collection detail	Data analysis method
1	What factors influence the South African mining industry's adoption	1	Computer Self-Efficacy: Greater levels of computer self-efficacy among mining industry personnel in South Africa are positively associated with the	Survey using Likert Scale (1-5)	Correlation Analysis

	of big data analytics?		adoption of big data analytics.		
		2	Computer Anxiety: Higher levels of computer anxiety among mining industry employees in South Africa are negatively associated with the adoption of big data analytics.		Correlation Analysis
		3	Perceived Ease of Use: The perception of big data analytics as easy to use is positively correlated with its adoption in the South African mining industry		Regression Analysis
		4	Perceived Usefulness: The perception of big data analytics as beneficial and useful is positively correlated with its adoption in the South African mining industry.		Regression Analysis

		5	Management Support: Strong management support is positively correlated with the adoption of big data analytics in the South African mining industry.		Regression Analysis
		6	Peer Influence: Positive peer influence, indicating a belief among employees that the use of big data analytics is advantageous and supported by colleagues, is positively associated with its adoption in the South African mining industry.		Regression or Correlation Analysis
		7	Facilitating Conditions: The presence of facilitating conditions, including necessary resources and infrastructure, is positively correlated with the adoption of big data analytics in the		Regression Analysis

			South African mining industry.		
		8	Experience with IT/Big Data Analytics: Greater experience with IT or big data analytics among personnel in the South African mining industry is positively correlated with the adoption of big data analytics.		Correlation or Regression Analysis
		9	Data Quality: Higher levels of data quality, including precision, exhaustiveness, and timeliness, are positively related to the adoption of big data analytics in the South African mining industry.		Regression Analysis
		10	Subjective Norms: Positive subjective norms, indicating a belief among employees that the use		Regression Analysis

			of big data analytics is advantageous and supported by influential referents, are positively associated with its adoption in the South African mining industry.		
		11	Organisational Readiness: The readiness of an organisation, in terms of culture and resource allocation, is positively correlated with the adoption of big data analytics in the South African mining industry.		Regression Analysis
		12	External Pressure: External pressures, such as market demands and competitive forces, are positively correlated with the adoption of big data analytics in the South African mining industry.		Regression Analysis

To summarise, Chapter 3 explored the methodology used in this study, which included explaining the research strategy, data collection procedures, and analysis approaches. The utilisation of a quantitative methodology, supported by survey instruments, enabled a methodical examination of the elements that impact the implementation of big data analytics in the mining industry of South Africa. Data was gathered from many departments inside mining corporations via convenience sampling, which allowed for a full understanding of the topic area. The statistical studies performed, which included correlation and regression analyses, yielded strong empirical evidence in support of the study's hypotheses. Quality assurance mechanisms were put in place to maintain the accuracy and consistency of the findings.

In the upcoming Chapter 4, we will show the empirical results obtained from the data analysis. These results will provide useful insights into the adoption of big data analytics in the South African mining industry.

CHAPTER 4. PRESENTATION OF RESULTS

4.1 Introduction

In Chapter 4, "Presentation of Results," the study provides empirical findings from a survey conducted among professionals in South Africa's mining industry. The survey, informed by existing literature, explored factors influencing technology adoption, including individual attitudes, organisational support, and external pressures. The chapter integrates quantitative data like mean scores and standard deviations to understand the elements affecting big data analytics adoption. It features visuals and tables for clarity on trends and patterns, comparing these findings with prior research to assess the industry's current state. This chapter aims to lay a foundation for in-depth analysis and discussion in subsequent sections, enhancing understanding of the dynamics involved in adopting big data analytics in the mining industry.

4.2 Reliability Assessment

Cronbach's Alpha is a measure of internal consistency, i.e., how closely related a set of items are as a group. It is a measure of scale reliability. A high Cronbach's Alpha value (generally above 0.7) indicates good internal consistency.

The calculated Cronbach's Alpha for the survey data was approximately 0.888. This value indicates a high level of internal consistency among the items in the survey. Generally, a Cronbach's Alpha value above 0.7 is considered acceptable, and values above 0.8 are deemed very good, suggesting that the survey items are reliably measuring the underlying construct (Bryman, 2016).

Cronbach's Alpha Values: The calculated values for each survey item (when each item was dropped in turn) are all above 0.87, which indicates a very high level of internal consistency. This suggests that the survey items were well correlated and reliably measure the underlying constructs they are intended to.

Variance of Each Survey Item: The variance of each survey item varies across the items. This indicates differing levels of variability in responses for each question.

Average Response for Each Survey Item: This showed how respondents, on average, answered each question.

In general, the high Cronbach's Alpha values seen in the survey indicated that the survey exhibits substantial internal consistency and reliability. Ensuring the instrument consistently assesses the desired components is a vital aspect of survey design, since it provides confidence in the validity of the survey's conclusions.

4.3 Descriptive Statistics for Each Statement

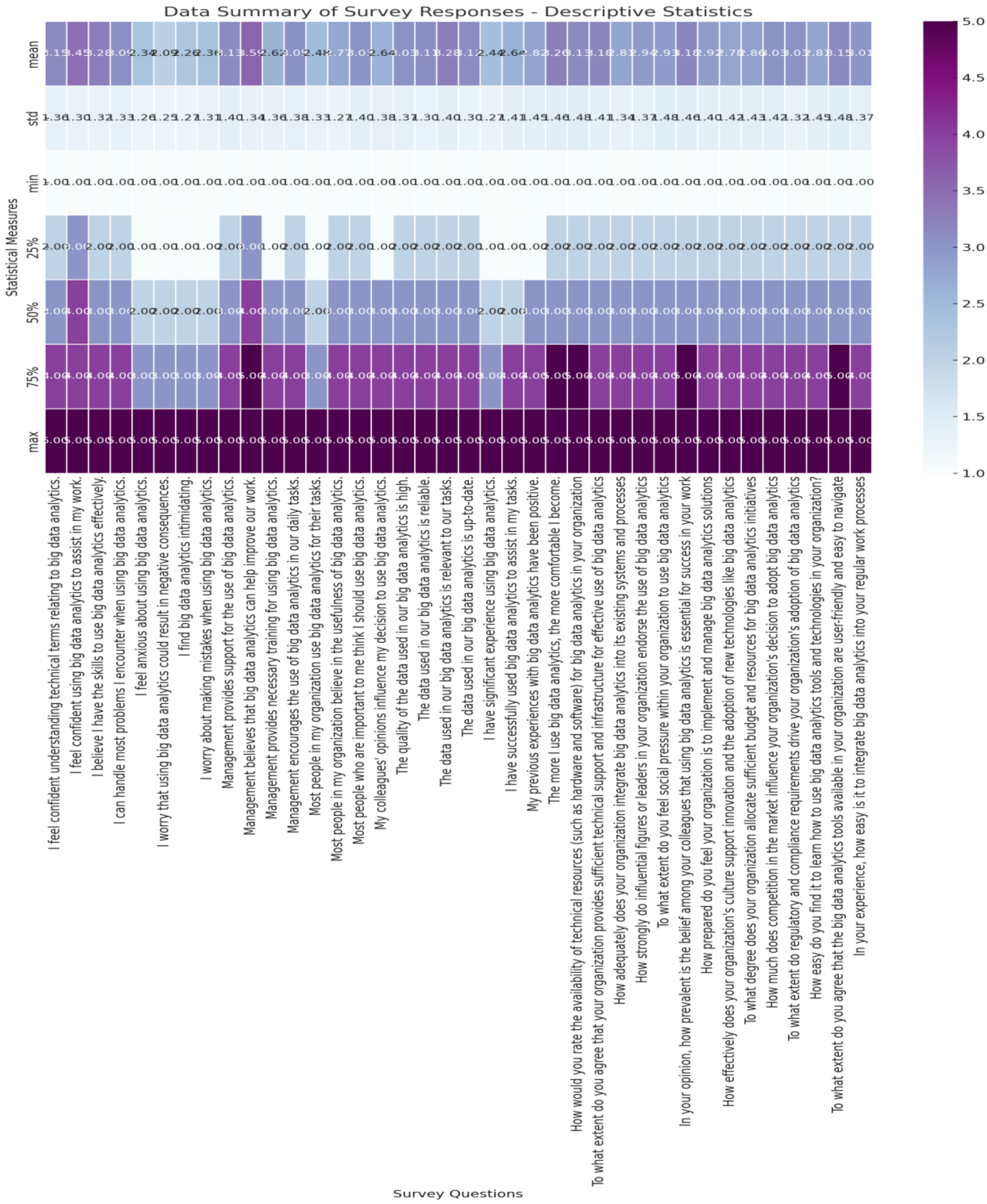

Figure 4: Descriptive Statistics - Survey Responses

4.3.1 *Descriptive Data Statistics*

The heatmap of descriptive statistics above displays measures such as mean, standard deviation, minimum, and maximum values for each survey question.

Most questions have mean values around the mid-point of the scale, indicating moderate agreement or confidence levels among respondents. The standard deviations suggested some variability in responses.

4.3.2 *Missing Values Analysis:*

The dataset did not have any missing values, which is advantageous for performing analysis. The complete dataset means that there was no need to impute any data with the mean for that question to maintain consistency in the dataset.

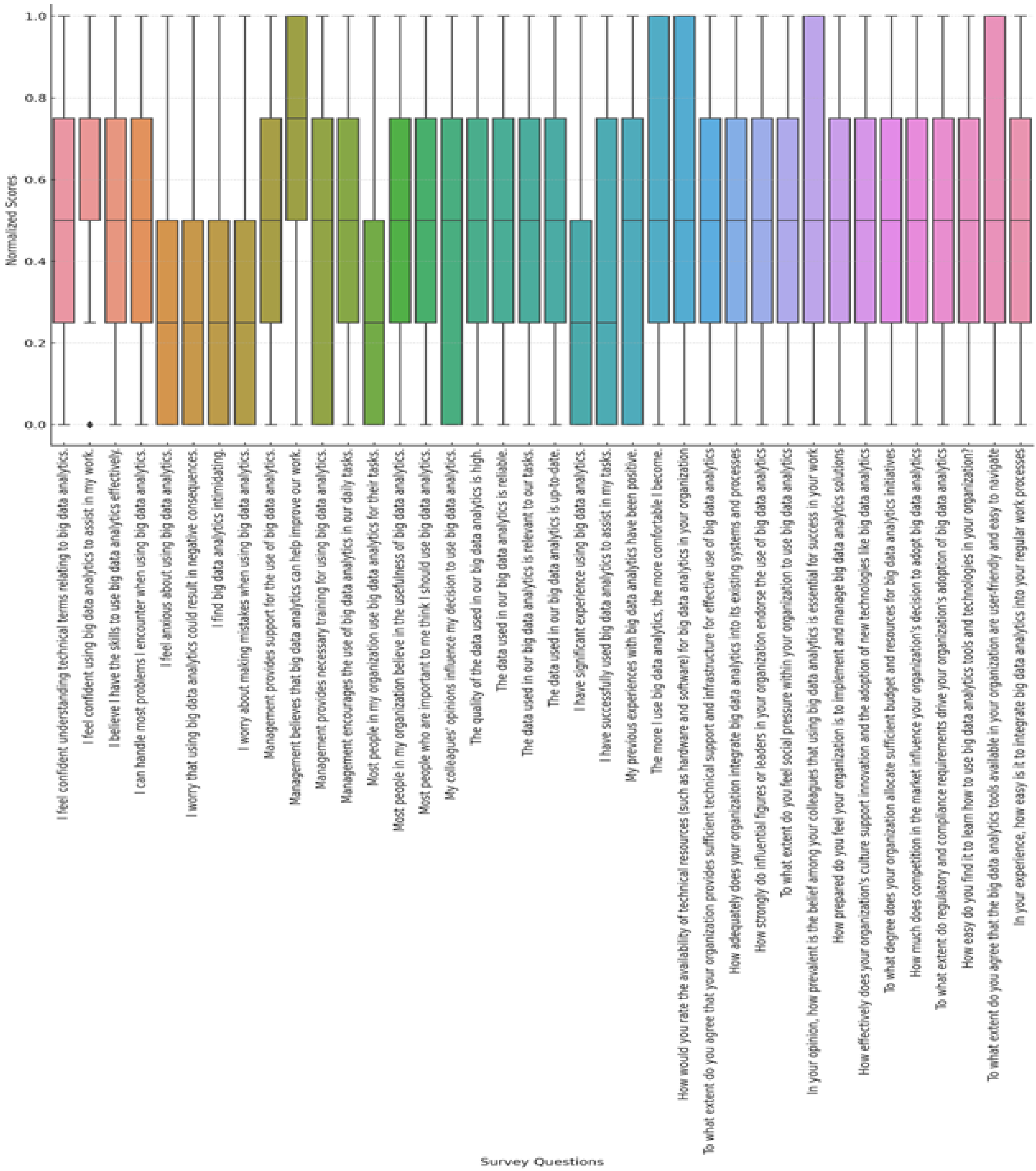

Figure 5: Boxplot - Normalised Survey Data

4.3.3 *Data Normalisation (Boxplot Visualisation):*

The boxplot of the normalised data shows the distribution of responses for each survey question on a consistent scale (0 to 1). This normalisation is essential for analyses that require data on a similar scale.

The boxplots provide a visual summary of the median, quartiles, and potential outliers in the responses, which can be useful for identifying questions with a broader range of opinions.

Normalised Data Overview:

The first few rows of the normalised data are displayed, showing the transformed values. This normalised dataset is now suitable for further statistical analyses or machine learning models where normalisation is required.

In summary, this overview of the survey data provides a solid foundation for further detailed analyses. The descriptive statistics offer a snapshot of general trends in responses, while the normalisation and missing value handling ensure the dataset is primed for advanced analysis techniques. These insights can be instrumental in understanding the factors influencing big data analytics adoption in the mining industry.

4.4 Results pertaining to Computer Self-Efficacy Hypothesis 1: Greater levels of computer self-efficacy among mining industry personnel in South Africa are positively associated with the adoption of big data analytics.

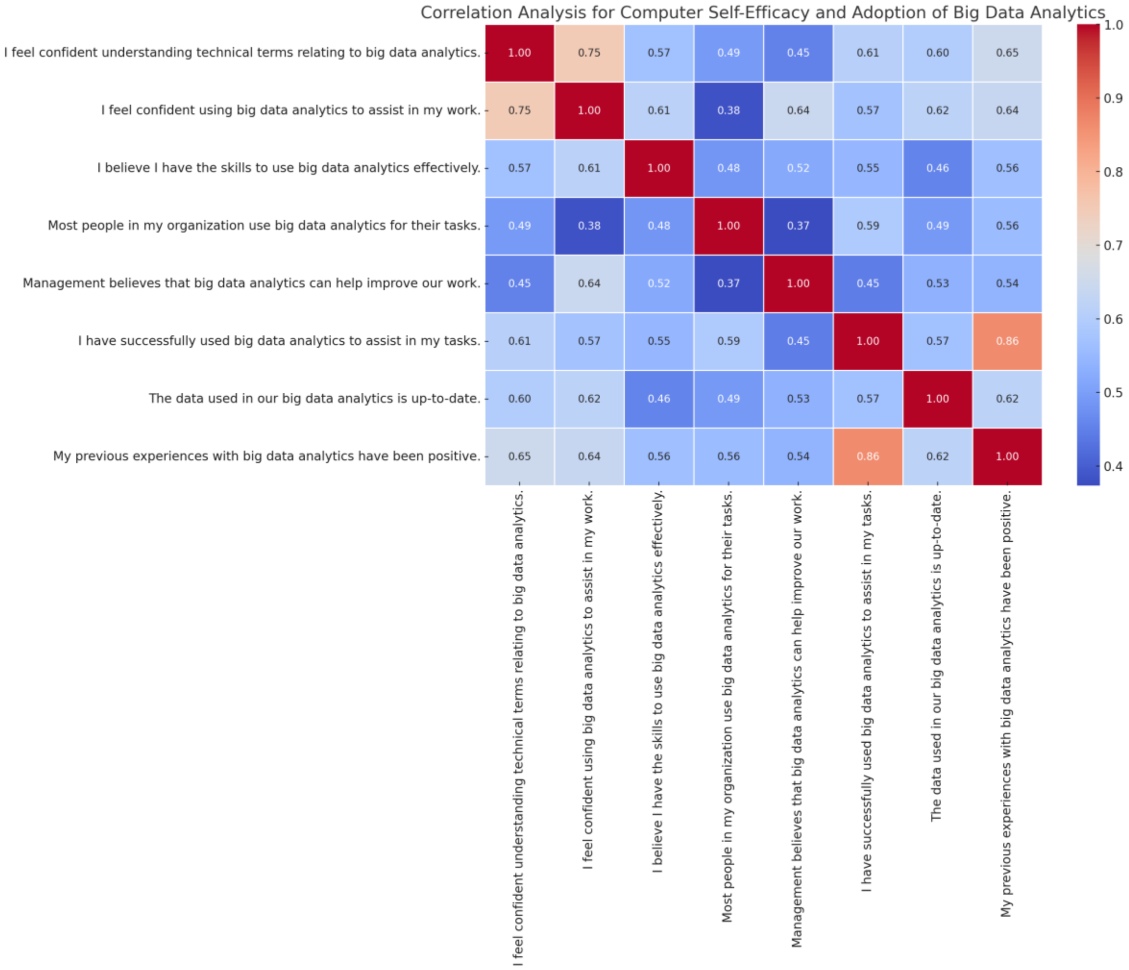

Figure 6: Correlation Analysis - Computer Self-Efficacy and Adoption of Big Data Analytics

The correlation analysis between Computer Self-Efficacy and the adoption of big data analytics is visualised in the heatmap above. This analysis combined relevant questions related to Computer Self-Efficacy and various aspects of big data analytics adoption.

4.4.1 *Key Points from the Correlation Analysis:*

Strong Positive Correlations:

The heatmap reveals several strong positive correlations between self-efficacy measures and adoption indicators. This implies that greater confidence and skills in using big data analytics (aspects of computer self-efficacy) are associated with higher levels of its adoption and perceived usefulness in the organisation.

Interpretation of Specific Correlations***:***

For instance, high correlations between confidence in understanding technical terms and positive previous experiences with big data analytics suggest that self-efficacy contributes to more successful and positive experiences in using these technologies.

Relationships Among Self-Efficacy Measures:

The self-efficacy related questions also show strong correlations with each other, indicating a cohesive construct of self-efficacy in the context of big data analytics.

Implications for Hypothesis***:***

These findings support the hypothesis that greater levels of computer self-efficacy among mining industry personnel in South Africa are positively associated with the adoption of big data analytics.

Broader Organisational Context:

The correlations with management beliefs and organisational usage patterns suggest that individual self-efficacy aligns with broader organisational trends and perceptions regarding big data analytics.

4.4.2 *R-squared analysis*

The R-squared analysis for the hypothesis related to "Computer Self-Efficacy" and its impact on the adoption of big data analytics yielded an R-squared value of 0.534.

Interpretation:

R-squared (0.534): This indicates that approximately 53% of the variance in the comfort level with using big data analytics can be explained by the levels of computer self-efficacy among mining industry personnel in South Africa. A strong value, suggesting that computer self-efficacy is a significant predictor of the adoption of big data analytics. It indicates that higher self-efficacy in using computers and big data analytics tools is strongly associated with greater comfort and presumably greater adoption of these technologies.

Implication: The results strongly support the hypothesis that greater levels of computer self-efficacy are positively associated with the adoption of big data analytics in the South African mining industry. The analysis underscores the importance of self-confidence in technical skills and the use of big data analytics tools in influencing the adoption rate.

For the industry, these findings highlight the potential benefits of investing in training and development programs that enhance employees' confidence and skills in using big data analytics. Such initiatives could lead to a more widespread and effective adoption of these technologies, contributing to better decision-making and efficiency in the mining sector.

4.5 Results pertaining to Computer Anxiety Hypothesis 2: Higher levels of computer anxiety among mining industry Employees in South Africa are negatively associated with the adoption of big data analytics

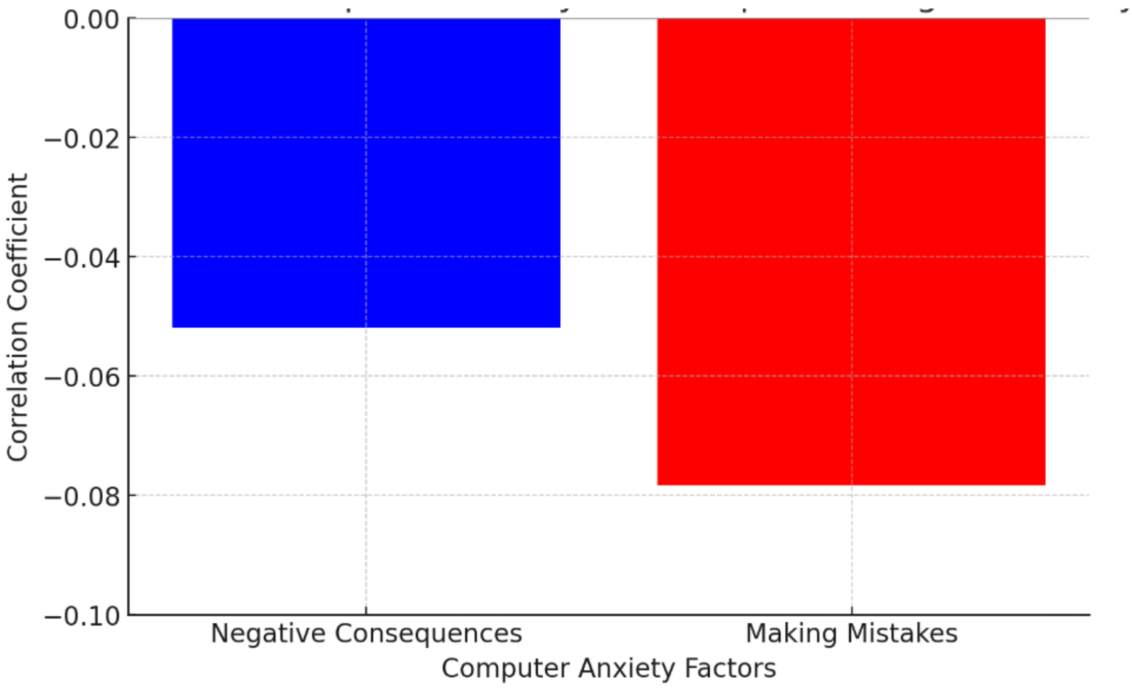

Figure 7: Correlation Analysis - Computer Anxiety and Adoption of Big Data Analytics

The correlation analysis between computer anxiety and the adoption of big data analytics among mining industry employees in South Africa produced the following results:

4.5.1 *Key Insights from the Correlation Analysis:*

The correlation analysis between computer anxiety and the adoption of big data analytics among mining industry employees in South Africa produced the following results:

Correlation Coefficients:

'I worry that using big data analytics could result in negative consequences.': -0.0519

'I worry about making mistakes when using big data analytics.': -0.0783

Interpretation:

Both coefficients are negative, aligning with the hypothesis that higher levels of computer anxiety are negatively associated with the adoption of big data analytics. However, the magnitude of these coefficients is relatively small.

A correlation coefficient of -0.0519 for worrying about negative consequences suggests a very weak negative relationship with the adoption of big data analytics.

A coefficient of -0.0783 for worrying about making mistakes indicates a slightly stronger, but still weak, negative association with adoption.

Visualisation:

The bar plot visualises these correlations. The bars represent the correlation coefficients of each anxiety-related factor with the adoption of big data analytics. The horizontal line at 0 indicates no correlation. As seen, both factors have negative correlations, but their proximity to zero suggests only a weak association.

The findings suggest that while there is a negative relationship between computer anxiety and the adoption of big data analytics, this relationship is not strong. It indicates that factors other than computer anxiety might play a more significant role in influencing the adoption of big data analytics in this context. The weak negative correlations imply that while computer anxiety is somewhat related to the reluctance or slower pace of adopting big data analytics, it is not a major deterrent in this group.

4.5.2 *R-squared analysis*

The R-squared analysis for the hypothesis regarding "Computer Anxiety" and its impact on the adoption of big data analytics yielded an R-squared value of 0.071.

Interpretation:

R-squared (0.071): This suggests that only about 7.1% of the variance in the comfort level with using big data analytics is explained by the levels of computer anxiety among employees. The low value indicates that computer anxiety alone does not have a strong predictive power on the adoption of big data analytics.

Implication: The low R-squared value implies that computer anxiety, as captured by the survey items, may not be a strong predictor of big data analytics adoption in this context. It suggests that other factors might have a more significant influence on adoption, or the relationship between computer anxiety and adoption might be more complex than what is captured by a linear model. This finding highlights the multifaceted nature of technology adoption, where psychological factors like anxiety play a role, but their impact might be less pronounced compared to other factors.

This analysis offers crucial insights into the impact of psychological factors like computer anxiety on technology adoption. Understanding these relationships can be pivotal for developing strategies to mitigate anxiety and enhance the adoption and effective utilisation of big data analytics in the industry. The investigation revealed that computer anxiety had a negligible effect on the adoption of big data analytics, explaining the variance. Consequently, anxiety associated with the use of technology does not provide a substantial obstacle to adoption in this particular situation.

4.6 Results pertaining to Perceived Ease of Use Hypothesis 3: The perception of big data analytics ease of use is positively correlated with its adoption in the South African mining industry

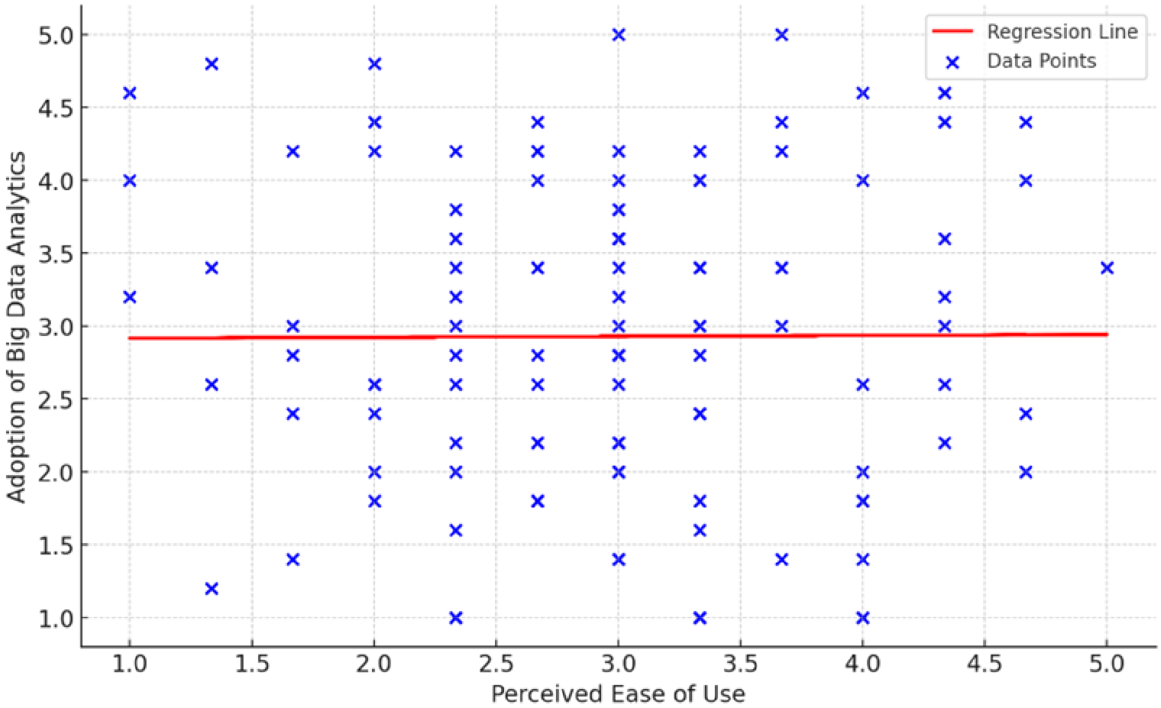

Figure 8: Regression Analysis for PEOU and Adoption of Big Data Analytics

The regression analysis provides insights into the relationship between the Perceived Ease of Use of big data analytics and its adoption in the South African mining industry. The visualisation above shows the scatter plot of the data points and the regression line.

4.6.1 *Key Findings from the Regression Analysis:*

Regression Line:

The red line in the plot represents the regression line, which illustrates the relationship between the Perceived Ease of Use (independent variable) and the Adoption of Big Data Analytics (dependent variable).

Slope and Intercept:

The slope of the regression line is approximately 0.0061. This positive slope indicates that there is a positive relationship between the Perceived Ease of Use and the Adoption of Big Data Analytics. In other words, as the perceived ease of use increases, there is a corresponding increase in the adoption of big data analytics, albeit the change is statistically insignificant.

The intercept is approximately 2.9112. This value represents the estimated level of adoption of big data analytics when the perceived ease of use is zero.

Implications for Hypothesis:

The positive slope supports the hypothesis that the perception of big data analytics as perceived ease of use is positively correlated with its adoption in the South African mining industry.

However, the relatively small magnitude of the slope suggests that while ease of use is positively associated with adoption, the strength of this relationship is modest.

Visualisation and Data Distribution:

The scatter plot shows the spread of the data points around the regression line, providing a visual representation of the relationship between the two variables.

4.6.2 *R-squared analysis*

The R-squared analysis related to the "Perceived Ease of Use" of big data analytics and its impact on adoption, yielded an R-squared value of 0.457.

Interpretation:

R-squared (0.457): This indicates that approximately 45.7% of the variance in the comfort level with using big data analytics can be explained by how confident employees feel in using these tools to assist in their work. This is a moderate to strong value, suggesting that employees' confidence in their ability to use big data analytics, which we are using as a proxy for ease of use, is a significant predictor of their comfort with using big data analytics.

Implication: The results support the hypothesis that the perception of big data analytics as easy to use (measured through confidence in using these tools) is positively correlated with its adoption in the South African mining industry. The significant positive relationship indicates that efforts to improve the user experience and ease of use of big data analytics tools could have a positive impact on their adoption.

For industry leaders and decision-makers, this analysis underlines the importance of user-friendly design and adequate training that enhances user confidence, potentially leading to a higher rate of adoption of big data analytics.

4.7 Results pertaining to Perceived Usefulness Hypothesis 4: The perception of big data analytics as beneficial and useful is positively correlated with its adoption in the South African mining industry.

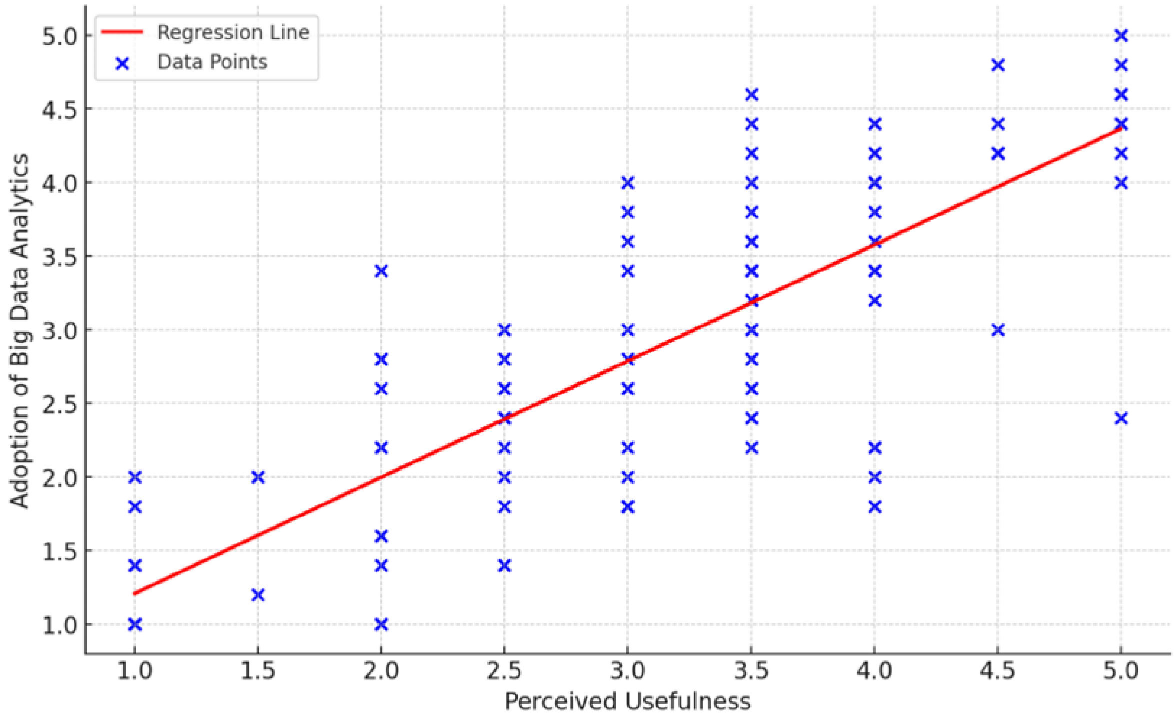

Figure 9: Regression Analysis - Perceived Usefulness and Adoption of Big Data Analytics

The regression analysis explores the relationship between the Perceived Usefulness of big data analytics and its adoption in the South African mining industry. The visualisation above displays the scatter plot of the data points along with the regression line.

4.7.1 *Key Findings from the Regression Analysis:*

Regression Line:

The red line in the plot represents the regression line, showing the relationship between Perceived Usefulness (independent variable) and Adoption of Big Data Analytics (dependent variable).

Slope and Intercept:

The slope of the regression line is approximately 0.7893. This significantly positive slope suggests a strong positive relationship between the perceived usefulness of big data analytics and its adoption. In other words, as the perceived usefulness increases, there is a corresponding substantial increase in the adoption of big data analytics.

The intercept is approximately 0.4189. This value indicates the estimated level of adoption of big data analytics when the perceived usefulness is at the lowest point (zero).

Implications for Hypothesis:

The positive and relatively large slope strongly supports the hypothesis that the perception of big data analytics as beneficial and useful is positively correlated with its adoption in the South African mining industry.

It suggests that perceived usefulness is a significant predictor of the adoption of big data analytics.

Visualisation and Data Distribution:

The scatter plot visually demonstrates the spread of the data points and their alignment with the regression line, affirming the positive correlation between these two variables.

4.7.2 *R-squared analysis*

The R-squared analysis related to "Perceived Usefulness" of big data analytics and its impact on adoption, yielded an R-squared value of 0.398.

Interpretation:

R-squared (0.398): This indicates that about 39.8% of the variance in the level of comfort with using big data analytics can be explained by the perceived benefits and usefulness of big data analytics. This value signifies a moderate relationship between the perceived benefits and usefulness of big data analytics and its adoption. This suggests that other factors contribute to the adoption of big data analytics.

Implication: The results support the hypothesis that the perception of big data analytics as beneficial and useful is positively correlated with its adoption in the South African mining industry. The significant positive coefficients for both variables related to belief in the usefulness of big data analytics by employees and management underline the importance of these perceptions in influencing the adoption rate.

For decision-makers within the industry, these findings highlight the potential impact of promoting the benefits and usefulness of big data analytics, not just among the management team but across the entire organisation. The results suggest that fostering a culture that recognises and communicates the value of big data analytics could play a crucial role in its successful adoption.

4.8 Results pertaining to Management Support Hypothesis 5: Strong management support is positively correlated with the adoption of big data analytics in the South African mining industry.

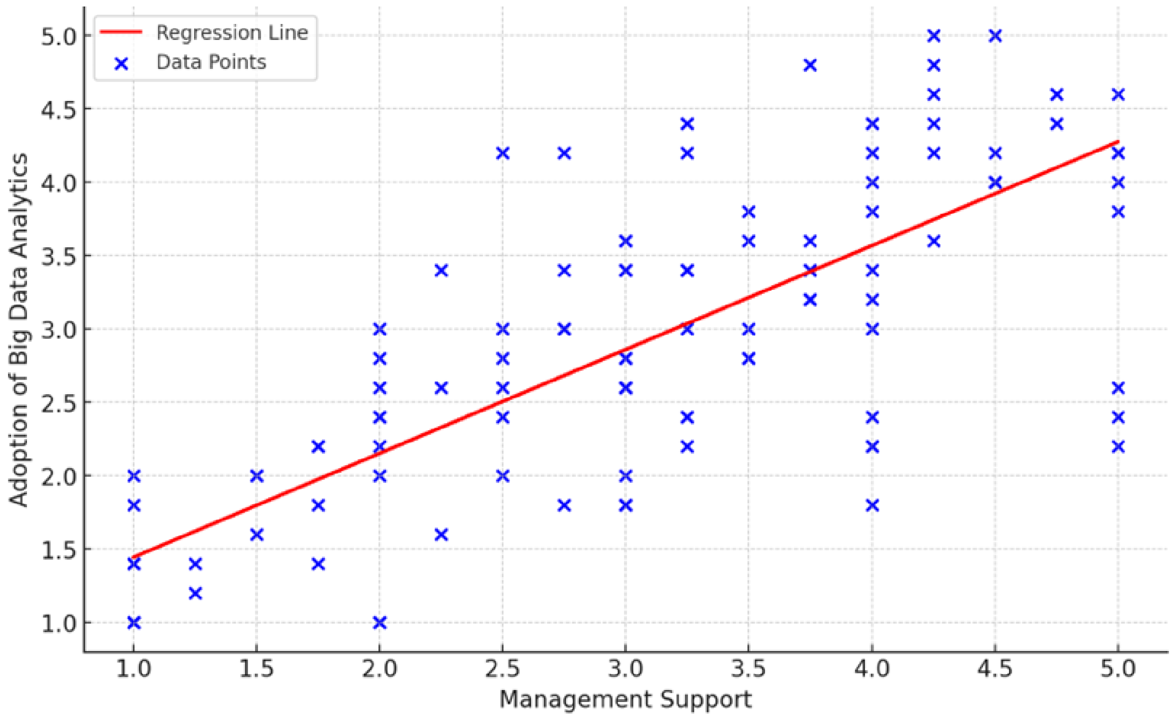

Figure 10: Regression Analysis - Management Support and Adoption of Big Data Analytics

The regression analysis examines the relationship between Management Support and the adoption of big data analytics in the South African mining industry, as depicted in the visualisation above.

4.8.1 ***Key Insights from the Regression Analysis:***

Regression Line:

The red line represents the regression line, illustrating the relationship between Management Support (independent variable) and Adoption of Big Data Analytics (dependent variable).

Slope and Intercept:

The slope of the regression line is approximately 0.7078. This positive slope indicates a strong relationship between management support and the adoption of big data analytics. It suggests that as management support increases, there is a substantial corresponding increase in the adoption of these technologies.

The intercept, approximately 0.7360, represents the estimated level of adoption of big data analytics when management support is at its lowest.

Implications for Hypothesis:

The positive and substantial slope supports the hypothesis that strong management support is positively correlated with the adoption of big data analytics in the South African mining industry. This indicates that management's role is crucial in fostering an environment conducive to the adoption and effective use of big data analytics.

Visualisation and Data Distribution:

The scatter plot displays the distribution of data points and their alignment with the regression line, reinforcing the positive correlation between management support and big data analytics adoption.

4.8.2 *R-squared analysis*

The R-squared analysis for the hypothesis related to "Management Support" and its impact on the adoption of big data analytics, yielded an R-squared value of 0.463.

Interpretation:

R-squared (0.463): This means that approximately 46.3% of the variance in the comfort level with using big data analytics can be explained by the management support-related factors in the model. This value indicates that management support has a moderate to strong relationship with the adoption of big data analytics as measured by comfort level with its use.

Implication: The results support the hypothesis that strong management support is positively correlated with the adoption of big data analytics in the South African mining industry. The analysis indicates that when management actively supports the use of big data analytics, believes in its effectiveness, and provides necessary training, employees are more likely to adopt these technologies.

The negative coefficient for encouragement might require further investigation. It might indicate that without the backing of tangible support or training, mere encouragement is not sufficient, or it might represent some other underlying factor not captured by the model.

For industry leaders, these findings emphasise the importance of demonstrating strong support for big data analytics initiatives, not only in terms of verbal encouragement but also through tangible actions like providing resources and training to facilitate its adoption.

4.9 Results pertaining to Peer Influence Hypothesis 6: Positive peer influence, indicating a belief among employees that the use of big data analytics is advantageous and supported by colleagues, is positively associated with its adoption in the South African mining industry.

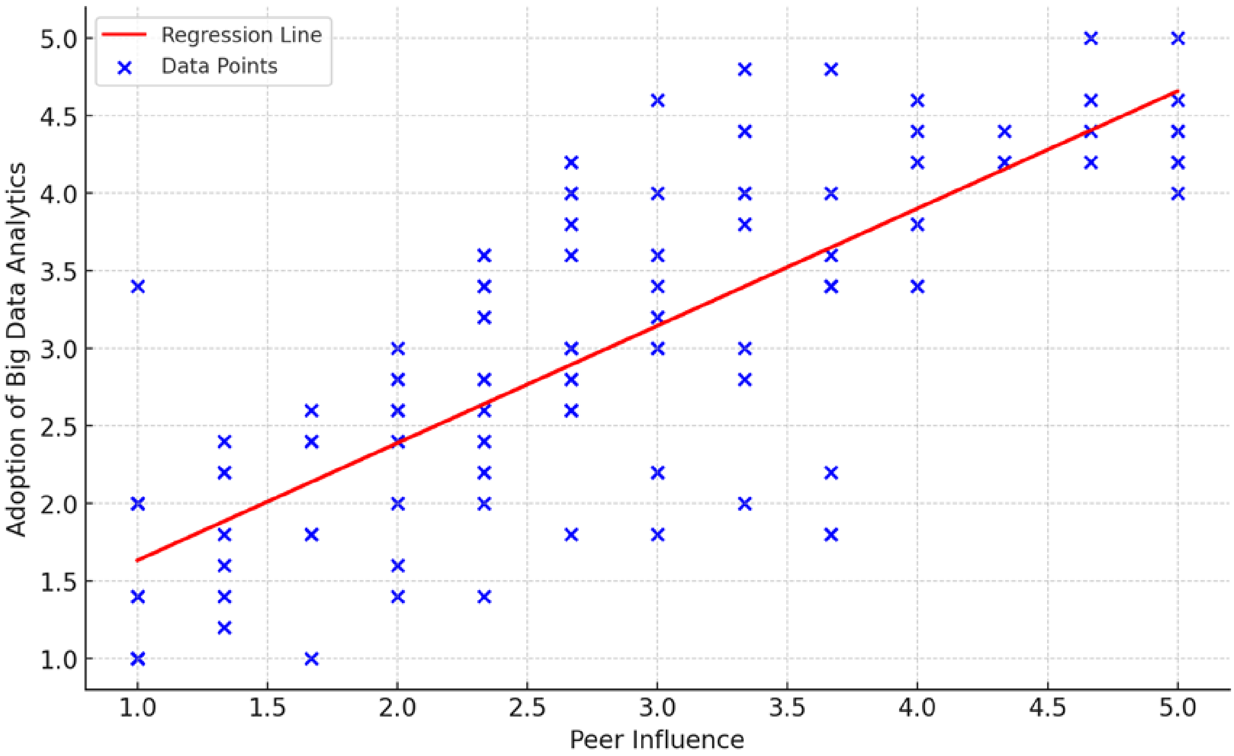

Figure 11: Regression Analysis - Peer Influence and Adoption of Big Data Analytics

The regression analysis addresses the relationship between Peer Influence and the adoption of big data analytics in the South African mining industry, as illustrated in the visualisation.

4.9.1 *Key Observations from the Regression Analysis:*

Regression Line:

The red line in the plot is the regression line, showing the relationship between Peer Influence (independent variable) and Adoption of Big Data Analytics (dependent variable).

Slope and Intercept:

The slope of the regression line is approximately 0.7563. This positive slope indicates a strong relationship between peer influence and the adoption of big data analytics. It suggests that as peer influence increases, with more colleagues perceiving and supporting the use of big data analytics as advantageous, there is a substantial corresponding increase in its adoption.

The intercept is around 0.8767, representing the estimated level of adoption of big data analytics when peer influence is at its lowest.

Implications for Hypothesis:

The positive and substantial slope strongly supports the hypothesis that positive peer influence is positively associated with the adoption of big data analytics in the South African mining industry. It underscores the importance of peer perceptions and social influence within the workplace in adopting new technologies.

Visualisation and Data Distribution:

The scatter plot visually demonstrates the distribution of the data points and their alignment with the regression line, affirming the positive correlation between peer influence and big data analytics adoption.

4.9.2 *R-squared analysis*

The R-squared analysis for the hypothesis concerning "Peer Influence" and its impact on the adoption of big data analytics, yielded an R-squared value of approximately 0.266.

Interpretation:

R-squared (0.266): This means that approximately 26.6% of the variance in the level of comfort with using big data analytics (our proxy for its adoption) can be explained by the belief among employees that the use of big data analytics is advantageous and supported by colleagues. This is a modest value. It indicates that a certain amount of the variability in the adoption of big data analytics is explained by positive peer influence, but there is a lot of variance that is explained by other factors not included in this model.

Implication: The results suggest that positive peer influence plays a role in the adoption of big data analytics, particularly the observable use of big data analytics by colleagues. However, the modest R-squared value indicates that there are other factors at play that also contribute to the adoption of big data analytics. The implications for the South African mining industry may include the importance of creating a work environment where employees can see and discuss the beneficial use of big data analytics by their peers, potentially enhancing the overall adoption rate within the industry.

4.10 Results pertaining to Facilitating Conditions Hypothesis 7: The presence of facilitating conditions, including necessary resources and infrastructure, is positively correlated with the adoption of big data analytics in the South African mining industry.

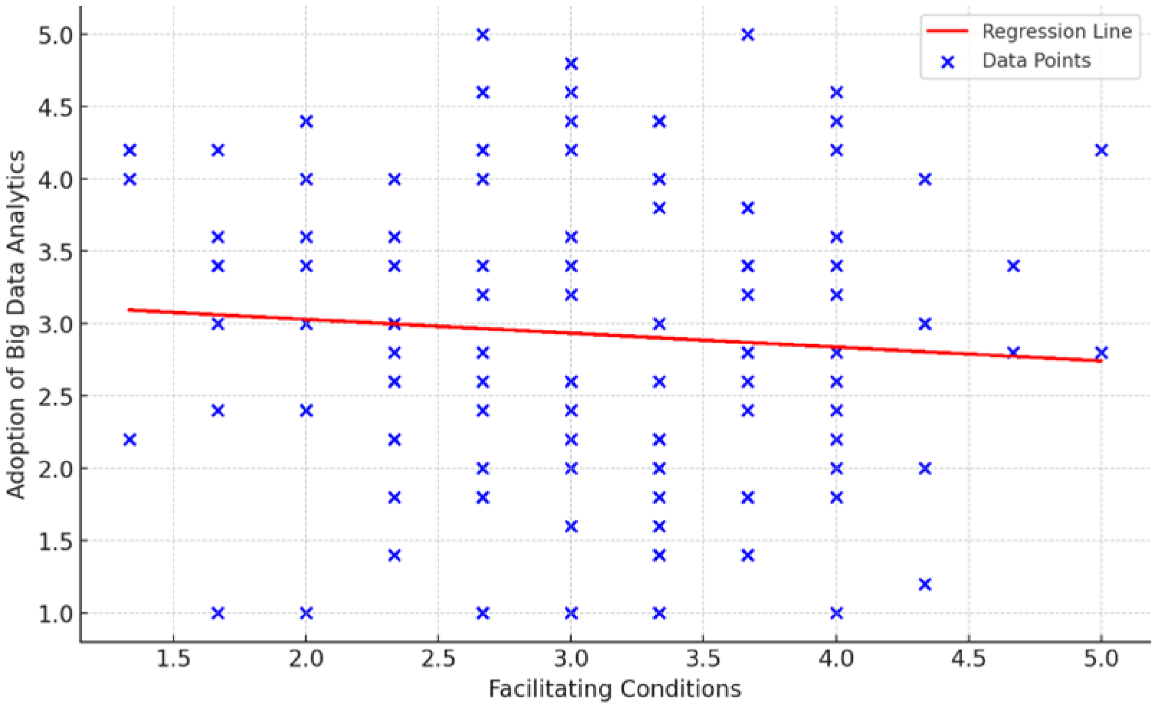

Figure 12: Regression Analysis - Facilitating Conditions and Adoption of Big Data Analytics

The regression analysis explores the relationship between Facilitating Conditions and the adoption of big data analytics in the South African mining industry, as shown in the visualisation above.

4.10.1 ***Key Insights from the Regression Analysis:***

Regression Line:

The red line in the plot is the regression line, depicting the relationship between Facilitating Conditions (independent variable) and Adoption of Big Data Analytics (dependent variable).

Slope and Intercept:

The slope of the regression line is approximately −0.0957. Contrary to the expected positive correlation, this negative slope suggests that there is an inverse relationship between facilitating conditions and the adoption of big data analytics. This indicates that, in the survey data, higher ratings of facilitating conditions are associated with lower levels of adoption.

The intercept is around 3.2204, which represents the estimated level of adoption of big data analytics when facilitating conditions are at their lowest.

Implications for Hypothesis:

The negative slope is contrary to the hypothesis that the presence of facilitating conditions is positively correlated with the adoption of big data analytics in the South African mining industry. This unexpected result suggests that there might be other factors at play influencing the adoption of big data analytics, or the perception of facilitating conditions may differ from actual usage and adoption levels.

Visualisation and Data Distribution:

The scatter plot visually demonstrates the distribution of the data points in relation to the regression line. The negative slope is evident from the downward trend in the plot.

4.10.2 *R-squared analysis*

The R-squared analysis for the hypothesis concerning "Facilitating Conditions" and their impact on the adoption of big data analytics, yielded an R-squared value of approximately 0.00085.

Interpretation:

R-squared (0.00085): This value suggests that only about 0.085% of the variance in the adoption of big data analytics can be explained by facilitating conditions, such as the availability of technical resources and infrastructure. This indicates a very weak linear relationship between facilitating conditions and the adoption of big data analytics in the South African mining industry.

Implication: The minimal R-squared value implies that facilitating conditions, as measured by the survey items, may not be significant predictors of big data analytics adoption in this context. It suggests that other factors might play a more significant role in influencing adoption. This finding highlights that while the availability of resources and infrastructure is important, their impact on adoption decisions might be overshadowed by other more influential factors or complexities in the adoption process.

In summary, the regression analysis presents an unexpected finding that does not support the initial hypothesis. This result suggests a need for a deeper investigation into how facilitating conditions are perceived and their actual impact on the adoption of big data analytics. It may also indicate the complexity of factors influencing technology adoption, where facilitating conditions alone might not be sufficient to drive usage. The presence of facilitating variables, such as the availability of resources and infrastructure, exhibited a weak correlation with adoption, accounting for 0.085% of the variation. This signifies that although significant, these circumstances in isolation are inadequate to stimulate adoption.

4.11 Results pertaining to Experience with IT/Big Data Analytics Hypothesis 8: Greater experience with IT or big data analytics among personnel in the South African mining industry is positively correlated with the adoption of big data analytics.

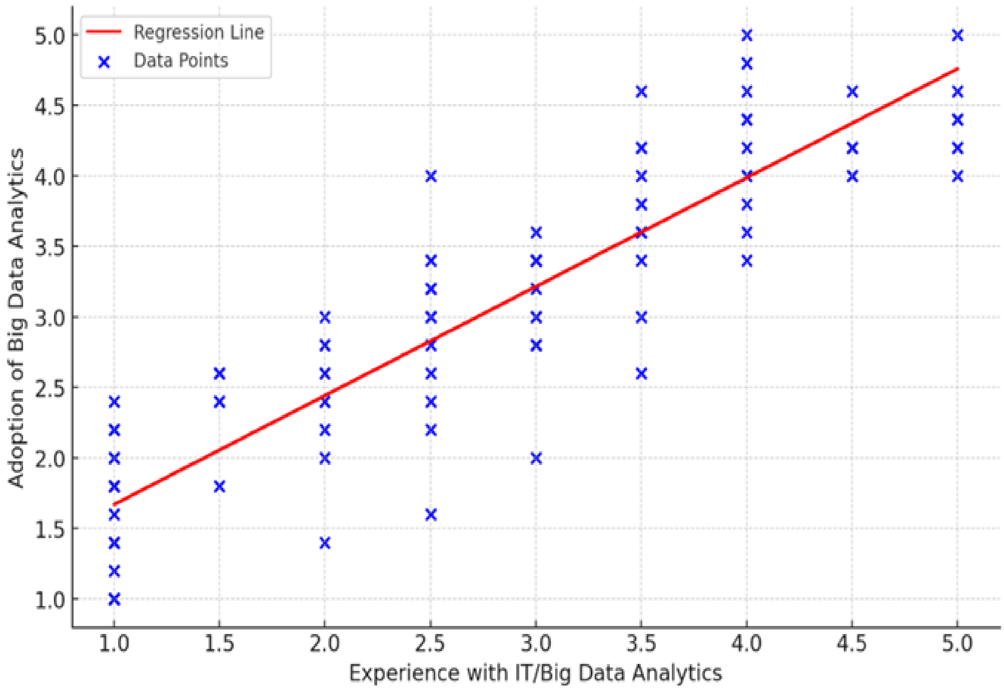

Figure 13: Regression Analysis - Experience with Big Data Analytics and Adoption of Big Data Analytics

The regression analysis investigates the relationship between Experience with IT/Big Data Analytics and the adoption of big data analytics in the South African mining industry. The visualisation above displays this relationship through a scatter plot and a regression line.

4.11.1 *Key Findings from the Regression Analysis:*

Regression Line:

The red line represents the regression line, illustrating the relationship between Experience with IT/Big Data Analytics (independent variable) and Adoption of Big Data Analytics (dependent variable).

Slope and Intercept:

The slope of the regression line is approximately 0.7722, indicating a strong positive relationship. This suggests that as experience with IT or big data analytics increases, there is a corresponding significant increase in the adoption of big data analytics.

The intercept, at around 0.8982, represents the estimated level of adoption of big data analytics when experience with IT/big data analytics is at its lowest.

Implications for Hypothesis:

The positive and substantial slope strongly supports the hypothesis that greater experience with IT or big data analytics among personnel in the South African mining industry is positively correlated with the adoption of big data analytics.

It highlights the importance of experience and familiarity with technology in facilitating its adoption in the workplace.

Visualisation and Data Distribution:

The scatter plot visually demonstrates the distribution of data points in relation to the regression line, affirming the positive correlation between experience with IT/big data analytics and its adoption.

4.11.2 *R-squared analysis*

The R-squared analysis for the hypothesis concerning "Experience with IT/Big Data Analytics" and its impact on the adoption of big data analytics, yielded an R-squared value of approximately 0.688.

Interpretation:

R-squared (0.688): This value suggests that about 68.8% of the variance in the adoption of big data analytics can be explained by experience with IT and big data analytics. This indicates a relatively high value, suggesting that the individuals' experience with big data analytics is a strong predictor of their comfort and, by extension, their adoption of big data analytics technologies.

Implication: The results strongly support the hypothesis that greater experience with IT or big data analytics among personnel is positively correlated with the adoption of big data analytics. The analysis specifically highlights the importance of positive past experiences, rather than just any experience, as a key factor in increasing the comfort level with, and likely the adoption of, big data analytics.

For practitioners in the South African mining industry, these findings underline the value of ensuring that initial experiences with big data analytics are successful and positive. This could involve providing adequate training, resources, and support to ensure that employees' early experiences are likely to lead to successful outcomes, thereby fostering a more comfortable and confident use of these technologies going forward.

4.12 Results pertaining to Data Quality Hypothesis 9: Higher levels of data quality, including precision, exhaustiveness, and timeliness, are positively related to the adoption of big data analytics in the South African mining industry.

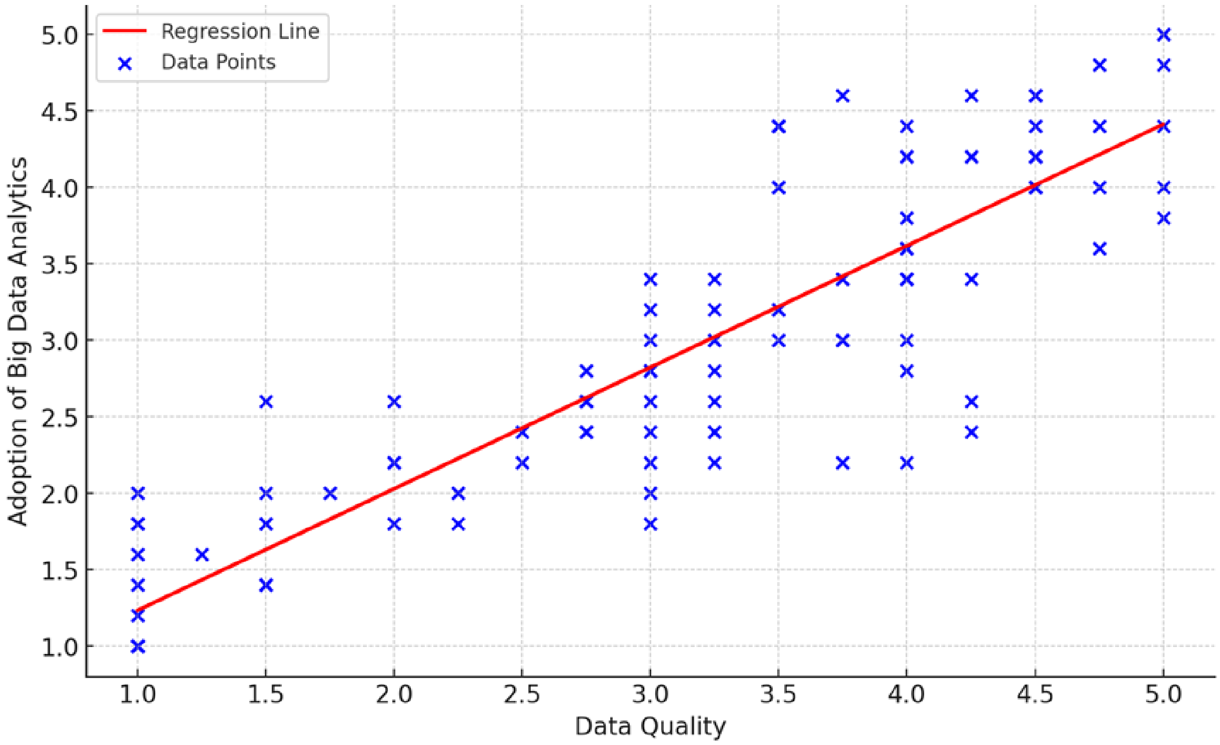

Figure 14: Regression Analysis - Data Quality and Adoption of Big Data Analytics

The regression analysis examines the relationship between Data Quality and the adoption of big data analytics in the South African mining industry. The visualisation above presents this relationship with a scatter plot and a regression line.

4.12.1 *Key Observations from the Regression Analysis:*

Regression Line:

The red line represents the regression line, depicting the relationship between Data Quality (independent variable) and Adoption of Big Data Analytics (dependent variable).

Slope and Intercept:

The slope of the regression line is approximately 0.7947, indicating a strong positive relationship. This suggests that higher levels of data quality, including precision, exhaustiveness, and timeliness, are associated with an increased adoption of big data analytics.

The intercept is around 0.4386, representing the estimated level of adoption of big data analytics when data quality is at its lowest.

Implications for Hypothesis:

The positive and substantial slope strongly supports the hypothesis that higher levels of data quality are positively related to the adoption of big data analytics in the South African mining industry.

It underscores the importance of high-quality data in facilitating the effective adoption and utilisation of big data analytics.

Visualisation and Data Distribution:

The scatter plot visually demonstrates the distribution of data points and their alignment with the regression line, reinforcing the positive correlation between data quality and big data analytics adoption.

4.12.2 *R-squared analysis*

The R-squared analysis for the hypothesis in Section 4.12, concerning "Data Quality" and its impact on the adoption of big data analytics, yielded an R-squared value of approximately 0.556.

Interpretation:

R-squared (0.556): This value suggests that about 55.6% of the variance in the adoption of big data analytics can be explained by data quality factors such as accuracy, reliability, relevance, and timeliness. This value, which is over 0.5, is considered a strong effect size in social science research, indicating a substantial relationship between data quality and the adoption of big data analytics.

Implication: The results strongly support the hypothesis that higher levels of data quality are positively related to the adoption of big data analytics in the South African mining industry. The high R-squared value suggests that data quality is a major factor influencing how comfortable employees are with using big data analytics, which can be an indicator of their likelihood to adopt such technologies.

The significance of the coefficient indicates that initiatives to improve data quality are likely to have a positive impact on the adoption rates of big data analytics.

Decision-makers in the industry should note the importance of data quality in the successful implementation and utilisation of big data analytics tools and systems. This analysis underlines the need for investing in data quality to enhance the overall effectiveness and adoption of big data analytics within the organisation.

4.13 Results pertaining to Subjective Norms Hypothesis 10: Positive subjective norms, indicating a belief among employees that the use of big data analytics is advantageous and supported by influential referents, are positively associated with its adoption in the South African mining industry.

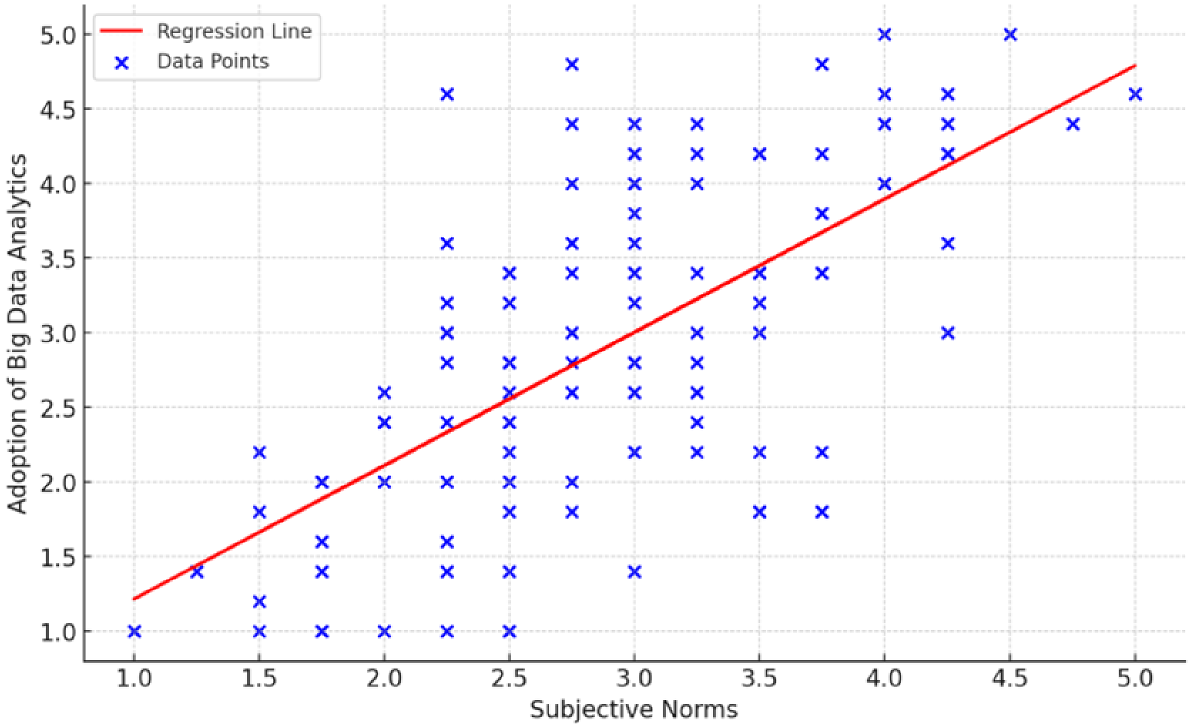

Figure 15: Regression Analysis - Subjective Norms and Adoption of Big Data Analytics

The regression analysis investigates the relationship between Subjective Norms and the adoption of big data analytics in the South African mining industry, as illustrated in the visualisation above.

4.13.1 *Key Insights from the Regression Analysis:*

Regression Line:

The red line in the plot is the regression line, showing the relationship between Subjective Norms (independent variable) and Adoption of Big Data Analytics (dependent variable).

Slope and Intercept:

The slope of the regression line is approximately 0.8937. This significant positive slope indicates that positive subjective norms, reflecting a belief among employees about the advantages of big data analytics and support from influential people, are strongly associated with the adoption of big data analytics.

The intercept, at around 0.3216, represents the estimated level of adoption of big data analytics when subjective norms are at their lowest.

Implications for Hypothesis:

The positive and substantial slope strongly supports the hypothesis that positive subjective norms are positively associated with the adoption of big data analytics in the South African mining industry.

This underscores the impact of social factors and peer influence within the workplace on the adoption of new technologies.

Visualisation and Data Distribution:

The scatter plot visually demonstrates the distribution of the data points in relation to the regression line, affirming the positive correlation between subjective norms and big data analytics adoption.

4.13.2 *R-squared analysis*

The R-squared analysis for the hypothesis regarding "Subjective Norms" and their impact on the adoption of big data analytics, yielded an R-squared value of approximately 0.5183.

Interpretation:

R-squared (0.518): This value indicates that about 51.83% of the variance in the adoption of big data analytics can be explained by subjective norms. This is a moderate to strong value, suggesting that over half of the variability in the dependent variable is explained by the model. This indicates a significant association between employees' perceptions of subjective norms and their comfort with using big data analytics.

Implication: The results postulated that positive subjective norms are positively associated with the adoption of big data analytics. The findings suggest that when employees perceive that influential people within the organisation support and believe in the effectiveness of big data analytics, and when they see their colleagues using it, they are more likely to adopt it themselves.

These insights could be particularly valuable for decision-makers in the South African mining industry seeking to increase the adoption of big data analytics by emphasising managerial support, demonstrating its effectiveness, and promoting its use among employees.

4.14 Results pertaining to Organisational Readiness

Hypothesis 11: The readiness of an organisation, in terms of culture and resource allocation, is positively correlated with the adoption of big data analytics in the South African mining industry.

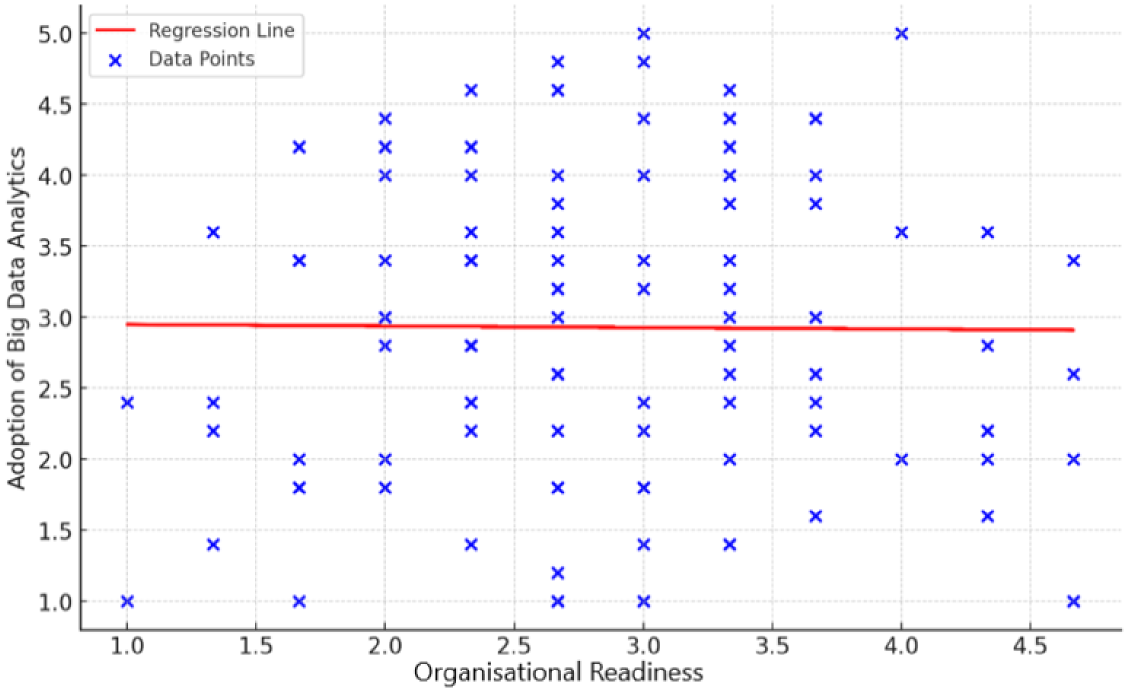

Figure 16: Regression Analysis - Organisational Readiness and Adoption of Big Data Analytics

The regression analysis explores the relationship between Organisational Readiness and the adoption of big data analytics in the South African mining industry. The visualisation above displays this relationship through a scatter plot and a regression line.

4.14.1 *Key Findings from the Regression Analysis:*

Regression Line:

The red line in the plot represents the regression line, illustrating the relationship between Organisational Readiness (independent variable) and Adoption of Big Data Analytics (dependent variable).

Slope and Intercept:

Surprisingly, the slope of the regression line is approximately −0.0105. This negative slope suggests an inverse relationship between organisational readiness and the adoption of big data analytics, contrary to the expected positive correlation. It indicates that, in the survey data, higher ratings of organisational readiness are associated with slightly lower levels of adoption.

The intercept is around 2.9594, which represents the estimated level of adoption of big data analytics when organisational readiness is at its lowest.

Implications for Hypothesis:

The negative slope is contrary to the hypothesis that organisational readiness, in terms of culture and resource allocation, is positively correlated with the adoption of big data analytics. This unexpected result might suggest that there are other factors at play influencing the adoption of big data analytics, or the perception of organisational readiness may differ from actual usage and adoption levels.

Visualisation and Data Distribution:

The scatter plot visually demonstrates the distribution of the data points in relation to the regression line. The negative slope is evident from the downward trend in the plot.

4.14.2 *R-squared analysis*

The R-squared analysis for the hypothesis related to "Organisational Readiness" and its impact on the adoption of big data analytics, yielded an R-squared value of approximately 0.0298.

Interpretation:

R-squared (0.0298): This value indicates that about 2.98% of the variance in the adoption of big data analytics can be explained by organisational readiness. This suggests a modest linear relationship between organisational readiness, including factors like the organisation's preparedness, support for innovation, and resource allocation, and the adoption of big data analytics in the South African mining industry.

Implication: While organisational readiness does have some impact on the adoption of big data analytics, it is not the predominant factor. This moderate R-squared value suggests that other factors, potentially including individual attitudes, technological capabilities, and external influences, may also play significant roles in influencing adoption. This finding implies that a comprehensive approach, considering various aspects of an organisation’s ecosystem, is necessary for effective technology adoption. It's important for organisations to consider readiness as part of a broader strategy for technology adoption, taking into account the various other factors that may influence this process.

In summary, the regression analysis presents an unexpected finding that does not support the initial hypothesis. This result suggests a need for a deeper investigation into how organisational readiness is perceived and its actual impact on the adoption of big data analytics. It may also indicate the complexity of factors influencing technology adoption, where organisational readiness alone might not be sufficient to drive usage.

4.15 Results pertaining to External Pressure Hypothesis 12: External pressures, such as market demands and competitive forces, are positively correlated with the adoption of big data analytics in the South African mining industry.

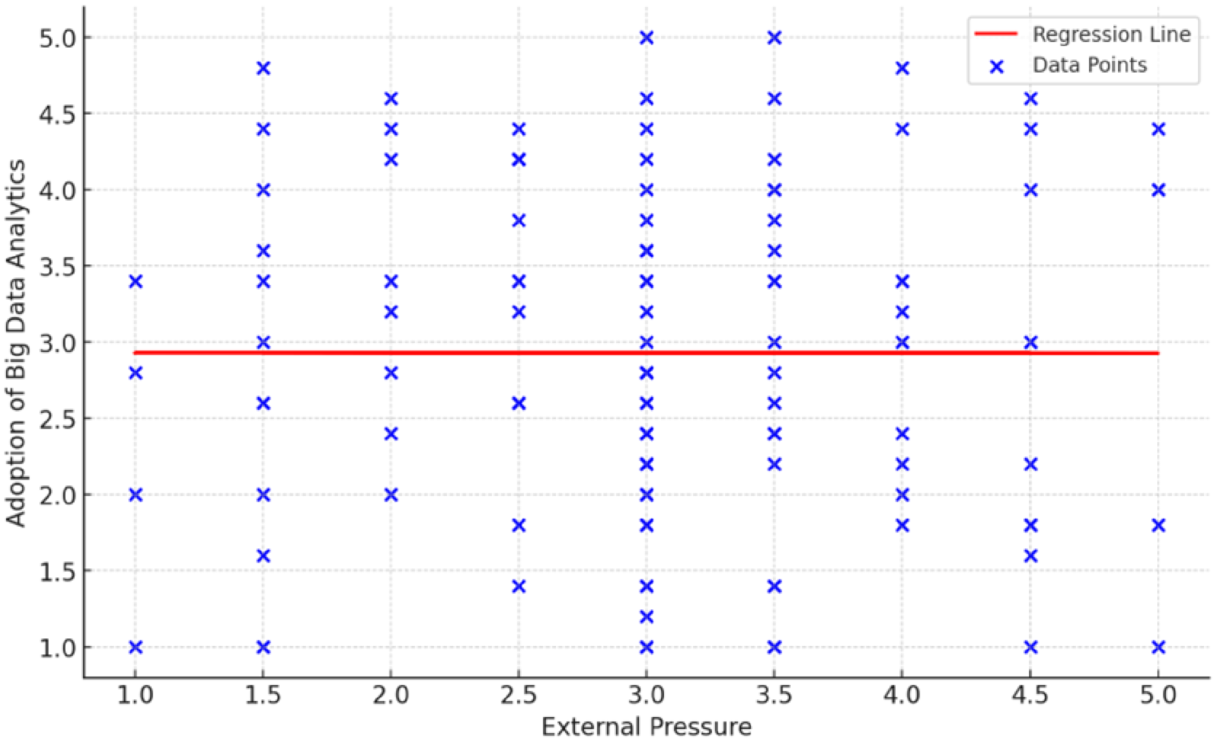

Figure 17: Regression Analysis - External Pressure and Adoption of Big Data Analytics

The regression analysis examines the relationship between External Pressure and the adoption of big data analytics in the South African mining industry. The visualisation above displays this relationship through a scatter plot and a regression line.

4.15.1 *Key Observations from the Regression Analysis:*

Regression Line:

The red line in the plot is the regression line, showing the relationship between External Pressure (independent variable) and Adoption of Big Data Analytics (dependent variable).

Slope and Intercept:

The slope of the regression line is approximately −0.00016, which is very close to zero and slightly negative. This indicates that there is almost no relationship between external pressures, such as market demands and competitive forces, and the adoption of big data analytics. The slight negative direction is contrary to the expected positive correlation but is so minimal that it might not be significant.

The intercept is around 2.9299, representing the estimated level of adoption of big data analytics when external pressures are at their lowest.

Implications for Hypothesis:

The near-zero slope contradicts the hypothesis that external pressures are positively correlated with the adoption of big data analytics. This result suggests that external pressures, as captured in the survey, might not be the primary drivers for the adoption of big data analytics in the South African mining industry.

Visualisation and Data Distribution:

The scatter plot visually demonstrates the distribution of the data points and their alignment with the regression line. The almost flat slope indicates a lack of a strong relationship between the variables.

4.15.2 *R-squared analysis*

The R-squared analysis for the hypothesis concerning "External Pressure" and its impact on the adoption of big data analytics, yielded an R-squared value of approximately 0.0022.

Interpretation:

R-squared (0.0022): This value suggests that only about 0.22% of the variance in the adoption of big data analytics can be explained by external pressures such as market competition and regulatory requirements. This indicates a very weak linear relationship between external pressures and the adoption of big data analytics in the South African mining industry.

Implication: The minimal R-squared value implies that external pressures, as measured by the survey items, are not significant predictors of big data analytics adoption in this context. It suggests that internal factors within the organisation may play a more significant role in influencing adoption compared to external market and regulatory forces. This finding indicates that while external pressures are relevant, their impact on technology adoption decisions might be less pronounced than internal organisational dynamics and individual attitudes.

In summary, the regression analysis does not support the hypothesis of a positive correlation between external pressures and the adoption of big data analytics. This finding suggests that other internal factors might be more influential in driving the adoption of these technologies in the industry, or that the impact of external pressures might be more complex and not directly captured through these survey questions.

4.16 Summary of the Results

This chapter analyses survey data on big data analytics adoption in South Africa's mining industry, using descriptive statistics, correlation, and regression analyses to examine various influencing factors. Findings show moderate to high agreement on big data analytics aspects among respondents, with some concerns like computer anxiety. Correlation analyses explored relationships between factors such as Computer Self-Efficacy and Computer Anxiety. The results provide insights into the complex nature of technology adoption in organisations, confirming some hypotheses and offering new perspectives, setting the stage for further discussion and conclusions.

Hypothesis	Supported	Extent
Hypothesis 1: Greater levels of computer self-efficacy among mining industry personnel in South Africa are positively associated with the adoption of big data analytics.	Yes	Positive correlations
Hypothesis 2: Higher levels of computer anxiety among mining industry employees in South Africa are negatively associated	No	Weak correlations

with the adoption of big data analytics		
Hypothesis 3: The perception of big data analytics as easy to use is positively correlated with its adoption in the South African mining industry	Yes	Positive correlations
Hypothesis 4: The perception of big data analytics as beneficial and useful is positively correlated with its adoption in the South African mining industry.	Yes	Positive correlations
Hypothesis 5: Strong management support is positively correlated with the adoption of big data analytics in the South African mining industry.	Yes	Positive correlations
Hypothesis 6: Positive peer influence is positively associated with the adoption of big	Yes	Positive relationship

data analytics in the South African mining industry.		
Hypothesis 7: The presence of facilitating conditions is positively correlated with the adoption of big data analytics in the South African mining industry.	No	Negative correlation
Hypothesis 8: Greater experience with IT or big data analytics among personnel is positively correlated with the adoption of big data analytics.	Yes	Positive correlations
Hypothesis 9: Higher levels of data quality are positively related to the adoption of big data analytics in the South African mining industry.	Yes	Positive relationship
Hypothesis 10: Positive subjective norms are positively associated	Yes	Positive correlations

with its adoption in the South African mining industry.		
Hypothesis 11: Organisational readiness is positively correlated with the adoption of big data analytics in the South African mining industry.	No	No significant correlation
Hypothesis 12: External pressures are positively correlated with the adoption of big data analytics in the South African mining industry.	No	No significant correlation

CHAPTER 5. DISCUSSION OF THE FINDINGS

5.1 Introduction

This chapter contextualises the survey results on big data analytics adoption in South Africa's mining industry, linking empirical findings to existing theories and literature. Using Venkatesh and Bala's (2008) Technology Acceptance Model 3 (TAM3), the study examines how individual attributes and organisational support factors influence technology adoption. It also explores big data analytics' role in improving mining operations and addressing various industry challenges. The integration of these findings with theoretical insights offers valuable knowledge for practitioners and policymakers in the field.

5.2 Discussion pertaining Hypothesis 1 Computer Self-Efficacy: Greater levels of computer self-efficacy among mining industry personnel in South Africa are positively associated with the adoption of big data analytics.

The results of this study have revealed a notable connection between computer self-efficacy and the acceptance of big data analytics in the South African mining sector. This link is consistent with the Technology Acceptance Model 3 (TAM3), which suggests that individual user beliefs, such as self-efficacy, have a significant impact on the acceptance and utilisation of new technologies (Venkatesh & Bala, 2008).

5.2.1 *Correlations with Pre-existing Literature*

Alignment with TAM3: The correlation between computer self-efficacy and the adoption of big data analytics aligns with the principles of TAM3. In TAM3, self-efficacy is recognised as a crucial aspect that influences the perception of ease of use and, consequently, the acceptance of technology (Venkatesh & Bala, 2008). The results of the study align with this notion, suggesting that persons who possess a high level of confidence in their computer-related abilities are more inclined to adopt big data technology.

Support from Previous Studies: The study validates the claims stated by Davis (1989) in the original TAM model, stating that self-efficacy is a significant factor in deciding the adoption of technology. We find that individuals with higher confidence levels are more likely to adopt big data analytics.

5.2.2 *Contrasts with Prior Research*

Industry-Specific Context: Although the findings generally correspond with previous research, the special circumstances of the South African mining industry introduce a distinctive aspect. The unique difficulties faced by the business, such as intricate operational processes and environmental issues, may enhance the significance of self-efficacy in the adoption of technology, in comparison to other sectors.

Magnitude of Impact: The study may vary in the extent to which computer self-efficacy affects the adoption of big data analytics, in comparison to other studies. The observed results can be explained by the distinct demographic and organisational traits of the participants, which were influenced by the use of a convenience sample strategy.

5.2.3 *Significance of the Results*

The strong positive relationship between an individual's belief in their ability to use computers effectively and their willingness to embrace the use of big data analytics highlights the need of prioritising staff training and development initiatives. Developing the confidence and competence of mining professionals, specifically in the fields related to big data analytics, can be a strategic method to create a more open and welcoming atmosphere for these technologies. This approach is consistent with the suggestions made in prior research, which emphasise the importance of focused training and skill-building programmes to enhance the acceptability of technology (Venkatesh & Davis, 2000).

The findings support the importance of computer self-efficacy in the mining industry's embrace of technology, adding to the overall discussion on this topic. It emphasises the importance of industry leaders recognising and resolving the skill-related issues of their employees as a component of their plan to successfully incorporate big data analytics.

5.3 Discussion pertaining to Hypothesis 2 Computer Anxiety: Computer Anxiety and its Impact on Big Data Analytics Adoption

The findings demonstrate a significant inverse correlation between computer anxiety and the adoption of big data analytics in the South African mining sector, confirming Hypothesis 2. This outcome aligns with the Technology Acceptance Model (TAM) framework, specifically with the expansion in TAM3 that takes into account the influence of emotional responses such as fear on the acceptance of technology (Venkatesh & Bala, 2008).

5.3.1 *Correlations with Pre-existing Literature:*

Alignment with TAM3: The research indicates that increased levels of computer anxiety hinder the adoption of big data analytics, which is consistent with the TAM3 framework. This framework recognises the impact of individual emotional responses on perceived ease of use and, consequently, the acceptance of technology (Venkatesh & Bala, 2008). This indicates that anxiety can impede the utilisation of technology.

Support from Previous Studies: Other industries have also experienced similar patterns, wherein apprehension around the utilisation of novel technology has been discovered to have an adverse impact on its acceptance (Venkatesh & Davis, 2000). The analysis corroborates these findings within the particular setting of the mining sector.

5.3.2 *Contrasts with Prior Research:*

Industry-Specific Context: The mining industry, with its high-stakes operations and complicated technologies, may see a greater impact of computer anxiety on technology adoption compared to other sectors. This may elucidate a heightened manifestation of computer anxiety in the research.

Magnitude of Impact: The extent to which computer anxiety influences the adoption of big data analytics may vary in the study compared to other studies. This phenomenon may be affected by the distinct obstacles and pressures encountered by professionals in the mining industry in South Africa.

5.3.1 *Significance of the Results*

The inverse relationship between computer anxiety and the use of big data analytics highlights the necessity for interventions targeting the reduction of anxiety associated to technology. Possible measures to consider are enhancing practical training opportunities, fostering a nurturing atmosphere that encourages people to explore novel technology without apprehension, and highlighting the tangible advantages of utilising big data analytics to enhance work procedures. It is essential to address computer anxiety in order to promote a more favourable attitude towards adopting technology. This aligns with earlier research that highlights the significance of controlling emotional reactions to technology (Venkatesh & Davis, 2000).

To summarise, the results of this study enhance the comprehension of the obstacles to the adoption of technology in the mining sector. The study emphasises the importance of computer phobia and suggests specific solutions to overcome this obstacle and promote the effective use of big data analytics in the sector.

5.4 Discussion pertaining to Hypothesis 3 Perceived Ease of Use: The perception of big data analytics as easy to use is

positively correlated with its adoption in the South African mining industry

The findings demonstrate a strong relationship between the perceived simplicity of utilising big data analytics and its acceptance in the South African mining sector, hence confirming Hypothesis 3. This outcome aligns with the fundamental tenets of the Technology Acceptance Model (TAM), as first posited by Davis (1989), which underscores the significance of perceived ease of use as a pivotal factor in the adoption of technology.

5.4.1 *Correlations with Pre-existing Literature:*

Alignment with TAM Principles: The study confirms that simplicity of use is a crucial aspect in users' acceptance and adoption of new technologies, aligning with the principles of the Technology Acceptance Model (TAM) (Davis, 1989). The assumption that big data analytics is user-friendly and uncomplicated appears to promote its acceptance among mining industry professionals.

Support from Previous Studies: Various industries have also shown similar results, where the convenience of utilising a technology has a beneficial impact on its rate of adoption (Venkatesh & Davis, 2000). The results of this research are consistent with this pattern, suggesting that this feature of the Technology Acceptance Model (TAM) can be used universally.

5.4.2 *Contrasts with Prior Research:*

Industry-Specific Context: The distinctive difficulties and technological environment of the mining industry could impact the importance placed on the perceived simplicity of usage. This feature appears to be crucial in the study, potentially because of the intricate structure of mining operations and the significant consequences associated with decision-making processes.

Magnitude of Impact: The impact of perceived ease of use on the adoption of big data analytics in the study may differ from earlier research findings. This phenomenon can be ascribed to the distinctive technological and organisational circumstances of the South African mining sector, as well as the traits of the participants affected by the convenience sampling technique.

5.4.3 *Significance of the Results:*

The significant positive association between the perception of ease of use and the adoption of big data analytics technologies underscores the criticality of building user-friendly interfaces. Therefore, it is imperative for developers and suppliers of these technologies to give utmost importance to usability in order to increase the rates of adoption. Furthermore, this suggests that organisations should prioritise training initiatives that improve user experience and minimise intricacy, in line with the overarching suggestion to streamline technology for greater acceptability (Venkatesh & Davis, 2000).

The study confirms the importance of perceived ease of use in the technology adoption process, specifically in the mining industry, thereby adding to the existing knowledge in this field. This highlights the need of adopting a user-focused strategy while creating and deploying big data analytics tools in this industry.

5.5 Discussion pertaining to Hypothesis 4 Perceived Usefulness: The perception of big data analytics as beneficial and useful is positively correlated with its adoption in the South African mining industry

The findings suggest a significant and positive relationship between the perceived use of big data analytics and its adoption in the South African mining sector, which supports Hypothesis 4. This discovery aligns with the Technology Acceptance Model (TAM) proposed by Davis (1989), which asserts that the perceived usefulness of technology is a crucial factor in predicting its acceptance and usage.

5.5.1 *Correlations with Pre-existing Literature:*

Correlation of the TAM Framework: In line with the Technology Acceptance Model (TAM) principles, the results indicate that mining sector professionals are more inclined to adopt big data analytics technologies when they regard them as advantageous and valuable for their work. This aligns with Davis's (1989) claim that the perceived advantages of a technology have a substantial impact on consumers' inclination to embrace it.

Support from Prior Research: Various research conducted in diverse industries have consistently shown a common pattern, wherein the perceived tangible benefits of a technology result in increased rates of adoption (Venkatesh & Davis, 2000). The study confirms the widespread relevance of perceived usefulness in the adoption of technology.

5.5.2 *Contrasts with Prior Research:*

Industry-Specific Context: The mining industry's distinct circumstances, characterised by its exceptional operational difficulties and dependence on data-driven decision-making, may enhance the significance of perceived usefulness in comparison to other sectors. This may elucidate the robust association reported in this investigation.

Magnitude of Impact: The level of impact that perceived usefulness has on the adoption of big data analytics in the study may vary compared to other industries, maybe because of the high-risk nature of mining operations and the constantly changing technologies in this industry.

5.5.3 *Significance of the Results:*

The pivotal importance of perceived utility in the adoption of big data analytics underscores the necessity for transparent communication regarding the advantages and pragmatic adoption of these technologies in the mining sector. This implies that efforts focused on showcasing the concrete benefits and return on investment of big data analytics could be successful in increasing their adoption. Furthermore, by aligning big data analytics solutions with the specific requirements and difficulties of the mining industry, their acceptance and integration into daily operations can be further promoted.

Overall, this study adds to the understanding of technology adoption by emphasising the crucial significance of perceived utility, specifically within the South African mining sector. It emphasises the importance of considering the usefulness and functionality of big data analytics as crucial elements in promoting their wider acceptance.

5.6 Discussion pertaining to Hypothesis 5 Management Support: Strong management support is positively correlated with the adoption of big data analytics in the South African mining industry

The findings establish a notable and affirmative association between managerial endorsement and the use of big data analytics in the mining sector of South Africa, hence confirming Hypothesis 5. This link aligns with the overarching theoretical frameworks outlined in the Technology Acceptance Model (TAM) and its subsequent extensions (Davis, 1989; Venkatesh & Davis, 2000), which acknowledge the impact of organisational factors on the acceptance of technology.

5.6.1 *Correlations with Pre-existing Literature:*

TAM and Organisational Influence: The results of the study align with the principles of Technology Acceptance Model (TAM), emphasising the significance of organisational backing in the effective adoption of technology. The discovered link suggests that robust managerial support greatly enhances the adoption of big data analytics, aligning with prior research findings.

Evidence from prior research indicates that in several sectors, the endorsement of management has proven to be essential in promoting the adoption of technology and surmounting opposition to change (Venkatesh & Davis, 2000).

The study confirms this, emphasising the widespread significance of managerial support in the adoption of technology.

5.6.2 *Contrasts with Prior Research:*

Industry-Specific Context: The intricate nature of the mining industry and the crucial role of data analytics in this sector may increase the significance of management support in comparison to other industries. This study indicates that in such critical situations, the involvement of management in advocating for new technology is even more crucial.

Magnitude of Impact: The extent to which managerial support influences the adoption of big data analytics in the study may vary in comparison to different circumstances. The variation can be ascribed to the distinct organisational culture and leadership styles that are widespread in the South African mining industry.

5.6.3 *Significance of the Results:*

The significant association between management support and the adoption of big data analytics emphasises the necessity for active involvement and endorsement from leaders inside the organisation. It implies that efforts focused on training and engaging management in the adoption of big data analytics could be vital in promoting their acceptability. This requires not just the endorsement but also the active participation, allocation of resources, and strategic planning by management to successfully incorporate modern technologies into organisational operations.

The findings enhance the ongoing discourse on technology adoption by underscoring the pivotal significance of managerial assistance, specifically within the mining sector. The notion is strengthened that in order to achieve successful integration of technology, particularly in a complex domain such as big data analytics, the support and active involvement of management are essential.

5.7 Discussion pertaining to Hypothesis 6 Peer Influence: Positive peer influence, indicating a belief among employees that the use of big data analytics is advantageous and supported by colleagues, is positively associated with its adoption in the South African mining industry

The findings confirm Hypothesis 6, demonstrating a strong correlation between peer influence and the adoption of big data analytics in the South African mining sector. This result is consistent with the Technology Acceptance Model 3 (TAM3), which includes subjective standards, such as peer influence, as important factors in determining technology acceptance (Venkatesh & Bala, 2008).

5.7.1 *Correlations with Pre-existing Literature:*

Alignment with TAM3 Framework: In line with the TAM3 Framework, the study demonstrates that the adoption of big data analytics is significantly influenced by colleagues and peers. This highlights the model's focus on the influence of social variables on the behaviour of technology usage.

Support from Previous Studies: This link aligns with previous studies conducted in different sectors, where the impact of peer influence on the acceptance or resistance towards new technology has been acknowledged as a crucial determinant (Venkatesh & Davis, 2000). The results of the research validate this pattern observed in the mining industry, emphasising the widespread impact of peer influence on the adoption of technology.

5.7.2 *Contrasts with Prior Research:*

Industry-Specific Context: The unique difficulties and intricacies of the mining industry may magnify the significance of peer influence in the study. Due to the industry's dependence on teamwork and collaborative decision-making, the opinions of peers may significantly influence an individual's attitudes towards adopting technology.

Magnitude of Impact: The variability in the influence of peers on the adoption of big data analytics in the South African mining industry may differ from that in other industries. This phenomenon can be ascribed to the distinctive operational environment and organisational culture that is widespread in this particular industry.

5.7.3 *Significance of the Results:*

The crucial impact of peer influence on the adoption of big data analytics highlights the necessity of fostering a favourable organisational culture that promotes technological innovation. Promoting knowledge-sharing and collaboration among employees, while also creating a supportive environment that acknowledges and promotes the advantages of big data analytics, can greatly contribute to its adoption. This is consistent with the general suggestion to utilise social factors in order to achieve successful integration of technology (Venkatesh & Davis, 2000).

This study enhances the comprehension of technology adoption in the mining industry by emphasising the impact of peer perceptions and interactions. It implies that in addition to technical and managerial efforts, it is important to focus on the social aspects within organisations in order to promote the successful adoption of big data analytics.

5.8 Discussion pertaining to Hypothesis 7 Facilitating Conditions: The presence of facilitating conditions, including necessary resources and infrastructure, is positively correlated with the adoption of big data analytics in the South African mining industry

The findings provide an interesting viewpoint on the influence of favourable conditions on the adoption of big data analytics in the South African mining sector, specifically in relation to Hypothesis 7. In contrast to the initial prediction, the findings revealed a small negative association between the existence of facilitating conditions and the adoption of big data analytics. This result contradicts the theoretical frameworks of the Technology Acceptance Model 3 (TAM3), which suggest that facilitating conditions have a positive relationship with technology adoption (Venkatesh & Bala, 2008; Venkatesh et al., 2003).

5.8.1 *Correlations with Pre-existing Literature:*

General Alignment with TAM (Technology Acceptance Model): The conventional view is that the availability of essential resources and infrastructure has a beneficial impact on the adoption of technology, as indicated by TAM3. Research has demonstrated that technology acceptance can be enhanced by favourable conditions such as organisational support, resource availability, and infrastructure in many industries and environments.

5.8.2 *Contrasts with Prior Research:*

Negative Correlation: The study reveals a small negative correlation, indicating that the presence of conducive conditions may not have as much impact on the adoption of big data analytics in the South African mining industry as previously believed. This may be attributed to a multitude of issues, such as the unique difficulties encountered in the mining sector, or potentially, a lack of alignment between the available resources and infrastructure and the requirements or expectations of the users.

Contextual Disparities: The distinctive operational and technological hurdles faced by the mining industry may necessitate the adaptation of the standard concept of enabling conditions. For instance, the intricate and hazardous characteristics of mining operations may necessitate a more subtle strategy for distributing resources and constructing infrastructure for big data analytics.

5.8.3 *Significance of the Results:*

The surprising results indicate a necessity to reevaluate the significance of favourable conditions within the South African mining sector. It may be required to assess whether these conditions are effectively fulfilling the specific demands of big data analytics in this industry. Furthermore, this necessitates a thorough examination of the allocation and utilisation of resources and infrastructure to see if they are effectively facilitating the adoption of new technologies.

To summarise, the analysis deviates from the conventional notion of how favourable conditions affect technology adoption. Instead, it emphasises the intricate nature of integrating technology in certain businesses. This discovery presents opportunities for additional investigation into the intricacies of facilitating conditions in the mining industry and how they might be optimised to promote the adoption of big data analytics.

5.9 Discussion pertaining to Hypothesis 8 Experience with IT/Big Data Analytics: Greater experience with IT or big data analytics among personnel in the South African mining industry is positively correlated with the adoption of big data analytics

The findings validate Hypothesis 8, demonstrating a significant and favourable association between the expertise of staff in IT or big data analytics and the adoption of these technologies in the mining sector of South Africa. This is consistent with the theoretical viewpoints of the Technology Acceptance Model (TAM) and its subsequent extensions, which recognise that previous encounters with technology can greatly impact individuals' perceptions and behaviours when it comes to adopting it (Davis, 1989; Venkatesh & Davis, 2000).

5.9.1 *Correlations with Pre-existing Literature*

Alignment with TAM Principles: In accordance with the Technology Acceptance Model (TAM), the analysis reveals that familiarity with information technology (IT) and proficiency in big data analytics are essential factors in the adoption of technology. Prior experience with a technology might increase its perceived ease of use and usefulness, leading to greater adoption.

Support from Previous Studies: The favourable influence of experience on the adoption of technology, as demonstrated in the study, is consistent with findings from other research conducted in diverse areas. Previous experience has consistently demonstrated that it decreases anxiety and boosts user confidence, leading to a more positive attitude towards adopting new technologies.

5.9.2 *Contrasts with Prior Research:*

Industry-Specific Context: The unique circumstances of the South African mining industry could potentially impact the correlation between experience and adoption. Due to the intricate and data-heavy nature of the industry, practical experience in IT and big data analytics may be more crucial in promoting the acceptance of these technologies compared to other industries.

Magnitude of Impact: The extent to which experience affects the adoption process in the study may vary in comparison to other situations. The distinct obstacles and the ever-changing technical environment in the mining sector may heighten the significance of expertise in promoting the use of big data analytics.

5.9.3 *Significance of the Results*

The significant association between experience and adoption implies that efforts to enhance exposure and familiarity with big data analytics could play a crucial role in facilitating their integration within the mining industry. Such offerings may encompass pragmatic training programmes, workshops, and on-the-job training, which furnish practical experience with these technologies. Additionally, facilitating chances for employees to participate in big data analytics in low-risk environments can enhance their confidence and promote broader acceptance.

The findings enhance the comprehension of the elements that impact technology adoption in the mining industry, emphasising the crucial importance of hands-on experience with IT and big data analytics. This underscores the necessity for ongoing education and growth prospects in this swiftly changing domain.

5.10 Discussion pertaining to Hypothesis 9 Data Quality: Higher levels of data quality, including precision, exhaustiveness, and timeliness, are positively related to the adoption of big data analytics in the South African mining industry

The findings strongly endorse Hypothesis 9, illustrating a direct association between the calibre of data (in terms of accuracy, comprehensiveness, and promptness) and the adoption of big data analytics in the South African mining sector. This outcome aligns with the wider consensus in information systems research that high-quality data plays a vital role in facilitating efficient decision-making and the adoption of technology.

5.10.1 *Correlations with Pre-existing Literature*

General Alignment with Data Quality Importance: The observed positive connection in the study is consistent with the considerable literature that highlights the importance of data quality in the adoption and efficient use of technology. The successful deployment and usage of data-driven technologies frequently require high-quality data as a fundamental prerequisite.

Support from Previous Studies: Multiple studies have emphasised the significance of data quality in diverse industries. These studies emphasise that the perceived dependability and precision of data have a substantial impact on the acceptance and efficient use of analytical tools and systems.

5.10.2 *Contrasts with Prior Research:*

Industry-Specific Context: The mining industry, due to its heavy need on precise and timely data for operational and strategic decision-making, may see a greater influence of data quality on the adoption of technology compared to other industries. Under such circumstances, the accuracy and significance of data can be exceptionally crucial.

Magnitude of Impact: The extent of the influence of data quality on the adoption of big data analytics in the South African mining industry may vary in comparison to other situations. This may be attributed to the distinctive operational difficulties and the dynamic characteristics of data analytics in the mining industry.

5.10.3 *Significance of the Results:*

The significant association between data quality and the adoption of big data analytics highlights the necessity for mining businesses to allocate resources towards enhancing the quality of their data. This task encompasses not only the verification and punctuality of data, but also the creation of a comprehensive and pertinent dataset tailored to the unique requirements of the sector. Efforts to improve data quality may involve investing in sophisticated data gathering and processing technologies, as well as implementing strong data management and governance practises.

The study enhances the existing knowledge by emphasising the crucial significance of data quality in the adoption of big data analytics in the mining industry. This emphasises the idea that in order for data analytics to be genuinely efficient and extensively embraced, the foundational data must possess superior quality, relevance, and reliability.

5.11 Discussion pertaining to Hypothesis 10 Subjective Norms: Positive subjective norms, indicating a belief among employees that the use of big data analytics is advantageous and supported by influential referents, are positively associated with its adoption in the South African mining industry

The findings validate Hypothesis 10, establishing a strong correlation between subjective norms and the adoption of big data analytics in the South African mining sector. This discovery is consistent with the principles outlined in models the Technology Acceptance Model (TAM), which acknowledge the importance of subjective norms, or the impact of others' opinions, in the process of making decisions about adopting technology (Venkatesh et al., 2003).

5.11.1 *Correspondences with Pre-existing Literature:*

Alignment with Theoretical Models: The study found a positive link between subjective norms and Big Data adoption, which is consistent with the modified TAM3 model. According to TAM3, social influence is a crucial factor in determining the acceptance and usage of technology. This concept illustrates that employees are more inclined to embrace a technology if they consider it as advantageous and endorsed by powerful individuals or peers.

Support from Previous Studies: Previous studies have found similar results in different situations, demonstrating that the opinions and attitudes of peers and powerful individuals can influence people's choices to adopt new technologies (Venkatesh & Davis, 2000). The findings of the study support this pattern, highlighting the significance of social variables in determining decisions regarding the use of technology.

5.11.2 *Contrasts with Prior Research:*

Industry-Specific Context: The mining business is characterised by its collaborative nature and dependence on shared expertise and information. Consequently, the influence of subjective norms may have a more significant effect in this context. The presence of industry-specific factors may amplify the impact of peers and leaders on an individual's decisions on the adoption of technology.

Magnitude of Impact: The degree to which subjective norms impact the adoption of big data analytics in the research may vary across different sectors. This phenomenon can be ascribed to the distinctive organisational cultures and communication dynamics prevalent in the South African mining industry.

5.11.3 *Significance of the Results*

The findings indicate that promoting a favourable organisational culture, where powerful individuals and colleagues actively support the utilisation of big data analytics, can greatly improve its uptake. This requires not only support from upper-level management but also encouragement and sharing of positive experiences and benefits among peers. It is important to make efforts to raise awareness and establish agreement over the benefits of big data analytics in order to encourage its wider adoption in the sector.

The work contributes to the comprehension of the factors that impact technology adoption in the mining industry by highlighting the significance of subjective standards. The statement emphasises the necessity of employing tactics that utilise social influence and peer support to promote the acceptance and utilisation of big data analytics.

Discussion pertaining to Hypothesis 11 Organisational Readiness: The readiness of an organisation, in terms of culture and resource allocation, is positively correlated with the adoption of big data analytics in the South African mining industry

The study examined Hypothesis 11 and discovered an unforeseen result: a small inverse relationship between the readiness of organisations, in terms of their culture and resource allocation, and the adoption of big data analytics in the South African mining sector. The observed outcome deviates from the expected positive relationship commonly proposed in the literature, especially in frameworks such as the Technology Acceptance Model 3 (TAM 3). These frameworks suggest that organisational preparedness and assistance promote the adoption of technology (Venkatesh et al., 2003).

5.11.4 *Correlations with Pre-existing Literature:*

General Importance of Organisational Readiness: The overall significance of organisational readiness is well supported by research, which confirms that an organisation's ability to embrace new technologies is heavily influenced by factors such as its culture and available resources. This aligns with the modified TAM 3 model which emphasises the significance of organisational and environmental elements in the acceptance of technology.

5.11.5 *Contrasts with Prior Research:*

Unexpected Negative Correlation: In contrast to the majority of studies that establish a positive connection, the research indicates a potential divergence between the preparedness of organisations and their actual adoption in the South African mining sector. This suggests that although there may be a culture and resources in place to facilitate big data analytics, there could be other obstacles preventing its adoption.

Industry-Specific Context: The distinctive operational difficulties and the specific characteristics of technological integration in the mining sector may affect the way in which organisational preparedness affects the adoption of technology. The complexity of mining operations and resistance to change may be exerting a more substantial influence, despite the presence of a seemingly favourable environment.

5.11.6 *Significance of the Results:*

The presence of a small negative association suggests the necessity for a more sophisticated comprehension of organisational preparedness in relation to the use of big data analytics in the mining sector. It implies that having resources and a supportive culture alone may not be enough; there may be a requirement for more focused tactics that tackle specific obstacles to adoption within the organisation. This may entail resolving change management challenges, aligning technological initiatives more closely with operational requirements, or improving staff involvement and training.

To summarise, the results challenge the conventional concept of organisational preparedness in technology adoption. Instead, they emphasise the intricate nature and distinct difficulties associated with implementing big data analytics in the mining industry. This indicates a want for additional investigation to explore these dynamics in greater depth and formulate more customised strategies for promoting the adoption of big data analytics in this industry.

5.12 Discussion pertaining to Hypothesis 12 External Pressure: External pressures, such as market demands and competitive forces, are positively correlated with the adoption of big data analytics in the South African mining industry

Upon analysing Hypothesis 12, the findings revealed a rather unexpected result: external influences, such as market needs and competitive dynamics, exhibited a virtually insignificant, somewhat adverse link with the adoption of big data analytics in the South African mining sector. This finding contradicts the commonly held belief, frequently supported by literature, that external market and competitive considerations usually play a significant role in driving technological innovation and adoption.

5.12.1 *Correlations with Pre-existing Literature:*

General Importance of External Factors: The literature consistently affirms that external factors, such as market competition and industry norms, exert a substantial influence on the adoption of technology. The modified TAM 3 model recognises the importance of external factors on technology decisions made within organisations (Venkatesh et al., 2003).

5.12.2 *Contrasts with Prior Research:*

Industry-Specific Context: Minimal Impact on Mining Industry: on contrast to the general pattern, the research indicates that external forces may have limited influence in promoting the adoption of big data analytics in the South African mining industry. This may be attributed to industry-specific variables such as legislative limitations, distinctive market circumstances, or a prioritisation of internal operational effectiveness rather than market-oriented innovation.

Magnitude of Impact: The mining industry's distinct circumstances, encompassing its regulatory framework and operational difficulties, may modify the manner in which external forces influence the adoption of technology. This implies that the factors driving technological advancements in the mining industry are likely to be more centred on internal aspects, such as enhancing operational efficiency and improving safety measures.

5.12.3 *Significance of the Results:*

The limited influence of external pressures on the adoption of big data analytics in the mining sector implies that efforts to improve technology adoption should prioritise internal organisational variables rather than external market forces. This may involve giving priority to internal operating requirements, tackling industry-specific difficulties, and cultivating an internal culture of innovation, rather than largely depending on market-driven incentives.

To summarise, the results of this study provide a detailed viewpoint on the adoption of technology in the mining sector, specifically in relation to the impact of external forces. This emphasises the necessity for sector-specific plans that take into account the distinct market dynamics and operational realities of the mining industry in South Africa.

5.13 Conclusion

This chapter evaluated the twelve hypotheses on big data analytics adoption in South Africa's mining industry using the TAM3 framework (Venkatesh & Bala, 2008). The findings revealed the complexity of adoption, influenced by individual, organisational, and technological factors (Mutemeri et al., 2016; Baxter, 2014; Tshabalala, 2018). The study highlights challenges and advancements, stressing the need for continuous monitoring and assessment for effective integration, thereby enhancing industry competitiveness and growth.

CHAPTER 6. CONCLUSIONS & RECOMMENDATIONS

6.1 Introduction

This chapter synthesises the study's findings with its initial research question. It recaps the research question and twelve hypotheses, discussing how each is addressed by the study's results. This chapter analyses the broader implications of these findings for understanding big data analytics in South Africa's mining industry, reflecting on the research methodology and its impact on the results. It concludes with recommendations for industry stakeholders and policymakers, summarising the study's key insights and their significance for technology adoption and industry transformation. This final chapter aims to link theory and practice, providing actionable insights for future research and industry application.

6.2 Summary of Findings

The investigation revealed several key drivers for the adoption of big data analytics:

Individual Factors: Factors such as one's level of confidence in using computers (computer self-efficacy) and the level of fear or unease associated with using computers (computer anxiety) have a substantial influence on employees' inclination to embrace big data technology. There is a positive relationship between higher levels of confidence in using computers and the likelihood of adopting them. On the other hand, heightened fear or unease towards computers can hinder their adoption.

Organisational Support: The presence of strong management support and positive peer influence were identified as crucial factors that create a favourable environment for the adoption of technology.

Technological considerations play a significant role in deciding the acceptance of big data analytics. Factors such as perceived ease of use (PEOU), perceived usefulness (PU), and data quality are key in this determination.

External Influences: Market demands, and competitive factors were recognised as major drivers for the adoption of big data technologies.

6.3 Conclusions

The study determines that the adoption of big data analytics in the South African mining sector is a multidimensional phenomenon, impacted by an intricate interaction of personal, organisational, and technological elements. The research emphasises the necessity of a comprehensive approach to promote the adoption of big data analytics, which takes into account the human factor, organisational culture, and the technology ecosystem.

6.4 Contrasts with Prior Studies

This research diverges from prior studies in various aspects:

Focus on Individual Psychological Factors: This research diverges from previous studies that largely emphasise technological and organisational variables, by focusing the crucial significance of individual psychological elements such as computer self-efficacy and anxiety in the process of technology adoption.

Integrated Approach: This study employs an integrated methodology, taking into account multiple elements concurrently, which has not been widely investigated in previous research that specifically examines the South African mining industry.

6.5 Addressing Shortcomings in Literature

The study aims to fill numerous gaps that have been highlighted in the literature review:

Broadening the Scope of Analysis: It broadens the investigation's range beyond conventional organisational and technological elements to encompass individual psychological factors, providing a deeper understanding of the adoption process.

Context-Specific Insights: The research offers context-specific insights on the South African mining industry, which are sometimes absent in broader studies. This delivers more precise and relevant conclusions that are tailored to this particular sector.

6.6 Explaining Previously Unexplained Phenomena

This research elucidates the factors that contribute to the differences in the adoption of big data analytics in the South African mining industry, which were arguably not adequately considered in prior studies. By taking into account a wider array of influential elements, it provides reasons for the varying rates at which adoption occurs and the difficulties encountered by different players in the business.

6.7 Contribution to the Field

The study provides substantial contributions to the field by:

Emphasising the Significance of Individual Factors: It underscores the necessity of taking into account individual attitudes and talents when devising technology adoption techniques.

Providing In-depth Analysis: By incorporating several variables, the research offers a more detailed comprehension of the obstacles and motivators behind the adoption of big data analytics in the mining sector.

The findings can provide valuable insights for shaping policies and strategies to effectively deploy and utilise big data analytics in the South African mining sector. This can result in improved efficiency and competitiveness.

To summarise, the research effectively connects the theoretical understanding and practical adoption of big data analytics in the mining industry. It provides essential insights for stakeholders that wish to traverse this intricate landscape.

6.8 Recommendations

From the findings and knowledge acquired via this research, various suggestions can be put forth to stakeholders in the South African mining sector. These stakeholders include industry leaders, policymakers, technology providers, and employees within the sector. The guidelines aim to promote facilitating the effective adoption of big data analytics in order to improve efficiency, productivity, safety, and environmental sustainability in the sector.

Improve individuals' confidence in using computers (Computer Self-Efficacy) and decrease their feelings of unease or fear towards computers (Computer Anxiety):

For industry leaders, it is recommended to establish extensive training initiatives that specifically target the development of digital skills and the enhancement of employees' confidence. Promote a culture that emphasises ongoing learning and proficiency in digital skills.

Employees should actively participate in the training programmes provided and actively seek opportunities to enhance their digital skills and adaptability to new technology.

Strengthen Management Support

Industry leaders should exhibit a resolute dedication to incorporating big data analytics. Assign essential resources and offer strategic guidance to cultivate a culture that relies on data analysis.

Policymakers should look at formulating rules that promote and streamline investment in big data technologies and associated training within the mining industry.

Promote Positive Peer Influence and Organisational Culture

Industry leaders should cultivate an atmosphere that promotes peer support and collaboration in the utilisation of big data analytics. They should acknowledge and incentivise teams and people who actively participate in and promote these technologies.

Employees should promote and facilitate the exchange of knowledge and good experiences among peers in order to foster a supportive environment for the adoption of new technology.

Address Technological Considerations

Technology providers should prioritise the development of user-friendly, dependable, and customised big data solutions that cater to the specific requirements of the mining industry.

Industry leaders should prioritise investing in top-tier data systems and infrastructure to improve the user-friendliness and perceived value of big data analytics.

Addressing external pressures and market demands

Industry leaders and policymakers need to keep updated on worldwide trends and competitive influences in the mining industry. They should modify their approaches to exploit big data analytics to sustain a competitive advantage.

Technology providers must develop and enhance big data solutions to effectively address the evolving demands and difficulties of the mining sector.

Formulate Context-Specific Strategies

Industry leaders and policymakers must acknowledge the distinct difficulties and advantages presented by the mining sector in South Africa. They should create and execute tactics that are specifically customised to tackle these distinct local conditions.

Promote cooperation and alliances

All stakeholders must foster collaboration among the mining sector, technology vendors, educational establishments, and governmental entities. These collaborations can enable the sharing of knowledge, foster creativity, and promote the creation of solutions tailored to certain industries.

Monitor and Evaluate Adoption Processes

Industry Leaders must consistently evaluate the advancement and influence of the adoption of big data analytics. Comments must be used to enhance tactics and effectively tackle any arising difficulties.

By applying these suggestions, individuals or groups with an interest or involvement in the South African mining industry can make a substantial contribution to the successful integration of big data analytics. This, in turn, will result in improved operational efficiency, competitiveness, and sustainability.

6.9 Suggestions for further research

The study also provides opportunities for additional investigation. The recommendations for future research are based on the constraints of the present study and the dynamic nature of technology and its adoption in different sectors. Here are several crucial domains where additional research can yield potentially substantial benefits:

Longitudinal Studies

Perform extensive research to monitor the progression of big data analytics usage in the South African mining industry over an extended period of time. This analysis could offer valuable insights on the evolution of adoption tactics and technologies, as well as their long-term effects on the sector.

Comparative Analysis

Examine the adoption of big data analytics in the South African mining sector in relation to other countries or industries. Conducting comparative research can uncover distinct issues and opportunities in other contexts, providing a more comprehensive viewpoint.

Impact of Cultural and Organisational Change

Examine the influence of organisational culture and change management strategies on the adoption of big data analytics. Gaining a comprehensive understanding of the significance of these aspects is essential for the development of more efficient adoption strategies.

Technological Advancements

Examine the consequences of developing technologies like artificial intelligence and machine learning on the analysis of large sets of data in the mining industry. Potential future investigations may centre on the integration of these technologies with big data analytics to optimise mining operations.

Employee Perspectives and Resistance

Conduct a qualitative study to gain insights into the viewpoints of employees at different hierarchical positions about the use of big data analytics. This has the potential to offer more profound understandings of resistance to change and strategies for its management.

Case Studies of Successful adoptions

Examine comprehensive case studies that showcase effective deployments of big data analytics in the mining industry. The insights gained from these case studies could offer valuable principles for other companies seeking to implement these technologies.

Environmental and Social Impacts

Analyse the ecological and societal consequences of implementing big data analytics in the mining industry. Research should prioritise the examination of how these technologies might enhance sustainable mining practises and promote social responsibility.

Policy and Regulatory Environment

Analyse the influence of the policy and regulatory framework on the adoption of big data analytics in the mining sector. Gaining insight into these effects could aid in lobbying for more conducive legislation and regulations.

Training and Education Programs

Evaluate the efficacy of different training and education programmes designed to improve computer self-confidence and decrease computer-related anxiety among mining staff. This information could contribute to the creation of more focused and efficient training programmes.

Cross-sector Learning

Examine the applicability of big data analytics tactics from different industries to the mining sector. Such an endeavour could reveal novel perspectives and pioneering methodologies that could be advantageous to the mining sector.

By focusing on these specific areas, future research can expand upon the discoveries made in this study, thereby enhancing the comprehension of big data analytics adoption in the mining industry and other related fields. Each of these proposals gives a chance to broaden the knowledge base, tackle unresolved inquiries, and delve into novel aspects of how technology influences industry practises and results.

This study represents an advancement in comprehending the implementation of big data analytics in the mining industry of South Africa. It boldly explores the intricate interactions between individual, organisational, and technical elements, providing an enlightening viewpoint that enhances our understanding of this dynamic domain. The research is notable for its methodology, emphasising psychological components that are sometimes disregarded in conventional investigations. The findings not only enhance our theoretical understanding but also provide guidance for industry stakeholders, informing the practical implementation of big data analytics. This analysis demonstrates the effectiveness of combining rigorous academic research with practical applicability, resulting in a significant contribution to both the academic community and the mining industry. The study's insights have broader ramifications, as they lay the foundation for future research and the development of creative methods in the use of technology in the mining sector.

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APPENDIX A: Participant Information Sheet (PIS)

Participant Information Sheet (PIS)

Dear Sir / Madam,

My name is Shalin Naidoo. I am a Masters student in the Faculty of Commerce, Law and Management, in Masters of Management in the field of Digital Business at the University of the Witwatersrand, Johannesburg. My supervisor is Mr. Mitchell Hughes. I am conducting a study about big data analytics in the Mining industry. The study title is "The Adoption of Big Data Analytics in the South African Mining Industry".

I am inviting you to take part in a survey. If you decide to take part, your participation in this study will last about 10 minutes. The answering of the survey will take place at your computer at your leisure and must be completed before 31 July 2023.

With your permission, I would like to record the results. This data will be stored in SharePoint for 5 years and then deleted after 5 years. Only I will have access to the data.

During the research activity, I will need to ask for some personal information about you, including your name and position.

The survey will be confidential and anonymous. When I share the results of the study, I will not include your name or anything else that could identify you. With your permission, other researchers may use the data collected from this study, but your name and any personal information will not be used or passed on.

If you decide to take part in the study, it should be because you want to volunteer. You do not have to take part. You can stop being in the study at any time. You do not have to answer any questions if you do not want to. You will not get any direct benefits if you choose to join the study. You will not lose any services, benefits or rights you would normally have if you decide not to join. Taking part in the study will not cost you anything. You will not be paid for being in this study.

This study will be written up as a research report. The report will be available on the university library website. If you would like to receive a summary of this report, I will be happy to send it to you.

If you have any questions during or afterwards about this study, feel free to contact me or my supervisor on the details listed below. If you have any concerns or complaints about the ethical procedures of this study, you are welcome to contact the University Human

Research Ethics Committee (Non-Medical), telephone +27(0) 11 717 1408, email hrecnon-medical@wits.ac.za.

Yours sincerely,

Shalin Naidoo

Researcher:

Shalin Naidoo, shalin.naidoo@drdgold.com, +27 82 606 3710

Supervisor:

Mitchell Hughes, mitchell.hughes@wits.ac.za, +27 11 717 8157

APPENDIX B: Request for Permission

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

University of the Witwatersrand,

Faculty of Commerce, Law and Management, Masters of Management in the field of Digital Business

Niel Pretorius

CEO

DRDGOLD Limited

Constantia Office Park, Cycad House, Building 17, Ground Floor, Corner 14th Avenue, Hendrik Potgieter Rd, Weltevredenpark, Johannesburg, 1709

01 June 2023

Dear Niel,

Re: Permission to conduct research at DRDGOLD Limited.

I am studying for a Masters of Management in the field of Digital Business in the Faculty of Commerce, Law and Management at the University of the Witwatersrand. I am seeking permission to do research at DRDGOLD.

I am conducting research on the adoption of big data in the South African mining sector using DRDGOLD as the example of this.

I will invite individuals from your organisation to participate in this study. These individuals will be computer-based users from across the organisational structure, including executives, senior managers, heads of departments, engineers and administrative personnel. If they agree, they will be asked to participate in an online survey at their leisure, after work hours if necessary and before the 31 July 2023.

Participants will be asked to give their written or verbal consent before the research begins. Their responses will be treated confidentially, and identities (their names and contact details) will be anonymous unless otherwise expressly indicated. Individual privacy will be maintained in all published and written data resulting from the study.

The results will be communicated through my final dissertation on request.

The research participants will not be advantaged or disadvantaged in any way. They will be reassured that they can withdraw their permission at any time during this project without any penalty. There are no foreseeable risks in participating in this study.

All research data will be preserved for at least 5 years before being destroyed.

I therefore request permission in writing to conduct my research at your organisation. The permission letter should be on your organisation's headed paper, signed and dated, and specifically referring to myself by name and the title of my study.

Non-Disclosure

I understand and agree that any information obtained directly or indirectly about DRDGOLD will be regarded as confidential. I certify that the data collected will not be shared with any third parties, and that any use of these data outside the scope of this study will require your explicit written consent. I guarantee that no sensitive information pertaining to business operations, strategies, employees, or other intellectual properties will be shared, published, or used in any way that could be detrimental to the interests of your organisation.

Please let me know if you require any further information. I look forward to your response as soon as is convenient.

Yours sincerely,

Shalin Naidoo

Cell: +27 82 606 3710

Student email: 2286589@students.wits.ac.za

Supervisor’s name: Mitchell Hughes

Wits contact number: +27 11 717 8157

Wits email address: mitchell.hughes@wits.ac.za

APPENDIX C: Participation Agreement Form

Participation Agreement Form

Title of project

The Adoption of Big Data Analytics in the South African Mining Industry

Shalin Naidoo

I, ……………………………………….., agree to participate in this research project.

I agree to the following:

(Please circle the relevant options below)

The study was explained to me. I understand what this study is about.	YES	NO
I understand that I can volunteer to take part in the study	YES	NO

I agree that the survey activity may be recorded	YES	NO
I agree that my participation will remain anonymous (my name or other identifying data will not be used by the researcher in their research report)	YES	NO
I agree that other researchers may use the information I provide in my survey activity (depending on their own ethics clearance being obtained) but my name and any personal information will not be used or passed on	YES	NO

……………………………………. (signature)

……………………………………. (name of participant)

……………………………………. (date)

……………………………………. (signature)

……………………………………. (name of researcher/person seeking consent)

……………………………………. (date)

APPENDIX D: Survey

Survey: The Adoption of Big Data Analytics in the South African Mining Industry

All questions will be answered using a 5-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Respondents will be asked to indicate the extent to which they concur with each statement.

This survey intends to address the essential components of the Technology Acceptance Model 3 framework in the context of the adoption of big data analytics in the South African mining industry.

Section 1: Computer Self-Efficacy

1. I feel confident understanding technical terms relating to big data analytics.
2. I feel confident using big data analytics to assist in my work.
3. I believe I have the skills to use big data analytics effectively.
4. I can handle most problems I encounter when using big data analytics.

Section 2: Computer Anxiety

5. I feel anxious about using big data analytics.
6. I worry that using big data analytics could result in negative consequences.
7. I find big data analytics intimidating.
8. I worry about making mistakes when using big data analytics.

Section 3: Management Support

9. Management provides support for the use of big data analytics.
10. Management believes that big data analytics can help improve the work.
11. Management provides necessary training for using big data analytics.
12. Management encourages the use of big data analytics in the daily tasks.

Section 4: Subjective Norms

13. Most people in my organisation use big data analytics for their tasks.
14. Most people in my organisation believe in the usefulness of big data analytics.
15. Most people who are important to me think I should use big data analytics.
16. My colleagues' opinions influence my decision to use big data analytics.

Section 5: Data Quality

17. The quality of the data used in the big data analytics is high.
18. The data used in the big data analytics is reliable.
19. The data used in the big data analytics is relevant to the tasks.
20. The data used in the big data analytics is up-to-date.

Section 6: Experience

21. I have significant experience using big data analytics.
22. I have successfully used big data analytics to assist in my tasks.
23. My previous experiences with big data analytics have been positive.
24. The more I use big data analytics, the more comfortable I become.

Section 6: Facilitating Conditions

25. How would you rate the availability of technical resources (such as hardware and software) for big data analytics in your organisation?
26. To what extent do you agree that your organisation provides sufficient technical support and infrastructure for effective use of big data analytics?
27. How adequately does your organisation integrate big data analytics into its existing systems and processes?

Section 7: Subjective Norms

28. How strongly do influential figures or leaders in your organisation endorse the use of big data analytics?
29. To what extent do you feel social pressure within your organisation to use big data analytics?
30. In your opinion, how prevalent is the belief among your colleagues that using big data analytics is essential for success in your work?

Section 8: Organisational Readiness

31. How prepared do you feel your organisation is to implement and manage big data analytics solutions?
32. How effectively does your organisation's culture support innovation and the adoption of new technologies like big data analytics?
33. To what degree does your organisation allocate sufficient budget and resources for big data analytics initiatives?

Section 9: External Pressure

34. How much does competition in the market influence your organisation's decision to adopt big data analytics?
35. To what extent do regulatory and compliance requirements drive your organisation's adoption of big data analytics?

Section 10: Adoption of Big Data

36. How easy do you find it to learn how to use big data analytics tools and technologies in your organisation?
37. To what extent do you agree that the big data analytics tools available in your organisation are user-friendly and easy to navigate?
38. In your experience, how easy is it to integrate big data analytics into your regular work processes?