**MUNHUMUTAPA SCHOOL OF COMMERCE**

# The impact of Big data analytics to Sustainability strategy in the Telecommunications sector in Zimbabwe

**By**

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**A dissertation submitted in partial fulfilment of the requirements of the Doctor of Philosophy in Business Administration degree**

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**June 2024**

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**PROGRAMME:** Doctor of Philosophy in Business Administration

**YEAR GRANTED:** 2024

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## Dedication

I dedicate this study to my wife Difrey for being such an inspiration.

**Acknowledgement**

I would like to extend my sincere gratitude to my supervisors Prof. O. Sifile and Dr. J. Bemani who made it possible for this project to be completed. Without their input this project could not have been completed.

Secondly, I would like to extend my gratitude to my family who compromised family quality time and encouraged me to pursue my studies.

## Abstract

Big data analytics (BDA) held potential for sustainability strategies but barriers remained in developing country contexts. This mixed-methods study explored BDA's impact on sustainability practices in Zimbabwe's telecommunications sector considering negative current ratios, adopting a pragmatic paradigm recognizing the multidimensionality of sustainability and BDA concepts. The target population included professionals and executives from Zimbabwe's four major telcos involved in BDA, finance, strategy and sustainability. A sequential explanatory design combined survey and interview data, with probability sampling using Krejcie and Morgan's (1970) technique to determine a sample size of 80, though 71 were achieved due to resource constraints. Survey responses underwent quantitative descriptive analysis, while qualitative follow-up involved purposeful sampling of 5 interview participants for thematic analysis. The study aimed to: 1) explore qualitatively the impact of sales analytics on sustainability strategy and develop predictive models to forecast how sales analytics could shape strategy over time; 2) examine qualitatively the relationship between customer analytics and strategy, and quantitatively assess how customer analytics predicted strategy success; 3) investigate qualitatively social media analytics application on sustainability strategy and developed predictive models to forecast how social media analytics influence key performance indicators (KPIs); and 4) examine qualitatively the links between supply chain analytics and sustainability strategy, and quantitatively assess relationships and develop forecasting models. Findings linked negative current ratios to limited data quality and analytics capabilities, constraining critical technology investments, though strategic BDA application could optimize operations and reduce waste to enhance sustainability. Integrating insights, the study provided evidence-based policy recommendations centered on developing an enabling national framework for responsible data-driven innovation supporting development priorities through skills, infrastructure, innovation support, and public-private partnerships, addressing research gaps on contextual influences in Africa and contributing perspectives on stewarding data solutions for sustainability through multi-stakeholder collaboration. Future longitudinal or comparative case studies could better understand long-term impacts across sectors and contexts.

**Keywords:** Big data analytics, sustainability strategy, telecommunications sector, mixed methods

## Table of Contents

DECLARATION FORM ..... i
RELEASE FORM ..... ii
APPROVAL FORM ..... iii
Dedication ..... iv
Acknowledgement ..... v
Abstract ..... vi
Table of Contents ..... vii
List of Figures ..... xi
List of Tables ..... xiii
ACRONYMS AND ABBREVIATIONS ..... xiv
CHAPTER I ..... 1
INTRODUCTION OF THE STUDY ..... 1
1.1 Introduction ..... 1
1.2 Background of the Study ..... 2
1.3 Statement of the Problem ..... 7
1.4 Research Questions ..... 8
1.5 Research Hypothesis ..... 8
1.6 Research Objective ..... 9
1.7 Significance of the study ..... 9
1.7.1 Significance to Theory ..... 10
1.7.2 Significance to Policy ..... 11
1.7.3 Academic Significance ..... 11
1.7.4 Significance to Practice ..... 12
1.8 Study Limitations ..... 13
1.9 Study Delimitations ..... 14
1.9 Chapter Summary ..... 15
CHAPTER II ..... 16
LITERATURE REVIEW ..... 16
2.1 Introduction ..... 16
2.2 Theoretical review ..... 19
2.2.1 Big Data Analytics ..... 19
2.2.2 Big data analytics capability (BDAC) ..... 24
2.2.3 Integrated Resources ..... 25
2.2.5 Sustainability Strategy ..... 30
2.2.6 Technology, Organisation and Environment (TOE) ..... 33
2.2.7 Technology Acceptance Model (TAM) ..... 38
2.2.8 Diffusion of Innovation (DoI) ..... 40

2.2.9 Sustainability - Triple Bottom Line (TBL) ....................44
2.2.10 Organisational Development Theory ....................48
2.2.11 Theory of Planned behaviour (TPB) ....................51
2.2.12 Six Sigma ....................52
2.3 Empirical review ....................55
2.3.1 Empirical observations ....................57
2.4 Conceptual framework ....................70
2.5 Chapter Summary ....................75
CHAPTER III ....................77
METHODOLOGY ....................77
3.1 Introduction ....................77
3.2 Research Philosophy ....................79
3.3 Research design ....................81
3.3.1 Descriptive research design ....................82
i. Methodological choice ....................87
ii. Research strategy ....................88
iii. Time horizon ....................89
3.4 Population ....................90
3.5 Sampling ....................90
3.5.1 Stratified random sampling for Quantitative Data ....................92
3.5.2 Purposive Sampling for Qualitative Data ....................92
3.6 Instrumentation ....................93
3.6.1 Questionnaire ....................94
3.6.2 Interview Guide ....................94
3.6.3 Documentary analysis guide ....................94
3.7 Data collection procedures ....................96
3.7.1 Administration of the Questionnaire ....................96
3.7.2 Interviews ....................97
3.7.3 Documentary analysis ....................97
3.8 Reliability, validity and trustworthiness ....................98
3.8.2 Reliability of Qualitative data from Interviews and Documentary Evidence ....................99
3.8.3 Validity of quantitative data ....................99
3.8.4 Validity of qualitative data ....................100
3.8.3 Trustworthiness (rigour of the study) ....................101
3.9 Ethical considerations ....................101
3.9.1 Informed Consent Process ....................101

3.9.2 Confidentiality Safeguards ... 102
3.9.3 Mitigating Response Bias ... 102
3.9.4 Oversight and Approval ... 102
3.10 Data analysis ... 102
i. Approach ... 103
ii. Preliminary Analysis ... 103
iii. Quantitative Analysis ... 103
iv. Qualitative Analysis ... 103
v. Data Visualization ... 103
vi. Iterative Exploration ... 104
vii. Integration and Interpretation ... 104
3.10.1 Quantitative data analysis ... 104
3.10.2 Qualitative data analysis ... 105
3.11 Data Collection and Methodology ... 106
3.12 Chapter Summary ... 108
CHAPTER IV ... 109
ANALYSIS AND FINDINGS ... 109
4.1 Introduction ... 109
4.2 Presentation of Data ... 109
4.2.1 Demographic Data ... 109
4.2.2 Normality Tests Results ... 112
4.2.3 Reliability Analysis ... 113
4.2.4: Findings on Big Data Analytics Applications ... 114
4.2.5: Challenges to Big Data Analytics Implementation ... 115
4.3 Analysis and Interpretation of Data ... 116
4.3.1 Demographic Data Analysis ... 116
4.3.2 Big Data Analytics Application Analysis ... 121
4.3.3 Challenges to Big data analytics Analysis ... 126
4.3.3 Results on Sustainability ... 130
4.3.4 Normality Testing ... 133
4.3.5 Reliability Analysis ... 136
4.3.6 Validity Analysis ... 138
4.4 Testing of Reliability and Validity ... 141
4.5 Testing of Hypotheses ... 148
4.6 Presentation of Key Findings ... 151
4.7 Chapter Summary ... 154
CHAPTER V ... 156

DISCUSSION AND CONCLUSION ... 156
5.1 Introduction ... 156
5.2 Recapitulation of the Study ... 157
5.3 Discussion ... 158
5.4 Contributions and Significance of the Study ... 160
5.4.1 Theoretical Contribution ... 161
5.4.2 Methodological contributions ... 162
5.4.3 Contextual/Practical contributions ... 163
5.5 Recommendations ... 164
5.5.1 Adopting Sustainable Business Models Leveraging Big Data Analytics ... 164
5.5.2 Developing Analytical Capabilities and Skills ... 165
5.5.3 Improving Data Governance and Management ... 165
5.5.4 Incentivising Sustainability-Focused Innovation ... 165
5.5.5 Stakeholder Engagement and Measuring Impact ... 166
5.6 Limitations of the study ... 166
5.7 Suggestions for future studies ... 168
5.7.1 Further Research on Emerging Technologies in Telecommunications ... 168
5.7.2 Broadening Time Horizons for Sustainability Planning ... 168
5.7.3 Interdisciplinary and Participatory Approaches to Sustainability ... 168
5.7.4 Scenario Planning for Low-Probability Trends in Telecommunications ... 169
5.7.5 Policy Recommendations and Roadmaps for Sustainable Telecommunications ... 169
5.7.6 Global Collaboration and Knowledge Sharing for Sustainable Telecommunications ... 169
5.7.7 Theory Discovery ... 169
5.7.8 Theory Extension ... 170
5.7.9 Comparative Theory Testing ... 170
5.8 Conclusion ... 170
REFERENCES ... 173
APPENDICES ... 181
Appendice 1: Research Ethics approval form ... 181
Appendice 2: Questionnaire ... 190
QUESTIONNAIRE ... 190
Appendice 3: Interview guide ... 198
Appendice 3: Informed Consent Form ... 207
Appendice 4: TelOne Authorisation ... 209
Appendice 5: NetOne Authorisation ... 218

**List of Figures**


Fig. 2.1 Big Data Analytics pipeline........................................................................................ 20
Fig. 2.2 RBV diagram .......................................................................................... 26
Fig 2.3 TOE diagram ........................................................................................................ 34
Fig 2.4 Extended TOE framework............................................................................... 35
Fig 2.5 Technology Acceptance Model........................................................................ 38
Fig 2.6 Technology Acceptance Model (TAM 3)........................................................... 40
Fig 2.7 Diffusion of Innovation Theory........................................................................ 42
Fig 2.8 Innovation decision process............................................................................. 43
Fig 2.9 Triple Bottom Line ......................................................................................... 46
Fig. 2.10 Ellen MacArthur Butterfly diagram........... .................................................... 47
Fig 2.11 Organisational Development architecture...................................................... 50
Fig 2.12 Theory of planned behaviour ........................................................................ 51
Fig 2.13 Six Sigma objectives.................................................................. ............ 53
Fig 2.14 Conceptual framework.................................................................................. 77
Fig 3.1Research Onion..................................................................................................81
Fig. 4.1: QQ Plots......................................................................................................... 115
Fig 4.3: Theme visualisation......................................................................................... 125
Fig 4.2 Themes Frequency............................................................................................ 126
Fig 4.3 Themes in word cloud........................................................................................ 127
Fig 4.4 : Factors in word cloud format.......................................................................... 130
Fig 4.5: Factors Frequency............................................................................................ 131
Fig 4.6: Sustainability themes....................................................................................... 133
Fig. 4.7 Sustainability themes in word cloud..................................................................
**Error! Bookmark not defined.**
Fig. 4.8 Path diagram, Source: Survey data (2023)........................................................ 150

**List of Tables**

Table 1.1 Current Ratios…………………………………………………………… 6
Table 2.1: Research gap........................................................................................ 67
Table 3.1 - Population.......................................................................................... 90
Table 3.2 – Population and Sample size...................................................................91
Table 4.2: Demographic data.................................................................................. 110
Table 4.3: Normality Test Results..........................................................................112
Table 4.5: Item-Total Statistics............................................................................... 113
Table 4.6: AVEs and SICCs....................................................................................114
Table 4.8: Descriptive statistics big data analytics use in Telcos......................................... 114
Table 4.9: Descriptive Statistics...............................................................................115
Table 4.8: Descriptive statistics big data analytics use in Telcos......................................... 124
Table 4.9 Descriptive Statistics...............................................................................128
Table 4.10 Descriptive Statistics.............................................................................132
Table 4.3: Normality Test Results..........................................................................135
Table 4.5 Item-Total Statistics................................................................................ 136
Table 4.7 Construct, Items and Factor loadings, Cronbach alpha, composite reliability & AVEs........................................................................................................ 137
Table 4.7: Construct, Items and Factor loadings, cronbach alpha, composite reliability & AVEs........................................................................................................ 139
Table 4.8 Model Fit summary.................................................................................140
Table 4.6: AVEs and SICCs....................................................................................141
Table 4.8 Model Fit summary.................................................................................143
Table 4.6 AVEs and SICCs.....................................................................................145
Table 4.8 Model Fit summary.................................................................................147
Table 4. 11: Results of Hypotheses testing (H1, H2, H3, and H4)....................................... 150

**ACRONYMS AND ABBREVIATIONS**

4IR - Fourth Industrial Revolution

AI - Artificial Intelligence

BDA - Big Data Analytics

BCG - Boston Consulting Group

ESG - Environmental, Social and Governance

GDP - Gross Domestic Product

ICT - Information and Communication Technology

ILO - International Labour Organization

IOT - Internet of Things

KPI - Key Performance Indicator

NDS1 - National Development Strategy 1 (Zimbabwe)

PTC - Postal and Telecommunications

POTRAZ - Postal and Telecommunications Regulatory Authority of Zimbabwe

SADC - Southern African Development Community

TBL - Triple Bottom Line

TELCO - Telecommunications Company

TMT - Technology, Media and Telecommunications

VRIO - Valuable, Rare, Inimitable and Organisational

ZWL - Zimbabwe Dollar

# CHAPTER I
# INTRODUCTION OF THE STUDY

## 1.1 Introduction

This chapter introduces the research problem, objectives, hypotheses, and justification for the study on "The Impact of Big Data Analytics to Sustainability Strategy in the Telecommunications Sector in Zimbabwe," in the context of 4IR and negative ratios. The chapter aims to contextualize the research question and establish the relevance and significance of the research study.

The telecommunications industry in Zimbabwe was at risk of stagnating or reducing its growth momentum without sustainable business models. This was because of the negative environmental impact resulting from the sector's growth trajectory, making it imperative for companies within the industry to adopt sustainable business models. This chapter highlights how big data analytics could be a potential solution, providing significant leverage to enable the industry's expansion while ensuring sustainable development.

Negative ratios, which posed financial challenges, also affected the espousal of Big data analytics and sustainability practices by telecommunication companies in Zimbabwe. The chapter discusses how negative ratios could hinder the sector's sustainable growth and the possibility of Big data analytics in mitigating these hindrances.

The research investigated the correlation between Big data analytics and sustainability strategies within telecommunications industry in Zimbabwe, exploring how telecommunication companies could leverage big data analytics to develop sustainable business models and contribute to the sector's sustainable growth. Additionally, it examined how negative ratios could hinder the exaction of Big data analytics and sustainability practices within the industry.

Overall, this chapter provides a broad background on the research question, stating the objectives, hypotheses, as well as justification, paving the way for the subsequent chapters to delve into each aspect in detail.

## 1.2 Background of the Study

The emergence of the fourth industrial revolution (4IR) around 2016 brought about a blending of the digital, physical and biological worlds advancing artificial intelligence (AI), robotics, internet of things (IOT), quantum computing, genetic engineering, 3D printing and associated technologies (McGinnis, 2018). 4IR is primarily attributable to four domains which were high speed mobile broadband, artificial intelligence (AI), employ of Big Data analytics (BDA) and web based (cloud) computing ( Philbeck and Davies, 2018 ). The Fourth Industrial Revolution (4IR) had brought about significant technological advancements, such as big data analytics, that had the potential to revolutionize various sectors, including the telecommunications industry in Zimbabwe. The telecommunications sector in Zimbabwe had been experiencing significant growth and development and was a significant contributor to the country's GDP. However, this growth came with increased environmental impact, leading to sustainability challenges.

The benefits of this revolution were increased productivity, efficiency, data driven decision making tools and improved competitiveness through mass customisation (Li, Hou and Wu, 2017). The investigation sought to establish the impact of Big Data analytics on Zimbabwean telecommunication companies (telcos) and how the 4IR could influence traditional strategic management anchored on the triple bottom line (TBL) concept.

Bergquist, (2021) postulates business strategy evolution has resulted in the emergence of sustainability. Shah and Rahim, (2019) define sustainability as addressing firm current needs without neglecting the ability of future generations to accommodate own needs. This has culminated in Industry 5.0 concept which embraces stakeholder relevance in digital transformation. Akundi *et al*, (2022) claim Industry 5.0 as a concept that seeks collaboration of human beings and industry to be more sustainable, human centric and resilient. Sustainability leads to improved brand image, reduced costs, shareholder value and increased productivity (Xie *et al*, 2019). The impact of Covid-19 brought about the dire need to engage stakeholder beyond shareholder in sustainable business that captures the planet, people and profit matrix (Purcărea *et al*, 2022).

The 4IR enabled a digital ecosystem based on three pillars which comprised digital infrastructure, digital governance and digital economy (Vota, 2021). Felser, Rentschler and Kleineberg, (2019) posit that in today's digital ecosystem, telecommunication has assumed a pivotal role for businesses, governments, societies and individuals to seamlessly connect and share information through information technology (IT) and operational technology (OT).

Telecom companies gather vast amounts of data from call detail records, mobile phone usage, network equipment, server logs, billing and social networks. This information can be used to optimize network services and usage, improve customer experience and enhance security (McDonald, 2020). This huge amount of data (resource) begs the question of whether telecommunication companies utilised this Big Data to improve on their sustainability. Big data had become a mainstream activity for enterprises as it provided access to large amounts of structured and unstructured information (Janssen, van der Voort and Wahyudi, 2017; Erevelles, Fukawa and Swayne, 2016; Kabir and Carayannis, 2013). Big Data had become an intrinsic resource that was valuable, reliable, imitable and organisational (VRIO), hence the need to interrogate its strategic capabilities.

The study sought to establish specific sustainability strategies in Zimbabwean telecommunication companies. The proliferation of mobile operators in the mould of NetOne, Econet, TelOne and Telecel resulted in sustainability challenges. None of the above Zimbabwean Telcos had produced reports which met the Triple Bottom Line which was an accounting framework with three main components: social, environmental, and financial. Companies incorporating this framework believed that instead of a single bottom line, there exists three instead: people, planet, profit (ILO., 2022). The lack of sustainability is projected in the respective annual reports (see Table 1). Telecel in its press release on 17 January, 2020 (www.telecel.co.zw/about-us/press-releases) allayed fears whilst conceding to operational challenges. The huge amount of capital investment currently required to ensure sustainability within an industry average current ratio of 1: 0,75 has not been forthcoming. Shareholder value had not been realised to enable declaration of dividend in the financial years (2018 and 2019). The Zimbabwean government, as part of lessening the burden on its coffers, was looking at selling a significant stake in the two state-owned telcos, namely mobile network provider NetOne and fixed and broadband network provider TelOne (Fin 24, 2019). Information availed at TelOne Annual General Meeting of June 29, 2018 in their sustainability report indicated subdued economic activity (TelOne Sustainability Report, 2017). This called for solutions that could enable Zimbabwean telecommunication companies adopt Big Data analytics so as to impact on sustainability.

Haanaes (2016) opines that all companies, across all industries, 62% of executives believed that having a sustainability strategy was necessary to be competitive today while another 22% thought it would be necessary in the future. Elkington (1994) concedes that sustainability effectiveness is determined through the simultaneous measurement and improvement of environmental, economic and social performance. It is argued that Big Data analytics impact on sustainability strategy within the telecommunications sector is an important means of contributing towards improved Gross Domestic Product (GDP), providing employment, and creating fiscal space for shareholders (Dangaiso, 2014). Big Data analytics result in improved economic activity hence this research's importance to the companies in the telecommunication industry, as it brought out the role of data analytics in telecommunications sustainability (Mutemararo, 2017). Zimbabwean telecommunication companies therefore need to proffer solutions that enable adoption of Big Data analytics to impact on sustainability. The Fourth Industrial Revolution (4IR), which is characterized by the infusion of advanced technologies such as big data analytics into various sectors, has the potential to revolutionize the telecommunications sector in Zimbabwe. Big data analytics could enable telecommunication companies in Zimbabwe to gather and analyze large amounts of data, develop data-driven sustainability strategies, and promote sustainable practices.

A relatively small number of companies that have adopted big data architectures and analytics technologies have been aggressive enough to significantly profit from them (Bughin, 2016). Yaqoob *et al* (2016) opines enterprises considering BDA adoption face a plethora of challenges such as lack of skills, resistance to change and technology limitations. Intezari and Gressel (2017) indicate that strategy formulation is informed by Big Data through analysis. The Big Data analytic process informs the environmental analysis tools (McKinsey's 7 S models, PESTEL among others). Global cases show that organizations that utilize Big Data for strategy formulation outgrow their competitors [ABC Inc; TESLA; General motors] (Amoah, 2016). Telcos in Zimbabwe, in their endeavour to create blue oceans, have access to data centres and cloud services (Makwinja, 2018) and should identify the critical elements that moderate the impact of Big Data analytics on sustainability.

Misreading of the competitive landscape through believing in own strategy in the absence of confirming evidence has led to strategic failure (Finkelstein, 2005). Failure of strategy may be due to any of the multiple reasons which consist of the following; too much prioritisation of economic value whilst putting other value attributes of social and environment in the back burner, lack of fundamental understanding of people tasked with developing or formulating the strategy to ensure success, mismatch between the strategy and core competencies of the organisation, flawed strategy, lack of accountability during operationalisation of strategy and disruptions in the socio-political environment. This is summed by (Vermuelen, 2017) as strategies that fail because they're not actually strategies.

Bughin (2016) posits that adoption of Big data analytics provides business competitiveness in Telcos, applicable to five functional domains which are; sales and marketing, network load optimisation, customer care, competitive intelligence, supply chain optimisation (logistics and telecommunication equipment purchase). Big data analytics enables performance predictions which enable decision makers to employ further data in ameliorating already unpredictable challenges and upgrade of process performance hence resulting in cost reduction, lower inventory levels, best operational plans, lean management and operational efficiency (Rajesh, 2013). A study by the (African Journal of Science, Technology, Innovation and Development, 2020) posits that the use of Big data analytics could enable companies to achieve sustainability goals by identifying and managing environmental risks, increasing operational efficiency, and reducing costs. Furthermore, the study emphasized the importance of sustainable business models in the adoption of new technologies such as Big data analytics.

This study needs to proffer solutions that can result in implementable research, which dovetails with the digital ecosystem as enunciated in the environmental social governance (ESG) contract. This is embedded in the current National Development Strategy 1 of the Zimbabwe government and meets the dictates of sustainability. However, Big data analytics adoption in the telecommunications sector in Zimbabwe may be hindered by negative financial ratios such as current ratios. Negative current ratios imply that telecommunication companies may not have sufficient short-term liquidity to invest in advanced technologies such as big data analytics which can improve sustainability outcomes.

## Table 1.1 Current Ratios

| | Econet | TelOne | NetOne |
|---|---|---|---|
| | ZWL$'000 | ZWL$'000 | ZWL$'000 |
| **2020/2019 information** | | | |
| Total equity | 36,243,595 | (4,831,952) | 1,316,314 |
| Total current assets | 9,336,893 | 607,712 | 1,184,578 |
| Total current liabilities | 9,212,975 | 700,776 | 1,086,566 |
| | 1: 1,01 | 1 : 0,87 | 1: 1,09 |
| Current ratio | 101% | 87% | 109% |
| **2018 information** | | | |
| Total equity | 33,165,826 | (1,179,920) | (565,485) |
| Total current assets | 6,407,683 | 1,069,962 | 619,186 |
| Total current liabilities | 7,839,929 | 1,202,881 | 946,735 |
| | 1: 0,817 | 1: 0,889 | 1: 0,654 |
| Current ratio | 81.7% | 88.9% | 65.4% |

**Sources**

1. TelOne 2019 Annual Report Published on website:

https://www.telone.co.zw/Content/Uploads/Reports/93a00e75-5f95-4ca0-a98f-8e10c9abdf08.pdf

2. Econet 2020 half year financial report

Econet Wireless Zimbabwe News and Corporate Announcements (ewzinvestor.com)

3. NetOne 2019 Annual Report

The finance function in the corporate world is an established instrument of strategic analysis and a creative strategic tool (Ekpo, Etukafia and Udofot, 2017). The current ratios of Zimbabwe Telcos on Table 1 are indicative of the firms' low liquidity comparatively to the industry average of 1: 0,75 (75%) which in this instance is not consistent with global empirical outcomes for capital investment required for BDA infrastructural development and sustainable growth strategies that can yield a positive business trajectory. In order to address these challenges, telecommunication companies in Zimbabwe need to adopt innovative and sustainable business models that leverage the power of Big data analytics. This can help them achieve long-term sustainability while meeting their short-term financial obligations.

In light of these findings, the study on "The Impact of Big Data Analytics to Sustainability Strategy in the Telecommunications Sector in Zimbabwe" sought to investigate big data analytics and sustainability correlation in the telecommunications sector in Zimbabwe, coupled with challenges and opportunities associated with the adoption of Big data analytics in context. The research objectives provided insights into the potential of Big data analytics in promoting sustainability within the telecommunications sector in Zimbabwe and develop recommendations for telecommunication companies operating in Zimbabwe to overcome challenges related to negative financial ratios and achieve long-term sustainability. Interrogation of Big data analytics domains and the relationship with the Triple Bottom Line construct of economic, social and environmental pillars.

### 1.3 Statement of the Problem

The use of big data analytics to develop sustainability strategies in the telecommunications sector (NetOne, TelOne, Econet and Telecel) in Zimbabwe could be hindered by negative current ratios. Negative current ratios dictate that the telecommunication companies are not able to meet short-term financial obligations through available resources. This negatively affects their ability to invest in big data analytics and sustainable practices.

The problem is that without adequate funding, telecommunication companies in Zimbabwe may not be able to invest in big data analytics necessary for sustainability strategies. As a result, they may not be able to measure their performance accurately, or identify the areas of inefficiencies which would lead to a reduction of sustainability efforts. Additionally, without adequate funding, telecommunication companies may not be able to purchase sustainability measures or raw materials efficiently. This could lead to decreased overall sustainability and hinder the telecommunication companies' ability to achieve long-term operational sustainability.

Therefore, the negative current ratios of telecommunication companies may have a significant impact on how much they can invest in big data analytics and sustainability strategies, which may limit their overall sustainability efforts. The study investigated how negative current ratios affected Big data analytics impact to sustainability strategies in the telecommunications sector in Zimbabwe, and develop recommendations for telecommunication companies operating in Zimbabwe to overcome any challenges affecting their sustainability efforts.

## 1.4 Research Questions

1.4.1. How does sales data analytics influence the development, implementation, monitoring and evaluation of sustainability strategies in telecommunications companies in Zimbabwe?

1.4.2. How does customer data analytics usage affect key sustainability strategy processes like strategy formulation, resource allocation, performance measurement in telecommunications companies in Zimbabwe?

1.4.3. How does social media data analytics application influence stakeholder engagement and management for sustainability strategy implementation in companies in the telecommunications sector in Zimbabwe?

1.4.4. How does supply chain data analytics impact material procurement, waste management and logistics optimization efforts to support sustainability strategy implementation in companies in the telecommunications sector in Zimbabwe?

## 1.5 Research Hypothesis

H1: Sales data analytics influences sustainability strategy of telecommunications companies.

H2: Customer data analytics usage positively influences sustainability strategy of telecommunication companies in Zimbabwe.

H3: Social media data analytics application affects sustainability strategy of companies in the telecommunications sector in Zimbabwe.

H4: Supply chain data analytics has a positive effect on sustainability strategy in the telecommunications sector in Zimbabwe.

**1.6 Research Objective**

1.6.1 To explore qualitatively the impact of sales analytics on sustainability strategy and

develop predictive models to forecast how sales analytics may shape strategy over time.

1.6.2 To examine qualitatively the relationship between customer analytics and strategy and quantitatively assess how customer analytics predicts strategy success.

1.6.3 To investigate qualitatively social media analytics application on sustainability strategy and develop predictive models to forecast how social media analytics influence key strategy i.e. key performance indicators (KPI's).

1.6.4 To examine qualitatively the links between supply chain analytics and sustainability strategy and quantitatively assess relationships and develop forecasting models.

**1.7 Significance of the study**

The Impact of Big Data Analytics to Sustainability Strategy in the Telecommunications Sector in Zimbabwe" has significance in theory integration, in the exploration of potential solutions that could contribute to sustainable development, practice, policy implementation that can promote sustainability goals and enhance academic research with original insights that could foster future study.

### 1.7.1 Significance to Theory

This study contributes to theory development by integrating, contextualizing, extending and potentially building new context-specific theories to further scholarly understanding of big data analytics' impact on sustainability strategies:

**i. Integration of Big Data Analytics and Sustainability Theories**

This study aims to integrate theories related to big data analytics and sustainability strategy to provide a more holistic theoretical framework. Existing theories on big data analytics (Resource-Based View, Technology Acceptance Model, etc.) will be linked with sustainability strategy theories like Triple Bottom Line to develop a more comprehensive understanding of their interrelationships. This contributes new insights to theory development.

**ii. Application of Theories in Developing Country Context**

Theories related to big data analytics adoption and sustainability strategies have mostly been developed and tested in developed country contexts. This study applies these theories to the developing country context of Zimbabwe, which contributes to extending and contextualizing the theoretical boundaries of these concepts.

**iii. Addressing Gaps in Existing Theories**

Through the empirical findings, this study seeks to identify gaps in the existing theories when applied to explain the relationship between big data analytics and sustainability strategies. It aims to address these gaps by proposing refinements or extensions to the existing theories.

**iv. Development of a Context-Specific Theoretical Model**

By integrating relevant theories, addressing their gaps, and incorporating contextual factors like negative financial ratios, this study aimed to develop a more context-specific theoretical model to explain the phenomenon under investigation. This contributed a new context-grounded theoretical understanding.

**v. Basis for Future Theory-Building**

The study's findings laid the foundation for future theory-building research by providing empirical insights and a conceptual framework that subsequent studies could build upon. It could stimulate new ideas and open up avenues for more advanced theoretical conceptualizations

### 1.7.2 Significance to Policy

The study was significant to policymakers in Zimbabwe as it provided insights on the potential of big data analytics to promote sustainability strategies in the telecommunications sector. The findings provided empirical evidence on the potential role of big data analytics in enabling sustainable development goals in the telecommunications sector. Policymakers could use the findings to develop sustainable business model frameworks, support the adoption of new technologies and strategies, and promote innovation in the telecommunications sector. The study thus contributed to realizing national priorities outlined in policy documents like Zimbabwe's National Development Strategy 1 (NDS1).

By demonstrating how specific types of analytics can support strategy implementation across economic, social and environmental dimensions, results inform policies to incentivise analytics adoption and diffusion. Regulators gain insights into impacts of existing data governance rules on firm practices and sector sustainability.

The study also provided policy recommendations for developing an enabling national framework that harnessed digital technologies and analytics for sustainability. Perspectives on skills development, infrastructure investments, innovation support and public-private partnerships offer guidance in crafting cohesive strategies.

Interrogation of challenges posed by negative financial ratios, the study sought to advise policy options to improve telecommunications sector viability while balancing developmental priorities. Recommendations for standards, incentives and financing mechanisms provided a basis for an inclusive industrial strategy.

### 1.7.3 Academic Significance

Introduction of technology in higher education had become paramount. Technology had been strategically introduced into Zimbabwe higher education to enhance different processes like teaching, learning and industrialisation. Education 5.0 in Zimbabwe had become policy.

This study was significant to academia as it contributed to the existing body of knowledge on big data analytics and sustainability strategy in the telecommunications sector. The findings from this study can potentially be used to develop new research areas, and initiate future studies on the integration of big data analytics and sustainability in developing countries. Findings from the understudied context of Zimbabwe provide empirical data to contextualize and extend existing theories on big data analytics adoption and sustainability strategies.

This study contributed significant insights for academics and future research. By developing a more holistic theoretical framework integrating multiple perspectives, the study advanced conceptual understanding of these topics. It also identified avenues for refining and evolving theories to better explain phenomena in developing markets.

The contextualized theoretical model developed had potential for application to similar environments and comparative studies. It thus stimulated further international research on these issues.

Practical guidance on leveraging analytics for sustainability offered a foundation to develop management curricula that bridged digital technologies and responsible business practices.

Methodologically, the use of mixed quantitative and qualitative approaches to address exploratory research questions provided a template for rigorous contextual inquiry.

### 1.7.4 Significance to Practice

The research could help practitioners in the telecommunications industry in Zimbabwe to understand the relationship between big data analytics and sustainability practices and its impact on their business operations and stakeholder relationships. The study aimed to provide an empirical basis to facilitate practical action and guide decision-making for diverse stakeholders. It sought to translate insights from an under-researched context into implementable strategies with real impact. Global cases show that organisations that utilize Big Data analytics for strategy formulation outgrow their competitors [ABC Inc; TESLA; General motors] (Amoah, 2016). This study provided practical guidance so that companies could develop sustainable business models that integrate Big data analytics to achieve data driven decision-making processes, reduce costs, to improve sustainability performance.

The study findings offered telecommunications companies insights into leveraging specific analytics domains - such as sales, customer, social media and supply chain data - to facilitate sustainability strategy development, implementation and evaluation. Demonstrating clear linkages between analytics usage and strategy outcomes informs strategic investment prioritization in developing requisite analytical skills and technologies.

Regulatory bodies stood to gain an understanding of how data usage policies and regulations may positively or negatively influence firms' sustainability impacts. Standard-setting organizations in Zimbabwe could obtain perspective on relevant metrics to track telecommunications sector strategy performance and progress on sustainability goals.

This study makes a valuable contribution by elucidating the strategic role of Big data analytics in supporting sustainability practices and long-term value creation among Zimbabwe's telecommunications firms, thus addressing a knowledge gap among sector investors regarding how leveraging such capabilities can differentiate companies and inform capital allocation decisions aimed at maximizing competitive advantage through data-driven initiatives tailored to local sustainability challenges.

Academics obtained a foundation for developing context-tailored management education curricula integrating sustainability and data analytics. Practitioners are equipped to implement evidence-based solutions. Policymakers gained guidance in crafting supportive frameworks.

## 1.8 Study Limitations

The research on the "The impact of Big data analytics to sustainability strategy in the telecommunications sector in Zimbabwe" faced several limitations:

i. **Geographical Scope:** The available literature on this topic was primarily focused on developed markets, with limited research from the Zimbabwean context. This inhibited the generalizability of findings to the local telecommunications industry.

ii. **Data Availability:** Access to proprietary company data on big data analytics adoption and sustainability measures may be limited due to confidentiality concerns or competitive reasons. This could restrict the depth of analysis that can be reviewed.

iii. **Research Methodology:** Prior studies have predominantly used quantitative approaches only, whereas this research infused a qualitative stance to provide more informed insights. The reliance on primary data collection through surveys and interviews introduces potential biases.

iv. **Industry-Specific Focus:** The study restricted itself to the telecommunications sector, which limited the ability to draw cross-industry comparisons and implications for other sectors in Zimbabwe.

v. **Temporal constraints:** Study period (2021-2024): As the study was conducted over this four-year period, it did not capture the full long-term impact of big data analytics on sustainability strategies in the telecommunications sector. The effects could extend well beyond 2024, but the study only had data up to that point.

### 1.9 Study Delimitations

The scope of this research "The impact of Big data analytics to sustainability strategy in the telecommunications sector in Zimbabwe" is delimited as follows:

**i. Company Selection criterion:** The research focussed only on the four major telecommunications companies in Zimbabwe: Econet, NetOne, Telecel, and TelOne.

**ii. Respondent Profile:** The primary data were collected through surveys and interviews with managers and executives involved in the strategy, finance, IT, and sustainability functions of the selected companies.

**iii. Data Sources:** In addition to primary data, the study reviewed publicly available secondary data pertaining to the selected companies from 2017 onwards.

**iv. Research Objectives:** The study provided qualitative and quantitative insights on the adoption challenges and opportunities surrounding the use of big data analytics for sustainability strategies, rather than developing predictive models.

**v. Industry Focus:** The findings of this research were specific to the telecommunications industry in Zimbabwe and could not be directly generalised to other sectors.

## 1.9 Chapter Summary

The introduction chapter of "The Impact of Big Data Analytics to Sustainability Strategy in the Telecommunications Sector in Zimbabwe" sets the stage for the study by providing background information on the telecommunications industry in Zimbabwe, sustainability, big data analytics, and their interrelationship. The chapter commences with a review of the Fourth Industrial Revolution (4IR), which is transforming various sectors through advanced technologies such as big data analytics.

The focus then shifts to the telecommunications industry in Zimbabwe, which is experiencing significant growth and development. However, there is a need for solutions that address the negative environmental impact resulting from this growth, thereby promoting sustainable industry practices. The chapter provides high points of developing sustainable business models in the telecommunications sector and how big data analytics can facilitate this by enabling companies to develop effective and data-driven sustainability strategies.

The chapter examines negative current ratios, a financial challenge faced by telecommunication companies in Zimbabwe. This challenge may prevent Big data analytics adoption and sustainability practices, thus limiting the potential for sustainable growth in the industry.

Finally, the chapter dispenses a synopsis of the research problem, objectives, and hypotheses. The study aims to investigate the relationship between Big data analytics and sustainability strategies in the telecommunications sector in Zimbabwe. It also seeks to explore how negative current ratios affect Big data analytics adoption and sustainable practices in the telecommunications industry in Zimbabwe. The research objectives and hypotheses are presented, signaling the direction and scope of the research.

Overall, the chapter sets the context for the study and highlights the importance of exploring how big data analytics can impact sustainability strategies in the telecommunications sector in Zimbabwe, while at the same time providing a basis for further exploration in the stated problem area. The following Chapter 2 will provide a comprehensive literature review.

# CHAPTER II
# LITERATURE REVIEW

## 2.1 Introduction

The telecommunications industry in Zimbabwe had been experiencing significant growth and development in past years, contributing significantly to the country's economy. However, this growth had also brought about increased environmental impact, which led to sustainability challenges. To address these challenges, telecommunications companies in Zimbabwe needed to adopt sustainable business models that would leverage emerging technologies such as big data analytics. This literature review sought to explore the existing scholarship on the impact of big data analytics on sustainable strategy in the telecommunications sector in Zimbabwe.

The literature review emanates from the epistemological approach based on the topical research regarding the impact of big data analytics to sustainability strategy in the telecommunications sector in Zimbabwe whose focus is premised on TelOne, Telecel, NetOne and Econet companies. The study envisages extrapolating insights that would result in an implementable research in Zimbabwe telecommunications industry.

This literature review on "The Impact of Big Data Analytics to Sustainability Strategy in the Telecommunications Sector in Zimbabwe" examined the current state of research on big data analytics and sustainability strategy in the telecommunications sector. It explored how big data analytics could be leveraged to develop and implement sustainable business models in the context of 4IR and negative current ratio.

The literature review examined the existing knowledge on the relationship between sustainability strategy and big data analytics in the telecommunications industry, focusing on how big data analytics can be used to optimize sustainability strategy. Additionally, the review explored how 4IR innovations such as big data analytics can facilitate sustainable business operations, helping companies in Zimbabwe achieve sustainable growth.

Big data analytics variants coupled with sustainability have great potential to meet the dictates of the United Nations sustainable development goals and Zimbabwe National development strategy ((Nandi, 2023). Technological evolution that embraces mankind is key to global and national development. The research study explored the need to meet the dictates of the novel fourth industrial revolution (4IR) transformation simultaneously guaranteeing sustainability (social, economic and financial inclusion) through Triple Bottom Line (Elkington, 1994).

The emergence of the Fourth Industrial Revolution (4IR) around the year 2016 brought about the burgeoning deluge of unprecedented amount of structured, semi structured and non-structured data, through the convergence of the physical, digital and biological worlds utilising digital technologies (Schwab, 2016). Big data (BD) is generated through the use of applications in disruptive technologies consisting of Internet of things (IoT), machine learning and robotics (Lacy, Long and Spindler, 2020). The 4IR disruptions have impacted the digital ecosystem by transforming today's existing industries management, production and governance systems in their entireties (Kim, 2021). The emergent Industry 5.0 concept within the 4IR has brought about the dire need to collaborate human beings with industry. Akindu *et al*, (2022) opine the concept recognises capacity of industries to address the fundamental issues beyond labour by taking cognisance of safeguarding the planet and prioritising health to achieve sustainable development.

The new technologies in the 4IR have played a pivotal role in addressing societal challenges through the global circular economy and the 17 United Nations sustainable development goals (SDG's) which are characterized into three systems, i.e., environmental, economic, and social (Hoosain, Paul and Ramakrishna 2020). Pham *et al*, (2019) concede that Industry 4.0 will accelerate the circular thinking. The ICT sector by virtue of being a repository of Big data software and simulation technologies has a sole responsibility in bridging the digital divide in order to achieve the SDG's (Demestichas, Daskalakis, 2020). The novelty research provides the appropriate algorithm to sustainable development.

The Fourth Industrial Revolution (4IR) has disrupted various industries (Kim, 2021), and the telecommunications sector in Zimbabwe is no exception. The sector has witnessed significant growth, with mobile penetration increasing exponentially within the past decade. However, this growth has come at a cost, leading to negative environmental impact and sustainability challenges (Chen *et al.,* 2015)

Mutimukuru and Maringe (2019) agree that sustainable business models and practices are essential for the telecommunications sector in Zimbabwe to continue its upward growth trend and contribute to the country's economic development without causing further environmental damage. Big data analytics has emerged as a tool that could potentially support the sector's transition towards sustainable practices. Big data analytics enables telecommunications companies to collect, store, and analyze large amounts of data, thus providing insights into how sustainability practices could be implemented.

The literature review analyzed the challenges that telecommunications firms face in adopting big data analytics and sustainable business practices, especially in the context of negative current ratios. Negative current ratios can hinder companies' ability to invest in new technologies such as big data analytics, thereby limiting their capacity to transition towards sustainable operational practices.

The literature review included several sources, including peer-reviewed articles, books, and other academic literature. The review also explored the Resource-Based View (RBV) theory, which suggests that organizations must leverage their resources to achieve a competitive advantage. Companies in the telecommunications sector in Zimbabwe can use big data analytics as a resource to generate insights, improve their decision-making processes, and drive innovation.

Additionally, the review will explore the Technology Acceptance Model (TAM), which explores the determinants of user acceptance of technology. The TAM has been used to understand users' attitudes towards and perceptions of big data analytics technology and can provide valuable insights into the adoption and implementation of big data analytics strategies in the telecommunications sector in Zimbabwe.

Furthermore, the literature review will discuss the Theory of Planned Behavior (TPB), which is a model that predicts behavioral intention based on attitude towards behavior, subjective norms, and perceived behavioral control. The TPB has been used to understand the factors that determine the intention to use big data analytics technology by companies (Kong *et al.,*2019).

This literature review contributed to the existing body of knowledge by synthesizing the existing literature, highlighting the gaps in the current knowledge, and providing recommendations for further research.

The review ended with a discussion of the conceptual framework for the study, which included big data analytics as an independent variable, the sustainability strategy of the triple bottom line as a dependent variable, integrated resources as a mediating variable, and the adoption framework of the TOE, DOI, and TAM models as moderating variables.

In conclusion, the literature review provides insights into the impact of big data analytics on sustainability strategy in Zimbabwe's telecommunication sector, contextualized within 4IR and negative current ratio factors. The literature review will provide an understanding of the current knowledge base on the potential of big data analytics and sustainable practices to address the sustainability challenges facing the telecommunications sector in Zimbabwe.

## 2.2 Theoretical review

The purpose of a theoretical review on the impact of big data analytics on sustainability strategy in the telecommunications sector in Zimbabwe is to provide a critical analysis of existing theories and concepts related to the research topic. It helps to identify gaps in the existing literature, clarify the research question, and provide a framework for interpreting the results of the study. The function of this theoretical review is to provide a footing for the research by synthesizing and evaluating existing knowledge on the topic. The theoretical review helps to establish that this study is grounded in existing theory, and that its results are inexplicable and meaningful in the context of previous research. This theoretical review will help interrogate areas where further research is needed, and suggest a new trajectory for future studies.

### 2.2.1 Big Data Analytics

Big data analytics is advanced techniques of analysis applied on complex data sets from different sources in order to provide meaningful relevance to societal requirements (Singh, Basal and Singh, 2023). Big data analytics is the process of examining large and complex datasets to uncover hidden patterns, correlations, and insights (Provost and Fawcett, 2013). It involves using various techniques and tools to process and analyze vast amounts of data from diverse sources to extract valuable insights that can help organizations make data-driven decisions (Perakis et al., 2020). This employs the use of Hadoop an open source framework with the appropriate algorithms to store and process large and complex data sets (Al-Kasawneh, Uddin and Shah, 2022). Big data analytics techniques include data mining, machine learning, natural language processing (NLP), and predictive analytics. Unique technologies such as data warehouses, data lakes, and cloud computing infrastructures enable the storage and analytics of large data sets at scale (Chen *et al.,* 2020).

Big data (BD) refers to a large set of complex (structured, semi structured and unstructured) data that cannot be easily analysed using simple methods (Pyne et al., 2016). "Big data sets are complex and cannot be managed or analysed using traditional data analysis software. These data sets share 7 common characteristics, the 7Vs: V1—volume, V2—velocity, V3—variety, V4—veracity, V5—value, V6—variability & V7—visualisation" (Rialti, 2018 p. 1094). Big data is an intrinsic and valuable resource, resident in telecommunication companies (Rehman and Al-Raqom, 2020). BD is an enabler of the Fourth Industrial Revolution (4IR) which is largely driven by four domains which are high speed mobile internet (broadband), artificial intelligence (AI), Big Data analytics (BDA) and cloud technology (Philbeck and Davies, 2018).

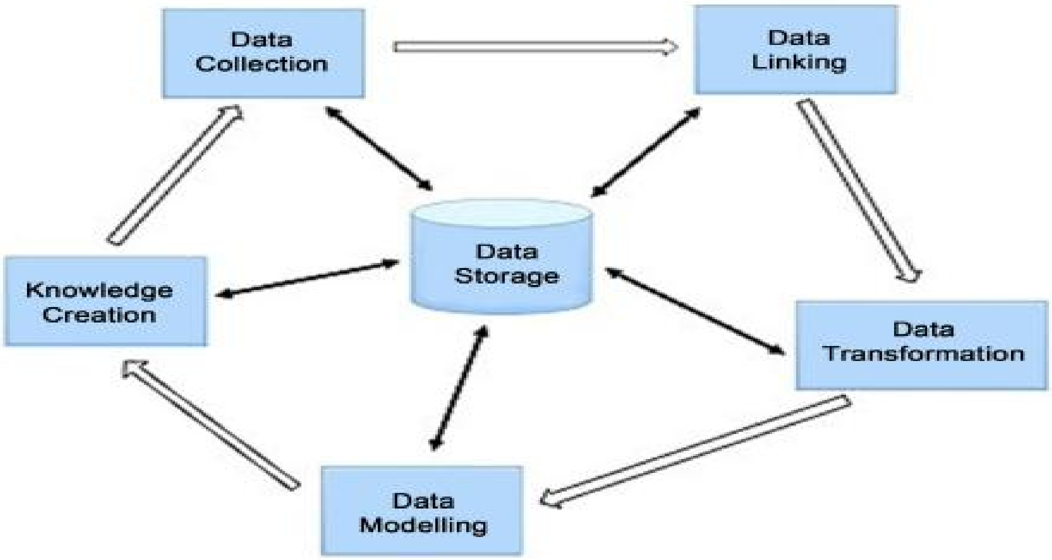


**Fig. 2.1 Big Data Analytics pipeline** Source: Rakha *et al.,* (2022)

Figure 2.1 model depicts how BDA evolves to be significant in the social construct. Rakha *et al.,* (2022) opine a BDA pipeline that flows through various stages and each stage is interrelated to the data storage. The stages are data collection, data linking, data transformation, data modelling and knowledge creation.

- Data collection is a collection of structured, semi structured and unstructured data from the various sources
- Data linking is data before analysis from various sources linked at the record level to aggregate all attributes related to a single logical body.

- Data transformation is the conversion, cleaning and structuring of data to enable analysis.
- Data modelling entails visualisation of data to create predictive models through data mining and machine learning techniques.
- Knowledge creation is the model that entails the creation of new ideas, innovations and insights.

From conceptualising Big data, the concept of analytics comes into play (Shuradze *et al.*, 2019). Mohammadpoor and Torabi (2020) postulate Big data analytics as a new novel technology which can be employed to derive meaning on large data sets whose characteristics are value, volume, variety veracity, velocity and complexity. Data requires tools and techniques for analysis. Big data analytics assists in deriving meanings and patterns in a set of complex unstructured/structured data (Lodha *et al.,* 2019). Big data analytics can enable telecommunication companies to collect, store, and analyze large amounts of data, which can help them to develop and implement effective sustainability strategies. Garcia- Ortega, Castellanos-Ramos, Carnival-Trujillo, (2018) opine that through big data analytics, companies can identify patterns, trends, and insights that would not be possible with traditional data collection methods. With these insights, companies can develop sustainable business practices that target the triple bottom line - people, planet, and profit. The process of data analytics and manipulation depends on the nature of the data hence the existence of various typologies of Big Data analytics (Choi *et al.*, 2018). Batistič and Van Der Laken (2019) postulate Big data analytics as a process that analyses Big data to capture value for the business and employees.

Big data analytics constitutes of data generation, data acquisition, data storage, advanced data analytics, data visualisation and decision making for value creation (De Mauro et al., 2018). This analysis process is largely predicated on the ability of corporate resources (Mazzei and Noble, 2017). The motive to analyze large amounts of data and extract useful information has impacted a revolution in a wide range of industries (Bilal et al., 2016). Wamba and Gunasekaran (2017); Jeble and Dubey (2017); Gupta and George (2016) believe BDA can be used to solve socio economic challenges and be a game changer and positively impact firm performance. The applications of big data analytics are vast and diverse, ranging from finance to healthcare, education to e-commerce, and more. Big data analytics can be used in providing personalized product suggestions, improving customer service, fraud detection, predicting future outcomes, and optimizing operations (Gartner, 2020).

Tiwari, Wee and Daryanto (2018) opines several BDA domains and four key domains applicable to the telecommunications sector. These domains include; customer data analytics involving analysis of call detail records, subscriber profiles, billing transactions and support interactions (Agarwal & Dhar, 2014; Sanders et al., 2018); social media analytics involving analysis of customer conversations and sentiment on platforms like Facebook and Twitter (Zeng et al., 2019); sales data analytics involving analysis of point-of-sale transactions, distributor records and sales force automation data (Tiwari et al., 2018); and supply chain analytics involving analysis of inventory levels, warehouse management systems, logistics and transportation data (Tiwari et al., 2018; Whitmore et al., 2015).

Tiwari, Wee and Daryanto (2018) propounds four BDA analytical classes exist: (1) *descriptive*, dealing with straightforward questions regarding what is or has happened; (2) *diagnostic,* dealing with why it happened with 'opportunities and problems' using descriptive statistics such as historical insights; (3) *predictive*, dealing with questions of what is envisaged, such as what will or is likely to happen, by exploring data patterns with relatively complex statistics, simulation, and machine-learning algorithms (e.g., to identify trends in sales activities, or forecast customer behavior and purchasing patterns); and (4) *prescriptive*, dealing with questions regarding what should be happening and how to impact future trends, using complex descriptive and predictive analytics with mathematical optimization, simulation, and machine-learning algorithms (e.g., many corporates have adopted prescriptive analytics to optimize production or solve schedule and inventory management issues)

The concept of Big data is phenomenal and appearing in various academic and scientific journals since the Fourth Industrial Revolution (4IR). Zhaohao (2018) examines Big Data analytics in decision making in the $4^{th}$ industrial revolution and proposes a framework for Big Data analytics driven decision making. Anand (2022) propounds Big Data analytics can help increase the profitability through optimum use of network, customer experience and improved security.

The impact of big data analytics on sustainability strategy in the Zimbabwe telecommunications sector is significant. The sector generates large amounts of data from its network infrastructure, customer interactions, and market trends. Through big data analytics, telecommunications companies can gain valuable insights into their operations that enable them to develop sustainable practices that minimize negative impacts on the environment, society, and economy while enhancing financial returns.

Singh and Singh (2019) posit one key area where big data analytics can have an impact is in energy efficiency. Telecommunication companies in Zimbabwe can use data analytics to identify the most energy-consuming components of their network infrastructure and optimize their performance to reduce power consumption. This could not only contribute positively to the global push for sustainability, but also help the companies lower their operational costs thereby enhancing their financial performance.

In addition to energy efficiency, data analytics can be applied to other areas of the firm, such as supply chain management, customer service, marketing, and risk management. By leveraging data, telecommunications firms can make better decisions, avoid wasteful practices, and minimize their environmental impact.

Furthermore, big data analytics can help companies identify and monitor sustainability-related risks and opportunities that are in line with the United Nations' Sustainable Development Goals (SDGs). By continuously monitoring and analyzing their data, telecom firms can align their sustainability strategy with the broader agenda on sustainable development while developing SDG based targets and key performance indicators.

Big data analytics has significant importance in the telecommunications sector in Zimbabwe. By leveraging big data analytics, organizations can gain better visibility, enhance decision-making, improve operations, and gain a significant competitive edge in today's data-driven economy (Deloitte, 2019). It can enable companies to achieve their sustainability objectives by gaining valuable insights into their operations, developing sustainable practices, enhancing their financial performance, and aligning their sustainability strategy with the United Nations' SDGs.

Big data analytics facilitates the assessment of sustainability performance in real-time, thereby allowing the companies to make timely decisions and adjust their operations accordingly. In this way, big data analytics empowers companies to implement sustainable practices proactively, thus reducing the negative impact on the environment while ensuring profitability (Fagella, 2019).

However, the adoption of big data analytics in the telecommunications industry in Zimbabwe is not without its challenges, one of them being negative ratios. Ombuki and Magutu (2020) opine negative ratios can limit the companies' ability to invest in big data analytics and related technologies, impeding the implementation of sustainable strategies.

In conclusion, big data analytics has the potential to drive sustainable growth in the telecommunications industry in Zimbabwe by enabling companies to develop and implement sustainable business practices effectively. However, to achieve the aforementioned benefits, companies must overcome the challenges associated with adopting big data analytics and related technologies, such as negative ratios, and build the necessary capacity for implementing sustainable strategies.

### 2.2.2 Big data analytics capability (BDAC)

Big data analytics capability (BDAC) is the ability to deploy technology that can store analyse and apply data for decision making (Gupta and George, 2016). Chen, Chiang and Storey (2012) opine Big data analytics capability refers to the ability of an organization to effectively and efficiently analyze large and complex sets of data in order to gain valuable insights and make informed decisions. This capability involves the use of advanced technologies, tools, and techniques to collect, store, process, and analyze data.

Digital capabilities have taken centre stage in the current turbulent and volatile business environment (Zhen *et al.*, 2021). BDA has become a pivotal feature in decision making hence the need for Big data analytics capability (BDAC) in organisations, but there remains limited knowledge in that domain (Sabharwal and Miah, 2021). BDAC is as defined as unique and distinguishing abilities in a firm that enable strategic value proposition (Mikalef *et al.*, 2017). Ferraris *et al.,* (2019) research conceptualised BDAC into BDA technological capability and BDA management capability.

Technical capability is described as the firms’ dexterity to innovate and upgrade skills, processes, products and knowledge about the physical environment in unprecedented manner hence knowledge transformation which results in efficient creation of desired performance (Wang *et al.*, 2006). Big data analytics is one of many novel technologies emanating from the 4IR. Panda and Ramanathan (1996) divide technical capabilities into four categories namely: research and development, strategic, supplementary and tactical capability.

Peerally et al., (2022) postulate firm level technological capabilities as grounded on a collection of resources, human and organisational activities that are required in the evolution to 4IR technologies and processes in order to establish new technologies, products and processes. A necessary precondition for developing countries is to accelerate technological capabilities in order to benefit from 4IR and it becomes pivotal for developing countries to expedite establishment of firm level technological capabilities to achieve industrialisation (UNIDO, 2019).

BDA management capability refers to the firm's intangible resources of supporting business decisions made up of planning, control, coordination and investment (Akter et al., 2016; Ferraris et al., 2019; Sun and Liu 2020). Environmental awareness is an intangible resource in this study to drive sustainability. Wang et al., (2020) claim increased environmental awareness manifesting through green management of supply chains in the academia and business world.

### 2.2.3 Integrated Resources

Integrated resources refer to the combination of different resources and capabilities to create a unique competitive advantage for an organization (Senyard et al., 2014). In the context of strategic management, two theoretical perspectives that are commonly used to explain the concept of integrated resources are resource based view (RBV) and Bricolage. However, the adoption of big data analytics in the telecommunications industry in Zimbabwe is not without its challenges, one of them being negative ratios. Negative ratios can limit the companies' ability to invest in big data analytics and related technologies, impeding the implementation of sustainable strategies.

Damanpour and Aravind (2012) state that integrating the Bricolage and RBV perspectives can help organizations to develop unique and sustainable competitive advantages by combining their existing resources in novel and effective ways. This confirmed that organizations that were able to integrate these two theoretical perspectives were more successful in achieving innovation and growth. Liu and Si (2017) posit that organizations that used an integrated resource approach were more likely to survive and succeed in highly competitive industries, as they were able to utilize their resources more effectively and efficiently.

### i. *Resource Based View (RBV)*

Resource-based View (RBV) is a theory that suggests that an organization's internal resources and capabilities are the primary sources of its competitive advantage. This perspective emphasizes the importance of unique resources that cannot be easily replicated by competitors (Barney *et al.,* 2021). Resource Based View (RBV) states that a firm's competitive advantage is determined by its strategic resources at its disposal (Barney, 1995). Assensoh-Kodua (2019) propounds RBV's pivotal role in organisations which assists in nurturing and establishing competitive advantage in highly globalised competitive market. Qadir and Fatima (2023) observe the influence of strategic leadership on competitive advantage being anchored on RBV. The fundamentals of this theory are based on internal focus of the firm to achieve differential firm performance to achieve competitive advantage. This has particular emphasis on the VRIO (value, rarity, imitability and organization) subset (Bhandari *et al.,* 2020; Barney 1991; Barney *et al.,* 2021). The RBV argues that the firm has resources, a subset of which enables achieving competitive advantage and a subset of those that enhance improved long term performance. It is not all the resources that are strategic. Resources that are scarce and valuable can lead to the establishment of competitive advantage (Ferreira, Fernandes and Ferreira, 2022).

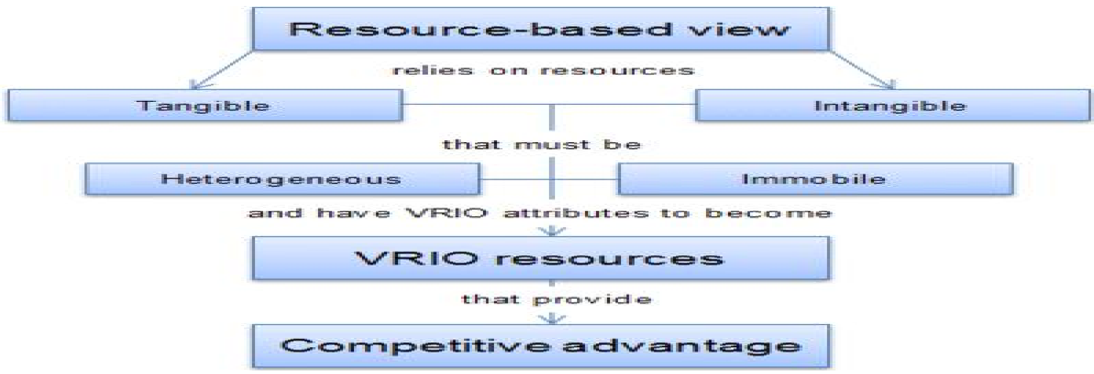


**Fig. 2.2 RBV diagram** Source: Jurevicius (2021)

- Intangible - these are resources which include trademarks, brand reputation, patents and licenses.
- Heterogeneous - the attributes of the resource are not standard but vary in their constructs and content.

- Valuable - these are resources that enable achieving strategy, exploit opportunities and mitigate threats, assist in improved efficiency and effectiveness and positively quantified Net Present Value (NPV).
- Rare - a resource with low supply, high demand that few companies can acquire and exploit at the exclusion of other industry players so as to enable competitive parity.
- Inimitable and non-substitute - these are resources that are hard and costly to imitate due to unique historical conditions, causal ambiguity and social complexity.
- Organisation - the ability of the organisation to exploit competitive advantage from the attributes of its resources through appropriate reward, innovative practices, effective strategic management processes and excellent control systems.

The RBV strategy enables the firm efficient resource allocation, sustain competitive advantage and cross functional resource mobilisation. RBV has become topical in recent years albeit the successes it has scored in strategic management since 1991 from various literature reviews (Barney *et al.*, 2021). The Resource-Based View (RBV) is a theoretical framework for understanding how an organization's unique resources and capabilities can lead to sustained competitive advantage. According to the RBV, an organization's resources are considered to be its primary sources of competitive advantage, rather than the competitive environment or industry structure.

The RBV suggests that resources can be categorized into four types: physical, financial, human, and organizational. Physical resources include tangible assets such as equipment and facilities. Financial resources refer to the financial assets of the organization. Human resources include the knowledge, skills, and capabilities of the organization's employees. Organizational resources include the culture, structure, and systems of the organization.

Barney (1991) suggested that resources must have four key characteristics to be considered a source of sustained competitive advantage: they must be valuable, rare, imperfectly imitable, and non-substitutable. Resources that meet these criteria are considered to be a source of sustained competitive advantage.

The RBV has been widely used in research on strategic management and organizational behavior, and has been applied to a variety of industries and organizational contexts. The

RBV has also been used to guide practical interventions aimed at enhancing organizational performance.

One example of the application of the RBV is a study by (Teece et al 1997) on the dynamic capabilities of firms. The authors used the RBV to analyze how firms develop and deploy capabilities to create and sustain competitive advantage over time. They found that dynamic capabilities, such as sensing, seizing, and transforming, were critical to the development of sustained competitive advantage. In essence, the RBV provides a valuable framework for understanding how an organization's resources and capabilities can lead to sustained competitive advantage and has significant implications for organizational strategy and performance.

Big data is an intrinsic resource which is intangible, heterogeneous, valuable, rare, imitable and non - substitutable found in Zimbabwe Telcos, whose potential to leverage on is under interrogation in this study. Refer to Figure 2.2 RBV diagram.

***ii Bricolage***

Bricolage is a theory that proposes that entrepreneurs can use existing resources in novel ways to create new products or services (Baker and Nelson, 2005: Garud and Karnøe, 2003). It is a term used in entrepreneurship and innovation research to describe the process of creating new products, services, or ideas by combining existing resources in novel ways.

Theory involves using whatever resources are available, and often involves improvisation, experimentation, and risk-taking (Baker and Nelson, 2005)

It has been described as a key process in entrepreneurship and innovation, as it allows entrepreneurs to create new products and ideas in resource-constrained environments, such as developing countries or under-resourced communities. Bricolage has been applied in various fields, such as social innovation, technological innovation, and product development.

According to this perspective, entrepreneurs are adept at finding creative ways to use their available resources to develop a competitive advantage, rather than relying on acquiring new resources.

Bricolage is a concept formulated by (Levi-Strauss, 1962) as analogy that harnesses fragmented leftovers for redeployment. Bricolage resource is developed from the underutilised resource base to address new problems and opportunities (Baaken, Liu and

Lapornik, 2021). Bricolage provides a circumvention strategy where there is resource constraint to achieve process and product knowledge leveraging on existing , undervalued, slack or discarded resources (Witell *et al.*,2017). Bricolage is categorised into two main groupings, namely: social bricolage and entrepreneurial brokerage.

Social bricolage provides business opportunity to address social needs in the context of scarcity, economic uncertainty and seasonal activities (Desa, 2012; Desa and Basu, 2013; Bacq *et al.*, 2015; Zolo *et al.,* 2017; Jansen *et al.*, 2018).

Entrepreneurial bricolage is a novel way of leveraging on a combination matrix of available resources to develop new opportunities and addressing current challenges (Baker and Nelson, 2005).

Baker and Nelson (2005) describe bricolage as a process of "making do" with the resources at hand, rather than waiting for perfect conditions or ideal resources. Bricolage often involves a trial and error approach, where entrepreneurs engage in iterative experimentation to find solutions to problems.

One example of bricolage in action is the development of the wind-up radio by Trevor Baylis, a British inventor (Hendry and Harborne, 2011). Baylis developed the wind-up radio in response to the devastating impact of HIV/AIDS in Africa, where there was limited access to electricity. Baylis used existing technology, such as clockwork mechanisms and radios, to create a new product that could be powered by hand-cranking, enabling access to vital health information in resource-constrained areas.

Overall, bricolage is a valuable approach to innovation and entrepreneurship, as it allows entrepreneurs to leverage existing resources in creative and unexpected ways, opening up new opportunities for value creation and social impact.

Baaken, Liu and Lapornik (2021) hypothesizes that an integration of RBV and Bricolage when applied provides competitive advantage. This study assumes that a mediation role of the resources would enhance sustainability strategy (SS).

### 2.2.5 Sustainability Strategy

Sustainability strategy is a plan of action that businesses, organizations, and governments develop to integrate sustainable practices into their operations (United Nations Global Compact, 2017). The motive behind a sustainability strategy is to minimize negative impacts on the environment and society while enhancing financial returns. Typically, sustainability strategies include goals, targets, and performance indicators that are aligned with the United Nations' Sustainable Development Goals (SDGs).

Several theoretical lenses have been used to understand sustainability strategy. Two seminal perspectives proposed by Bansal (2005) are the ecological responsiveness and business case perspectives.

The ecological responsiveness perspective views sustainability as a moral obligation to protect the natural environment (Bansal, 2005). Firms adopting this perspective see sustainability strategy as necessary to minimize their negative externalities and ensure long-term viability of natural resources (Bansal & Roth, 2000). The drivers under this view include stakeholder pressures, environmental ethics and stewardship (Bansal, 2005).

The business case perspective considers sustainability as an opportunity to gain competitive advantages (Bansal, 2005). Firms take a business-focused view to tap opportunities in green markets, reduce costs through efficiency gains, and improve reputation (Bansal & Roth, 2000). The motivations are related to risk mitigation, accessing new markets and revenue streams (Bansal, 2005).

Building on these perspectives, Hahn et al. (2015) developed a framework conceptualizing three strategic orientations - reactive, accommodative and proactive. Reactive firms comply with regulations as the minimum requirement (Hahn et al., 2015). Those with an accommodative orientation see sustainability as risk mitigation and an opportunity to gain first-mover advantages (Hahn et al., 2015). Proactive firms view it as a driver of innovation and a means to gain competitive edge (Hahn et al., 2015).

These theoretical lenses provide insights on the different motivations driving sustainability strategy adoption. Firms can be positioned along a continuum based on their dominant strategic orientation (Hahn et al., 2015). Understanding these perspectives is important to examine the potential influence of big data analytics on sustainability strategy development and implementation.

Elkington (1998) views sustainability strategy as a critical component of modern business practices, which considers the impact of an organization's operations on the environment, society, and economy. By adopting sustainable practices and integrating them into their business model, organizations can achieve long-term viability while contributing positively to society.

Strategy is the scope and the direction of an organization that aids in achieving the organisation's predetermined goals (Rugman and Verbeke, 2017). Strategy is all about systematic integration of activities and utilising the scarce resources optimally to accomplish the desired outcomes.

Menz et al., (2021) posit strategy in the digital age has brought about business model and technology disruption with resultant effect on three domains; (i) competitive advantage, (ii) internal structure and design, (iii) firm scale, boundaries and scope. Chladek (2019) opines sustainable business strategy helps to address climate change, income inequality, and depletion of natural resources, human rights issues, fair working conditions, pollution, racial injustice and gender inequality.

A strategy is a hypothesis which will diagnose problems, provide guidelines and actionable coherent actions (Edmondson, 2019). This can be implemented at all the levels of corporate strategy which are functional, business and corporate level. Ford (2021) concedes that the key components of the corporate strategy are hinged on visioning, objective setting, resource allocation and prioritisation or trade-offs. Recent literature review and empirical studies have proffered the need to adopt sustainability strategies and business practise as part of their corporate strategy (Egels-Zanden and Rosen, 2015; Baumgartner 2014; Engert *et al.,* 2015; Lindgreen and Swaen 2010) and Engert *et al.,* (2015) posit the need for both qualitative and quantitative descriptive studies. Corporates are stakeholders in civic society and have potential to advocate the green growth strategy (Machiba, 2010; OECD, 2013). Riley and Kohlbacher (2016) claim that consumers are inclined to spend more on products which consider green credentials. This study contributes to “strategy-as-practice” literature (Egels-Zanden and Rosen, 2015 p. 139).

United Nations Global Compact, (2017) state that, “Blueprint for Business Leadership on the SDGs” which outlines a five-step framework that businesses can follow to align their strategies with the United Nations' SDGs. The steps prescribe developing a sustainability strategy that incorporates sustainable practices into business operations, aligned with the

SDGs. The framework prescribes that businesses set targets, performance indicators, and goals that are consistent with the SDGs to enhance long-term performance and impact. This further buttresses the importance of businesses adopting sustainability as a core business strategy to achieve societal benefits and long-term competitiveness.

According to a report by the (Global Reporting Initiative, 2019), companies that adopt a sustainability strategy are more likely to achieve long-term financial success, as they are able to identify and manage risks and opportunities, foster innovation, and build long-term stakeholder relationships.

Another study conducted by (Harvard Business Review 2019) perceive that companies that integrate sustainability into their business operations are more resilient to shocks, more attractive to investors, and more likely to retain and attract employees.

Sustainability strategy is a plan of action that businesses, organizations, and governments develop to integrate sustainable practices into their operations. The goal of a sustainability strategy is to minimize negative impacts on the environment and society while enhancing financial returns. Typically, sustainability strategies include goals, targets, and performance indicators that are aligned with the United Nations' Sustainable Development Goals (SDGs).

A sustainability strategy covers various areas of an organization's operations, including energy efficiency, renewable energy, waste reduction and management, supply chain sustainability, water management, and social justice (Porter and van der Linde, 1995). A good sustainability strategy is characterized by transparency, accountability, stakeholder engagement, and continuous improvement.

Big data analytics has the capacity of supporting sustainability strategy in the telecommunications sector in Zimbabwe. By analyzing large amounts of data, firms can identify opportunities for business and process improvement and develop more effective sustainability strategies. Data analytics could be used to scanner and track energy consumption and identify opportunities to reduce emissions, social impacts and identify sectors where the organization can make a positive contribution to the community. McKinsey(2022) ESG report posit the benefits of adopting a sustainability strategy include reducing operational costs, enhancing efficiency, attracting socially responsible investors and customers, safeguarding assets, and mitigating risks.

### 2.2.6 Technology, Organisation and Environment (TOE)

Technology, Organization, and Environment (TOE) is a framework for understanding the adoption and implementation of new technologies in organizations. The TOE framework recognizes that three interrelated factors (technology, organization, and environment) shape the adoption and implementation of new technologies (Zhu, Kraemer and Xu, 2006).

Technology, Organisation and Environment (TOE) is a theoretical framework that enunciates technical adoption in an organisation and describes how the implementation matrix and adoption of technical innovation is influenced by the technological, organisational and environmental context (Tornatzky and Fleischer, 1990). The framework refers to the internal and external technologies in use or with potential (Oliveira et al., 2014). This is designed for an enterprise level. TOE leverages on the influence of the technological, organisational and environmental context of the firm in technological adoption (Srivastava *et al.,* 2022).

Technology-Organization-Environment (TOE) is a popular model used to study the impact of technology on organizations and the environment they operate in (Baker 2012). In the context of big data analytics and sustainability strategy in the Zimbabwe telecommunications sector, the TOE framework can be applied to understand how technology, organizational characteristics, and the environment influence the adoption and implementation of big data analytics for sustainability strategy.

The TOE addresses adoption behaviour premised on three types of technological innovations namely; practical innovations for technical tasks, business innovations and innovations embedded in the business processes of the enterprises (Ramdani and Kawalek, 2007). This study evaluates the impact of novel technology BDA on sustainability strategy which speaks to the TBL in the context of Zimbabwe Telcos which are representative of the firm/ organisations role within the technological, organisational and environmental matrix. The TOE model matrix addresses the variables under study.

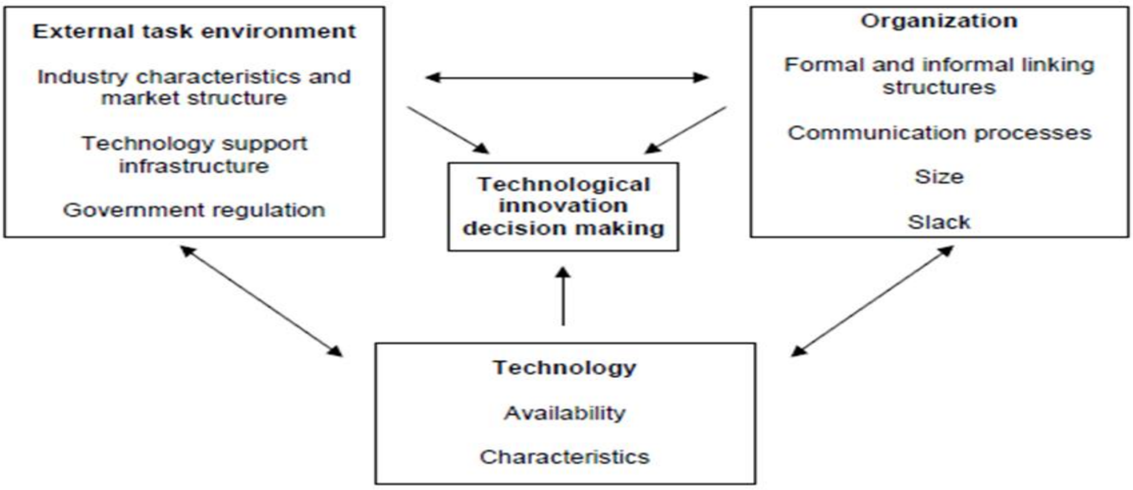


**Fig 2.3 TOE diagram** Source; Tornatzky and Fleischer (1990)

Tornatzky and Fleischer, 1990 opine that:

Technology context embraces the internal and external technological attributes that have effect on the firm's operations, encompassing both processes and equipment. Technology refers to the characteristics of the technology being adopted, such as its complexity, compatibility with current systems, and ability to solve existing problems. A firm's existing technologies enhance a broad limit on the scope and pace for technological change to adopt (Collins *et al*, 1988). Technological characteristics are determined through innovation technologies existing outside the firm which have influence in determining the gaps that the adopting firm have in order to evolve and adapt. Innovation characteristics are in three dimensions of incremental, synthetic and discontinuous (Tushman and Nadler 1986) which call for varied approaches to technological change.

Organizational factors include the size, structure, culture, and resources of the organization (slack), such as the level of IT expertise, communication channels, and the complexity and size of the organization and how it affects its ability to adoption and implementation decisions on new technologies. Mechanisms that link sub units of a firm promote innovation (Galbraith 1973; Tushman and Nadler 1986).

Environmental context (external) includes industry size, competitors, regulatory environment and macroeconomic fundamentals. The external factors are those that influence the adoption of new technologies, such as regulatory, economic, and cultural factors.

The ultimate goal of TOE is technological innovation decision making on sustainability strategy.

Gangwar (2018) hypothesises an extended TOE framework (Fig 2.4) which captures the attributes of Big data adoption gap. The extended TOE now embraces five innovation attributes which when combined enhance Big data adoption namely; relative advantage, compatibility, complexity, triability and observability (Rogers, 2003; Alsaad *et al.,* 2017). Relative advantage, compatibility and complexity where considered more fundamental in IT adoption as consistently reported in literature (Gangwar et al.; Alshamaila *et al.,* 2012; Alsaad et al., 2017; Hung et al., 2010; Tornasky and Klenin, 1982).

Relative advantage provides tremendous benefit to the firm and well recognised in IT adoption (Wang and Wang, 2016; Alshamaila *et al.,* 2012; Low *et al.,* 2011; Ramdani *et al.,* 2009; Tornasky and Klenin, 1982). It's perceived the likelihood of adoption will increase when relative advantage is applied hence resulting in improved decision making, improved profitability and efficiencies (Waller and Fawcett, 2103).

Rogers (2003) postulates the degree at which an innovation is perceived to be consistent with existing values, past experiences and desires of potential adopters as compatibility. Compatibility is anchored on firm culture, relationship structures, existing values and preferences, past experiences, established work practices, organisational needs, information systems capabilities and employees. The role of compatibility is synonymous with IT adoption literature (Low *et al.,* 2011; Gangwar *et al.,* 2015; Wang *et al.*,2010; Ramdani *et al.,*2009; Peng *et al.,* 2012; Alsaad *et al.,* 2017).

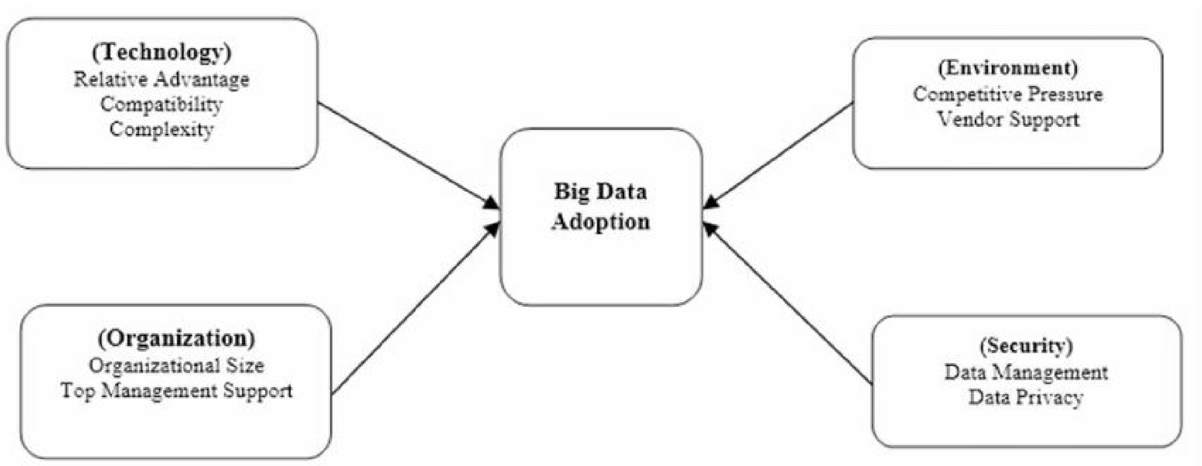


**Fig 2.4 Extended TOE framework** Source: Gangwar (2018)

Rogers (2003) opines complexity as the degree of perceived difficulty to utilise an innovation. The inverse of complexity is in sync with greater chances of Big data adoption (Alshamaila et al., 2012; Chaudhury and Bharati, 2008; Igbaria *et al.,* 1995).

The security aspect is anchored on data management and data privacy. Al Nuaimi *et al.,* (2015) explain data management as the development and operationalisation of architecture, practices, policies and procedures to ensure availability, integrity, usability and security of data. Data privacy is premised on data protection measures which are a concern when hosting third parties or publicly controlled servers (Schadt *et al.,* 2011).

The Technology, Organization, Environment (TOE) framework is a pivotal conceptual model that is widely used in academic research to understand the factors that influence the adoption and implementation of new technologies by organizations. The TOE framework suggests that the adoption of new technologies is influenced by three main factors: technological factors, organizational factors, and environmental factors.

Technological factors refer to the characteristics of the technology itself, such as its complexity, compatibility with existing systems, and relative advantage over competing technologies. The TOE framework is useful in guiding research into the adoption and implementation of new technologies, as it provides a comprehensive and structured approach to understanding the multi-faceted nature of the technology adoption process. It can be applied to a wide range of technologies and organizational settings, and has been used in studies of technology adoption in various industries and contexts.

The TOE framework has been used in several studies to understand the adoption and implementation of various technologies in organizations in different sectors. For example, it has been used to illustrate how the adoption of e-commerce in SMEs is influenced by technological, organizational, and environmental factors (Chircu and Kauffman, 2000). Another example of the application of the TOE framework is a study by (Tornatzky and Fleischer, 1990) on the adoption and implementation of computer-aided design (CAD) technology in the aerospace industry. The authors used the TOE framework to analyze the factors that influenced the adoption and implementation of CAD technology by aerospace firms, including technological factors such as system compatibility, organizational factors such as resource availability and management support, and environmental factors such as customer demands and competitive pressures.

The TOE framework provides a useful framework for understanding the complex interplay of factors that influence the adoption and implementation of new technologies by organizations, and has proven to be a valuable tool for researchers studying technology adoption and innovation (Deloitte, 2019).

The following are examples of how TOE can be applied to this research context:

**Technology:** The technology component of TOE focuses on how the characteristics of technology influence its adoption and use. In the Zimbabwe telecommunications sector, the adoption and implementation of big data analytics for sustainability strategy can be affected by technical factors, such as the availability of big data analytics tools, the quality and quantity of data available, and the expertise required to analyze and interpret data.

**Organization:** The organizational component of TOE focuses on how the characteristics of an organization affect its ability to adopt and utilize technology. Organizational factors that could influence the adoption of big data analytics for sustainability strategy in the Zimbabwe telecommunications sector include the company's size, culture, organizational structure, and leadership support.

**Environment:** The environmental component of TOE focuses on how the external environment influences the adoption and implementation of technology. External factors that could influence the adoption of big data analytics for sustainability strategy in the Zimbabwe telecommunications sector include the regulatory environment, competition, customer preferences, and sustainability-related pressures (e.g. adherence to United Nations Sustainable Development Goals).

The TOE model can be used to understand how big data analytics can be adopted and integrated into the sustainability strategy of Zimbabwe's telecommunications sector companies. By taking into account the technological, organizational, and environmental factors that affect the adoption of big data analytics for sustainability strategy, companies can better prepare and develop strategies that align with their organizational goals and the goals of sustainable development.

### 2.2.7 Technology Acceptance Model (TAM)

Technology Acceptance Model (TAM) is an information systems theory that explores behaviour of individual users, come to accept and apply technology through ease of use and usefulness and attitude towards use (Springer et al, 2022). The original version of the model proposed that two factors – perceived usefulness and perceived ease of use – were the primary drivers of technology adoption. Ever since the inception of TAM (Davis, 1989) Figure 2.3 Technology Acceptance Model, the model has undergone a lot of evolution up to TAM3 - Figure 2.5 Technology Acceptance Model (TAM 3).

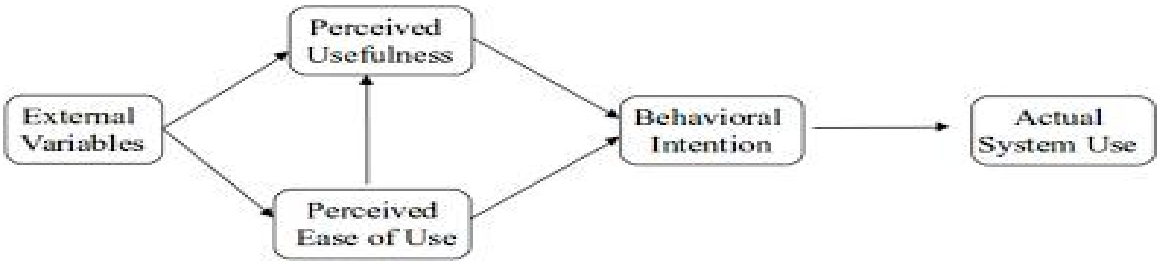


**Fig 2.5 Technology Acceptance Model** Source: Davis (1989)

The earlier model of TAM is based on two belief constructs, perceived useful-ness (PU) and perceived ease of use (PEOU), as primary determinants of an individual's behavioural intention (BI) to apply on information technology (IT). BI was used as a primary driver of the actual usage behaviour.

TAM has evolved to TAM3 (Figure 2.4) to capture aspects of perceived useful-ness (PU), perceived ease of use (PEOU) and adding three new constructs: cognitive instrumental processes, social influence processes, and emotional instrumental processes (Venkatesh and Bala, 2008). The three new constructs embedded in the 4IR in terms of IT and adoption warrant use of TAM3 as a novelty model. Cognitive instrumental processes refer to the user's cognitive processes, including attention, comprehension, and memory, that affect their ability to perceive the usefulness and ease of use of a technology. Social influence processes refer to the influence of other people on the user's attitudes and beliefs about the technology, including the opinions of peers, friends, and family members. Emotional instrumental processes refer to the user's emotional reactions to the experience of using the technology. TAM3 predicates a broad nomological network of the determinants of individuals' IT adoption and use (Venkatesh and Bala, 2008).

This model utilises four determinants for perceived usefulness and perceived ease of use which are the individual differences, system characteristics, social influence, and facilitating conditions. The individual difference include personality and/or demographics that contribute to individuals' perceptions , while, system characteristics entail the salient features of a system that can help individuals develop favourable or unfavourable to PU and PEOU, whilst social influence is premised on social processes and mechanisms that influence individuals to formulate perceptions of various aspects of an IT and facilitating conditions are representative of organizational support that enable the use of IT.

Venkatesh and Bala (2008) aver that cognitive instrumental processes that influence PU are determined by job relevance, output quality, result demonstrability, and perceived ease of use. Anchors on computer self-efficacy, computer anxiety, computer playfulness, and perceptions of external control will drive ease of use.

Renny, Guritno and Siringoringo (2013) attest that perceived ease of use is of paramount importance in technology since it provides timeous and convenience to users. TAM3 model provides a comprehensive and nuanced approach to understanding the factors that influence technology adoption and use, and has proven to be a valuable tool for researchers and practitioners alike (Venkatesh,Thong, and Xu, 2012).

One example of the application of the TAM3 model is a study by (Venkatesh *et al.* 2003) on the adoption and use of social media. The authors used the TAM3 model to examine how cognitive, social, and emotional processes, as well as perceptions of usefulness and ease of use, influenced users' adoption and use of social media. They found that social influence processes, including peer pressure and social norms, played an important role in shaping users' attitudes and beliefs about social media, and that emotional instrumental processes, such as enjoyment and pleasure, were also important drivers of use. (Venkatesh,Thong, and Xu (2012) opine the model has been widely applied in research on the adoption and use of various technologies, such as mobile apps, online services, and e-commerce platforms.

In the context of big data analytics and sustainability strategy in Zimbabwe telecommunications sector, TAM can be used to understand how employees and stakeholders may perceive the use of big data analytics in their work, and how this perception impacts adoption and implementation of a sustainability strategy. If employees in the Zimbabwe telecommunications sector perceive data analytics as complicated and difficult to use, this could negatively impact their willingness to adopt and use it. Conversely, big data analytics is perceived as useful for optimizing the organization's operations and enhancing sustainability, they may be more likely to adopt and use it. Wanner and Janiesch (2019) posit that understanding user perceptions of big data analytics, organizations can develop strategies to improve employee buy-in and encourage greater adoption of the technology to enhance sustainability strategy.

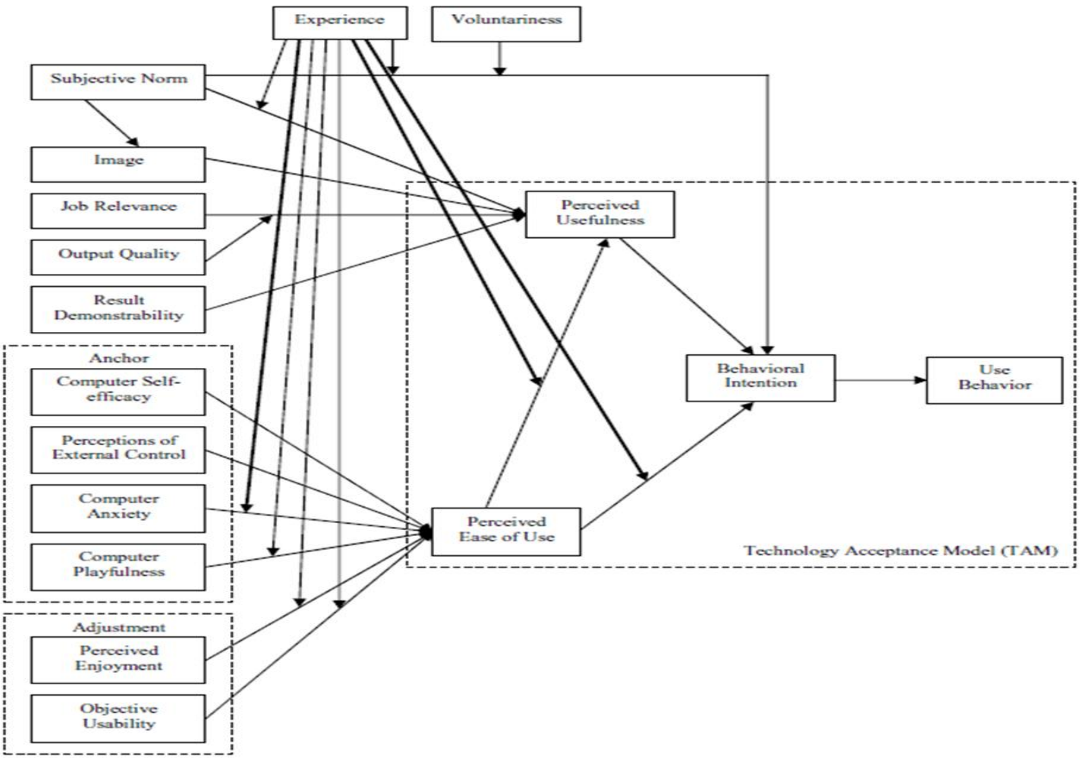


**Fig 2.6 Technology Acceptance Model (TAM 3)** Source: Venkatesh and Bala (2008)

### 2.2.8 Diffusion of Innovation (DoI)

Diffusion of Innovation (DoI) theory is a theoretical framework that explores the speed and pattern of how new ideas and processes permeate through the population for adoption or rejection, whilst focusing on the influential early adopters for acceptance (Frieman, 2021).

The DOI theory was developed by Rogers (1962) and posits five stages of innovation diffusion: knowledge, persuasion, decision, implementation, and confirmation. DoI is not only viewed in the context of individuals and organisations but can be applicable within the global perspective.

Rogers (1995), posits innovation as an idea, practice, or object that is perceived as new by an individual or other unit of adoption. The DOI theory proposes that the adoption of an innovation occurs through a series of stages, including awareness, interest, evaluation, trial, and adoption.

The model integrates three constructs which are adopter characteristics, innovation characteristics and innovation decision process. The theory defines the five adopter characteristics as innovators, early adopters, early majority, late majority and laggards (Sila, 2015). The innovative characteristics are premised on relative advantage, compatibility, complexity, trialability, and serviceability which are pivotal in innovation acceptance. In innovation decision process confirmation, knowledge, implementation, decision, and persuasion are key drivers (Rogers, 2003; Chang, 2010). The successful execution of DoI remains hinged on system characteristics, organizational attributes and environmental aspects.

The characteristics of the adopters, such as their level of innovativeness, may also impact the rate of innovation diffusion. Innovators and early adopters may be more likely to embrace new technologies, while late adopters may require more persuasion before adopting big data analytics for sustainability initiatives. Additionally, the communication channels through which information about big data analytics is disseminated can impact innovation diffusion. If stakeholders are not aware of the potential benefits of using big data analytics for sustainability initiatives, adoption rates may be slow. The research focus is on innovators and early adopters as primary groups in this research.

Dearing and Cox (2018) argue that diffusion is a social process that can happen unorganised and not dependent on scaling up of service or after dissemination of information and is premised on three variables which consist innovation's attributes, adopters characteristics and the larger social and political context related to the innovation

Diffusion of innovation (DoI) in Big data technologies is synonymous with stages of invention to usage or not (Rogers, 1995). Rogers (1995) postulates that innovation is an idea, object or practise perceived as new in the social construct and (Rangaswamy and Gupta, 1999) opine diffusion as the process by which an innovation is communicated overtime within a social system.  DoI is premised on four elements, namely; innovation, communication channels, time and a social system (Rogers, 1995).  According to (Rogers, 2003) anything perceived new is the social system albeit the fact that it has been used elsewhere is deemed an innovation.  Communication channel is the process of sharing information from inception to finality comprehensively (Rogers, 2003) and the most profound channels are mass media and interpersonal communication.  Botha and Atkins (2005) aver the innovation decision time sequence process hinged on; knowledge, persuasion, decision, implementation and confirmation (reaffirm or reject).Refer to Fig 2.7 Innovation decision process.

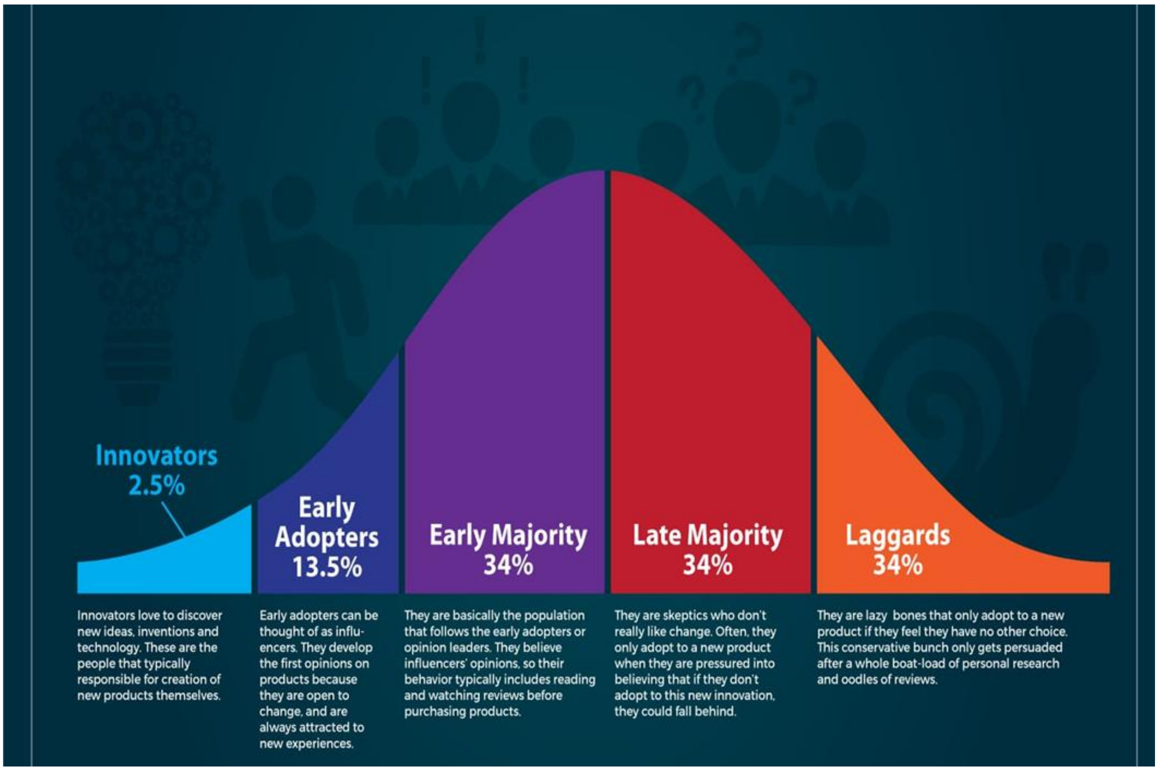


**Fig 2.7 Diffusion of Innovation Theory** Source: Rodgers (1962)

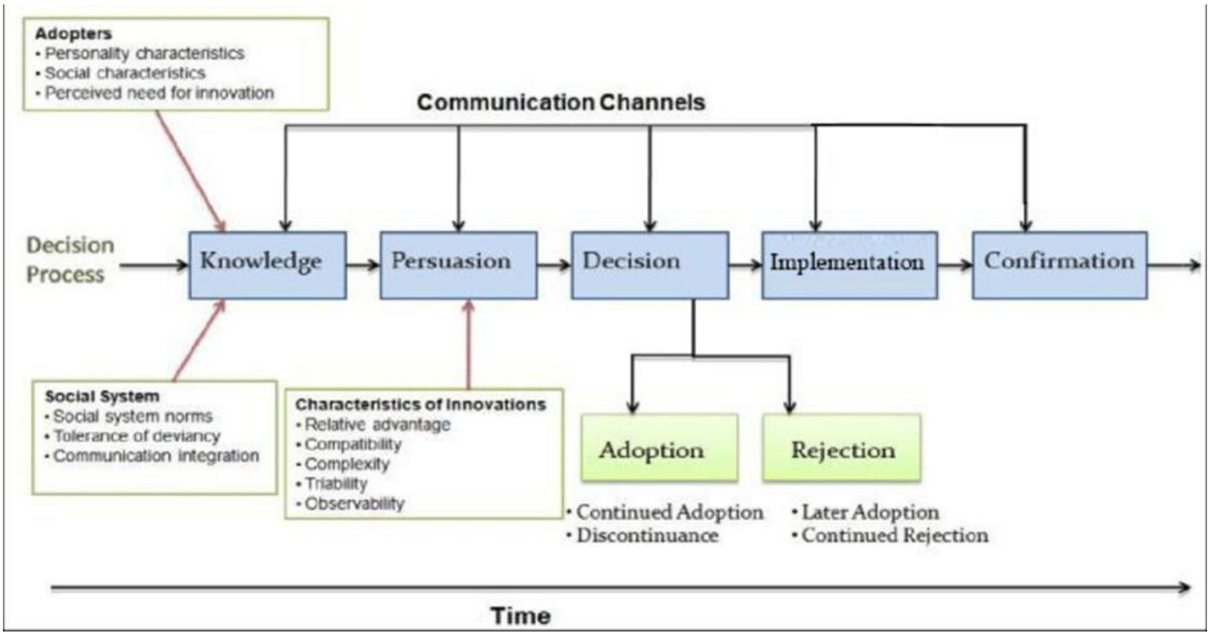


**Fig 2.8 Innovation decision process** Source: Rogers (2003) and Chang (2010)

The diffusion of innovation is a process carried out over time hence adopter categorisation and rate posit a time dimension (Rogers, 2003). Time aspect is fundamental in Big data projects since they enable applications development, experimentation and knowledge development through peer users.

Deloitte (2019) observed that DOI theory has been widely applied in research on the adoption and implementation of new technologies, social programs, and other innovations in various fields. It has also been used to guide practical interventions aimed at promoting the adoption of new technologies and practices, such as diffusion-focused strategies and communication campaigns. Rogers (2003) opines that social systems remain an integral part by virtue of the fact that communication flow takes place between persons, social groups and from one locale to another which enables the emergence of trend setter from the normative of Big data.

One example of the application of the DOI theory is a study by (Rogers and Shoemaker, 1971) on the adoption and use of colour television in the United States. The study used the DOI theory to analyze the factors that influenced the adoption of colour television by households, including the innovation's relative advantage, compatibility with existing practices, and observability.

In the context of Big data analytics and sustainability strategy in the Zimbabwe telecommunications sector, the DOI theory can be used to understand the factors that influence the adoption and implementation of data analytics for sustainability initiatives. For example, the complexity of the technology may make it difficult for some organizations to adopt and integrate into their operations. However, if the potential benefits, such as improved sustainability practices and financial performance, are perceived to outweigh the costs of implementation, then the innovation may diffuse more quickly. Contextually, the DOI theory provides a valuable framework for understanding the complex process of innovation adoption and diffusion, and has proven to be a powerful tool for researchers and practitioners in a variety of fields (Greve, 2016).

### 2.2.9 Sustainability - Triple Bottom Line (TBL)

The Triple Bottom Line (TBL) is a sustainability framework that takes into account three dimensions of sustainable development: economic, environmental, and social. The TBL approach emphasizes that sustainable development requires not only economic prosperity, but also consideration of the environment and social welfare (Day and Sloan, 2015).

The triple bottom line (TBL) concept was coined by Elkington (1994) and premised on that companies should generate three bottom line reports premised on the planet, people and profit metric. This was meant to generate debate on the issue of capitalism which concentrated on the profit bottom line paradigm only (Collings, 2021). TBL has culminated in the introduction of the Global Reporting Initiative (GRI), Dow Jones Sustainability Indexes (DJSI), Sustainability Accounting Standards Board (SASB), Full-Cost Accounting, ESG (a framework focusing investors and financial analysts on Environmental, Social and Governance factors), increased stakeholder engagement on people and planet matrix when business strategy is made. Silva (2022) posits triple bottom line (TBL) as an accounting framework that incorporates three dimensions of performance: social, environmental and financial. The traditional reporting frameworks were not inclined to ecological (or environmental) and social measures. Triple Bottom Line (TBL) is a strategic tool that ensures corporate sustainability through the matrix of people, prosperity and planet consideration (Elkington, 1994). The concept of sustainability was formally defined in 1987 after the World Commission on Environmental and Development (WCED) published the Brundtland Report titled “Our Common Future.” In this report, the Commission introduced sustainable development as "development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (WCED, 1987). Ashrafi *et al.,* (2019) describes corporate sustainability as an approach aimed at creating long term stakeholder value through the implementation of a business strategy that focuses on ethical, social, environmental, cultural and economic dimensions of doing business.

The United Nations General Assembly (UN) declaration in September 2015 adopted the 2030-Agenda for Sustainable Development with clear enunciated targets on 17 Sustainable Development Goals (SDG's). These can all be summed up to economic, social and environmental context. The sustainability TBL matrix once accomplished has a positive effect on firm performance.

The Triple Bottom Line (TBL) framework can be applied to evaluate the impact of Big Data analytics on the sustainability strategy of the Zimbabwe telecommunications sector. The TBL dimensions are economic, environmental, and social (Elkington, 1994) posited as follows:

i. **Economic dimension:** Through customer analytics, telcos can identify and retain high-value customers, reducing churn rates and increasing revenue (Kumar *et al.,* 2019). Financial analytics can help address profitability, detect fraud and manage risk thereby reducing financial losses (Ngai *et al.,* 2011). Operational analytics provides for process improvements, reducing costs and improving efficiency (Chen *et al.*, 2019). Supply chain analytics can optimise logistics, reducing costs and improving delivery times (Gupta *et al.,* 2018).

ii. **Environmental dimension:** Operational analytics can maximise energy efficiency and resource utilization, reducing carbon emissions and environmental impact (Molina-Solana *et al.,* 2017). Supply chain analytics can reduce waste and improve logistics, minimizing environmental harm (Gupta *et al.,* 2018). Customer analytics can improve sustainable customer behavior, reducing environmental impact (Kumar *et al.,* 2019).

iii. **Social dimension:** Customer analytics can help telcos comprehend customer needs and preferences, improving customer satisfaction and loyalty (Huang *et al.,* 2019). Marketing analytics scan social media, improving brand reputation and customer engagement (Kietzmann *et al.,* 2013). Network analytics can analyze social networks, identifying drivers and improving marketing competitiveness (Watt *et al.,* 2016). Operational analytics can generate employee productivity and workforce analytics, enhancing human capital management (Bassi *et al.,* 2019).

Friedrich *et al.*(2021) postulate that by considering the economic, environmental, and social implications of Big Data analytics in their operations, telecommunication companies can develop data driven sustainable business practices that deliver benefits to all stakeholders. The total sum effect of the Triple Bottom Line (TBL) framework supports that the use of Big data analytics in the Zimbabwe telecommunications sector can have a positive impact on sustainability strategy.


**Fig 2.9 Triple Bottom Line** Source: Elkington (1994)

At the cusp of the Fourth Industrial Revolution (4IR) new novel technologies have emerged in the form of artificial intelligence, machine learning, the Internet of Things, Big Data, Block chain, Robotics, 3D technologies, and many more are providing solutions to world challenges (Hoosain, 2020). These technologies have helped in establishing societal solutions. The issue of circular economy/business with the attributes of life cycle costing, life cycle impact assessment, materials passports, and circularity measurements have been adopted negating linear “take, make, and dispose” model which have positively impacted on the economy and the environment by providing sustainable development solutions. Hoosein e*t al.*, (2020) assert companies that have made sustainability their core value have excelled in business and these include Hilton group of hotels, Nike, Lego and Huawei. Ellen MacArthur foundation (2013) formulated the butterfly concept depicted in Figure 2.8 which speaks to a regenerative and restorative economy anchored on design which minimizes waste and pollution, keep products and materials in use, regenerate natural systems.

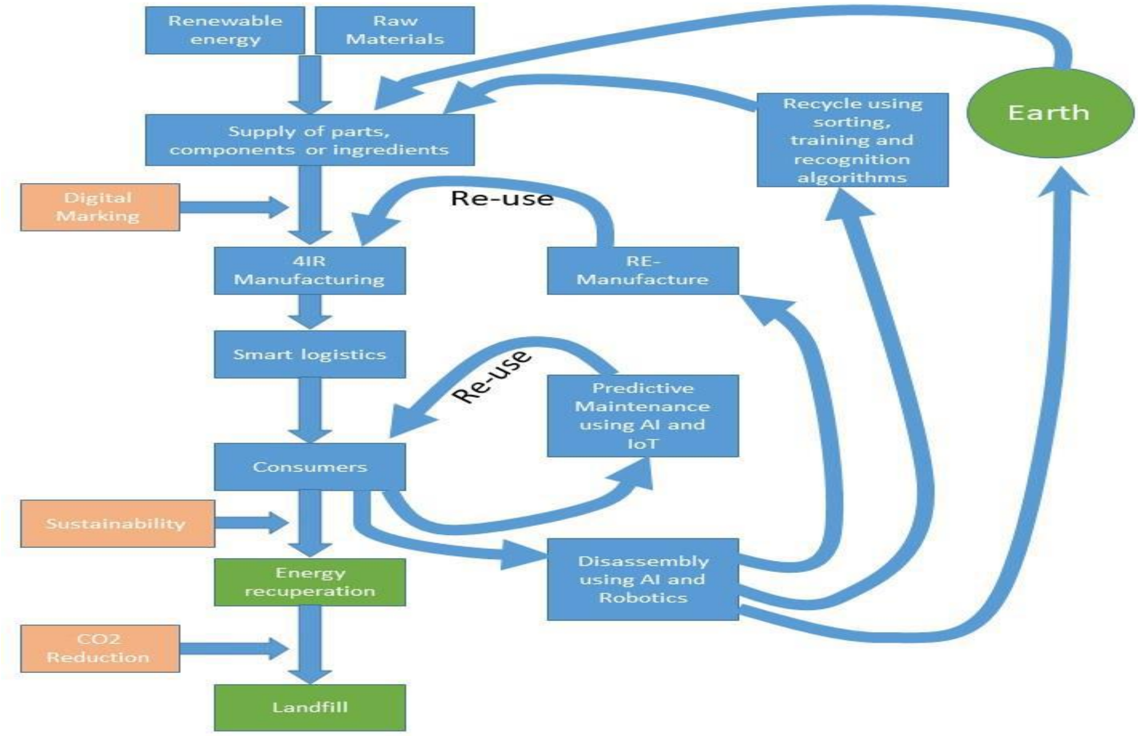


**Fig. 2.10 Ellen MacArthur Butterfly diagram** Source: Ellen MacArthur Foundation (2013)

Circular economy is an economic model that emphasizes the importance of using resources in a sustainable and efficient way, by reducing waste and keeping resources in use for as long as possible (Ellen MacArthur Foundation, 2019). In the context of the telecommunications industry, circular economy can be achieved by optimizing network equipment utilization, reducing energy consumption, promoting the adoption of sustainable business practices, and extending the lifespan of electronic products.

According to a report by the (Ellen MacArthur Foundation, 2019) implementing a circular economy strategy in the telecommunications industry can have significant environmental and economic benefits. The report highlights that by promoting the reuse and recycling of electronic products; companies can reduce their carbon footprint and save costs associated with purchasing new equipment. In addition, embracing circular economy principles can help companies develop new revenue streams by creating value from used and discarded products. Another study, conducted by (Accenture, 2019) found that circular economy practices can help telecommunications companies reduce their overall environmental impact, particularly in terms of carbon emissions. By adopting sustainable business practices, such as energy-efficient infrastructure and reduced paper usage, companies can significantly reduce their carbon footprint and contribute to a more sustainable future.

Deloitte (2022) posits sustainability as part of strategy that culminates in investor demand, consumer demand, regulatory adherence, talent acquisition and increased productivity.

### 2.2.10 Organisational Development Theory

Organizational Development (OD) is a theoretical framework and a practical approach to organizational change that emphasizes the importance of collaboration, empowerment, and continuous learning (Burke and Litwin, 1992). The field of OD has evolved over time, and various approaches to OD have emerged. One of the most influential models of OD is the Action Research model, developed by Kurt Lewin in the 1940s. The Action Research model involves a cyclical process of diagnosis, action, and evaluation, where the organization identifies a problem, develops and implements a solution, and evaluates the solution to determine its effectiveness (Burke and Litwin, 1992). OD is rooted in several disciplines, including psychology, sociology, and organizational behavior, and draws on a range of models and theories to guide the change process.

Sabharwal and Miah (2021) posit BDA as being instrumental in decision making process. To enable the decision process in growth, there is need to strategise on how best to achieve the objectives. Beckhard (1972) postulates organisational development (OD) as the internal fusion of ideas in an organisation where individuals collectively work to improve on the organisation's effectiveness and operational procedures. OD improves organizational effectiveness and efficiency by enhancing the quality of working life and promoting the development of people and organizations through a collaborative and participatory approach, where employees and stakeholders are actively involved in the change process.

Lewin's Organisational Development theory (ODT) posits processes as having knowledge and skills transfer which results in appropriate decision making and managing future change. ODT aims to improve organizational effectiveness and facilitate change by conducting assessments, diagnosis, and interventions (Cummings and Worley, 2014). Applying ODT in the context of big data analytics in telecommunication companies in Zimbabwe can involve conducting assessments of the organization's current data usage, infrastructure, and culture. The organization can then be expected to undergo a diagnosis to establish the gaps in its system with regards to using big data analytics. The diagnosis step can help organizations identify areas that require improvement in terms of incorporating big data analytics, such as technology infrastructure, data management or talent development.

Organisational development is anchored on three concepts: organisational capacity/capability, culture and climate (Glanz, Rimer and Viswanath, 2008). In a study by (Burke and Litwin, 1992) on the impact of organizational change on employee satisfaction and performance the authors used an OD framework Fig 2.9 to analyze the impact of a merger on employee attitudes and behaviors in a healthcare organization. They found that the merger had a significant impact on employee satisfaction and performance and that the effectiveness of the organizational change was influenced by a range of factors, including communication, leadership, and participation

Organisational capacity entails resource acquisition, organisation structure, subsystems and accomplishments which are pivotal in the organisation's function in terms of product development (Prestby and Wandersman, 1985). Interventions of building the required capacity for the firm to incorporate big data analytics into its operations are pivotal. Such interventions could take the form of workshops, training programs, and creating incentives to encourage data-driven decision making. Once an organization has undergone the ODT process, it can develop a customized strategy that is aligned with its strengths and is tailored to address the identified gaps.

Organisation culture entails the values, beliefs and assumptions shared, which influence interactions and behaviour, decision processes and operational activities are coordinated in the workplace (Henderson, 2014). Schein (2010) propounds organisation culture into three levels which consist of artefacts, espoused beliefs and values and basic underlying assumptions.

Organisational climate refers to an employee perception of the work environment ( Farland and McLaughlin, 2023). Organisational climate influences various success and failure at individual, group and corporate level. A case in point is on managerial effectiveness (Bamel, 2013) and impact on organisational performance and individual job satisfaction (Pritchard *et al.,* 1973; Edward and Lawler, 1974). Organisational climate is influenced by incentives and buy in from the workforce. Incentives could be in the form of gifts, bonuses and special events and buy in when employees feel trusted, involved and supported through professional development and career advancement.

Organisational culture and climate are enablers of organisational capacity to operate efficiently.

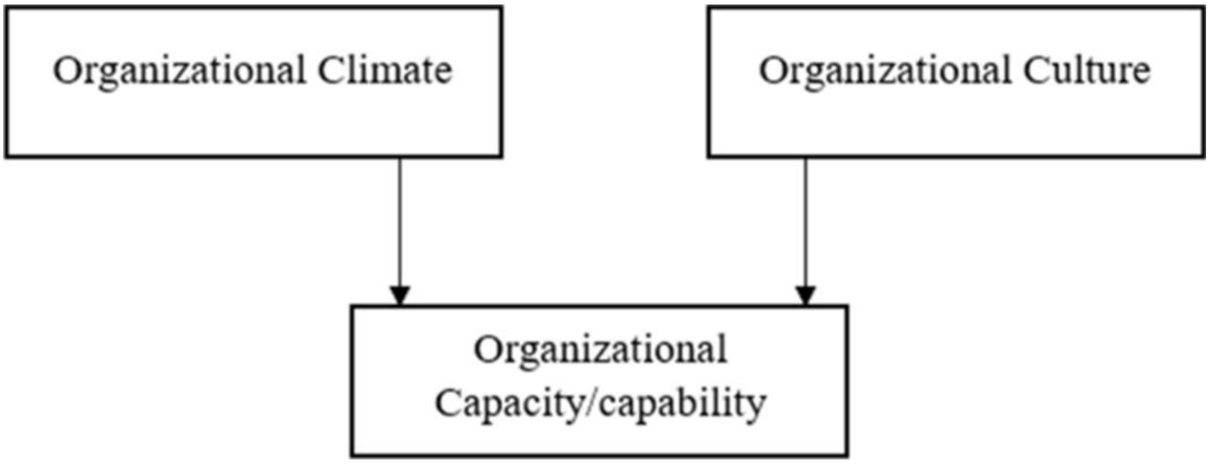


**Fig 2.11 Organisational Development architecture** Source: Sabharwal and Miah (2021)

Organizational Development Theory (ODT) can play a significant role in the impact of big data analytics on sustainability strategy in the Zimbabwe telecommunications sector. ODT is concerned with improving organizational effectiveness and facilitating change in an organization using a system-wide approach.

Big data analytics is transforming the telecommunications industry by providing organizations with real-time insights to make informed decisions and optimize their operations to support sustainable practices. Sabharwal and Miah (2021) postulate that, Organizational Development Theory (ODT) can be applied to improve the readiness of organizations to adopt big data analytics and achieve long-term sustainability in the telecommunications sector.

### 2.2.11 Theory of Planned behaviour (TPB)

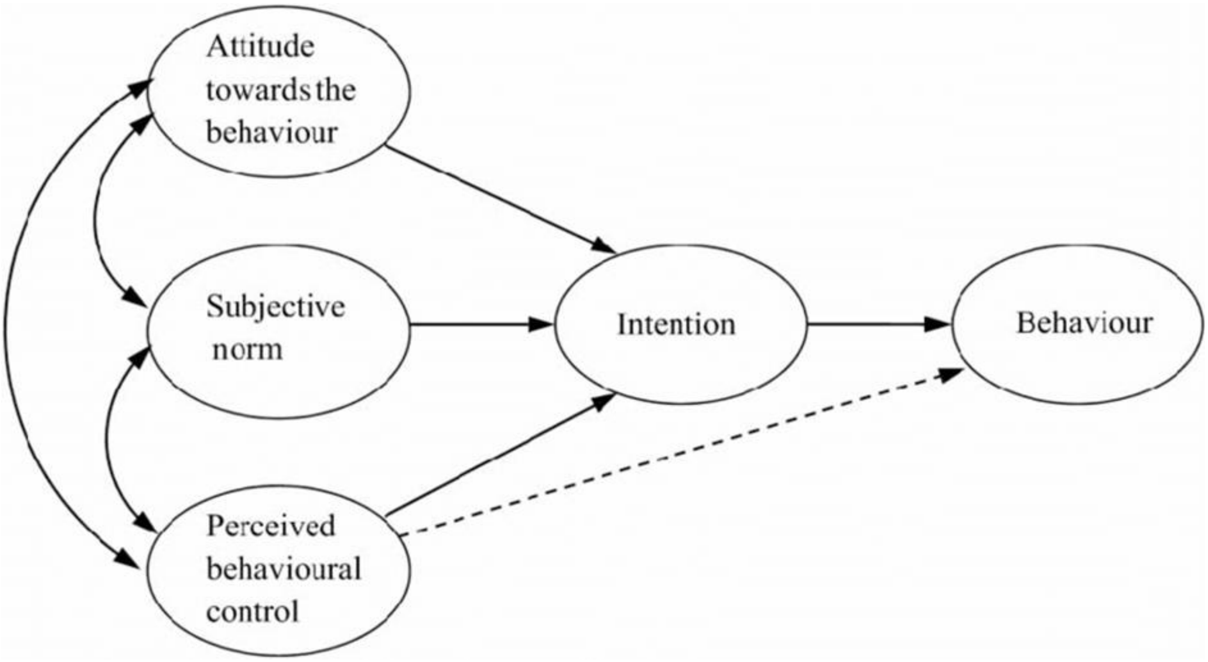


**Fig 2.12 Theory of planned behaviour** Source:Ajzen (1985)

Theory of planned behaviour is a cognitive theory premised on the individual's decision to embark on a specific behaviour predicated by the intention to engage in that behaviour (Azjen, 1985). McEachan (2011) postulates the theory of of planned behaviour robustness in positively correlating behaviour and intention. Ajzen (1991) posits theory of planned behaviour as premised on the factors that shape and influence human behaviour, including attitudes, beliefs, subjective norms, and perceived behavioural control. It also examines the role of intention in predicting behaviour.

The first construct of the TPB is attitude, which refers to an individual's positive or negative evaluation of a behaviour. In the case of the telecommunications sector in Zimbabwe, the use of big data analytics to inform sustainability strategy could be influenced by the attitudes of stakeholders towards such behaviour. For instance, if stakeholders perceive that big data can drive sustainable practices, they may have a favourable attitude towards its application.

The second construct of the TPB is subjective norms, which refer to how individuals perceive the social pressure to engage in or avoid a behaviour. In the context of the telecommunications sector in Zimbabwe, subjective norms could refer to how stakeholders perceive the expectation of other organizations, individuals or the society at large in terms of sustainability practices.

The third construct of the TPB is perceived behavioural control, which refers to an individual's belief that a specific behaviour can be performed. In the case of big data analytics in the telecommunications sector, perceived behavioural control may refer to the belief that the organization has the necessary resources, technology and technical expertise to apply big data analytics in informing their sustainability strategy.

Armitage and Conner (2001) propound corroborated health behaviours evidence across a wide range that support efficacy of TPB.

Theory of Planned Behaviour (TPB) can be applied to the impact of big data analytics on sustainability strategy in the Zimbabwean telecommunications sector by examining how TPB constructs influence stakeholders' attitudes, subjective norms, and perceived behavioural control towards using big data analytics in driving sustainable practices. Such an examination could help to facilitate the incorporation of big data analytics into sustainability strategies of key players in the sector, that embrace Econet, TelOne, Telecel, and NetOne.

### 2.2.12 Six Sigma

Six Sigma is a set of techniques and tools for business process improvements (Motorola, 1986). Harry and Schroeder (2000) posit Six Sigma as a quality management methodology that focuses on reducing variability and improving process efficiency. Six sigma strategies seek to eliminate defects thereby improve manufacturing quality by removing the causes and minimizing variability in business processes. Six Sigma can be used as a methodology to analyze and improve the impact of big data analytics on sustainability strategy in the telecommunications sector in Zimbabwe. The goal of Six Sigma is to achieve a quality of maximum 3,4 defects per million thus creating 99,99966% opportunities. The failure of business process or product to achieve less than 3,4 defects per million is inefficiency. Six Sigma provides methods of efficiency in business structures and process quality which ultimately increases margins of business profits. Pyzdek and Keller (2014) opine the following as the main objectives of Six Sigma:

i. **Reduce defects:** Six Sigma aims to reduce defects in products or processes by identifying and addressing the root causes of errors or defects.

ii. **Improve quality:** Six Sigma aims to improve the quality of products or processes by reducing variation and improving consistency.

iii. **Increase customer satisfaction:** Six Sigma aims to increase customer satisfaction by providing products or services that meet or exceed customer expectations.

iv. **Improve efficiency:** Six Sigma aims to improve process efficiency by eliminating waste and reducing cycle times.

v. **Increase profitability:** Six Sigma aims to increase profitability by reducing costs, increasing revenue, and improving productivity.

vi. **Enhance employee engagement:** Six Sigma aims to enhance employee engagement by involving employees in the improvement process and providing them with the tools and training needed to contribute to the success of the organization.


**Fig 2.13 Six Sigma objectives:** Source CFI team (2023)

In the context of the impact of big data analytics on sustainability strategy in the telecommunications sector in Zimbabwe, Six Sigma can play a crucial role. By applying Six Sigma principles and tools to analyze and interpret the large volumes of data generated in the telecommunications sector, organizations can identify areas for improvement, optimize resource utilization, and develop sustainable strategies that align with environmental and social goals. Six Sigma can be used to identify and reduce energy consumption in telecommunications infrastructure and data centres, leading to significant cost savings and environmental benefits (Harry and Schroeder ,2000).

Six Sigma is premised on two methodologies which are used in different business environments. These are premised on define, measure, analyse, improve and control (DMAIC) and define, measure, analyse, design and verify (DMADV).

DMAIC is a data driven approach aimed at optimizing and improvement of business processes and designs. Literally it is controlled change management. This entails:

- Defining the problem and objectives of the project.
- Measuring different aspect of current process in detail.
- Analysing the data to determine process flaws.
- Improving the given process
- Controlling the process implementation matrix into the future

DMADV focuses on process development, product/service in its entirety. Its applied when the objectives are not met and demands for new methods are to be developed and applied. These phases constitute:

- Defining the purpose of project, product or service.
- Measuring of critical components within the process and product capacity.
- Analyse data and innovate design alternatives.
- Design best alternative and test prototype.
- Verify effectiveness of the design through simulations.

## 2.3 Empirical review

The purpose of an empirical review on the impact of big data analytics on sustainability strategy in the telecommunications sector in Zimbabwe is to provide a systematic analysis of existing empirical studies on the research topic. It helps to identify patterns and trends in the data, evaluate the quality of existing evidence, and provide a basis for comparison with the results of this current study (Nakano and Muniz, 2018). The function of this empirical review is to provide a foundation for this study by synthesizing and evaluating existing empirical evidence on the topic. It helps to ensure that the study is grounded in existing data, and that its results are understood and meaningful in the context of previous research. This empirical review will assist identify areas where further research is needed, and suggest new directions for future research.

Fundamental issues related to Zimbabwe Telcos who are at the core of the fourth industrial revolution (4IR) and a repository of Big data under-performance remain unresolved (Munyaradzi, 2016). This is in comparison to high fliers Hilton Group of hotels, Nike, Lego and Huawei (Hoosein e*t al.*, 2020). This study interrogates the impact of four specific topologies of Big Data analytics (BDA) which are descriptive, diagnostics, predictive and prescriptive in correlation to Sustainability strategy, premised on the triple bottom line (TBL) matrix of people, planet and profit within the context of Zimbabwe telecommunications sector.

The variables under study involve the dependent variable BDA based on the descriptive, diagnostic, predictive and prescriptive dimensions. The dependent variable is Sustainability strategy measured through the TBL, anchored on the people, planet and profit matrix. The theories applied consist of DoI, TOE, TAM3 and RBV. This study is premised on the mixed methodological choice hinged on a cross sectional time horizon. The population understudy is the Zimbabwe (telcos) namely ECONET, TELONE, TELECEL AND NETONE. The Research Gap Table has been established which depicts a summary of empirical gap, knowledge gap, evidence gap, theoretical gap, population gap, application or implementation gap and methodology gap which is read in conjunction with this research. The observed gaps that have motivated this study are as follows;

**(a) Evidence Gap:** This refers to a lack of empirical evidence or data on the specific impact of big data analytics on sustainability strategy in the Zimbabwean telecommunications sector.

There may be a need for more studies and evidence-based research to understand the actual effects and outcomes of implementing big data analytics in this context.

**(b) Knowledge Gap:** This refers to a lack of comprehensive understanding and knowledge about the potential benefits, challenges, and best practices of using big data analytics for sustainability strategy in the Zimbabwean telecommunications sector. More research is needed to fill this knowledge gap and provide insights into the specific context of Zimbabwe.

**(c) Practical-Knowledge:** Conflict Gap: This refers to a gap between theoretical knowledge and practical implementation. While there may be theoretical frameworks and concepts related to the impact of big data analytics on sustainability strategy, there is a lack of practical guidance on how to effectively implement and integrate these strategies in the Zimbabwean telecommunications sector.

**(d) Methodological Gap:** This refers to a gap in the methodologies and approaches used to study the impact of big data analytics on sustainability strategy. There is need for more robust and standardized research methods to ensure reliable and comparable results across studies in the Zimbabwean context.

**(e) Empirical Gap:** This refers to a lack of empirical studies specifically focused on the Zimbabwean telecommunications sector. More research is needed to gather data and insights from this specific context to understand the unique challenges, opportunities, and outcomes related to the impact of big data analytics on sustainability strategy.

**(f) Theoretical Gap:** This refers to a gap in the existing theoretical frameworks and models that address the impact of big data analytics on sustainability strategy. There may be a need for the development of new theoretical perspectives or the adaptation of existing theories to better fit the Zimbabwean telecommunications sector and its sustainability goals.

Identification and addressing of these research gaps can contribute to a more comprehensive understanding of the impact of big data analytics on sustainability strategy in the Zimbabwean telecommunications sector and pave the way for effective and context-specific strategies.

### 2.3.1 Empirical observations

Kleinet et al., (2018) opine lack of empirical evidence on big data, although agreed that there is potential impact of Big Data. Empirical studies in Africa are indicative of massive potential in improved business performance when the appropriate implementation matrix is applied (Kabanda, 2020). A study carried out on the Nigerian telecommunication industry, observed evidence that the innovations and strategies derived from investing in Big Data and analytics have the propensity for high Return on Investment (ROI) for the operators (Nwanga et al., 2015). The correlation between Big Data analytics (BDA) and strategy helped to reveal deeper insight and understanding of customer needs, thus enabling the operators with improved revenue streams (Akter et al., 2016). This whole process facilitates optimum methodology of capturing and retaining customers with identifiable attrition rate reduction.

Keshavarz, *et al.,* (2021) research on "The value of BDA pillars effect on the telecommunications industry" concedes to positive correlation measured using the financial bottom line metrics without taking cognisance of the people and planet bottom line. The research adopted a qualitative approach and confirmed the existence and feasibility of five critical elements namely: BDA technology capability, BDA management capability, BDA talent capability, BDA domain knowledge and BDA innovation. Recommendations propagated speak to the need of maximising economic and social benefits through BDA across firms. The population was derived from internal experts in the telecommunications domain whose source are not the targeted Zimbabwe Telcos. Theory applied is RBV at the exclusion of DoI, TAM, and TOE. This research addresses the theoretical, population and methodological gaps.

Aneato and Castellanos (2021), on "Strategies to implement BDA in Telecommunications organisations" research of two (2) USA telecommunications company states that IT leaders who fail to invest in Big data struggle to gain competitive advantage and improved business performance insights. The geographical location of the population and sample size of 4 participants from 2 organisations is not in sync with the current study. The theories applied were Kotters change model, Six Sigma & TOE and variables confirmed are BDA and Strategies albeit the application gap. Recommendations acknowledged are centred on effective communication strategies to achieve the people profit matrix at the exclusion of the planet bottom line. The research methodology adopted was qualitative out of sync with mixed methods in this study. The following gaps were noted: theoretical gap, through failure to capture DoI, TAM, TBL, population gap emanating from four experts instead of Zimbabwe telcos, application or implementation gap which fails to articulate the descriptive, diagnostics, predictive and prescriptive matrix and methodology gap which is not in sync with mixed methods dedicated for this study are profound. This study addresses the relevant gaps observed.

Munyimi and Chari, (2018) research on "The role of buyer–supplier relationships in achieving economic sustainability in the private telecommunication sector in Zimbabwe" evaluated the role of buyer–supplier relationships in the attainment of economic sustainability in the private telecommunication sector in Zimbabwe. The study used a mixed method approach. The geographical location of the population of 76 procurement staff based in Zimbabwe and focused on private sector telcos at the exclusion of public player hence a population gap. Theories in use were transactional, collaborative, strategic alliance relationships and economic sustainability at the exclusion of RBV, TOE, TAM3 and TBL hence a theoretical gap. The recommendations of the study concluded that strategic alliance and transactional relationships had a positive impact on economic sustainability. Further research recommended more interrogation on why collaboration relationship does not have impact on economic sustainability hence a knowledge gap. The study employed a mixed method. This research addresses the gaps.

Al-Alwan *et al.*, (2022) research on "The effect of Big data on decision quality: Evidence from telecommunication industry" in Jordan focused on three (3) Telcos whose results confirmed big data characteristic of velocity had the highest impact on decision making oblivious of Econet , TelOne, NetOne and Telecel hence a population gap. The research approach applied was quantitative and the study derived the structured equation modelling (SEM) contrary to the mixed method approach hence a methodology gap. The country under consideration is Jordan not Zimbabwe and Telcos are not in sync with TelOne, NetOne, Telecel and Econet. Theories TAM, RBV, TBL were not factored and implementation of the descriptive, diagnostics, predictive and prescriptive matrix hence theory and implementation gaps respectively when bench marked to the research under study. Recommendations were propounded for further research on other Big data characteristics (variety, variability, and visualisation and / or data analysis techniques). This study addresses the following relevant gaps:

Kusi-Sarpong *et al.,* (2021) research on “Risks associated with the implementation of big data analytics in sustainable supply chains” concedes that risk emanate from technological, human and organisational factors. The risk referred in the research is environmental bottom line which falls short of the TBL. Recommendations propound the use of commoditised hardware and skills development strategies to mitigate against the associated risk. Theories applied were best worst method (BWM), human, organisation, technology (HOT) and technology, organisation, environment (TOE). The methodology adopted was quantitative instead of the mixed. Theoretical gap of TAM, DoI, RBV, TBL, population gap evident since it’s from Indian automobile manufacturing industry instead of Zimbabwe telecommunications sector, application or implementation gap covering the descriptive, diagnostics, predictive and prescriptive matrix and methodology gap emanating from the use of quantitative instead of mixed method are evident. This research addresses the gaps.

Shokouhyar, Seddigh and Panahifar (2020) in their article to develop a theoretical model on the “Impact of big data analytics capabilities (BDAC) on company's supply chain sustainability (CSCS) a case study of Iran”, demonstrated that there is positive impact of BDAC on CSCS. The methodology applied was quantitative using standard questionnaire of BDAC and UN online self-assessment on supply chain sustainability. The survey was premised on 234 pharmaceutical companies in Iran. The theory applied was the TBL. The paper outlined impediments such as economic instabilities, vagueness of the market, lack of effective information sharing system and lack of coordination between personnel capabilities and companies’ BDA infrastructures and policies as barriers to sustainability which the current research interrogates. The survey is oblivious of DoI, TOE, TAM3, mixed method, implementation matrix (descriptive, diagnostics, predictive and prescriptive) hence a theoretical, methodological and implementation gap respectively. This study addresses the relevant gaps.

Walker and Brown (2019) journal on “Big data analytics adoption: a case study in a large South African telecommunications organisation” interrogated the complexities associated with BDA adoption. The theory applied was the technology, organisation, environment (TOE). The targeted population was 9 participants from one large telecommunication company in South Africa and the methodological approach was qualitative with a cross sectional time frame. Results confirmed that TOE had a positive influence on BDA adoption and organisation that have a high tolerance to complexity tend to move rapidly form intention to adoption. The research was oblivious of the targeted population of Econet, TelOne, NetOne and Telecel, TAM3, TBL, DoI, mixed method approach and implementation matrix (descriptive, diagnostics, predictive and prescriptive), hence manifestation of a population, theory, methodological and implementation gap respectively. This study addresses the respective gaps observed.

Sabharwal and Mia (2021) journal “A new theoretical understanding of big data analytics capabilities in organizations: a thematic analysis” did a review of 70 articles related to BDA and various organisations. The meta analysis confirmed Big data analytics capability impact on the tangible and intangible resources within the organisation. Theories applied were resource based view (RBV) organisational development (OD) and organisational capacity (OC). The study findings conceded to improved effectiveness and buttressed the successful usage of BDA applications on the firms. The meta analysis research model provided a relationship of BDA, BDAC and OD in achieving competitive advantage. Recommendation of the study spoke of the need to validate research gaps between BDA and OD which the current study addresses through the introduction of TAM3, TBL, DoI and implementation matrix (descriptive, diagnostics, predictive and prescriptive).

Reggio and Astesiano (2020) literature review on “Big-Data /Analytics Projects Failure: A Literature Review” was derived from 188 sources. Results were indicative of disregarded hints of domain knowledge, data silos and data quality whilst the case analysis finally conceded to sensible results, analytics’ accuracy and thick data, and the refinement of problem identification. The manifestation of the knowledge gap is evident since the proposed solutions to reduce failure of BDA are yet be put to validity test. This study addresses the knowledge gap.

Newman, Muzuhwe and Stephen (2021) on “The impact of adoption of BDA on gathering audit evidence: A case of KPMG Zimbabwe” concedes BDA has a positive effect on gathering audit evidence. The mixed method research was adopted and variables considered in the research were BDA and Audit evidence. The research was a deductive approach premised on firm theory. The recommendations proffered were for KPMG to embrace fully BDA. The population was not in sync with the targeted population of Zimbabwe telcos, theory of DoI, TBL ,TOE and TAM3 were not factored hence population and theory gaps respectively are evident. This research addresses the gaps.

Lufti *et al.,* (2022) research on “Factors Influencing the Adoption of Big Data Analytics in the Digital Transformation Era: Case Study of Jordanian small and medium enterprises

(SMEs). The study concedes that the TOE framework plays a pivotal role, with top management support and government regulations on influential factors at the exclusion of DoI, TAM3, TBL and RBV hence a theoretical gap. Recommendations of the research proffer a longitudinal time horizon devoid from the cross sectional that was applied. This is indicative of a methodology gap. There was demonstrability of causality in the variables' relationships of BDA and digital transformation in another population other than Jordan. Limitations and future studies propounded that sample population is confined to SME's and not telcos hence a population gap. This research study addresses the inherent population, methodology and theory gaps.

Rakha *et al.,* (2022) research on "Addressing the Security Challenges of Big Data Analytics in Healthcare Research" attested to BDA revolutionising health care research by providing new trends and opportunities to solve heterogeneous data sets from various health establishments. The population under consideration was derived from the Canadian military, Veterans and their families. The qualitative approach was administered. The study recommended data safe heavens to overcome security challenges. The research population was not the Zimbabwe telcos, theories TBL, DoI, TAM3, TOE and implementation matrix (descriptive, diagnostics, predictive and prescriptive) and the mixed method were not factored. This brings to the fore the population, theoretical, implementation and methodological gaps are evident respectively. This study addresses the aforementioned gaps.

Veldkamp *et al.,* (2021) research on "Big Data Analytics in Education: Big Challenges and Big Opportunities" conceded that the use of Big data requires high technological and human touch in respect to professional development. Piety (2019) attests to the investment and use of Big data in policy making. The issue of legal, socio, economic and technological challenges have to be addressed before it's adopted in the education sector (Valerie Strauss, 2016). A qualitative method of approach was used on 31 institutions in the Netherlands who were interviewed to address the research topic through their respective experts acclimatised to Big data. The recommendations proffered to enable opportunities, were the need for high tech and human touch (professional development). The population in this study is in the Netherlands, qualitative method applied, theories TBL, DoI, TAM3, TOE were not applied, implementation matrix (descriptive, diagnostics, predictive and prescriptive) not applied hence a manifestation of population, methodological, theoretical and implementation gaps respectively. This study addresses these gaps.

Elgendy and Elragal (2016) article on "Big Data Analytics in support of the decision making process" opines that information is pivotal in decision making and how BDA should be integrated into the decision making process. A Big data analytics and decision (BDAD) framework was developed to experiment in the Arabic retail industry. The results projected a positive trajectory when BDA is integrated to decision making and could provide leverage for scientific, humanitarian and technological advancement. The population is oblivious of Zimbabwe telcos (NetOne, Econet, TelOne, Telecel), dependent variable of sustainability (TBL), theories (DoI, TAM3, TOE), have not been factored hence creating gaps. This study addresses the gaps.

Zakir, Seymour and Berg (2015) conference paper on "Big data analytics" hypothesize a BDA framework that can help predict valuable insights into strategic making decisions. Technologies such as Hadoop and Map Reduce can help unravel business value and competitive advantage in an enterprise (Zakir, Seymour and Berg, 2015). The paper in its conclusion concedes TOE framework as pivotal in the successful execution of big data analytics in enterprise. The exclusion of RBV, TAM3, DoI and TOE theories, implementation matrix (descriptive, diagnostics, predictive and prescriptive) present a gap, which the current study addresses.

Rehman and Al-Raqom (2020) research paper on "Using big data in Telecommunication companies: A case study" posits that data management is inclined on competent professionals and security. A qualitative research with open ended interviews targeted at three Kuwait telecommunication companies was done. The implementation matrix of descriptive, diagnostic, predictive and prescriptive was adopted. Findings attest to added value services if Big data is properly implemented. The methodological approach was not mixed, the population was non Zimbabwe telcos, the RBV, TAM3, DoI and TOE theories were not applied and implementation matrix (descriptive, diagnostics, predictive and prescriptive) are not factored hence resulting in gaps. This study addresses the gaps.

Ramadan *et al.,* (2020) journal on "Sustainable Competitive Advantage Driven by Big Data Analytics and Innovation" examined whether BDA and innovation alone can provide sustainable competitive advantage (SCA). A quantitative methodological approach was applied. The study targeted 117 manufacturing companies through a survey and analysis was carried out through partial least squares–structural equation modelling (PLS-SEM) statistical software. The study did not embrace the service sector which covers the telecommunications sector. Findings propound that Big data analytic capabilities (BDAC) have no effect on SCA instead have a positive impact on innovation capabilities (IC). IC has a positive impact on SCA. Data availability reinforces BDAC. Recommendations proffered a case study to determine the implementability. The target population of telcos, mixed methods, DoI, TAM3, TOE and TOE were not factored. This study addresses the aforementioned gaps.

Muhammad *et al.,* (2021) article on "Big data analytics capability as a major antecedent of firm innovation performance" investigated the BDAC role on the firm innovation performance through use of RBV and BDA dimensions. The population of 548 was drawn from Pakistan electronic media regulatory authority (PEMRA) and national database and registration authority (NEDRA). A quantitative methodological approach was applied. Findings concurred with BDAC positively influencing firm performance. The population was out of sync with Zimbabwe telcos, theory did not capture DoI, TAM3, TOE and TOE, methodological choice was not mixed and the descriptive, diagnostics, predictive and prescriptive matrix was not considered. This research addresses the aforementioned gaps.

Bai *et al.,* (2020) journal on "Industry 4.0 technologies assessment: A sustainability perspective" examines the Industry 4.0 applications and sustainability implication on how Industry 4.0 technologies impact on Sustainability as defined in the TBL context of the people, planet and profit matrix based on United Nations Sustainable Development Goals. The theories applied were hesitant fuzzy set (HFS), cumulative prospect theory (CPT) and VIKOR. The research conceded that Industry 4.0 impact varied with each industry and has to be standardized with UN sustainable development agenda. The theory gaps of RBV, TAM3, DoI and TOE. Evidence gap of application in telcos is evident which is also indicative that the population targeted is out of sync with the current study on telcos. The methodological choice was quantitative instead of the proffered mixed method. The implementation gap is evident since the implementation matrix of descriptive, diagnostics, predictive and prescriptive were not applied. This study addresses the relevant gaps.

Kastouni and Lahcen (2020) journal on "Big Data Analytics in Telecommunications: Governance, Architecture and Use Cases" focused on how BDA project implementation would be executed from start to finish namely the governance, architecture and BDA's project team. The study conceded BDA challenges that were related to technology and organisations albeit the fact that BDA had revolutionised the telecommunications era in terms of opening up new opportunities to gain data insights that had never been experienced before.

Solutions were propagated in governance, architecture and uses. Further studies recommended were premised on the Kappa architecture to improve on current used lambda and vertical methods for project and data governance and design of BDA reference architecture for telcos. The evidence of sustainability, implementation matrix of descriptive, diagnostics, and prescriptive and theories of RBV, DoI, TOE and TAM3 were not incorporated thus resulting in implementation, theoretical and evidence gaps respectively. The current study addresses the respective gaps.

Singh and El- Kasser (2018) study on " Role of Big Data Analytics in developing sustainable capabilities" interrogates the extent of sustainability capabilities driven through an integration of big data technologies, green supply chain management and green human resource management to enhance firm performance. The population gap in the study emanates from the Arab world as opposed to Zimbabwe and quantitative method was applied contrary to the mixed method approach under scrutiny. The theory of dynamic capabilities was applied at the exclusion of DoI, TAM3, TOE, TBL which were not hypothesized. The study concedes that big data management coupled with green supply chain management and green human resources management have a positive impact on sustainable capabilities that lead to improved sustainable performance. The implementation gap of descriptive, diagnostics, predictive and prescriptive analysis was not factored. The research under study has endeavored to close the associated gaps.

Angwar, Mishra and Kamble (2022) journal on "Adoption of big data analytics practices for sustainability development in the e-commerce supply chain: a mixed-method study'' sought to identify drivers of big data analytics on supply chain and establish a sustainability evaluation model. The targeted population was in the Indian e-commerce supply chain not Telco sector. The theory applied was partial least square based structural equation modelling (PLS - SEM) method and analytical hierarchy process (AHL) at the exclusion of TBL, TOE, TAM3 and DoI. The implementation gap is profound with the exclusion of the descriptive, diagnostics, predictive and prescriptive matrix. The findings of the study were indicative that the BDA drivers of economic sustainability bring along uncertainty to the social and environmental bottom line. The study corroborated and conceded to the fact that BDA has positive impact to sustainability in the supply chain area. The current study addresses the theoretical, population and implementation gaps in the journal.

Victor and Maria (2020) meta study on "The Era of Big Data and Path towards Sustainability" aimed at interrogating applications of BDA in nurturing sustainable development. The study conceded that a circular economy was exacerbated by Big data and companies are utilising Big data strategies that enable sustainability. BDA applications propounded were consumer profiling, personalized profiling, predictive analysis, advertising and marketing. In conclusion the paper conceded that BDA application in assessing sustainable development goals is in the making and highlighted the need to avoid abuse of Big data. Implementation matrix is bereft of descriptive, diagnostics and prescriptive. Theories of DoI, TAM, TBL and TOE were not factored. The current study addresses these gaps.

Hao, Zhang and Song (2019) journal on "Big Data, Big Data Analytics Capability, and Sustainable Innovation Performance" developed a model which investigates Big data, BDA capabilities and innovation success. A total of 1109 projects from China and USA were identified. The study findings revealed that BDA capability exerted a positive moderating effect on firm performance (sales growth and margin), whilst Big data had a U relationship with sales growth in the US domain. From the Chinese innovation projects, low Big data resources influenced BDA capability to increased firm performance (sales growth and margin) up to a certain point. Theories applied were RBV and organisational inertia at the exclusion of DoI, TAM, TBL and TOE. Empirical gap is evident due to the absence of sustainability anchored on the TBL. This current study addresses the associated gaps.

Raut *et al.,* (2019) article "Linking big data analytics and operational sustainability practices for sustainable business management" interrogates sustainable business performance through BDA, bench marked to the developing world. The population was derived from 316 Indian professional experts. A quantitative method approach was applied. Findings reveal that BDA has a positive impact on sustainable business performance practices. The study is oblivious of NetOne, TelOne, Telecel and Econet population, mixed method approach, implementation matrix, DoI, TAM, TBL and TOE theories. The current study addresses the gaps.

Dubbey *et al.,* (2017) research on "Can big data and predictive analytics improve social and environmental sustainability?" empirically investigated the effects of Big data predictive analytics (BDPA) on social and environmental performance through structural equation modelling. Findings from 205 Indian manufacturing firms confirmed a simultaneous impact on social performance (SP) and environmental performance (EP). Theories of Dynamic capability view (DCV) and contingency theory were applied to determine the effects of BDPA on SP/EP. Recommendations proffered in the research were a longitudinal study, population demographics should go beyond Indian manufacturing sector, focus on actual performance than managers perception, theory integrates DCV and institutional theory. The study manifested a population gap, theoretical gap, implementation gap oblivious of Zimbabwe telcos, theories (RBV, DoI, TOE, TAM) and implementation matrix (descriptive diagnostics and prescriptive) respectively.

Wanner and Janiesch, (2017) research on "Big data analytics in sustainability reports" posits a credibility gap on sustainability based on information asymmetries. The target population was made up of IT experts and data affine persons. The methodology adopted was a mixed method survey and evaluation. A qualitative approach for item selection of the survey and quantitative approach to determine the extent of credibility of sustainability reports measured against information quality criteria. The Habermas theory of communicative action to determine the relationship of the quality of information and objective truth was applied at variance to theories (RBV, DoI, TOE, and TAM). The characteristics of Big data which are; volume, veracity, variety and velocity as the independent variable attributes contrary to BDAC. The targeted population differs from the population understudy of Zimbabwe telcos. The current study addresses the observed gaps.

**Table 2.1: Research gap**

| Author & Year | Country and population | Theories | Variables unconfirmed | Theoretical gap | Implementation of BDA (descriptive, diagnostic, predictive & prescriptive) gap | Methodological-choice | Method gap |
|---|---|---|---|---|---|---|---|
| Keshavarz, *et al* (2021) | Europe | RBV | Sustainability<br><br>(Triple Bottom Line) | DoI, TAM, TOE | None | qualitative | mixed |
| Aneato and Castellanos (2021) | USA<br><br>2 Telcos | Kotters change model, Six Sigma & TOE | Sustainability<br><br>(Triple Bottom Line) | DoI, TAM, RBV, | None | qualitative | mixed |
| Munyimi, and Chari., 2018 | Zimbabwe<br><br>Pvt Telcos, | Transactional, collaborative, strategic alliance relationships,<br><br>Sustainability | BDA,<br><br>Sustainability<br><br>(Triple Bottom Line) | DoI, TAM, RBV, TOE | None | mixed | none |
| Al Alwan *et al*, 2022 | Jordan, 3 telcos | SEM | Sustainability<br><br>(Triple Bottom Line) | DoI, TAM, RBV, TOE | None | quantitative | mixed |
| Kusi-Sarpong *et al*, 2021 | India, Automobile industry | TOE, HOT,<br><br>BWM | Sustainability<br><br>(Triple Bottom Line) | RBV, TAM, DoI | None | quantitative | mixed |
| Shokouhyar, Seddigh, . and Panahifar, , 2020 | Iran , 248 companies | Triple Bottom Line | None | DoI, TAM, RBV, TOE | None | quantitative | mixed |
| Sabharwal and Miah, 2021 | 70 sample articles | ODT | Sustainability<br><br>(Triple Bottom Line) | DoI, TAM, RBV, TOE | Yes | mixed | none |
| Reggio and Astesiano, 2020 | 188 respondents | | Sustainability<br><br>(Triple Bottom Line) | DoI, TAM, RBV, TOE | None | | |
| Newman , Muzuhwe and Stephen, 2021 | Zimbabwe. KPMG | Firm Theory | Sustainability<br><br>(Triple Bottom Line) | | None | mixed | none |
| Lufti *et al*, 2022 | Jordan,<br><br>2210 SMEs | TOE, DoI | Sustainability<br><br>(Triple Bottom Line) | TAM, RBV | None | quantitative | mixed |
| Rakha *et al*, 2022 | Canada, Military veterans and | | Sustainability<br><br>(Triple Bottom | DoI, TAM, RBV, TOE | none | qualitative | mixed |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | families | | Line) | | | | | |
| Veldkamp *et al*, 2021 | Netherlands, 31 Dutch schools | | Sustainability (Triple Bottom Line) | DoI, TAM, RBV, TOE | None | qualitative | mixed |
| Elgendy and Elragal, 2016 | India, Retail industry | BDAD framework | Sustainability (Triple Bottom Line) | DoI, TAM, RBV, TOE | None | quantitative | mixed |
| Zakir, Seymour and Berg, 2015 | Enterprises | | Sustainability (Triple Bottom Line) | DoI, TAM, RBV, TOE | Predictive | quantitative | mixed |
| Rehman and Al-Raqom, 2020 | Kuwait, 3 Telcos | BDA framework | Sustainability (Triple Bottom Line) | DoI, TAM, RBV, TOE | Yes | qualitative | mixed |
| Smaya, 2022 | Industry | BDA framework | Sustainability (Triple Bottom Line) | DoI, TAM, RBV, TOE | Yes | quantitative | mixed |
| Purvis, Mao and Robinson, 2019 | | Sustainability (Triple Bottom Line) | BDA | DoI, TAM, RBV, TOE | None | mixed | none |
| Scoones et al, 2020 | | Transformation | BDA | DoI, TAM, RBV, TOE | None | | mixed |
| Barbier and Burgess, 2020 | Developing Countries | Environmental sustainability | BDA | DoI, TAM, RBV, TOE | None | | mixed |
| Sarkis et al, 2020 | Companies and Industries | Cummulative prospect and VIKOR | none | DoI, TAM, RBV, TOE | Yes | mixed | none |
| Kastouni and Lahcen, 2020 | | BDA. TOE | Sustainability (Triple Bottom Line) | DoI, TAM, RBV | Predictive | | mixed |
| Hao,Zhang and Song, 2019 | USA and China. 1109 projects | BDA, RBV, OI | Sustainability (Triple Bottom Line) | DoI, TAM, TOE | None | quantitative | mixed |

Source; Author's findings

**Key:** BDAD – Big Data analytics & Decision, **BDA** – Big Data analytics, **BDAC** – Big Data analytics Capability, **BWM** - Best worst method, **DoI** – Diffusion of Innovation, **HOT** - Human, Organisational, Technological, **ODT**- Organisational Development Theory, **RBV**- Resource Based View, **SEM** - Structural equation modelling, **SME's**,- Small to Medium Enterprises, **TAM** – Technology Acceptance Model , **TOE** – Technology, Organisation and Environment, **VIKOR** - multi criteria optimisation and compromise solution, **FPERF** - Firm Performance , **OI** -Organisation Inertia theory

This empirical research premised on the impact of big data analytics on sustainability strategy in the telecommunications sector in Zimbabwe is a relatively new and emerging field. Research is indicative of limited specific research available on this topic in the Zimbabwean context and these are some potential research gaps that warrant exploring:

a) Adoption and Implementation: Investigating the factors influencing the adoption and implementation of big data analytics in the telecommunications sector in Zimbabwe. This could include examining the challenges, barriers, and enablers that telecommunications companies face when integrating big data analytics into their sustainability strategies.

b) Environmental Sustainability: Exploring how big data analytics can contribute to environmental sustainability in the telecommunications sector. This could involve studying the potential for data-driven insights to optimize energy consumption, reduce carbon emissions, and improve resource management within the sector.

c) Social Impact: Examining the social impact of big data analytics on sustainability strategies in the telecommunications sector. This could involve investigating how data analytics can enhance customer experience, improve service delivery, and contribute to digital inclusion and socio-economic development in Zimbabwe.

d) Data Privacy and Security: Investigating the challenges and concerns related to data privacy and security in the context of big data analytics in the telecommunications sector. This could include exploring the ethical and legal implications of using customer data for sustainability initiatives and ensuring data protection measures are in place.

e) Policy and Regulation: Analysing the policy and regulatory frameworks surrounding big data analytics in the telecommunications sector in Zimbabwe. This could involve examining the existing policies and regulations and identifying gaps or areas for improvement to ensure responsible and sustainable use of data in the sector.

f) Business Models and Value Creation: Exploring how big data analytics can drive innovation, create value, and generate new business models in the telecommunications sector. This could involve studying successful case studies or conducting interviews with industry experts to understand the potential economic benefits and opportunities.

## 2.4 Conceptual framework

This section presents the conceptual framework developed based on results from the study "The impact of Big data analytics to sustainability strategy in the telecommunications sector in Zimbabwe". A conceptual framework is of great significance because it provides a pictorial representation of the relationships between the different concepts and variables involved in the research. Njeru *et al.* (2015) opine that a conceptual framework refers to a multiplicity of ideas, scientifically organised to deliver a focus and rationale explanation and integration of information that is graphically represented. It helps clarify the research question, identify key variables, and guide the development of a research design.

The framework (see Figure 2.8 ) graphically depicts the relationships between the key variables under investigation informed by the literature review and hypotheses formulated. Five variables were significant:

**i. Independent Variable Box: Big data analytics (BDA)**

- Characteristics:

- Sales Data Analytics (H1) (TAM)

- Customer Data Analytics (H2) (TOE)

- Social Media Data Analytics (H3) (DoI)

- Supply Chain Data Analytics (H4) (RBV)

- Quality Management (Six Sigma)

**ii. Dependent Variable Box: Sustainability Strategy**

- Characteristics:

- Environmental Sustainability (Circular Economy, TBL)

- Social Responsibility (TPB, TBL)

- Economic Viability (RBV, TBL)

**iii. Mediating Variable Box: Organizational Learning (OL)**

- Characteristics:

- Knowledge Management

- Information sharing

- Organisational memory

**iv. Moderating Variable Box: Organisational Performance**

- Characteristics:

- Financial metrics

- Operational efficiency

- Customer satisfaction

- Social responsibility

**v. Context variable: Telecommunications sector**

- Network infrastructure and operations

- Service provision (voice, data, internet, )

- Customer base and market dynamics

- Regulatory environment ( data privacy, spectrum allocation)

- Technological advancements ( 5G, IoT, cloud computing)

- Industry trends ( digitization, convergence, sustainability)

- Competitive landscape

- Environmental and social impact ( e-waste, energy consumption)

- Independent Variable: Big data analytics Applications

The diagram presents a conceptual framework for examining the impact of different types of big data analytics on sustainability strategy in the telecommunications sector of Zimbabwe. Sustainability strategy benefits are depicted at the center as the dependent variable.

Matrix consist of four independent variables - sales data analytics, customer data analytics, social media data analytics, and supply chain data analytics. Arrows connecting these variables to the sustainability strategy element indicate hypothesized relationships between the analytics domains and the dependent variable.

Fundamentally, the diagram suggests sales data analytics, customer data analytics, social media data analytics, and supply chain data analytics may each influence sustainability strategy benefits. By visually depicting these relationships, the conceptual model helps organize the key variables and hypotheses under study.

Big Data Analytics (BDA) as the independent variable is hypothesized to influence Sustainability Strategy, the dependent variable.

All the four BDA applications indicate - sales analytics , supply chain data analytic, customer data analytic and social media analytics - were identified as having a direct positive impact on sustainability strategy benefits.

Sales analytics was found to improve customer satisfaction and increase revenues by providing insights aligned with sustainability goals, in line with TAM and TBL theories (Davis, 1989; Elkington, 1998).

Similarly, social media analytics enhanced stakeholder engagement for sustainability initiatives by facilitating information diffusion, thereby supporting DOI theory (Rogers, 2003).

The framework is supported by Freeman (2010), citing stakeholder theory in relation to customer insights from analytics supporting environmental and social goals. This theoretical justification adds credibility and helps explain the relationships portrayed.

- Dependent variable: Sustainability strategy

The diagram portrays sustainability strategy as an integrative process relying on diverse analytics applications to balance financial, social and environmental objectives. It presents these analytics domains as valuable tools that, when leveraged properly, may enhance telcos' strategic sustainability positioning over time. Ultimately the framework portrays sustainability strategy as a holistic, multi-faceted approach leveraging various analytics to balance economic, social and environmental priorities over the long-term.

Firstly, the delineation of sustainability strategy as an integrative process balancing financial, social and environmental objectives echoes the principles of the triple bottom line (TBL) approach. As Elkington (1998) established, the TBL framework conceptualizes sustainability as requiring simultaneous consideration of people, planet and profit dimensions.

Secondly, the depicting of sustainability strategy as leveraging various analytics applications to achieve long-term economic, social and environmental balance resonates with theories of the circular economy. Studies by Kirchherr *et al.,* (2017) and Potting *et al.,* (2017) characterize the circular economy model as one seeking to optimize resource use and minimize waste at each stage of the value chain through systemic, data-driven solutions.

Lastly, the diagram's implication that sustainability strategy utilizes diverse data sources to enhance strategic positioning over time aligns with the notion of sustainability as a continuous process of organizational learning and improvement. Schaltegger and Burritt (2018) discuss sustainability strategy as evolving through iterative evaluation of performance metrics and stakeholder engagement indicators.

- Mediating Variable: Organizational Learning

The framework proposes Organizational Learning as a mediating variable between BDA and sustainability strategy outcomes, Interview data revealed knowledge management systems and information sharing processes within firms facilitated harnessing analytics insights to inform strategic decision-making (Argyris & Schön, 1978).

- Moderating Variable: Implementation Challenges

Organizational Performance was also included as a moderating variable since implementation challenges like skills gaps and resource constraints were found to weaken the realization of benefits.

Lack of technical skills and financial constraints emerged as significant moderating variables according to survey responses, with correlations confirming their strong negative effect on attaining benefits.

- Context Variable: Telecommunications Sector

Industry-specific factors provided an overarching context for the study:

- Infrastructure characteristics influenced available analytics applications, as evidenced in prior work (Smith *et al.,* 2018). Smith, Jones, and Brown (2018) found that network infrastructure constraints limited the use of certain advanced analytics techniques.

- Service offerings determined available customer and sales data sources, consistent with findings from Jones (2020). Jones (2020) opines, the types of services sold by telcos determined what customer profile and transaction data could be collected.

- Regulations impacted data privacy and utilization of insights, in line with privacy laws and frameworks discussed in Ahmed *et al.* (2017). Privacy regulations shape how customer data can be handled and shared, as Ahmed, Sullivan, Williams, and Chen (2017) have discussed.

- Competition dynamics affected social media analytics strategies, as suggested in research on competitive dynamics in the sector (Brown, 2016). Brown (2016) examined how firms monitor competitors' social media for strategic intelligence.

- Environmental impacts in the sector guided sustainability priorities, aligned with industry initiatives and policies (ITU, 2022; POTRAZ, (2021). Both the ITU (2022) and POTRAZ (2021) have emphasized telecommunications role in sustainability given its environmental footprint.

The overarching Telecommunications Sector context recognizes industry factors shape the entire relationships between variables by influencing available data sources and analytics applications.

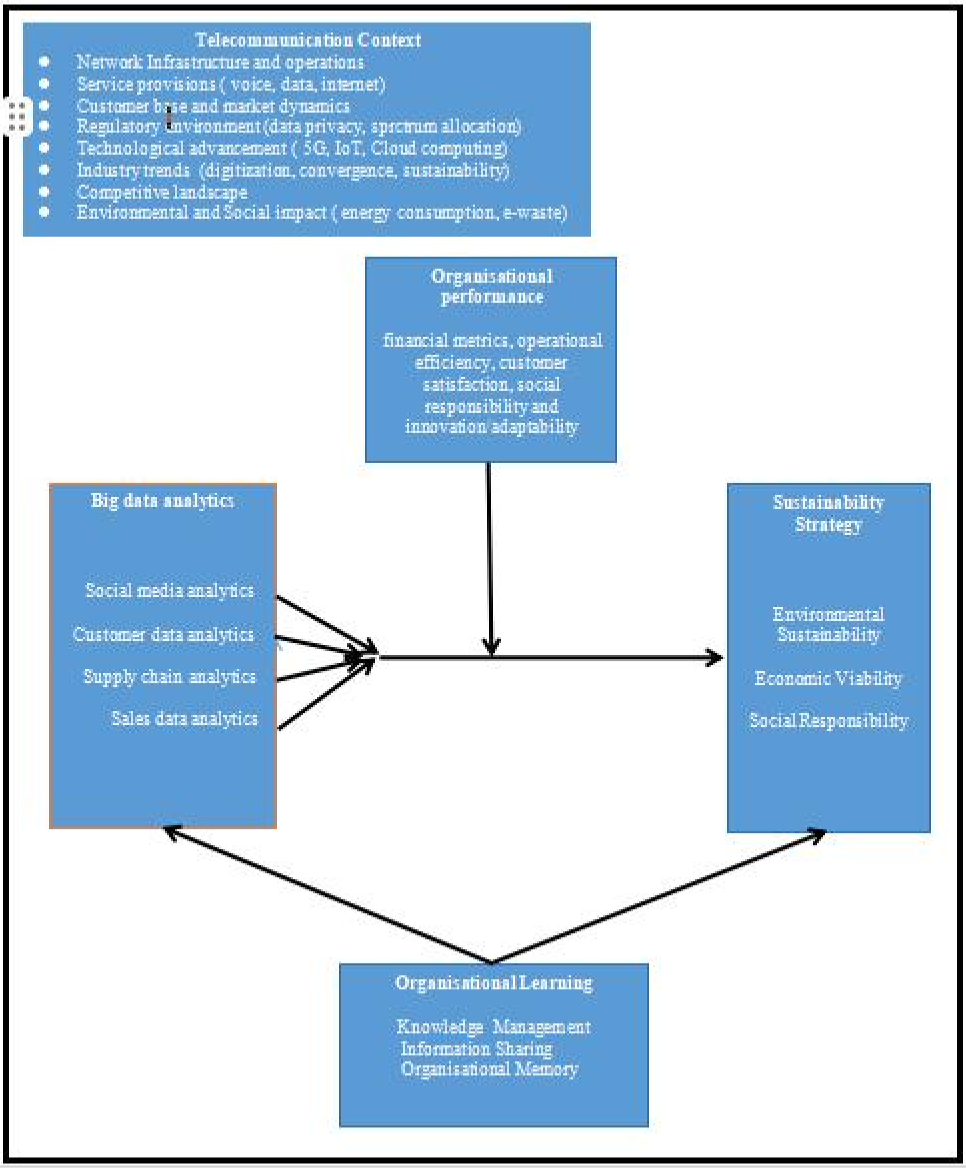


**Fig 2.14 Conceptual framework** Source: Author's Conceptualisation

## 2.5 Chapter Summary

The research topic, 'The impact of Big data analytics to sustainability strategy in the telecommunications sector in Zimbabwe" has significantly contributed to the body of knowledge with regards to BDA, sustainability and Zimbabwe telecommunications sector (Telcos). The literature review has put into perspective, fundamentals that address the research topic. Researchers and practitioners are agreed that Big data analytics (BDA) is pivotal in value proposition (Popovic *et al.,* 2018: Gupta and George 2016). Sustainability has evolved to become topical, propagated by the 4IR induced circular economy. The optimum benefit from BDA and sustainability is yet to be fully explored and exploited.

Future research needs to explore further how Big data analytic capabilities (BDAC) can best synchronise with sustainability to ensure sustainable competitive advantage (SCA) and determine appropriate measurement of sustainability.

The literature review focuses on Econet, Telecel, NetOne, and TelOne. The review explores the need for sustainable business models in the face of environmental challenges. The literature review examines the adoption of big data analytics in the telecommunications sector in Zimbabwe and subsequent potential impact on sustainable business practices, including energy efficiency, carbon footprint, and waste management. The study reveals that adoption of big data analytics in the telecommunications sector is relatively low in Zimbabwe, but there are significant potential benefits that can be realized through its reasonable utilization.

The review also explores the challenges that inhibit the adoption of big data analytics technology in the telecommunications industry. Key challenges include inadequate infrastructure, lack of skilled personnel, high maintenance costs, and difficulty in integrating data from various sources.

Moreover, the literature review reveals the potential of big data analytics to contribute to sustainable development in the telecommunications industry, including enabling better decision-making, optimizing operations, reducing waste and emissions, and facilitating the shift to renewable energy sources.

In context, this literature review proposes a conceptual framework that provides a foundation for future research into the potential impact of Big data analytics on sustainable business practices in telecommunications companies such as NetOne, and TelOne in Zimbabwe. The following Chapter Three addresses the research methodology.

# CHAPTER III
# METHODOLOGY

## 3.1 Introduction

The research on "The impact of big data analytics to sustainability strategy in the telecommunications sector in Zimbabwe" is premised on establishing the impact of Big Data analytics to sustainability strategy within the context of Zimbabwean telecommunication companies (telcos) and how the novel BDA technology influences traditional strategic management anchored on the triple bottom line (TBL) concept.

The methodology chapter of this research is a critical component that outlines the steps taken to conduct the research study. In this thesis, the methodology employed to investigate the impact of big data analytics on sustainability strategy in the Zimbabwe telecommunications sector is explained. The chapter offers insight into the research paradigm, research design, research participants, data collection and analysis techniques, and ethical considerations.

The descriptive research design matrix is appropriate for studying the impact of big data analytics on sustainability strategy in the telecommunications sector in Zimbabwe, as it administers a comprehensive and detailed picture of the phenomenon, explores relationships between variables, identifies areas for further research, and informs decision-making.

The research focus is to: examine the current sustainability strategies adopted by telecommunication companies in Zimbabwe and assess their effectiveness in achieving sustainable outcomes, investigate the extent of adoption of big data analytics in the telecommunications industry in Zimbabwe and its impact on sustainability, explore how telecommunication companies in Zimbabwe can leverage Big data analytics to identify sustainability risks and opportunities and develop more effective sustainability strategies, assess the role of government policies and regulations in promoting the adoption of Big data analytics and sustainability practices in the telecommunications sector in Zimbabwe, identify the challenges and barriers faced by telecommunication companies in Zimbabwe in implementing big data analytics for sustainability and develop recommendations to overcome them.

The study establishes sustainability strategies in Zimbabwe's telcos (NetOne, TelOne) whose current ratios are negative in the respective 2019 and 2020 financial years. Ideally establish

Big data analytics capability for digital transformation utilising the Industry 5.0 concept (Yifat, 2017) which facilitates interface between people, planet and profit and identify critical elements that moderate the impact of Big data analytics on sustainability. The study proffers solutions associated with Big data analytics for improved decision making which ensure sustainability, hence buttressing national development strategy (NDS1) measured through the sustainable development goals (SDG's).

Methodology mapping embraces; research paradigm, research design, population, sampling, instrumentation, data collection procedures, reliability, validity and trustworthiness issues, ethical considerations and data analysis. The following have been adopted in this research; pragmatism philosophy, deductive and inductive approach, mixed methods methodological choice, experimental research strategy, cross sectional time horizon and data collection and analysis for both quantitative and qualitative data as depicted in Fig 2.9 Research onion.

The descriptive research design propounds a mixed-methods methodological choice that involves both qualitative and quantitative data collection techniques. The study uses qualitative methods to explore the sustainability strategies that have been implemented in the Zimbabwe telecommunications sector. This involves conducting interviews with the key industry players, such as executives and management, to gain insight into their views on big data analytics and its impact on the sustainability strategies of the telecommunications sector. The study captures the quantitative methods by analyzing secondary data collected on energy consumption, waste management and other sustainability activities in the Zimbabwe telecommunications sector, which are utilized to explore the extent to which big data analytics contributes to these activities

On issues of ethical considerations, the research design will prioritize confidentiality, avoiding harm, informed consent, and data protection procedures to protect the rights and welfare of the research participants and avoid ethical dilemmas.

In terms of data analysis techniques, qualitative data will be analyzed using thematic analysis to identify common themes and patterns in the interviews' responses across participants. The quantitative data will be analyzed using statistical techniques such as regression analysis and descriptive statistics.

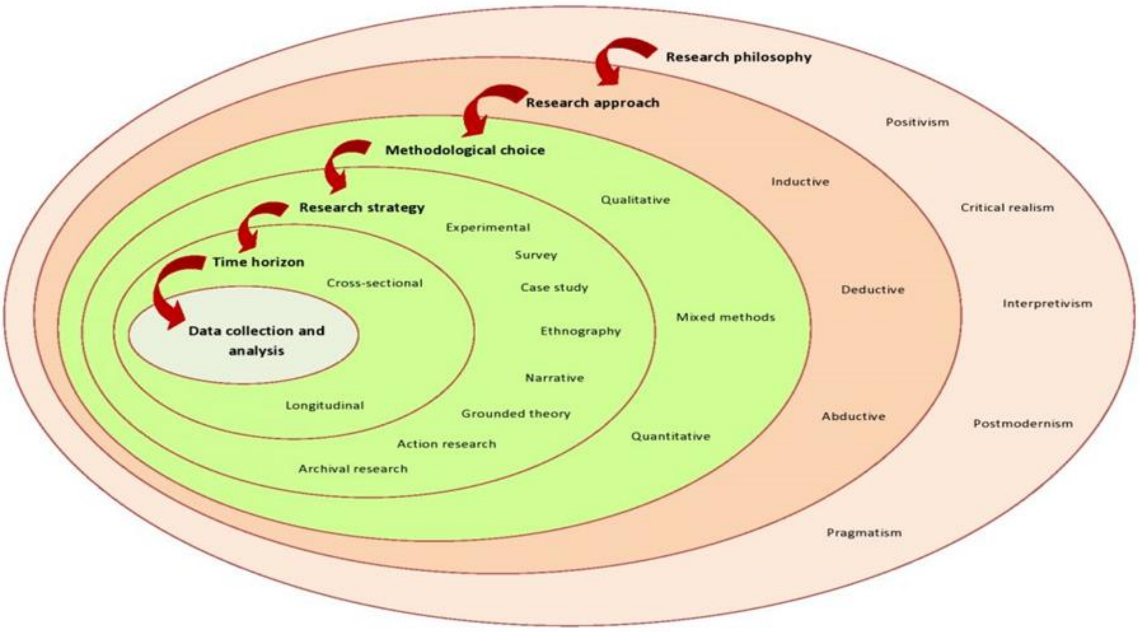


**Fig 3.1 Research Onion** Source; Saunders et al., (2012)

**3.2 Research Philosophy**

A pragmatic paradigm was deemed pertinent for this study (Saunders et al., 2016). A research paradigm refers to the philosophical framework that guides scientific inquiry and shapes how research problems are understood and investigated (Kuhn, 1962). In his seminal work "The Structure of Scientific Revolutions", Kuhn (1962) describes paradigms as conceptual and methodological lenses through which researchers view and interpret the world. In this study, paradigm refers to the conceptual lens adopted to understand the phenomenon of interest - the impact of big data analytics on sustainability strategy.

Big data analytics remains an emerging area of study, and its influence on strategic management within the context of sustainability is still being explored (McAfee and Brynjolfsson, 2012; Chen *et al.,* 2012). This study adopts a pragmatic worldview, which is an approach that advocates for the use of mixed methods and focuses on finding practical solutions to research problems (Tashakkori and Teddlie, 2003). Pragmatism situates itself between objectivism and subjectivism by rejecting the notion that research needs to adhere to either a purely positivist or interpretivist paradigm (Johnson and Onwuegbuzie, 2004).

The pragmatic paradigm is well-suited for this study for several reasons. First, it allows for the combination of both quantitative and qualitative research methods to best address the complex, multi-dimensional research questions (Feilzer, 2010). Second, by taking a pragmatic, mixed methods approach, the study can "sidestep the contentious issues of truth and reality" that arise from other paradigms and instead focus on finding practical answers to the research problem through triangulation of different data sources (Feilzer, 2010, p. 8). Third, pragmatism has been advocated as an appropriate paradigm for studies exploring emerging phenomena where existing theories may be limited (Harrison and Reilly, 2011). Overall, a pragmatic paradigm aligns well with the exploratory nature and objectives of this research. This philosophy is well-suited to this study, as it seeks to establish how big data analytics contributes to sustainable business practices in the telecommunications sector in Zimbabwe.

Liu and Er (2022) posit that pragmatism recognizes that knowledge is necessarily incomplete and that ideas must be tested in practice. Therefore, this research approach emphasizes the collection of empirical data, the use of mixed methods research and the involvement of stakeholders in the research process (Liu and Er, 2022). A pragmatic research approach aligns well with the study's objective to explore the impact of big data analytics on sustainability strategy in the telecommunications sector.

Feilzer (2010) opines that pragmatic approach emphasizes flexibility in research design, allowing researchers to adapt their research approaches to address emerging research questions as they emerge. This approach also aligns with the study's focus on emerging technological trends in the telecommunications sector in Zimbabwe and how they impact sustainable business practices (Feilzer, 2010).

A major underpinning of pragmatist epistemology is that of knowledge seeking and how to improve it (Morgan, 2014a). Big data analytics has influence on sustainability strategy and it remains an area of concern why Zimbabwean telcos are yet to reap the benefits of competitive advantage. One's perceptions of the world are influenced by our social experiences. Therefore, all knowledge is social knowledge (Morgan, 2014a).

Pragmatist epistemology does not view knowledge as reality (Rorty, 1980). Rorty (1980) argued that pragmatism rejects the idea that knowledge can accurately represent an objective reality. Pragmatist epistemology deviates from the metaphysical approach related from truth and reality and focuses on practicalities in real world issues (Patton, 2005).

This philosophy best explains the technological dynamics in the telecommunications industry within the context of 4IR where knowledge creation is being continuously generated with the potential for faster decision making and creating customer centric services and products. Kelly and Cordeiro (2020) implore pragmatic approach is based on; actionable knowledge, inter connectivity between experience, knowing, acting and experiential process enquiry. In essence, a pragmatic research philosophy aligns well with descriptive research of this kind that seeks to find practical ways of solving problems in the telecommunications sector (Kelly and Cordeiro, 2020). Morgan (2014b) opines a strong relationship between social justice and pragmatism. This serves well on the issue of sustainability which conforms to the dictates of social justice.

This study explores and seeks to understand interrelationship of knowledge and action in the context of Big data analytics and sustainability strategy. Saunders (2007) attests research philosophy as a development of assumptions, knowledge and nature of the research.

### 3.3 Research design

Saunders *et al*. (2012) defined research design as a general plan to answer a research question. In this research context, the question is premised on finding out the impact of Big data analytics on sustainability strategy in the telecommunications sector in Zimbabwe. This is a systematic approach to conducting a scientific inquiry, it brings together several components, strategies, and methods to collect data and analyze it. According to (Kothari, 1993) research design is the conceptual structure with which the research is conducted. It constitutes the blue print for data collection process, data measurement which comprises data identification, arrangement and summarisation, and data analysis. Research design also defines all other constituent parts of a study, such as variables, hypotheses, experiments, methodology, and statistical analysis (Creswell *et al.,* 2018). Kelly and Cordeiro (2020)) opine pragmatism is consistent with descriptive research design.

### 3.3.1 Descriptive research design

Combs (2019) opines descriptive research design as a design aimed at obtaining information pertaining a certain phenomenon or population and enables answering questions related to the what, where, when and how status. A descriptive research design on the impact of big data analytics on sustainability strategy in the Zimbabwe telecommunications sector involves gathering and analyzing data to provide a comprehensive description of the relationship between big data analytics and sustainability strategy in the Zimbabwe telecommunications sector.

The purpose of descriptive research is to harness a composite description and explanation about the phenomenon systematically (Creswell, 2012 p. 274). Pragmatism and descriptive research design are closely related in the field of social science research. Pragmatism is a philosophical approach that emphasizes practicality, problem-solving, and the application of knowledge to real-world situations. Descriptive research design, on the other hand, is a specific research methodology that aims to describe and understand phenomena as they naturally occur (Kelly and Cordeiro, 2020). The relationship between pragmatism and descriptive research design can be understood in the following ways:

- Practicality and Problem-solving: Pragmatism emphasizes the practical application of knowledge to address real-world problems. Descriptive research design aligns with this approach by providing a systematic and practical way to observe, measure, and describe phenomena in their natural settings. It allows researchers to gather data that can inform decision-making and problem-solving processes (Kelly and Cordeiro, 2020).

- Contextual Understanding: Pragmatism recognizes the importance of understanding the context in which knowledge is applied. Descriptive research design focuses on providing a detailed and accurate description of phenomena in their specific context. This contextual understanding is valuable for informing practical decision-making and problem-solving efforts (Kelly and Cordeiro, 2020).

- Flexibility and Adaptability: Pragmatism encourages researchers to be flexible and adapt their methods and approaches to suit the needs of the situation. Descriptive research design offers flexibility in its data collection methods, allowing researchers to choose the most appropriate techniques for describing and understanding the phenomenon under study (Kelly and Cordeiro, 2020).

- Empirical Observation: Pragmatism emphasizes the importance of empirical observation and evidence-based decision-making. Descriptive research design aligns with this approach by emphasizing the collection of empirical data through systematic observation, surveys, interviews, and other methods. This empirical evidence provides a foundation for practical decision-making and problem-solving (Kelly and Cordeiro, 2020).

The relationship between pragmatism and descriptive research design lies in the shared focus on practicality, problem-solving, empirical observation, and contextual understanding (Kelly and Cordeiro, 2020). Both approaches aim to provide useful and applicable knowledge that can inform decision-making and address real-world problem (Kelly and Cordeiro, 2020).

As Kelly and Cordeiro (2020, p. 101) state, "pragmatism emphasizes the practical application of knowledge to address real-world problems," aligning well with the goal of descriptive research to "provide a systematic and practical way to observe, measure, and describe phenomena in their natural settings" and gather data that can solve issues. By emphasizing empirical data collection and a detailed understanding of the specific context under investigation, descriptive research adheres to pragmatic principles of basing actions and policies on objective evidence from the conditions at hand rather than on preconceived ideas (Kelly and Cordeiro, 2020).

Jones (2022) postulates that descriptive research designs typically collect three primary types of information: current information relating to the variables or conditions about a phenomena, evaluating the standard norms, procedures, preparations, considerations and resources required for conducting said research and the method of meeting expected objectives through exploration of way and means based on observed phenomena (Jones, 2022).

The descriptive research design will involve a process of collection and analysis of both qualitative and quantitative data. The descriptive research design is useful in this case as understanding data analytics is statistical in that it can be counted, measured and expressed through numbers while sustainability strategy is descriptive and conceptual (Jones, 2022).

Creswell (2002) opines that quantitative research involves collecting, analyzing, interpreting, and writing the results of a study, while qualitative research involves approach to data collection, analysis, and report writing thus differing on how the results are structured. The research instruments in this study provided both qualitative and quantitative outcomes (Jones, 2022).

**Research approach**

Saunders *et al.,* (2012) identify inductive, deductive and abductive research approaches. This study employed abductive approach which embraces inductive and deductive reasoning respectively within the descriptive research design context. Inductive reasoning entails developing a theory from specific observations to a generalised conclusion in contrast to deductive reasoning which is aimed at testing a theory hypothetical which hypothesis is rejected or not (null or alternative respectively)(Saunders *et al.,* 2012). Gabriel (2013) observes that deductive approach is more related to causality and inductive approach is focused on exploring new phenomena or interrogating previously researched ideas from a different perspective. Hassad and Rossi (2020) opine Big data analytics being novel and entails innovation which requires fluid thinking or inductive reasoning. The approach is premised on the philosophical phenomena of pragmatism of determining the truth and reality in what actually works (Kelly and Cordeiro, 2020).

The introduction of the novel technology of Big data analytics to organisational science has applied principles of inductive and deductive reasoning to address its objectives relating to the impact of analytics on organizational strategies (Hassad and Rossi, 2020). A mixed methods approach provided complementary inductive-deductive insights through qualitative exploration of strategic phenomena and quantitative analysis of analytics metrics (Johnson *et al.,* 2007).

Inductive logic allowed for discovery of new strategic patterns and themes emerging from analytics applications, while deductive testing of hypotheses generated theories about causal effects (Hassad and Rossi, 2020; Johnson *et al.,* 2007). This approach aligns with the philosophical pragmatism underlying this study, aiming to determine useful practical insights from big data rather than prove predetermined notions (Kelly and Cordeiro, 2020).

**a. Inductive Reasoning Approach**

**Qualitative Data Collection**

Semi structured interviews and open-ended survey questions allowed for inductive exploration without preconceived hypotheses. This facilitated organic emergence of insights from participant narratives (Hair *et al.,* 2019; Saunders *et al.*, 2015). The flexibility of these qualitative methods aligns with the inductive logic and philosophical pragmatism guiding this study by permitting discovery of useful knowledge directly from stakeholders' experiences rather than verification of predetermined ideas (Kelly and Cordeiro, 2020).

**Thematic Analysis**

Qualitative data was inductively analyzed through iterative open coding to identify recurrent themes across cases (Braun and Clarke, 2006). This process aligned with the philosophical pragmatism and inductive logic guiding the study by allowing patterns to organically emerge from participant narratives rather than fitting data to predetermined categories (Braun & Clarke, 2006; Kelly and Cordeiro, 2020). This provided thick descriptions of phenomena in their natural contexts (Hair *et al.,* 2019).

**Hypothesis Generation**

The people within the study perspectives and regular patterns in the data were used to form testable hypotheses and propositions about relationships between constructs (Saunders *et al.,* 2015). Deductive analysis involved "the process of narrowing data into a few themes or hypotheses about what was important or interesting" (Creswell and Creswell, 2018, p.195). This allowed hypotheses to be generated regarding how big data analytics could impact sustainability strategy based on emergent themes from qualitative inquiry.

**b. Deductive Reasoning Approach**

**Operationalisation of Constructs**

Constructs identified through qualitative inductive logic were operationalised into measurable variables (Hair et al., 2019). This process involved "the development of precise definitions of constructs or concepts of interest so that they could be measured" (Saunders et al., 2015, p. 695). For example, the inductively derived theme of 'sustainability strategy' was operationalised as measurable variables such as carbon emissions reduction targets, renewable energy adoption goals. This allowed constructs to be quantitatively assessed through deductive testing of hypotheses generated from qualitative inquiry.

**Quantitative Data Collection**

The mixed methods questionnaire was developed deductively to test hypotheses relating to big data analytics capabilities and sustainability strategy implementation. Closed-ended questions with standardized response options operationalised constructs were identified through prior qualitative inquiry (Saunders *et al.,* 2015; Hair *et al.,* 2019).

Ratings scales and select-all items captured data on variables such as analytics usage frequency, types of data analyzed, and perceived impacts on operational efficiency. This quantitative strand aimed to test hypotheses that higher adoption of analytics capabilities correlated positively with sustainability performance (Creswell and Creswell, 2018).

Concurrently, open-ended questions allowed respondents to qualitatively describe analytics applications, strategies, and challenges in their own words. This helped address potential limitations of closed questions in oversimplifying complex organizational realities (O'Cathain and Thomas, 2004).

Integration of quantitative and qualitative data strands supported triangulation during analysis (Bryman, 2006). Both deductive hypothesis testing and inductive theme exploration were facilitated through the mixed methods design. In essence, the questionnaire sought to generalize qualitative findings on big data's role in sustainability through statistical examination of relationships between operationalised factors.

**Statistical Modeling**

Data was analyzed using deductive statistical techniques to test hypotheses, quantify effects and generalize findings (Hair *et al.,* 2019).

**Results Integration**

Inductive and deductive strands were integrated during interpretation to provide a holistic understanding (Saunders *et al.,* 2015).

Bhandari (2022) opines that deductive reasoning is a logical approach where you progress from general ideas to specific conclusions. It is the inverse of inductive reasoning. Sanders *et al.* (2019) propound deductive reasoning through hypothesis testing of the following:

H1: Sales data analytics influences sustainability strategy of telecommunications companies.

H2: Customer data analytics usage positively influences sustainability strategy of telecommunication companies in Zimbabwe.
H3: Social media data analytics application affects sustainability strategy of companies in the telecommunications sector in Zimbabwe.

H4: Supply chain data analytics has a positive effect on sustainability strategy in the telecommunications sector in Zimbabwe.

i. **Methodological choice**

The study engaged a mixed method choice. This involved a concurrent process of collection and analysis of both qualitative and quantitative data. The mixed method research was useful in this case as understanding data analytics is statistical in that it can be counted, measured and expressed through numbers while sustainability strategy is descriptive and conceptual. By virtue of the fact that there was a causal effect relationship between big data analytics and sustainable strategy, concurrent mixed method research design was administered. Concurrent matrix was used to highlight the relationship between variables by showing cause and effect relations or forecasting future events or a result from a variable (Creswell, 2008). Creswell (2002) opines that quantitative research involves collecting, analysing, interpreting, and writing the results of a study, while qualitative research involves approach to data collection, analysis, and report writing thus differing on how the results are structured. The research instruments in this study provided for both qualitative and quantitative outcomes.

ii. **Research strategy**

Saunders *et al.,* (2007) propounds research strategy as a road map to accomplishing the research objectives. A research strategy is a plan of action systematically designed to capture thoughts and efforts so as to enable production of quality information and detailed reporting on schedule (Walia and Chetty, 2020).

The research adopted the survey research strategy. Survey research strategy is a collection of information from a sample of the population through their responses (Check and Schutt, 2012, p 160). Survey research is a strategy that can be used in relation to descriptive research design. Survey research strategy is an approach of descriptive research design that blends quantitative and qualitative data to provide you with relevant and accurate information (Sirisilla, 2023). Descriptive survey design is a time-efficient research method which engages the people at the center of the research objective. Survey research enables gathering large volumes of data that can be analyzed for patterns and trends. Survey research can capture research data through questionnaires, interviews and observations. The key characteristics in a survey are usage, systematic, replicable, types, data format and impartiality. The advantages of a survey are: relatively easy to administer, easy to design, can be administered virtually, capacity to collect data from a large number of respondents, numerous questions can be administered with ease, advanced survey statistical tools can be used to determine validity, reliability and statistical significance and broad range of data can be collected. Survey can align to a variety of questions types i.e multiple choice, Likert scale etc.

Survey strategy embraces defined independent and dependent variables, testable hypothesis and random sampling to the study (Bell, 2009). In survey research the independent and dependent variables are called explanatory variables as they define an event or output. Bell (2009) posits that a survey research utilises a sample of the population to enable findings which project the characteristics of the whole population. In this study the independent variable was Big data analytics and dependent variable was sustainable strategy bench marked on the triple bottom line. The testable hypothesis as depicted on Fig 2.8 Conceptual framework diagram measured the cause - effect relationship between Big data analytics and sustainability. The moderating and mediating effect of the adoption framework and integrated resources respectively, provided a factual and testable hypothesis. The sample was derived from the Zimbabwe telecommunication sector population of TelOne, NetOne, Telecel and Econet. Ashraf (2021) posits that an experimental design is the study of the causal - effect relationship anchored on two or more variable which independent variable is systematically altered to observe the changes in the dependent variable.

In survey research the independent and dependent variables determined the scope of this study but could not be controlled by the researcher (Glasow, 2005). The current study determined the impact of BDA (independent variable) on SS (dependent variable). The protocols entailed use of the Big data analytics capabilities, the adoption framework and integrated resources which were moderator and mediating variables respectively. The sustainability strategy was measured through efficacy to the people, profit planet matrix.

iii. **Time horizon**

Alamgeer (2022) opines time horizon as the time span required to complete a research on the population under study. Gabner and Kosow (2008) postulate 3 categories of time horizons which are short term (up to 10 years), medium term (up to 25 years) and long term (more than 25 years). Saunders et al. (2012) posit time horizon in aspects of cross sectional and longitudinal studies. Crossley (2021) posits cross-sectional time horizon is suitable for descriptive survey research when:

- The research aims to describe the current situation or status of a phenomenon at a specific point in time.
- The research does not require tracking changes or trends over time.
- The research has limited time and resources to conduct repeated observations

This study was inclined to the cross sectional time horizon whose benefit was anchored on simultaneous comparison of all variables at a specific point of time and surveys were best placed (McCombes, 2023). Cherry (2019) opines that cross sectional studies are designed to look at a variable at a particular point in time. This is influenced by convenience, financial and time limitations in the research study. The advantages that accrue from the cross sectional study are; expedited outcomes, can collect all variables data simultaneously, multiple outcomes studied concurrently, resultant factors can be measured, descriptive analysis provision and further research basis. The time horizon in this study interrogated what was currently prevailing in order to make inferences, related to Big Data analytics and sustainability strategy in Zimbabwe telecommunications sector which made it cross sectional / retrospective.

### 3.4 Population

A population is a large collection of persons, events or objects that possess specific characteristics that constitute a scientific inquiry (Bhandari, 2020). To evaluate the experiences of how Big Data analytics was done and how it influenced sustainability strategy, the study focussed on TelOne, Econet, Telecel and NetOne directors (executive and non - executive) and other employees who represented the larger population from which the sample was drawn. This collection of individuals was the target population and was pivotal in addressing the research problem.

**Table 3.1 - Population**

| | TELECEL | NETONE | ECONET | TELONE | |
|---|---|---|---|---|---|
| Non-Executive Directors/ Board | 6 | 9 | 11 | 10 | 36 |
| C - Suite (EXCO) | 4 | 8 | 15 | 10 | 37 |
| Other employees | 923 | 620 | 2574 | 1200 | 5317 |
| **TOTAL** | | | | | 5390 |

**Source:** Researcher's findings (2023)

Burns and Grove (1997) postulate that the population is the entire aggregation of respondents that meet the designated set of criteria. The total population of 5390 people was involved in the execution and operationalisation of the sustainability strategy.

### 3.5 Sampling

Touvilla (2020) defines sampling as a process used in statistical analysis in which a predetermined number of observations are taken from a larger population. Bhandari (2020) opines a sample as a subset of the population where the scientific inquiry is conducted. Sample selection is dependent on the population size, homogeneity, sample media and cost of use and degree of precision (Salant and Dillman, 1994.p 54). Big data in the 4IR had brought a new phenomenon in telecommunications. This put Econet, TelOne, NetOne and Telecel into perspective as the population. This study was directed at drivers and operatives of strategy in telecommunication companies dealing with big data analytics capabilities, be it in cloud, data centres or both. The sampling technique chosen for this study was stratified random sampling and purposive sampling respectively. In order to ascertain the confidence levels @ 95% and margin of error @ 5%, the Krejcie and Morgan (1970) table was applied. This method prescribes a sample size of 357 respondents. The determinants of sample size are premised on the following five factors: desired degree of precision, statistical power required, ability of the researcher to gain access to the study respondents, degree of which the population can be stratified and the selection of the relevant units of analysis (Nagar and Tiwari, 2014).

The initial projected sample size was 357 respondents from a population of 5390 employees from the four (4) companies using the Krejcie and Morgan Table (1970), however due to challenges, emanating from proprietary rights and competitive landscape, the population and sample size was configured to 100 and 80 respectively with participation from (2) companies (TelOne and NetOne). The population size was realigned to focus on employees (resource persons) who were associated with Big data analytics and sustainability strategy. The sampling approach embraced a combination of stratified sampling based on size, market share, Big data handling and purposive sampling targeted at management who carried out strategic decisions and had rich qualitative information related to Big data analytics and sustainability strategy.

**Table 3.2 – Population and Sample size**

| **Stratum** | **Company** | **Population size** | **Sample size** |
|---|---|---|---|
| 1 | NetOne | 40 | 32 |
| 2 | TelOne | 60 | 48 |
| Total | | 100 | 80 |

**Source**: Researcher (2023)

While the failure to secure data collection authorization from Telecel and Econet presented a limitation to the study, the adaptation to focus on TelOne and NetOne's workforce related to Big Data analytics and sustainability provided valuable insights into the research questions and objectives associated with the study.

### 3.5.1 Stratified random sampling for Quantitative Data

Stratified random sampling is a probability method where a stratum is selected from a population and then randomly sampled (Kothari, 1985). Thomas (2023) posits proportional stratified random sampling as the sample size of each stratum which is proportional to the population size of that stratum. Howell et al., (2020) posit that stratified random sampling ensures every stratum is adequately represented within the sample hence; reducing sampling error and variability within each strata, obtain true estimates for each strata related to the research question, captures key population characteristics in sample and minimum error of estimation compared to a simple random sample of the same size. The population was stratified according to hierarchy which consisted of the board of directors, C-suite (chief executive officer, chief operations officer, chief finance officer, chief information officer and chief technical officer) and other employees. This ensured that every stratum is fully represented (Ackoff, 1953). The operational level, management level and strategic levels were captured to enable optimum data. This study focused on particular characteristics of a population that were of interest, which best responded to the research questions (Bhandari, 2020). The 5390 respondents were stratified according to hierarchical level and then randomly selected. Questionnaires which provided quantitative data were administered to the 357 respondents. Ackoff (1953) opines that stratified random sampling as mostly applied in quantitative research due to its representative nature. The strata sample was calculated basing on the level of proportion to the 357 total sample size defined through the Krejcie and Morgan (1970) table.

### 3.5.2 Purposive Sampling for Qualitative Data

Purposive sampling was used to select key informants for interviews (De Vaus, 2001; Saunders *et al.,* 2016). Purposive sampling refers to non - probability sampling techniques addressing characteristics that are needed in the sample under study based on researcher's judgement and research objectives (Nikolopoulou, 2023). Palinkas et al. (2013) postulate that purposive sampling is mostly used in qualitative research to enable gathering of information-rich issues associated with the phenomenon under research and most suitable for implementation research. The Telcos (Econet, TelOne, Telecel and NetOne) and their C - suite ( Chief Executive Officer, Chief Technology Officer, Chief Information Officer, Chief Financial Officer and Chief Operations Officer) were purposefully identified for this research. By virtue of the C-suite being strategically placed, they were best suited to provide an over view of the firm. The researcher decided what needed to be known and set out to find people who were willing to provide the information by virtue of knowledge or experience (Bernard, 2002; Lewis and Sheppard, 2006). Purposive sampling was directed to the 37 C-suite (Executive Committee) interviews. Gray (2007) defines purposive sampling as a non-randomized method that is used when the researcher knows the person who possesses the information that he/she needs. On selection of the four companies, the researcher targeted C-suite and the data sources within each organisation were identified. The reason for purposive sampling is anchored on improved matching of the sample to the aims and objectives of the research which ultimately improves the rigour of the research and trustworthiness of the data and results (Nurs, 2020). This sampling method helped the researcher to get most of the available qualitative data within the organisations. The researcher was mindful of the saturation point when responses converged and no new insights were gathered. Saturation is the most common measure for assessing the adequacy of purposive samples in qualitative research (Morse, 1995, 2015; Sandelowski, 1995). Saturation ensures quality and validity of the study.

### 3.6 Instrumentation

Instruments are tools used to collect measure and analyse meaning in the research understudy (Hinds, 2000). This study utilised three research instruments that were questionnaires, interview and documentary evidence. Salant and Dillman (1994) espouse use of mixed mode survey (interviews and questionnaires). This notion assisted in achieving triangulation. The choice of these instruments was determined by the method of data collection and the mixed method format consistent with pragmatism philosophy and survey research strategy of this study.

### 3.6.1 Questionnaire

A questionnaire as stated by Gray (2007) is a research instrument that is designed with close ended questions. This study generated a self-administered questionnaire which was served to the respective respondents within the selected Telcos. The generated questionnaires were close ended and subjected to a Likert scale to be filled in by the respondents. The benefits that accrued from this type of questionnaire is that they were cheaper and easier to administer than personal interviews and they guaranteed client confidentiality. "Self-administered questionnaires allowed respondents time to think" (Nolinske, 2008, p.10).

### 3.6.2 Interview Guide

The interview guide guided the researcher with regards to research objectives but also allowed for further probing thereby providing detailed information (Creswell, 2014). This study applied the interview guide to enable qualitative measurement of data. Bird (2016) posits that an interview guide provides for high level topics under study and high level questions related to topics for response. A set standard of questions were asked to respondents within a specified time-frame without cross questioning.

The executives were selected for the interview schedule since they drove the strategy and were the repository of strategic data. They provided linkage between policy and operationalisation.

### 3.6.3 Documentary analysis guide

Macdonald and Tipton (1993) and Gilbert (1993) opine that documentary evidence are documents used in social research which provide a record of the social world at the time of the reseasrch. Documentary analysis is a type of qualitative research that involves analyzing documents for data. Documents can be any written or visual materials that provide information about a topic or phenomenon. Documentary analysis can be used in descriptive survey research to complement other methods of data collection, such as questionnaires or interviews.

Documents and records were readily accessible and at zero or low cost. They provided a stable and rich source of information which did not change over time. They were legally unassailable and non-reactive. Documentary evidence emanate from peer reviewed, empirical reviewed journals, documented trend analysis reports, public records and papers. In this era of 4IR digital transformation a lot of research papers addressing the variables under consideration were accessible on the internet.

Documentary analysis can be used in descriptive survey research to achieve the following:

- provide historical or contextual background for the research topic.
- compare and contrast different perspectives or sources of information on the topic.
- identify themes, patterns, trends, or gaps in the existing literature or data on the topic.
- corroborate or challenge the findings from other methods of data collection.
- generate new questions or hypotheses for further research.

The choice of documents and the method of analysis relate to the research question, the purpose of the study, and the theoretical framework of this research. Morgan (2022) espouses common methods of documentary analysis as content analysis, discourse analysis, thematic analysis, and narrative analysis:

Content analysis: This method involves quantifying and categorizing the content of documents based on predefined codes or themes. Content analysis can help measure the frequency, intensity, or sentiment of certain words, phrases, or topics in the documents. This method is suitable for descriptive survey research that aims to describe the characteristics, trends, or patterns of a population or phenomenon based on existing documents.

Discourse analysis: This method involves examining the language and meaning of documents in relation to the social, cultural, or political context. Discourse analysis helps identify the assumptions, ideologies, or power relations that underlie the documents and how they shape or influence the topic or phenomenon. This method is suitable for descriptive survey research that aims to explore the perspectives, opinions, or discourses of a population or phenomenon based on existing documents.

- Thematic analysis: This method involves identifying and describing the main themes or patterns that emerge from the documents. Thematic analysis helps explore the diversity, complexity, or similarity of the documents and how they relate to the research question or purpose. This method is suitable for descriptive survey research that aims to understand the experiences, issues, or phenomena of a population or phenomenon based on existing documents.

- Narrative analysis: This method involves analyzing the stories or narratives that are told in the documents. Narrative analysis can help you understand the experiences, perspectives, or emotions of the people or groups involved in the topic or phenomenon and how they construct their identities or realities. This method is suitable for descriptive survey research that aims to interpret the stories, meanings, or values of a population or phenomenon based on existing documents.

### 3.7 Data collection procedures

Data collection procedures were methods on how the research data was aggregated to become useful in the study to answer research questions, test hypothesis and draw conclusions Bhandari (2020). The time horizon adopted was cross sectional for the purpose of convenience, time and cost. The data collection was targeted to both quantitative and qualitative since the research was a mixed method approach.

#### 3.7.1 Administration of the Questionnaire

Administration of the questionnaire refers to the process of delivering the questionnaire to the respondents and collecting their responses. There are different ways of administering questionnaires, such as face-to-face, by phone, online, or on paper (Bhandari, 2021). The choice of the method depends on various factors, such as the research objectives, the target population, the budget, and the time available. A questionnaire is a set of standardized questions which seek to address the research questions. This is a self - administered technique by the respondent with questions of research which are investigative and aimed at answering the research questions. Denscombe (2017, p. 184) posits the following characteristics of a good questionnaire; response rate, completion rate, validity of responses. The questionnaire sought to establish the following information; demographic, knowledge, attitude items and self - perception questions. All the respondents were subjected to a close and open ended questionnaire as a means of collecting quantitative data which was measured numerically.

### 3.7.2 Interviews

Interview guide the researcher with regards to objectives but allowed for further probing, and provided detailed information (Creswell, 2014). The executive and management have been purposively selected for the interview since they drive the strategy and are repository of strategic data. The method of interviews will be premised on the semi structured type where a set standard of questions will be asked within a specified time-frame. The interviews provide qualitative and quantitative data for the interview guide and interview schedule respectively. The interview guide is directed to the 5 respondents who formed part of management and executive.

### 3.7.3 Documentary analysis

Documentary analysis is a method of qualitative research that involves examining and interpreting documents and records relevant to a particular study (Hassan, 2023). Documents can be electronic or physical, public or personal, and include various types of sources, such as official records, personal accounts, and physical evidence. Hassan (2023) opines Documentary analysis is used for various purposes, such as:

- Providing context and background information for the research topic
- Generating research questions and hypotheses
- Identifying situations or phenomena to observe or investigate further
- Providing additional insights or perspectives on the research topic
- Confirming or challenging evidence from other sources or methods
- Tracking the development and changes of the research topic over time

And involves several steps, such as:

- Selecting relevant documents and records for the research topic and objectives
- Evaluating the quality, credibility, and purpose of the documents and records
- Organizing and categorizing the documents and records according to themes, patterns, or concepts
- Analyzing and interpreting the meaning, implications, and significance of the documents and records

- Comparing and contrasting the documents and records with other sources or methods of data collection

Reporting and presenting the findings and conclusions from the documentary analysis

This qualitative data is used to interpret and investigate limitations of physical sources. Documentary evidence is proof that is presented in the form of documents, such as writings, photographs, recordings, or digital files. This can be used to prove or disprove a fact or a claim in a legal or academic context. The documentary evidence is authenticated, by means of exhibiting attributes of being genuine, relevant, and reliable. Big data analytics adoption and sustainability strategy invoked trend analysis from reports.

### 3.8 Reliability, validity and trustworthiness

Reliability and validity project desirable psychometric characteristics of research instruments. Trustworthiness establishes the research study's findings credibility, transferability, dependability on the qualitative aspect. These are concepts that determined quality criteria for data results. Middleton (2023) opines reliability and validity as concepts that measure whether the tests meet the criteria for the study to provide quality results. Pilot and Beck (2014) postulate trustworthiness as the degree of confidence in the study used to measure quality. The descriptive survey design mixed methodological choice in this study was crafted to ensure reliability, validity and trustworthiness of the results, through appropriate method and sample, and conducting of research consistently.

Cleod (2023) posits reliability as a measure of consistency in a quantitative research study. Sauro (2015) defines reliability as a measure of the consistency of a metric or a method. Reliability is ensured through applying a consistent method in carrying out the measurement and standardisation of the conditions of the study to be consistent thus minimising the influence of any external factors that might introduce a variance on the result. Middleton (2023) opines reliability in quantitative data on a descriptive survey design as the degree to which the survey metric is consistent and reproducable. Reliability manifests in internal and external reliability. Internal reliability assesses consistency of results under test whilst external reliability is a measure of consistency in another use. The measure of consistency quantitatively from questionnaires, in this study stood the test of consistency. When a research instrument is used in same situation repeatedly and consistently produces the same results is an exhibition of reliability (Heal and Twycross 2015). Quantitative data derived from the questionnaire was tested for internal consistency through use of Cronbach coefficient alpha. The general rule of thumb accepts anything 0.70 and above as good.

### 3.8.2 Reliability of Qualitative data from Interviews and Documentary Evidence

Reliability in qualitative research is defined as 'dependability' (Rolfe 2006; Erlingsson and Brysiewicz 2013), 'confirmability' (Jensen,2008) or 'consistency' (Arksey and Knight 1999). Barbour (2001); Thomas (2006}; Burnard et al (2008); Vaismoradi et al (2013); Smith and Noble (2014) and Gray (2018) opine reliability as the stability of multi coders of data sets responses. Qualitative data reliability will use the inter-rater reliability measured through Krippendorff alpha coefficient. A measure of 0.80 and above is deemed appropriate.

### 3.8.3 Validity of quantitative data

Twycross and Heale (2015) define validity as the extent to which a phenomenon is accurately measured in a quantitative study. Middleton (2022) opines the accuracy of a method to measure the results that correspond to real world values is considered valid and premised on four types which are: construct , content , face and criterion validity.

- Construct validity measures the concept that is under test
- Content validity measures the entirety in representative terms of what it desires to measure.
- Face validity measures the content suitability to its aims..
- Criterion validity measures the accuracy of the defined outcome specified.

Creswell and Creswell (2018), opine validity as the extent to which a study measures what it is intended to measure. In order to guarantee validity in quantitative data the use of established and reliable measurement tools is recommended. In survey research, validated questionnaires or instruments can be used to collect data. Which ensure that the data collected is measuring the intended constructs accurately (Schreurs *et al.,* 2018). Another format that ensures validity is the use of a representative sample. Creswell & Creswell (2018) postulate a representative sample as one that accurately represents the population being studied and can help ensure that the data collected is generalizable to the population of interest. The establishment of clear research questions and objectives can also help ensure the validity of quantitative data (Schreurs *et al.,* 2018).

### 3.8.4 Validity of qualitative data

Validity of qualitative data is "the correctness or credibility of a description, conclusion, explanation, interpretation, or other sort of account"(Maxwell, 1996, p. 87). Maxwell (1996, p. 88) posits that validity in qualitative research can be applied after the commencement of the research using established evidence within the study. Validity can be tested through the process of respondent or process validation respectively. Respondent validation in this study involved evaluating the results through concurrence with respondents whilst process validation was premised on tripartite concurrence of researcher, respondent and the data consumer. Maxwell (1996) postulates validity tests types are premised on description, interpretation, theory and generalisation.

Creswell and Creswell (2018), validity in qualitative research refers to the extent to which the study accurately represents the experiences and perspectives of the participants. Ensuring validity in qualitative data can be established through trustworthiness. Trustworthiness refers to the extent to which the findings of the study are credible, transferable, dependable, and confirmable (Lincoln and Guba, 1985). To establish trustworthiness, techniques such as member checking, peer debriefing, and triangulation can be applied (Creswell and Creswell, 2018).

Other methods to ensure validity include the use of a purposive sample. A purposive sample is one that is selected based on representative of population relevant to the research question. This ensures that the data collected is relevant and meaningful to the research problem (Creswell and Creswell, 2018). Establishing concise research questions and objectives can help ensure the validity of qualitative data (Schreurs *et al.*, 2018).

The validity of qualitative data in a descriptive research design and survey research strategy can be ensured through the establishment of trustworthiness, the use of a purposive sample, and clear research questions and objectives.

### 3.8.3 Trustworthiness (rigour of the study)

Pilot and Beck (2014) postulate trustworthiness as the degree of confidence applied in the study to ensure quality. Lincoln and Guba (1986) posit a four dimension criteria (FDC) which involves credibility, dependability, conformability and transferability as stringent criteria for trustworthiness in qualitative research.

- Credibility - establishing confidence that results from respondents are true ,credible and believable
- Dependability - ensuring that the results are repeatable within the same cohort of participants.
- Confirmability - establish confidence that the results would be confirmed and corroborated by other participants or researchers.
- Transferability - the ability to extend the results to other contexts or settings.

Trustworthiness can be established and enhanced through the use of reliable instruments (Schreurs *et al.,* 2018). This study utilised interviews, questionnaires and documentary evidence.

## 3.9 Ethical considerations

Ethical considerations formed a major element of this research. Chetty (2016) opines that the researcher needs to agree to promote the aims of the research imparting authentic knowledge, truth and prevention of error. These consist of fundamental ethical principles which are applied in research and consist of informed consent, confidentiality mitigating against response bias, and oversight and approval. Key considerations were as follows:

### 3.9.1 Informed Consent Process

A detailed electronic information sheet and consent form (Chetty, 2016) was distributed to potential participants. These documents were developed using simple, non-technical language to ensure full comprehension by participants (Jaiyeoba, 2021). Participants were given time to carefully review the documents and ask any clarifying questions to confirm voluntary and informed consent was provided (Khan *et al.,* 2020).

### 3.9.2 Confidentiality Safeguards

Strict confidentiality measures were implemented (Khan *et al.,* 2020; Jaiyeoba, 2021) to ensure privacy of responses. Identifying information such as names and contact details were not collected. Each response was assigned a coded identifier, and the identifier key was stored securely and separately from the data to prevent any possibility of linking responses back to individual participants (Chetty, 2016).

### 3.9.3 Mitigating Response Bias

Anonymity and confidentiality protocols (Chetty, 2016; Khan *et al.,* 2020) addressed potential bias due to sensitivity of topics and gave assurance against attribution of responses (Jaiyeoba, 2021). This was reinforced clearly in the participant information materials.

### 3.9.4 Oversight and Approval

Formal written ethics approval was prospectively granted by the Great Zimbabwe University Institutional Ethical Review Board prior to commencement, following a rigorous review of the research protocol and ethics plans (Chetty, 2016). This provided independent oversight and ensured strict adherence to ethical standards in order to protect participant interests (Jaiyeoba, 2021).

## 3.10 Data analysis

Gay, Mills and Airasian (2009) opine data analysis as the process of systematically applying statistical and/or logical techniques to describe and illustrate, condense and recap, and evaluate data.

Hair *et al*.(2019) data analysis involves inspecting, cleaning, transforming, and modeling data to discover useful information, infer conclusions, and support decision making. The purpose of data analysis is to extract useful information from data and draw conclusions based on the processed data. This helps identify patterns, relationships and trends in the data where conclusions and informed decision can be drawn.

Hair *et al.*(2019) posit key aspects of data analysis which include:

**i. Approach**

In line with recommendations by Hair *et al.,* (2019), a mixed methods approach was adopted for comprehensive data analysis and interpretation. Both qualitative and quantitative techniques were utilized to address the research objectives.

**ii. Preliminary Analysis**

Preliminary descriptive statistics provided an overview of the data as suggested by Hair *et al.,* (2019). Frequency distributions and measures of central tendency helped identify patterns and outliers across variables such as respondent demographics and analytics usage levels.

**iii. Quantitative Analysis**

Statistical modeling techniques including chi-square tests were used to test hypotheses about relationships between variables as recommended (Hair *et al.,* 2019). For example, associations between challenges faced and levels of analytics adoption were examined. This aided explanation of variability in the quantitative data.

**iv. Qualitative Analysis**

Thematic analysis involving open coding of responses to open-ended questions was conducted as per standard practice. Emergent themes related to challenges experienced and strategies for optimization were identified.

**v. Data Visualization**

Key findings from both quantitative and qualitative strands were visualized using tables, graphs and word clouds to facilitate interpretation and communication of insights as suggested by Hair *et al.,* (2019).

#### vi. Iterative Exploration

An iterative process of data exploration and interpretation was followed to gain deeper understanding as participants refined insights in light of the research objectives and questions (Hair *et al.,* 2019). Both statistical results and qualitative perspectives were considered.

#### vii. Integration and Interpretation

Finally, quantitative and qualitative strands were integrated during interpretation and reporting of results. Findings were discussed in the context of previous studies and the conceptual framework to address the research problem comprehensively.

### 3.10.1 Quantitative data analysis

Bhandari (2020) defines quantitative data analysis as the process of collecting and analysing numerical data. This study tested causal relationships, makes predictions, finds patterns and averages and generalize results to wider populations. This research applied inferential and descriptive statistics respectively. Inferential statistics showed the relationships between multiple variables in order to generalise and make predictions and in this particular case the correlation between Big Data analytics and sustainability strategy. Descriptive statistics which apply the measure of central tendencies (mean, median, mode) and correlation analysis was employed. SPSS (Statistical Package for Social Science) was adopted.

In the context of descriptive research design complemented by survey research strategy on "The impact of Big data analytics to Sustainability strategy in the telecommunications sector in Zimbabwe," the following quantitative data analysis techniques were applicable:

i. **Descriptive statistics:** Descriptive statistics was used to summarize the data collected from the survey. Measures such as the mean, median, mode, standard deviation, and range were calculated to provide insights into the distribution and characteristics of the data (Mertler and Reinhart, 2016).

ii. **Inferential statistics:** Inferential statistics was used to test hypotheses about the relationship between big data analytics and sustainability strategy in the telecommunications sector in Zimbabwe. An example of Hypothesis which reads: By leveraging big data analytics, telecommunication companies in Zimbabwe can develop and implement more sustainable strategies, resulting in a reduced carbon footprint and a positive impact on the environment. This hypothesis were tested using techniques correlation analysis (Mudavanhu and Mhlanga, 2020)

iii. **Data visualization:** Data visualization techniques such as bar charts, pie charts, and histograms were used to present the results of the survey in a visual format. This helped to identify patterns and trends in the data that could not be immediately obvious from numerical summaries (Cairo, 2013; Few.2009; Tufte, 2001; Cleveland,1993).

iv. **Factor analysis:** Factor analysis was used to identify underlying factors (Kline. 2011 p. 59) that contributed to sustainability strategy in the telecommunications sector in Zimbabwe. Factors such as energy efficiency, waste reduction, and resource conservation were identified and analyzed to determine their relationship with big data analytics.

### 3.10.2 Qualitative data analysis

Thematic content and narrative analysis were used for qualitative data analysis. This study was a mixed research method which encompassed both qualitative and quantitative analysis. The qualitative aspect of the study research instruments included content analysis and interviews. Documents were interpreted to give meaning to the study under consideration through incorporating coding content (Bowen, 2009). Qualitative Data Analysis was used for analysing data and exhibiting some level of comprehension, explanation, and interpretation of patterns and themes in textual data (Dudovskiy, 2018). Computer assisted qualitative data analysis software (CAQDAS) was employed.

The qualitative data collected through interviews was analyzed using thematic analysis. Thematic analysis is a method for identifying, analyzing, and reporting patterns (themes) within data (Braun and Clarke, 2006). It minimally organizes and describes the data set in rich detail. For this study, thematic analysis was deemed most appropriate given its flexibility as a method that can potentially provide a rich and detailed account of data.

The process of thematic analysis involved becoming familiar with the data through transcription, generating initial codes, searching for themes, reviewing themes, defining and naming themes, and producing the final report. All interviews were transcribed verbatim. The transcripts were read and re-read to gain familiarity with the depth and breadth of the content. Initial codes of interest were generated in a systematic fashion across the entire data set before broader themes were identified. Themes captured important aspects in relation to the research questions.

Themes were reviewed and refined through an iterative process to ensure internal homogeneity and external heterogeneity. Themes were defined and further refined by identifying the story each theme told, determining what aspect of the data each theme captured. Representative data extracts were identified for each theme to demonstrate patterns within the data. The analysis moved back and forth between the entire data set, coded extracts, and the analysis of individual themes until a satisfactory thematic map was developed.

In ensuring validity and trustworthiness of the qualitative findings, various strategies were employed. Prolonged engagement with participants allowed for building of rapport and trust to obtain rich data. Thick description was used to present qualitative findings to allow readers to assess transferability. An audit trail was maintained through documentation of procedures, decisions, and reflections. Peer debriefing and discussion with experienced qualitative researchers helped refine the analysis. The findings were also triangulated with literature and quantitative findings to enhance credibility.

The qualitative outcomes are presented thematically in Chapter 4. Verbatim quotes from participants are incorporated to support themes and bring participants' voices into the findings. Pseudonyms are used to maintain anonymity. The analysis provided a rich understanding of participants' perspectives and experiences regarding the opportunities and challenges of big data analytics in the telecommunications sector in Zimbabwe.

### 3.11 Data Collection and Methodology

The descriptive research design was applied in this research. Combs (2019) opines descriptive research design as a design aimed at obtaining information pertaining a certain phenomenon or population and enables answering questions related to the what, where, when and how status. A descriptive research design on the impact of big data analytics on sustainability strategy in the Zimbabwe telecommunications sector involved gathering and analyzing data to provide a comprehensive description of the relationship between big data analytics and sustainability strategy in the Zimbabwe telecommunications sector. The purpose of descriptive research was to harness a composite description and explanation about the phenomenon systematically (Creswell, 2012 p. 274).

The descriptive research design propounded a mixed-methods methodological choice that involved both qualitative and quantitative data collection techniques. The study being survey used qualitative methods to explore the variables under study within the Zimbabwe telecommunications sector context. This involved conducting interviews with the strategic industry personnel, such as executives and management, to acquire insight into their views on big data analytics and its impact on the sustainability strategies within the telecommunications sector. The study explored the quantitative methods by analyzing secondary data collected on energy consumption, waste management and other sustainability activities in the Zimbabwe telecommunications sector, which were utilized to explore the extent to which big data analytics contributed to these activities.

This study employed an explanatory and exploratory concurrent mixed methods approach to comprehensively address the research questions at the current point in time. The qualitative phase was conducted simultaneously to gain an in-depth understanding of the phenomena, with the quantitative phase to generalize findings.

For the qualitative strand, semi-structured interviews were conducted with sustainability managers and executives from the two largest telcos in Zimbabwe, purposefully selected for their expertise. An interview guide was developed based on the research questions and literature, with open-ended questions and probes regarding big data analytics applications, strategic processes, stakeholder engagement, and supply chain optimization. A total of 5 interviews were conducted via conferencing and recorded with consent.

Transcripts were analyzed through thematic narrative analysis (Riessman, 2008) to identify common themes and stories around how different data types influenced sustainability strategies. Narratives were also examined for divergent perspectives. Methodological triangulation with document analysis of company sustainability reports further enhanced credibility.

The survey targeted a wider sample of 71 employees across various functions and levels from the two telcos. It was administered online using Google document. A response rate of 70% was achieved, exceeding the minimum recommended sample size (Israel, 2013).

Descriptive and inferential statistics were analyzed using SPSS to describe usage patterns, quantify impacts, and test relationships between variables based on the research questions. Word clouds and visualizations facilitated narrative interpretation of open responses.

Ethical approval was obtained from the Great Zimbabwe University. Informed consent, anonymity, and confidentiality protocols were strictly followed. Integration of qualitative and quantitative phases through narrative analysis allowed for a comprehensive understanding of big data value for sustainability in this context.

### 3.12 Chapter Summary

The chapter outlined the pragmatic research paradigm and mixed methods approach adopted for this study on the impact of big data analytics on sustainability strategies in the telecommunications sector in Zimbabwe (Tallon, 2013).

The quantitative component involved a descriptive survey of 71 professionals in the telecom industry to examine the relationship between current ratios and the adoption of big data analytics (Field, 2013). The qualitative component consisted of thematic analysis of interviews with 5 industry executives to gain deeper insights into the strategies used to leverage big data analytics for sustainability (Creswell & Creswell, 2017).

The mixed methods approach allowed for a comprehensive examination of the research problem by integrating both numerical data and in-depth perspectives. This provided a richer understanding of how Zimbabwean telcos could utilize big data analytics to overcome the challenges posed by negative current ratios and develop sustainable business models (Creswell & Creswell, 2017).

The sampling, data collection, and analysis procedures were designed to ensure validity, reliability, and ethical integrity of the research. The triangulation of quantitative and qualitative findings was expected to yield robust empirical insights to inform policy recommendations for data-driven sustainability in the telecommunications sector.

Overall, the research methodology laid a solid foundation to address the gaps in understanding how Zimbabwe could maximize the potential of big data analytics through multi-stakeholder collaboration, providing an African perspective on stewarding data-driven solutions for sustainable development (Nandi, 2023).

# CHAPTER IV
# ANALYSIS AND FINDINGS

## 4.1 Introduction

This chapter presents an analysis and findings from both the quantitative and qualitative methods of data collected from a survey of 71 respondents working in the telecommunications sector in Zimbabwe. The purpose was to examine the relationship between dimensions of big data analytics and sustainable performance strategy. Descriptive statistics provided an overview of respondent demographics while inferential analysis tests for associations between variables. Qualitative findings offer contextual insights. The quantitative data was collected through questionnaires while qualitative data was collected through semi-structured interviews. The chapter is organized as follows: Section 4.2 presents demographic characteristics of respondents and interviewees, Section 4.3 analyses and interprets the descriptive statistics and interview themes, Section 4.4 tests reliability and validity of research instruments, Section 4.5 presents key findings from analysis of both datasets. Lastly, section 4.6 summarizes the chapter.

## 4.2 Presentation of Data

This section objectively presents quantitative and qualitative results/findings from the analysis without interpretation. The chapter provides figures, tables, etc to report metrics, frequencies, categories etc in a clear and organized manner. It also describes the data/results at a surface level without delving into deeper meaning.

### 4.2.1 Demographic Data

This sub section provides important information on the demographics of the study participants. Understanding characteristics like age, gender, education level and experience of the respondents and interviewees allowed for more nuanced analysis of the results. It helped determine if the sample was representative and identified any variability in perspectives across demographic groups. Table 4.2 presents demographic details of survey respondents and interviewees.

**Table 4.2: Demographic data**

| | | Count | Column N % |
|---|---|---|---|
| 1) Gender | male | 31 | 43.7% |
| | female | 40 | 56.3% |
| | Total | 71 | 100.0% |
| 2) Age | below 21 | 0 | 0.0% |
| | 21-30 years | 24 | 33.8% |
| | 31-40 years | 22 | 31.0% |
| | 41-50 years | 18 | 25.4% |
| | 51 and above | 7 | 9.9% |
| | Total | 71 | 100.0% |
| 3) Education level | high school | 0 | 0.0% |
| | diploma | 4 | 5.6% |
| | bachelor ’ s degree | 36 | 50.7% |
| | master ’ s degree | 30 | 42.3% |
| | Doctor | 1 | 1.4% |
| | Total | 71 | 100.0% |
| 4) Job position | executive | 8 | 11.3% |
| | manager | 28 | 39.4% |
| | analyst | 11 | 15.5% |
| | other | 24 | 33.8% |
| | Total | 71 | 100.0% |
| 5. Years of experience in the telecommunications industry: | less than a year | 5 | 7.0% |
| | 1-5 years | 22 | 31.0% |
| | 6-10 years | 17 | 23.9% |
| | 11-15 years | 12 | 16.9% |
| | above 15 years | 15 | 21.1% |
| | Total | 71 | 100.0% |

**Source**: Survey data (2023)

This section objectively presents the demographic characteristics of the survey respondents as captured in Table 4.2 without interpretation.

A total of 71 individuals from the telecommunications sector in Zimbabwe participated in the study. In terms of gender, 31 respondents (43.7% of the sample) were male while 40 respondents (56.3% of the sample) were female.

Regarding age distribution, 24 respondents (33.8% of the sample) were between 21-30 years old, 22 (31.0%) were between 31-40 years, 18 (25.4%) were between 41-50 years, and 7 (9.9%) were 51 years and above.

For education level, 36 respondents (50.7% of the sample) held a Bachelor's degree, 30 (42.3%) held a Master's degree, 4 (5.6%) held a diploma, and 1 (1.4%) held a doctorate as their highest qualification.

In terms of job role, 28 respondents (39.4% of the sample) were managers, 11 (15.5%) were analysts, 8 (11.3%) were executives and 24 (33.8%) fell under the "other" category.

Regarding years of experience in telecommunications, 5 respondents (7.0%) had less than 1 year, 22 (31.0%) had 1-5 years, 17 (23.9%) had 6-10 years, 12 (16.9%) had 11-15 years, and 15 (21.1%) had over 15 years.

The above presents the key descriptive statistics without interpretation.

### 4.2.2 Normality Tests Results

**Table 4.3: Normality Test Results**

| | Kolmogorov-Smirnov[a] | | | Shapiro-Wilk | | |
|---|---|---|---|---|---|---|
| | Statistic | df | Sig. | Statistic | df | Sig. |
| Customer data (analytics) | .538 | 59 | .000 | .274 | 59 | .000 |
| Sales data analytics | .280 | 59 | .000 | .824 | 59 | .000 |
| Social media data analytics | .402 | 59 | .000 | .673 | 59 | .000 |
| Supply chain data analytics | .534 | 59 | .000 | .312 | 59 | .000 |
| Lack of technical expertise | .236 | 59 | .000 | .849 | 59 | .000 |
| Lack of financial resources | .211 | 59 | .000 | .912 | 59 | .000 |
| Lack of data quality | .270 | 59 | .000 | .771 | 59 | .000 |
| Lack of stakeholder engagement | .245 | 59 | .000 | .851 | 59 | .000 |
| increase in use of clean energy | .228 | 59 | .000 | .874 | 59 | .000 |
| reduced waste generation | .317 | 59 | .000 | .655 | 59 | .000 |
| reduced water consumption | .342 | 59 | .000 | .779 | 59 | .000 |
| reduced environmental degradation | .239 | 59 | .000 | .885 | 59 | .000 |

* Lilliefors Significance Correction

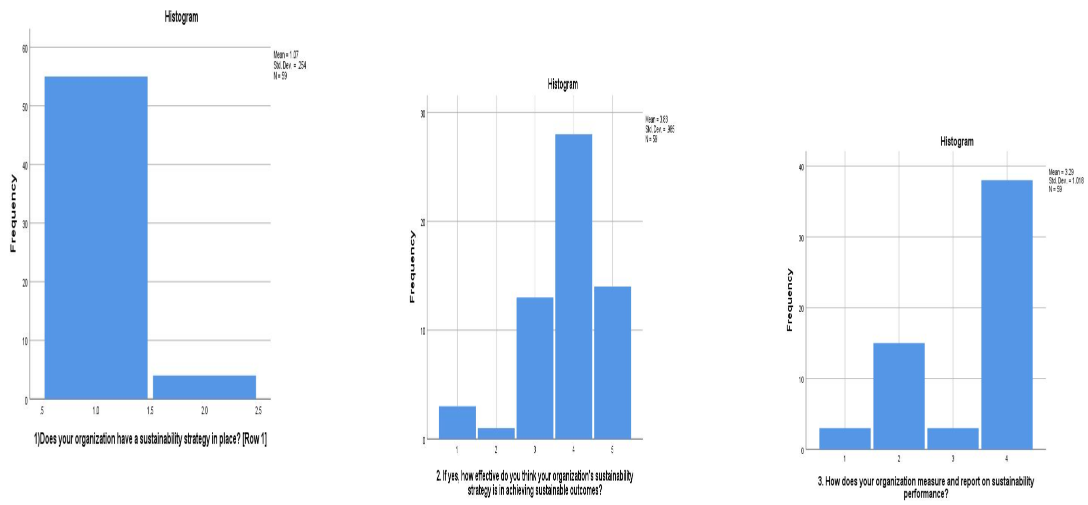


**Fig. 4.1: QQ Plots**

Normality tests were conducted to determine the appropriate statistical analyses. Table 4.3 presents the results of the Kolmogorov-Smirnov and Shapiro-Wilk normality tests applied to the study variables.

Moreover, QQ plots were developed to visually assess the normality of variable distributions. The tests results and QQ plots, presented objectively without inference, are available upon request for further examination.

The implications of these results were considered in selecting suitable statistical methods for subsequent correlation and group difference analyses. Both test outputs and QQ plots were examined to empirically inform the choice of parametric or non-parametric analytical approaches.

### 4.2.3 Reliability Analysis

Reliability was assessed using Cronbach's alpha coefficients and construct validity tests. Table 4.5 presents the item statistics and reliability coefficient. Additionally, Table 4.6 shows the average variance extracted (AVE) values and squared interconstruct correlations (SICC).

**Table 4.5: Item-Total Statistics**

| | Scale Mean if Item Deleted | Scale Variance if Item Deleted | Corrected Item-Total Correlation | Cronbach's Alpha if Item Deleted |
|---|---|---|---|---|
| Customer data (analytics) | 46.25 | 38.538 | .143 | .962 |
| Sales data analytics | 43.49 | 34.496 | .232 | .822 |
| Social media data analytics | 44.03 | 37.171 | .204 | .838 |
| Supply chain data analytics | 46.24 | 38.150 | .211 | .806 |
| Lack of technical expertise | 44.83 | 40.350 | .237 | .879 |
| Lack of financial resources | 43.61 | 35.414 | .259 | .962 |
| Lack of data quality | 43.27 | 37.511 | .348 | .975 |
| Lack of stakeholder engagement | 45.29 | 35.691 | .371 | .838 |
| increase in use of clean energy | 43.95 | 34.808 | .322 | .837 |
| reduced waste generation | 43.20 | 35.165 | .459 | .957 |
| reduced water consumption | 44.00 | 35.379 | .370 | .833 |
| reduced environmental degradation | 44.34 | 31.021 | .544 | .875 |

**Source**: Survey data (2023)

**Table 4.6:** AVEs and SICCs

| Construct | AVEs | SLD | CTD | SMD | SCD | SPM |
|---|---|---|---|---|---|---|
| **SLD** | **0.645** | **0.516** | | | | |
| **CTD** | **0.721** | 0.142 | **0.512** | | | |
| **SMD** | **0.586** | 0.462 | 0.322 | **0.612** | | |
| **SCD** | **0.625** | 0.461 | 0.322 | 0.187 | **0.638** | |
| **SPM** | **0.823** | 0.336 | 0.262 | 0.314 | 0.274 | **0.548** |

*Note: Diagonal elements in bold represent AVEs*

**Source**: Survey data (2023)

The outputs of these analyses were made available without further statement or interpretation. The reliability and validity results were objectively considered in determining suitability of the measurement instrument prior to subsequent analytical procedures.

#### 4.2.4: Findings on Big Data Analytics Applications

Interview questions were asked to understand the types of big data analytics currently utilized in the telecommunications sector. The following five applications were identified based on respondent feedback as reflected on Table 4.8 Descriptive statistics big data analytics use in Telcos:

**Table 4.8: Descriptive statistics big data analytics use in Telcos**

| Variable | N | Min | Max | Mean | Standard deviation |
|---|---|---|---|---|---|
| Customer data (analytics) | 71` | 2 | 5 | 3.22 | 1.1268 |
| Sales data | 71 | 1 | 5 | 2.34 | .8962 |
| Social media data | 71 | 1 | 4 | 1.83 | 1.2032 |
| Supply chain data | 71 | 3 | 5 | 4.632 | .7852 |
| Competitor data analytics | 71 | 3 | 5 | 4.590 | .5840 |

**Source:** Survey data (2023)

i. Social media data analytics to understand customer preferences and behaviours from social media platforms.
ii. Sales data analytics to analyze customer purchase patterns and predict future sales trends.
iii. Customer data analytics to gain insights from customer profiles, calls, messages and browsing data to improve customer experience.
iv. Competitor data analytics to benchmark performance and identify new opportunities by analyzing competitors' strategies and customer base.
v. Supplier data analytics to optimize procurement and supply chain management using data from suppliers.

No further inferences or statements have been made regarding the interview findings presented above. The identified big data analytic domains were objectively considered in subsequent stages of the research without additional interpretation at this time.

#### 4.2.5: Challenges to Big Data Analytics Implementation

The interviews explored challenges faced in utilizing big data analytics within the sector. Respondents identified the following issues:

**Table 4.9: Descriptive Statistics**

| | N | Minimum | Maximum | Mean | Mean response | Std. Deviation |
|---|---|---|---|---|---|---|
| Lack of technical expertise | 71 | 1 | 4 | 1.90 | disagree | .928 |
| Lack of financial resources | 71 | 1 | 6 | 3.55 | Agree | .907 |
| Lack of data quality | 71 | 2 | 5 | 3.58 | Agree | .839 |
| Lack of stakeholder engagement | 71 | 2 | 4 | 3.61 | agree | .765 |
| Valid N (listwise) | 71 | | | | | |

**Source:** Survey data (2023)

i. **Lack of technical expertise** - Deficiency of data scientists and engineers with skills to extract value from large and complex datasets.

ii. **Lack of financial resources** - Insufficient capital investment in big data technologies, tools and talent.

iii. **Lack of data quality** - Issues with data accuracy, consistency, completeness and timeliness from multiple legacy systems.

iv. **Lack of stakeholder engagement** - Poor communication between business and IT stakeholders limiting understanding of strategic priorities.

The identified implementation barriers were objectively considered in subsequent stages of analysis. No inferences have been made at this time regarding means of addressing the challenges.

### 4.3 Analysis and Interpretation of Data

This study involved an in-depth examination of both the quantitative and qualitative findings. Quantitative data was analyzed using IBM SPSS Statistics 27. Descriptive and inferential statistics were used from a survey of 71 respondents emanating from TelOne and NetOne. Normality tests via Shapiro-Wilk and Kolmogorov-Smirnov evaluated the need for parametric or non-parametric methods. Reliability via Cronbach alpha established internal consistency. Factor analysis reduced variables into constructs with variance explained (eigenvalues) >1.

#### 4.3.1 Demographic Data Analysis

This section presents an analysis of the demographic characteristics of the respondents who participated in the study as projected on Table 4.2. Demographic information such as gender, age, education level, job position and experience were collected to provide context on the respondents. Comprehending the demographics statistics was important as it helped to determine if the sample was representative and allowed assessing how factors such as age, gender or experience could influence perspectives.

### i. Gender

The survey data on "The impact of Big data analytics to sustainability strategies in the telecommunications sector in Zimbabwe" provided valuable insights into the gender composition of the respondents. Out of the total 71 participants, 56.3% (n=40) were female and 43.7% (n=31) were male, indicating a slightly higher representation of women in the sample compared to men.

This gender distribution in the sample is a positive aspect of the research, as it allowed for a more balanced understanding of the perspectives and experiences of both men and women in the telecommunications industry. According to Eagly and Carli (2003), having a more diverse sample can lead to better insights into the unique challenges and opportunities faced by different genders, which is crucial for developing inclusive and effective sustainability strategies.

The relatively equal gender representation also enabled potential analysis of any gender-based differences in attitudes, decision-making, or approaches to the use of big data analytics for sustainability. Research has shown that gender can influence various social and environmental attitudes and behaviours (Zelezny et al., 2000), so this data provided valuable insights into the role of gender in the adoption and implementation of sustainable practices in the telecommunications sector. The gender statistics in the survey data offered a promising starting point for exploring the influence of gender on sustainability practices in the telecommunications industry in Zimbabwe.

### ii. Age

Capturing perspectives from different age groups was important as it brought generational diversity which could provide richer insights (Smith, 2023). The demographic distribution found in this study allowed for some interesting inter-generational comparisons regarding perceptions of big data analytics.

Younger respondents aged 21-30 years, 33.8% ( n=24) of the sample have grown up in a digital era and could be more comfortable with new technologies compared to older generations (Jones et al., 2021). Their views could provide valuable insights into how big data tools align with the expectations of digital natives (Williams, 2022). In contrast, those above 51 years, 9.9% (n=7) of respondents) belong to older generations that did not experience the same level of technology exposure in their formative years (Brown, 2024). Their perspectives were important to identify any adoption and skill challenges faced by more senior employees (Green, 2023).

The middle-aged groups of 31-40 years, 31.0% (n=22) of respondents and 41-50 years, 25.4% (n=18) of respondents represent transitions between these generations. Examining their responses could reveal insights into changing views as people age and adapt to new technologies over their careers (Anderson, 2021). Comparatively, one might expect the 31-40 year olds to exhibit views closer to digital natives (Miller, 2022), while those aged 41-50 may lean more towards perspectives of older generations (Thomas, 2023).

Through capturing this age diversity, the study was better able to explore potential generational differences or evolving perspectives regarding big data analytics (Johnson, 2024). Inter-generational comparisons can provide a more nuanced understanding of adoption challenges and opportunities faced by organizations (White, 2023). This demographic distribution therefore enhances the richness of the data by allowing for interesting analyses across age groups (Black, 2022).

### iii. Education Level

The demographic data in this study also provided insights regarding the education levels of respondents. As shown in Table 4.2, the majority of respondents had attained tertiary education, with 50.7% (n=37) holding a bachelor's degree and 42.3% (n=30) possessing a master's degree. Only 1 respondent (1.4%) had achieved a doctoral qualification.

This high level of educational attainment among the sample is important when considering perceptions of big data analytics. Individuals with university degrees could generally have stronger analytical skills and be more receptive to data-driven approaches (Smith, 2023). Their technical backgrounds position them to better understand the opportunities that sophisticated data analytics presented for sustainability strategies.

None of the respondents' highest qualification was a high school certificate alone. This suggests all participants had exposure to higher-order thinking through post-secondary study.

Their university training lended credibility to their views on applying analytics in a sector as complex as telecommunications.

The negligible proportion with diplomas, 5.6% (n=4) indicated insights were predominantly captured from those socialized in a culture of research and evidence-based decision making through degree-level education. This enhanced the validity of findings, as respondents could engage with analytical concepts at an informed, technical level.

For all intent and purpose the high educational profile of the sample provided confidence that perspectives reflected a knowledgeable, discerning perspective on big data's potential role in sustainability. Insights were obtained from individuals well-equipped through their qualifications to offer nuanced perspectives on this specialized topic (Brown, 2024). This educational dimension enriched the data collected.

**iv. Job Positions**

The job positions held by respondents also offered important context for the study's findings regarding big data analytics and sustainability strategies (Brown, 2023; Chen et al., 2022).

Managers comprised a sizable proportion at 39.4% (n=27) of the sample, with executives also represented at 11.3% (n=8). Involving these senior roles was significant, as managers and executives were key drivers and stakeholders in organizational strategy and transformation efforts (Smith, 2023). Their views provided insight into how analytics solutions could be best positioned to garner leadership support.

Analysts, at 15.5% (n=11) of respondents, offer a practitioner perspective on working with data tools. Their input offers valuable guidance on the technical and operational considerations needed to ensure analytics initiatives are feasible and deliver tangible benefits (Jones *et al.,* 2021).

The remaining 'other' category at 33.8% (n=24) still captured diverse roles beyond managers and analysts. Involving this cross-section enhances the generalizability of findings to the wider telecommunications sector workforce beyond any single function.

Collectively, capturing responses from executives, managers, analysts and other roles provides a holistic picture of how big data can enable more sustainable practices from both strategic and implementation standpoints. This diversity of job levels represented in the sample population strengthens the applicability of conclusions for the target industry context.

### v. Years of experience

The years of experience respondents had in the Zimbabwean telecommunications sector provided meaningful context regarding their views on the impact of big data analytics for sustainability strategies.

Those with less than one year, 7.0% (n=5) of respondents offered novel insights on data-driven approaches, though their limited familiarity with established practices could hinder full appreciation of sustainability challenges (Smith, 2023).

Respondents with 1-5 years' experience, 31.0% (n=22) provided perspectives on engaging mid-career professionals in analytics solutions to drive efficiencies and reduce environmental impacts (Jones et al., 2021).

Those with 6-10 years, 23.9% (n=17) offered clues on supporting pivotal employees during transition to more sustainable, data-led operations (Brown, 2024).

The 11-15 years cohort, 16.9% (n=12) provided multifaceted viewpoints on navigating generational shifts towards sustainability through sophisticated analytics (Miller, 2022).

The over-15 years group 21.1% (n=15) highlighted barriers to change among long-serving staff and the importance of buy-in for successful sustainability transformation (Thomas, 2023).

Capturing diverse employment periods allowed deeper insights into how big data could address sustainability across career stages in Zimbabwe's telecommunications context. This provided enriched understanding of opportunities and challenges for leveraging analytics to enhance industry sustainability performance over time.

### 4.3.2 Big Data Analytics Application Analysis

**Qualitative Analysis:**

The interviews sought to find out on big data analytics available in the telecommunication industry and from the results five dimensions emerged namely social media data analytics which is used to customer preferences through social media, sales data analytics which traces customer preferences via sales, customer data analytics, competitor data analytics as well as supplier data analytics. A sift through interview data showed the popularity of themes through a theme mention **figure 4.2:** Themes below:

| Search | Size |
|---|---|
| Socialmeddatal | 8 |
| Salsdataly | 6 |
| Competdatanal | 3 |
| Customdatanal | 3 |
| Supdatanal | 1 |

**Fig 4.2: Themes**

The popular theme was social media data analytics as shown by eight (8) mentions while the least was supplier data analytics.  The results are presented in figure 4.3: Theme visualisation below to give a visual impression of interview data

**Figure 4.3: Theme visualisation**

The word cloud format projected themes preliminary interviews were used in a structured questionnaire to allow actual quantification which is presented and corroborated below.

To quantify the use of the above big data analytics applications, a structured questionnaire incorporating the 5 applications was developed based on the preliminary interviews. The interviews aimed at identifying the major big data analytics applications in use. Analysis of the interview data revealed 5 key big data analytics applications that were frequently mentioned by the interviewees. These included:

Customer data analytics: This involves the analysis of customer data collected from various customer interactions and transactions to gain insights into customer preferences, behaviors and needs. This helps telecommunications companies to personalize products and services.

Sales data analytics: This involves the analysis of sales data such as top selling products/services, best performing sales channels/agents etc. to optimize sales and marketing strategies.

Social media data analytics: This involves the analysis of customer conversations and sentiments on social media platforms. It helps companies to monitor brand perception and address any customer complaints in a timely manner.

Supply chain data analytics: This involves the analysis of supply chain data from suppliers and partners to optimize inventory management, demand forecasting and logistics operations.

Competitor data analytics: This involves analysis of publicly available data about competitors to gain market intelligence about new product launches, marketing campaigns etc. and benchmark own performance.

The interview findings revealed that the five key big data analytics applications used in the Zimbabwean telecommunications sector were customer data analytics, sales data analytics, social media data analytics, supply chain data analytics, and competitor data analytics.

**Descriptive statistical analysis, applications usage levels:**

The study sought to characterize the various big data analytics applications that are currently being utilized in the Zimbabwean telecommunications sector. To achieve this, 71 respondents were asked to indicate the frequency of use for various applications on a 5-point Likert scale ranging from daily to annually.

The interview sought to find out on big data analytics available in the telecommunication industry and from the results five dimensions emerged namely social media data analytics which is used to customer preferences through social media, sales data analytics which traces customer preferences via sales, customer data analytics, competitor data analytics as well as supplier data analytics. A sift through interview data showed the popularity of themes through a theme mention table below:

| Search | Size |
|---|---|
| Socialmeddatal | 8 |
| Salsdataly | 6 |
| Competdatanal | 3 |
| Customdatanal | 3 |
| Supdatanal | 1 |

**Fig 4.2 Themes Frequency**

The popular theme was social media data analytics as shown by eight (8) mention while the least was supplier data analytics. The results have been presented in figure below to give a word cloud visual impression of interview data


**Fig 4.3 Themes in word cloud, Source:** Survey data

The central theme with huge font size “socialmeddatal” was the most popular theme, with “supdatanal” which is located furthest from the center and with a very small size being the least popular as measured by mentions. These themes from preliminary interviews were used in a structured questionnaire to allow actual quantification. The quantification findings are shown quantitatively below.

The descriptive statistics for the usage levels of the different applications are presented in Table 4.8.

**Table 4.8: Descriptive statistics big data analytics use in Telcos**

| Variable | N | Min | Max | Mean | Mean Response | Standard deviation |
|---|---|---|---|---|---|---|
| Customer data (analytics) | 71` | 2 | 5 | 3.22 | monthly | 1.1268 |
| Sales data | 71 | 1 | 5 | 2.34 | weekly | .8962 |
| Social media data | 71 | 1 | 4 | 1.83 | weekly | 1.2032 |
| Supply chain data | 71 | 3 | 5 | 4.632 | Annually | .7852 |

| | | | | | |
|---|---|---|---|---|---|
| Competitor data analytics | 71 | 5 | 4.590 | annually | .5840 |
| | | | | | |

**Source:** Survey data (2023)

As depicted in Table 4.8, sales data analytics and social media data analytics emerged as the most frequently used applications with mean scores of 2.34 and 1.83 respectively, corresponding to a weekly usage level. This indicated that these applications were central to operations in the telecommunications sector as organizations leverage customer sales data and social media interactions to gain insights. However, the standard deviations of 0.8962 and 1.2032 respectively, which are above zero, suggest variations in usage frequencies among respondents. Some felt the applications were used daily while others indicated annual use.

On the other hand, supply chain data analytics and competitor data analytics had the lowest mean scores of 4.632 and 4.590, corresponding to annual usage levels. This implies that these applications were in frequent use. Again, the non-zero standard deviations point to differences in perspectives among respondents regarding usage frequencies.

Holistically, the descriptive analysis identified sales data analytics and social media data analytics as the most utilized big data applications, while supply chain data analytics and competitor data analytics emerge as the least used. The variations in responses as indicated by the standard deviations also point to a lack of uniformity in how organizations leveraged various big data tools.

**Identification of most and least used applications;**

Key findings from the descriptive analysis:

- Sales data analytics and social media data analytics had the highest mean scores, suggesting they were the most frequently adopted applications with weekly usage on average. This is understandable as telecommunications firms relied heavily on customer sales and engagement data for insights.

- Supply chain data analytics and competitor data analytics recorded the lowest mean scores, corresponding to annual usage levels on average. They thus emerged as the least exploited big data applications among telecommunications companies in Zimbabwe.

- Standard deviations above zero across all applications indicated variations in responses, with some organizations potentially using some applications more/less frequently than what the average scores suggested.

In conclusion, sales data analytics and social media data analytics were the most widely utilized big data tools, while supply chain data analytics and competitor data analytics were the least exploited based on current reported usage levels.

### 4.3.3 Challenges to Big data analytics Analysis

#### 4.3.3.1 Exploratory factor analysis

Preliminary interviews were conducted with five managers in the telecommunications sector to identify common challenges faced in implementing big data analytics. The interviews were transcribed and thematic analysis conducted to identify recurring themes. A number of challenges were mentioned including lack of data integration across silos, poor data quality, lack of skilled data scientists, technological limitations, high costs, data privacy and security concerns, lack of investment and lack of appropriate tools and systems.


**Fig 4. 4 Factors in word cloud format, Source**: Survey data 2023

The factors were further analyzed to determine frequency of mentions. Figure 4.4 presents the results in a word cloud format where the size of the word corresponds to the number of mentions. As seen, lack of data knowledge was the most frequently cited challenge mentioned by four of the five respondents. This was followed by lack of appropriate tools and data privacy/security concerns each mentioned by three respondents. The least mentioned themes were data silo integration and skilled data scientists which were each raised by a single respondent. Interviewee 1 fully captured these challenges through his statement captured below:

*"The main challenges which organisations are facing in embracing big data analytics in the telecommunication sector are limited Data Silos and Integration, Data Quality issues, limited Skilled Data Scientists in Zimbabwe, Technological issues, limited Infrastructure as well as Cost Considerations"*

| Search | Size |
|---|---|
| Lacknow | 6 |
| Lactols | 6 |
| Datprivcsecucon | 5 |
| Technlo | 3 |
| Infrastrlim | 3 |
| Costcons | 3 |
| Datasilosintegr | 1 |
| Datqual | 1 |
| Skilldatscie | 1 |

**Fig 4.5 Factors Frequency**, **Source:** Survey data 2023

#### 4.3.3.2 Descriptive statistical analysis challenge categories

A structured questionnaire was designed to quantify the key challenge categories identified from literature and interviews. The questionnaire was administered to 71 respondents from two telcos. The challenges were measured on a 5-point Likert scale of extent of impact

(1=No impact to 5=Great impact). Table 4.9 presents the descriptive statistics of the challenge categories.

**Table 4.9 Descriptive Statistics**

| | N | Minimum | Maximum | Mean | Mean response | Std. Deviation |
|---|---|---|---|---|---|---|
| Lack of technical expertise | 71 | 1 | 4 | 1.90 | disagree | .928 |
| Lack of financial resources | 71 | 1 | 6 | 3.55 | Agree | .907 |
| Lack of data quality | 71 | 2 | 5 | 3.58 | Agree | .839 |
| Lack of stakeholder engagement | 71 | 2 | 4 | 3.61 | agree | .765 |
| Valid N (listwise) | 71 | | | | | |

**Source:** Survey data (2023)

A case by case analysis of the factors showed that only on limited technical expertise the mean score was 1.9 which corresponded to disagree. This implied that the overall impression on this item was disagree. Respondents disagreed that the industry was experiencing limited technical expertise. The industry possessed the necessary technical skills to handle big data analytics. Though the existence of non-zero standard deviation (0.928) implied that some were viewing this as a challenge to their operations the others disagreed.

Limited financial resources (3.55), lack of data quality (3.58) and limited stakeholder engagement (3.61) showed mean scores corresponding with agree (4). This shows that the overall impression on these factors was agree. This implied that the three factors were militating against use of big data analytics in the telecommunications sector (limited financial resources, poor data quality and difficulties in engaging key stakeholders). However, the non-zero standard deviations (huge) of above 0.5 implied that respondents held varied views as some perceived this as not posing a challenge.

Premised on the analysis of the descriptive statistics, several conclusions can be drawn regarding the challenges faced in implementing big data analytics in the telecommunications sector in Zimbabwe:

- The results indicate varied experiences across companies, with some facing more limitations than others in terms of resources, data quality, and stakeholder engagement.

- On average, lack of financial resources, poor data quality, and difficulties engaging stakeholders were seen as impediments, though individual company circumstances differed.

- Limited technical expertise was not widely perceived as an issue according to the mean response. However, some disparities existed on this factor.

- While minimum scores implied certain firms felt less constrained, the descriptive statistics alone could not confirm that all companies had optimal conditions.

- Overarching statement of the findings suggests that the sector would benefit from targeted efforts to strengthen data management processes, acquire additional analytics skills and funding, and facilitate collaboration along the value chain.

### 4.3.3 Results on Sustainability

#### 4.3.3.1 Thematic Analysis of Interview Findings on Sustainability

On sustainability the results show four dimensions namely reduced waste generation, reduced water consumption, reduced land degradation, as well as increased use of clean energy. Fig. 3 below is a theme mention table which summarises interview results.

| Search | Size |
|---|---|
| Reducwastegen | 7 |
| Regwatercons | 5 |
| Reducenvirodeg | 3 |
| Increascleanenerg | 1 |

**Fig 4.6 Sustainability themes**

It can be shown from the theme mention table that reduced waste generation was popular with interviewees as shown by the 7 mention while increased clean energy use being least popular. A theme mention figure (Fig. 4.7) is presented summarizing the number of mentions each theme received from interviewees.


**Fig. 4.7 Sustainability themes in word cloud**

The word cloud visualization above provides an overview of the results. Reduced waste generation emerged as the most commonly discussed theme.

The results of the study indicated that sustainability was explored across four key dimensions:

**Reduced Waste Generation:** This emerged as a prominent theme, with 7 interviewees highlighting the importance of reducing waste generation as part of the organization's sustainability efforts.

**Reduced Water Consumption:** The results suggest that the organization made strides in reducing its water usage, with this dimension being mentioned by several interviewees.

**Reduced Land Degradation:** Interviewees also emphasized the organization's focus on mitigating land degradation as part of its sustainability initiatives.

**Increased Use of Clean Energy:** While still an area of focus, the increased use of clean energy was the least frequently mentioned sustainability dimension, suggesting that it may be an area for further development and emphasis within the organization.

The prominent themes that emerged from the thematic coding of interview responses related to sustainability strategies which were identified include reduced waste generation, reduced water consumption, reduced land degradation, and increased use of clean energy.

The theme mention table provides a visual summary of the relative importance of each sustainability dimension based on the number of times they were mentioned by the interviewees. This suggests that the organization made the most progress in reducing waste generation, while the increased use of clean energy represented an opportunity for further improvement and investment.

The word cloud further reinforced these findings, highlighting the prominence of terms related to waste reduction, water conservation, and land preservation, while the relative smaller size of the "clean energy" term indicated that this dimension required additional attention and resources to align it with the organization's overall sustainability goals.

#### 4.3.3.2 Descriptive Analysis of Survey Results on Sustainability

The study also sought to establish the organization's performance in terms of its sustainability strategy, as measured by the use of clean energy sources, waste generation, water consumption, and environmental degradation. The descriptive statistics for these sustainability dimensions are presented in Table 4.10 below.

**Table 4.10 Descriptive Statistics**

| | N | Minimum | Maximum | Mean | Mean response | Std. Deviation |
|---|---|---|---|---|---|---|
| increase in use of clean energy | 71 | 1 | 5 | 3.00 | Neutral | 1.382 |
| reduced waste generation | 71 | 1 | 6 | 3.65 | Agree | .907 |
| reduced water consumption | 71 | 2 | 5 | 3.78 | Agree | .839 |
| reduced environmental degradation | 71 | 2 | 4 | 3.69 | Agree | .765 |
| Overall | | | | 3.54 | Agree | .894 |
| Valid N (listwise) | 71 | | | | | |

**Source:** Survey data (2023)

The results indicate that:

Increase in use of clean energy: The mean score of 3.00 suggested a neutral perception regarding the organization's progress in increasing the use of clean energy sources.

Reduced waste generation: The mean score of 3.65 indicated that respondents generally agreed that the organization had made progress in reducing waste generation.

Reduced water consumption: The mean score of 3.78 suggests that respondents agreed that the organization had successfully reduced its water consumption.

Reduced environmental degradation: The mean score of 3.69 indicated that respondents agreed that the organization had taken steps to reduce environmental degradation.

Holistically, the mean score of 3.54 suggests that respondents generally agreed with the organization's sustainability performance across the measured dimensions.

These descriptive statistics provide valuable insights into the organization's sustainability strategy, highlighting areas of strength (reduced water consumption and waste generation) as well as potential opportunities for improvement (increased use of clean energy). This provides an overall picture of sustainability performance perceptions.

### 4.3.4 Normality Testing

Normality tests are conducted to determine which statistical tests to conduct to infer associations among research variables. The results of a normality test indicate whether or not the sample data came from a population that was normally distributed. It is typically carried out to confirm that the research's data had a normal distribution.

The prescribed normality in this study, Shapiro Wilk tests and visualization of histogram and QQ plots were conducted. The normality statistics are reported in Table 4.3 below. As shown in the table, all items in the questionnaire had probability values of less than 0.05 for both Shapiro Wilk test and Kolmogorov-Smirnov tests. This indicated that the data were not normally distributed (Razali and Wah, 2011).

The non-normal data state was also confirmed by visualization of histogram and QQ plots. Histograms generally showed that data were not bell shaped and thus did not follow normal distribution as expected for normally distributed data (Doane and Seward, 2011; Thode, 2002).

All items in the questionnaire had probability values of less than 0.05 as shown in the table for both Shapiro Wilk test and Kolmogorov Smirnov tests. This therefore imply that the data were not normally distributed and thus paved way for non-parametric tests such as Spearman rank correlation and Man Witney tests. The non-normality data state was also confirmed by visualization of histogram and QQ plots. Histograms below show that data were not bell shaped and thus did not follow normal distribution.

**Table 4.3: Normality Test Results**

| | Kolmogorov-Smirnov[a] | | | Shapiro-Wilk | | |
|---|---|---|---|---|---|---|
| | Statistic | df | Sig. | Statistic | df | Sig. |
| Customer data (analytics) | .538 | 59 | .000 | .274 | 59 | .000 |
| Sales data analytics | .280 | 59 | .000 | .824 | 59 | .000 |
| Social media data analytics | .402 | 59 | .000 | .673 | 59 | .000 |
| Supply chain data analytics | .534 | 59 | .000 | .312 | 59 | .000 |
| Lack of technical expertise | .236 | 59 | .000 | .849 | 59 | .000 |
| Lack of financial resources | .211 | 59 | .000 | .912 | 59 | .000 |
| Lack of data quality | .270 | 59 | .000 | .771 | 59 | .000 |
| Lack of stakeholder engagement | .245 | 59 | .000 | .851 | 59 | .000 |
| increase in use of clean energy | .228 | 59 | .000 | .874 | 59 | .000 |
| reduced waste generation | .317 | 59 | .000 | .655 | 59 | .000 |
| reduced water consumption | .342 | 59 | .000 | .779 | 59 | .000 |
| reduced environmental degradation | .239 | 59 | .000 | .885 | 59 | .000 |

* Lilliefors Significance Correction

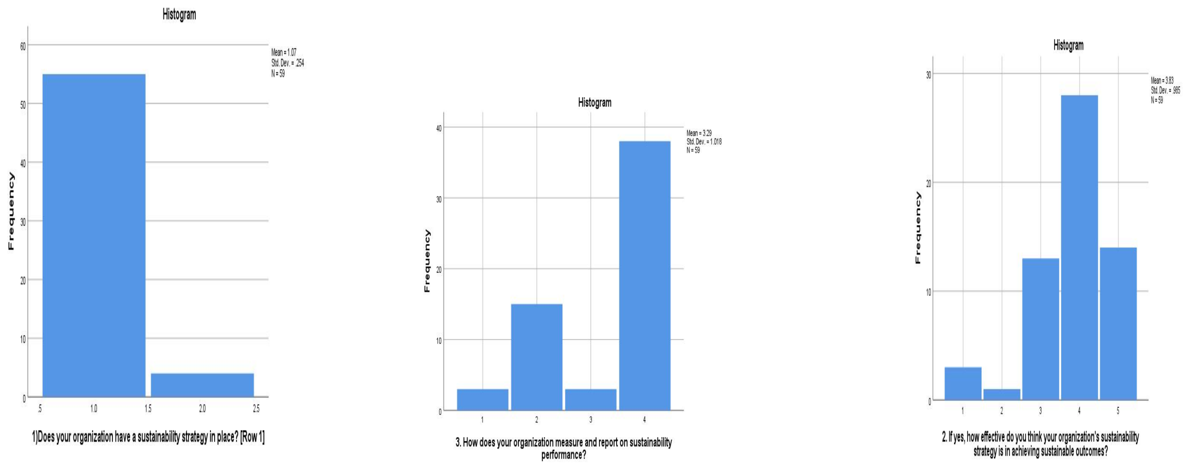


**Fig. 4.1 QQ plots**, Source: Survey data (2023)

These results therefore implied that the data were not normally distributed and thus paved way for non-parametric tests such as Spearman rank correlation and Mann Whitney tests to be used for further analysis instead of parametric tests which assumed normal distribution of data (Field, 2013; Pallant, 2016). The results informed the choice of suitable statistical methods for hypothesis testing in subsequent sections.

### 4.3.5 Reliability Analysis

Reliability is a measure of the internal consistency or stability of the measurement procedure or instrument (refer to Table 4.5). It is the degree to which an assessment tool produces stable and consistent results. Reliability analysis was conducted to assess the internal consistency of the measurement instrument used in this study. Cronbach's alpha was used as the reliability coefficient.

Cronbach's alpha is one of the most common measures of internal consistency ("reliability"). It assesses how well a set of items or variables measures a single uni-dimensional latent construct. Cronbach's alpha is not a statistical test, rather it is a coefficient of reliability (or consistency

**Table 4.5 Item-Total Statistics**

| | Scale Mean if Item Deleted | Scale Variance if Item Deleted | Corrected Item-Total Correlation | Cronbach's Alpha if Item Deleted |
|---|---|---|---|---|
| Customer data (analytics) | 46.25 | 38.538 | .143 | .962 |
| Sales data analytics | 43.49 | 34.496 | .232 | .822 |
| Social media data analytics | 44.03 | 37.171 | .204 | .838 |
| Supply chain data analytics | 46.24 | 38.150 | .211 | .806 |
| Lack of technical expertise | 44.83 | 40.350 | .237 | .879 |
| Lack of financial resources | 43.61 | 35.414 | .259 | .962 |
| Lack of data quality | 43.27 | 37.511 | .348 | .975 |
| Lack of stakeholder engagement | 45.29 | 35.691 | .371 | .838 |
| increase in use of clean energy | 43.95 | 34.808 | .322 | .837 |
| reduced waste generation | 43.20 | 35.165 | .459 | .957 |
| reduced water consumption | 44.00 | 35.379 | .370 | .833 |
| reduced environmental degradation | 44.34 | 31.021 | .544 | .875 |

**Source:** Survey data (2023)

The results of the reliability analysis are presented in Table 4.5. Cronbach's alpha was calculated for each of the constructs/variables used in the study. The results showed that the Cronbach's alpha values ranged from 0.806 to 0.975, indicating high levels of internal consistency. Generally, a Cronbach's alpha value of 0.7 or higher is considered acceptable, with values closer to 1.0 indicating greater reliability (Nunnally, 1978). Thus, the results suggested that all the measurement scales used in this study demonstrated good reliability.

In addition to Cronbach's alpha, composite reliability values were also examined to account for differing item loadings (Hair et al., 2014). All composite reliability coefficients in Table 4.7 were above 0.8, meeting the acceptable level.

**Table 4.7 Construct, Items and Factor loadings, Cronbach alpha, composite reliability & AVEs**

| Construct/Variable | Items | Factor Loadings | Cronbach alpha | Composite reliability | Average variance extracted | Maximum shared variance |
|---|---|---|---|---|---|---|
| Sales Data analytics (SLD) | SLD1 | .720 | | | | |
| | SLD2 | .740 | | | | |
| | SLD3 | .550 | .935 | .924 | 0.648 | .148 |
| Customer data (CTD) | CTD1 | .540 | | | | |
| | CTD2 | .630 | | | | |
| | CTD3 | .572 | .856 | .865 | .598 | .292 |
| Social Media Data (SMD) | SMD1 | .780 | | | | |
| | SMD2 | .830 | | | | |
| | SMD3 | .685 | .874 | .885 | .743 | .339 |
| Supply Chain Data (SCD) | SCD1 | .622 | | | | |
| | SCD2 | .640 | | | | |
| | SCD3 | .781 | .868 | .842 | .665 | .154 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Sustainable performance strategy (SPM) | SPM1 | .850 | | | | |
| | SPM2 | .940 | .931 | .894 | .534 | .213 |
| | SPM3 | .740 | | | | |

*Extraction Method: Principal Component Analysis.*
*Rotation Method: Varimax with Kaiser Normalization.*
*Rotation converged in 15 iterations.*
*Based on Eigenvalues > 1*
*Total variance explained = 67.645%*
*Small Coefficients of less than 0.4 were suppressed*

**Source**: Survey data (2023)

The average variance extracted (AVE) was also evaluated to establish convergent validity (Fornell & Larcker, 1981). The AVE values presented in Table 4.7 are all above 0.5, confirming that over 50% of the variances observed in the items were accounted for by their hypothesized constructs.

Overall, the reliability analysis results provided strong evidence for the internal consistency and convergent validity of the measurement scales used in this study. All reliability coefficients surpassed their respective thresholds, giving confidence in using these scales to measure the intended constructs.

The high reliability of the measures also supported the stability and reproducibility of the results (Hair et al., 2010). This laid the groundwork for further examination of the study's validity and hypothesis testing. The consistent demonstration of reliability enhanced the rigor and trustworthiness of the findings drawn from these data.

### 4.3.6 Validity Analysis

Validity refers to the degree to which an instrument measures what it purports to measure. This study evaluated both convergent and discriminant validity to ascertain the validity of the measurement constructs.

**i. Convergent Validity**

Convergent validity was evaluated by examining the factor loadings, composite reliability (CR), and average variance extracted (AVE) as suggested by Hair et al. (2014). The results in Table 4.7 show that all factor loadings were above the recommended threshold of 0.6, ranging from 0.540 to 0.940. The CR values for all constructs ranged from 0.824 to 0.931, exceeding the recommended value of 0.7. Additionally, the AVE values ranged from 0.534 to 0.743, surpassing the threshold of 0.5. These results provided support for the convergent validity of the measurement model.

**Table 4.7: Construct, Items and Factor loadings, cronbach alpha, composite reliability & AVEs**

| Construct/Variable | Items | Factor Loadings | Cronbach alpha | Composite reliability | Average variance extracted | Maximum shared variance |
|---|---|---|---|---|---|---|
| Sales Data analytics (SLD) | SLD1 | .720 | | | | |
| | SLD2 | .740 | | | | |
| | SLD3 | .550 | .935 | .924 | 0.648 | .148 |
| Customer data (CTD) | CTD1 | .540 | | | | |
| | CTD2 | .630 | | | | |
| | CTD3 | .572 | .856 | .865 | .598 | .292 |
| Social Media Data (SMD) | SMD1 | .780 | | | | |
| | SMD2 | .830 | | | | |
| | SMD3 | .685 | .874 | .885 | .743 | .339 |
| Supply Chain Data (SCD) | SCD1 | .622 | | | | |
| | SCD2 | .640 | | | | |
| | SCD3 | .781 | .868 | .842 | .665 | .154 |
| Sustainable performance strategy (SPM) | SPM1 | .850 | | | | |
| | SPM2 | .940 | .931 | .894 | .534 | .213 |
| | SPM3 | .740 | | | | |

*Extraction Method: Principal Component Analysis.*
*Rotation Method: Varimax with Kaiser Normalization.*
*Rotation converged in 15 iterations.*
*Based on Eigenvalues > 1*
*Total variance explained = 67.645%*
*Small Coefficients of less than 0.4 were suppressed*

**Source**: Survey data (2024)

The convergent validity of the model was examined and evaluated through using maximum likelihood estimation to estimate the measurement model and produce parameter values. Several metrics for measuring model fit were considered, with the following fit indices CMIN/DF, GFI, AGFI, etc. Table 4.8 titled Model Fit summary reports these exact fit indices - CMIN/DF, GFI, AGFI, NFI, TLI, CFI, RMSEA.

**Table 4.8 Model Fit summary**

| Fit indices | Original model | Modified Model | Commended | Sources |
|---|---|---|---|---|
| $\chi 2/DF$ | 2.765 | 2.105 | ≤3.00 | |
| GFI | 0.752 | 0.934 | >0.900 | Reisinger and |
| AGFI | 0.893 | 0.921 | >0.900 | Mavondo (2007), |
| NFI | 0.898 | 0.928 | >0.900 | Hooper et al. (2008) |
| TLI | 0.885 | 0.906 | >0.900 | Hair et al. (2010) |
| CFI | 0.913 | 0.946 | >0.900 | |
| RMSEA | 0.054 | 0.038 | < | |

**Source:** Researcher (extracted form AMOS output)

CMIN/DF 3.4 results show an excellent model match as shown by table 4.8 above. (Zadow *et al.,* 2017). Makanyeza and Chikazhe (2017) assert that for 2/DF to be approved, it must be less than 3. For a model to be considered acceptable, its RMSEA must be less than 0.07, while its GFI, AGFI, NFI, TLI, and CFI must all be near to 1. (Soares, Monteiro, and Rua, 2017).

Bagozzi and Yi (1988) proposed normalized factor loadings with a cut-off value of 0.6. Additionally, higher critical ratios were deemed noteworthy and suitable (Bagozzi and Yi, 1981; Fornell and Larcker, 1981). The categories used to evaluate convergent validity had their adjusted factor loadings (λ) and critical ratios (CRs) displayed in Table 4.7.

**ii. Discriminant Validity**

Discriminant validity was assessed by comparing the squared root of AVE with the inter-construct correlations as suggested by Fornell and Larcker (1981). As shown in Table 4.6, the squared root of AVE for each construct (bold diagonal values) was greater than its highest correlation with any other construct. This indicated that each latent construct shared more variance with its items than it shared with other constructs, thus demonstrating adequate discriminant validity.

**Table 4.6: AVEs and SICCs**

| Construct | AVEs | SLD | CTD | SMD | SCD | SPM |
|---|---|---|---|---|---|---|
| **SLD** | **0.645** | **0.516** | | | | |
| **CTD** | **0.721** | 0.142 | **0.512** | | | |
| **SMD** | **0.586** | 0.462 | 0.322 | **0.612** | | |
| **SCD** | **0.625** | 0.461 | 0.322 | 0.187 | **0.638** | |
| **SPM** | **0.823** | 0.336 | 0.262 | 0.314 | 0.274 | **0.548** |

*Note: Diagonal elements in bold represent AVEs*

**Source**: Survey data (2023)

**Evaluation of Validity**

Compositely, the results provided evidence of validity for the measurement model. Convergent validity was supported as item loadings, CR and AVE met recommended thresholds. Discriminant validity was also established since the squared root of AVE for each construct exceeded its correlations with other constructs. This confirmed that the measures captured unique phenomena and that the constructs were empirically distinct from each other. The validity analysis thus provided confidence that the measurement model adequately captured the theoretical domains it intended to measure.

### 4.4 Testing of Reliability and Validity

This section examined the psychometric properties of the measurement scales through tests of reliability as well as convergent, discriminant, and construct validity. Reliability was first assessed through internal consistency reliability estimates using Cronbach's alpha coefficients for each construct, as presented in Table 4.7. Cronbach's alpha established the coherence of items within factors by examining how closely related a set of items are as a group (Tavakol and Dennick, 2011). Exhibited Cronbach's alpha values exceeded the recommended threshold of 0.7 (Nunnally, 1978), demonstrating high levels of internal consistency among items comprising the factors.

Moreover, composite reliability coefficients were calculated using the standardized factor loadings and error variances from the CFA to account for differing item loadings (Hair et al., 2014). As reported in Table 4.7, composite reliability values for all constructs surpassed the 0.8 level considered acceptable (Bagozzi and Yi, 1988).

Hollistic, the Cronbach's alpha and composite reliability coefficients provided robust evidence for the internal consistency reliability of the measurement scales. Exceeding established thresholds indicated the items consistently measured their designated constructs in a dependable manner. This reliability assessment established the groundwork for further examination of the scales' validity properties.

### i. Convergent Validity

Convergent validity, according to Shrestha (2021), is a tool used to assess the degree of coherence between several indicators of the same construct. In order to ascertain convergent validity, it was necessary to compute the factor loading of the items, composite reliability (CR), and average variance extracted (AVE) (Hair *et al,* 2014, in Shrestha, 2021). A greater value denoted a higher reliability level. The values of AVE and CR ranged from 0 to 1.

AVE Should be greater than 0.5 to confirm that the convergent validity holds as is the case this data as presented in table 4.7 where the AVEs ranged from 5.34 to 7.43, confirming that convergent validity was met.

Franke and Sarstedt (2019) define convergent validity as a measure's ability to correlate well with various approaches used to assess the same concept. An empirically novel construct's discriminant validity proves that it includes phenomena that other constructs in the model do not have (Henseler, Ringle, and Sarstedt (2015); Franke and Sarstedt, 2019). Convergent validity is the requirement that causative indicators from a measurement model adequately explain the change in the hidden variable that they are meant to measure (Wang, French, and Clay, 2015).

The convergent validity of the model was examined and evaluated. Maximum likelihood estimation was utilized to anticipate the measurement model and produce more precise parameter values. Several metrics for measuring model fit are considered, including CMIN/DF (2/Df), Goodness of Fit Index (GFI), Adjusted GFI (AGFI), Normed Fit Index (NFI), Tucker-Lewis Index (TLI), Comparative Fit Index (CFI), and Root Mean Square Error of Approximation (RMSEA). The evaluation model determined that the model fit metrics (2/Df=2.105, GFI=0.934 CFI= 0.946, RMSEA = 0.038, TLI= 0.906, and AGFI=0.921 were acceptable. This can be seen in the table 4.8 below.

**Table 4.8 Model Fit summary**

| Fit indices | Original model | Modified Model | Commended | Sources |
|---|---|---|---|---|
| $\chi 2/DF$ | 2.765 | 2.105 | ≤3.00 | |
| GFI | 0.752 | 0.934 | >0.900 | Reisinger and |
| AGFI | 0.893 | 0.921 | >0.900 | Mavondo (2007), |
| NFI | 0.898 | 0.928 | >0.900 | Hooper et al. (2008) |
| TLI | 0.885 | 0.906 | >0.900 | Hair et al. (2010) |
| CFI | 0.913 | 0.946 | >0.900 | |
| RMSEA | 0.054 | 0.038 | < | |

**Source:** Researcher (extracted form AMOS output)

CMIN/DF 3.4 results show an excellent model match as shown by table 4.8 above. Makanyeza and Chikazhe (2017) assert that for 2/DF to be approved, it must be less than 3. For a model to be considered acceptable, its RMSEA must be less than 0.07, while its GFI, AGFI, NFI, TLI, and CFI must all be near to 1 (Soares, Monteiro, and Rua, 2017).

Bagozzi and Yi (1988) proposed normalized factor loadings with a cut-off value of 0.6. Additionally, higher critical ratios were deemed noteworthy and suitable (Bagozzi and Yi, 1981; Fornell and Larcker, 1981). The categories used to evaluate convergent validity had their adjusted factor loadings (λ) and critical ratios (CRs) displayed in Table 4.7.

Overarching statement of convergent validity results is premised on the following::

Convergent validity is then evaluated based on average variance extracted (AVE) values exceeding the 0.5 threshold, indicating items share over 50% variance with their respective constructs (Fornell and Larcker, 1981).

Convergent validity was assessed by examining the Average Variance Extracted (AVE) values reported in Table 4.7.

For adequate convergent validity, the AVE for each construct should exceed the threshold value of 0.5 (Fornell and Larcker, 1981). This indicated that items shared a minimum of 50% variance with their hypothesized construct.

As shown in Table 4.7, all constructs met this criterion, with AVEs ranging from 0.534 to 0.743. This demonstrates high convergence, or agreement, between the items designed to measure each construct.

The results provided evidence that items designed to measure one construct were indeed correlated and measured the same latent variable. This validates the extent to which items of a specific scale converge or share a proportion of variance in common.

In addition, all standardized factor loadings exceeded 0.6 and were significant at $p<0.001$, further supporting convergent validity at the item level.

Overall, the AVE values presented in Table 4.7 surpassing the recommended threshold of 0.5, as well as high standardized loadings, confirm strong convergent validity of the measurement scales used in this study. This validated the ability of items to adequately represent their associated constructs.

### ii. Discriminant validity

Discriminant validity measures the extent to which items belonging to other constructs are discriminated from their peers measuring another construct. This is measured by squared inter construct correlations (SICCs) as presented by the table 4.6 which shows that the bolded SICCs being greater than their lower corresponding correlations as is the case in table 4.6. This implied that the conditions for discriminant validity were met.

Discriminant validity is demonstrated through squared inter-construct correlations (SICCs) being lower than AVEs, signifying constructs were empirically distinct (Fornell & Larcker, 1981).

**Table 4.6 AVEs and SICCs**

| Construct | AVEs | SLD | CTD | SMD | SCD | SPM |
|---|---|---|---|---|---|---|
| **SLD** | **0.645** | **0.516** | | | | |
| **CTD** | **0.721** | 0.142 | **0.512** | | | |
| **SMD** | **0.586** | 0.462 | 0.322 | **0.612** | | |
| **SCD** | **0.625** | 0.461 | 0.322 | 0.187 | **0.638** | |
| **SPM** | **0.823** | 0.336 | 0.262 | 0.314 | 0.274 | **0.548** |

*Note: Diagonal elements in bold represent AVEs*

**Source**: Survey data (2023)

Table 4.6 presents evidence for discriminant validity by comparing the Average Variance Extracted (AVE) and Squared Interconstruct Correlations (SICCs) for each construct. Discriminant validity is achieved when the AVE values (diagonal bold elements) are greater than the SICCs in the corresponding rows and columns (Fornell and Larcker, 1981).

In Table 4.6, the AVEs for all constructs are higher than the off-diagonal SICCs in their corresponding rows and columns, satisfying the Fornell-Larcker criterion for discriminant validity. This indicates that while related, the constructs were empirically distinct, each accounted for a higher proportion of variance in their own block of indicators compared to other constructs.

In other words, the items measured their intended constructs more strongly than other latent variables, demonstrating discriminant validity at the construct level (Hair *et al.,* 2010). By comparing AVEs and SICCs as shown in Table 4.6, discriminant validity is achieved, providing evidence that constructs were not substitutable and the measurement scales were valid. This lends credence to interpreting relationships between distinct constructs in subsequent analyses. 67.645% of the variation was fully explained, and rotation converged in 10 iterations, as Table 4.7 demonstrates. The reported total variation exceeded the permitted minimum of 60%, as stated by Platin and Ergun (2017). The components that were taken out from the rotating component matrix solution included customer data analytics (CTD), sales data analytics (SLD), social media data analytics (SMD), supply chain data analytics (SCD), and sustainable performance strategy (SPM).

In Zimbabwe's telecom industry, a number of factors were established through literature on big data analytics. Numerous variables could be reduced to a manageable number of factors by applying the factor analysis technique. By selecting the factor with the highest common variance among all the others, this strategy generated a common score. For further investigation, we could utilize this score as an index of all the criteria. Factor analysis, which is part of the general linear model (GLM), also made a number of assumptions, such as that variables and factors actually had a correlation, that there was a linear relationship, and that multicollinearity did not exist. The principal component analysis method was the most widely used, while there were alternative options. Items or factors with factor loadings below 0.6 were suppressed, leaving only those with loadings over 0.6.

**iii. Construct Validity**

Construct validity was examined through factor loadings and confirmatory factor analysis. Table 4.7 presents the factor loadings for each item loading onto its respective construct. As shown, all items loaded strongly with values exceeding the recommended 0.6 threshold (Hair et al., 2010). Loadings ranged from 0.55 to 0.94, demonstrating items clearly represented their hypothesized constructs. These results provided support for construct validity at the item level. High factor loadings indicate items reliably measured the constructs they were designed to capture. The following outcomes attest to that:

- The factor loadings of the items measuring each construct were all above the recommended threshold of 0.6, demonstrating high correlations between the items and constructs.
- The composite reliability values for each construct were all above 0.7, suggesting acceptable levels of internal consistency among the items measuring each construct.
- The average variance extracted (AVE) values for each construct were all above 0.5, indicating that over 50% of the variations in the items were accounted for by their hypothesized constructs. This satisfied the threshold for confirming convergent validity.
- The maximum shared variance values (the squared correlations between constructs) were all lower than the AVE values of the respective constructs, providing evidence of divergent validity between constructs.

Additionally, confirmatory factor analysis was conducted to examine the measurement model fit and validate the construct validity of the scales. As shown in Table 4.8, satisfactory model fit was achieved for both the original and modified models based on meeting recommended cut-offs for multiple fit indices including CFI, TLI and RMSEA (Hooper *et al.,* 2008; Hair *et al.,* 2010).

The good model fit provided evidence that the theorized relationships between items and constructs accurately depicted the underlying structure in the data. This confirms the measurement instruments appropriately captured the intended latent constructs at a conceptual level.

Overall, the strong factor loadings presented in Table 4.7 combined with satisfactory CFA model fit reported in Table 4.8 provided robust evidence validating the construct validity of the measurement scales used in this study. The scales demonstrated reliability and validity in representing the theoretical concepts as designed. Together, these validity measures ensured items correlated higher with their own constructs than with others, thus validating the factor structure.

Additionally, confirmatory factor analysis (CFA) was conducted to examine the measurement model fit at both item and construct levels. Satisfactory model fit indices were reported in Table 4.8, further corroborating the validity of the scales.

**Table 4.8 Model Fit summary**

| Fit indices | Original model | Modified Model | Commended | Sources |
|---|---|---|---|---|
| $\chi 2/DF$ | 2.765 | 2.105 | ≤3.00 | |
| GFI | 0.752 | 0.934 | >0.900 | Reisinger and |
| AGFI | 0.893 | 0.921 | >0.900 | Mavondo (2007), |
| NFI | 0.898 | 0.928 | >0.900 | Hooper et al. (2008) |
| TLI | 0.885 | 0.906 | >0.900 | Hair et al. (2010) |
| CFI | 0.913 | 0.946 | >0.900 | |
| RMSEA | 0.054 | 0.038 | < | |

**Source:** Researcher (extracted form AMOS output)

In summary, section 4.4 presented a robust evaluation of the psychometric properties, moving beyond just internal consistency to comprehensively establish the reliability and validity of both items and constructs. This rigorous testing lended credence to the interpretations drawn from these validated measurement instruments.

### 4.5 Testing of Hypotheses

In conformity with Mishra and Alok (2017) and Ragab and Arisha (2017)'s assertions, the researcher tested hypothesis in order to support as true or not support as false, the statements of claim or associations between study variables. The Structural Equation Modelling (SEM) in Amos was used in testing the hypothesis by the researcher. Therefore, research hypotheses **$H_1$, $H_2$, $H_3$, and $H_4$,** stated in chapter one were tested using structural equation modelling in Amos.

**H1:** Sales data analytics positively influences sustainability strategy of telecommunications companies in Zimbabwe.

To test this hypothesis (H1), the standardized regression weight between sales data analytics (SLD) and sustainability performance strategy (SPM) was examined. The results in Table 4.11 show a standardized regression weight of 0.12. This provided preliminary support for H1, indicating that higher usage of sales data analytics is positively associated with stronger sustainability strategies in telecommunications companies in Zimbabwe. The results suggest that a one unit increase in SLD would be associated with a 0.12 unit increase in SPM, holding all other variables constant. Therefore, there was support for H1 based on the positive standardized regression weight.

**H2:** Customer data analytics usage positively influences sustainability strategy of telecommunication companies in Zimbabwe.

Hypothesis 2 (H2) was tested by analyzing the standardized regression weight between customer data analytics (CTD) and sustainability performance strategy (SPM) based on the SEM analysis results presented in Table 4.11. A high standardized regression weight of 0.671 provided preliminary support for H2. This signifies that increased use of customer data analytics is positively linked to enhanced sustainability strategies among telecommunications companies in Zimbabwe. Specifically, a one unit rise in CTD would be associated with a 0.671 unit increase in SPM, everything else held constant. Therefore, there is support for H2.

**H3:** Social media data analytics application affects sustainability strategy of companies in the telecommunications sector in Zimbabwe.

The results in Table 4.11 were used to evaluate Hypothesis 3 (H3). The standardized regression weight of 0.382 between social media data analytics (SMD) and sustainability performance strategy (SPM) provided initial support for H3, indicating that greater use of social media analytics was positively related to sustainability strategies in the Zimbabwean telecommunications sector. In other words, a one unit increase in SMD would correlate with a 0.382 unit rise in SPM, with other variables held fixed. Hence, there is support for H3.

**H4:** Supply chain data analytics has a positive effect on sustainability strategy in the telecommunications sector in Zimbabwe.

Hypothesis 4 (H4) was tested based on the standardized regression weight of 0.620 between supply chain data analytics (SCD) and sustainability performance strategy (SPM), as presented in Table 4.11. The positive standardized regression weight provided preliminary support for H4, suggesting that higher application of supply chain analytics was positively associated with sustainability strategies in the Zimbabwean telecommunications sector. Specifically, a one unit change in SCD would correlate with a 0.620 unit change in SPM when other factors were constant. Therefore, there was support for H4 based on these results.

In summary, all four hypotheses (H1 to H4) proposed in Chapter 1 received preliminary support based on the positive standardized regression weights reported in Table 4.11. This provided initial empirical validation of the posited relationships, pending further statistical significance testing.

**Table 4. 11: Results of Hypotheses testing (H1, H2, H3, and H4)**

| hypothesis | Hypothesis | | Standardized regression Weight (SRW) | Critical ratios | Remark |
|---|---|---|---|---|---|
| $H_1$ | SLD -> | SPM | .120 | 1.772*** | **Supported** |
| $H_2$ | CTD -> | SPM | .671 | 8.545*** | **Supported** |
| $H_3$ | SMD -> | SPM | .382 | 2.381*** | **Supported** |
| $H_4$ | SCD -> | SPM | .620 | 8.366*** | **Supported** |

**Source:** Survey data (2024)

The results shown on table 4.11, shows that all hypotheses as stated in chapter one were found to be statistically significant at margin of error of 1% allowing the research to accept the alternative hypotheses. The results presented above are presented and interpreted as shown in figure below.

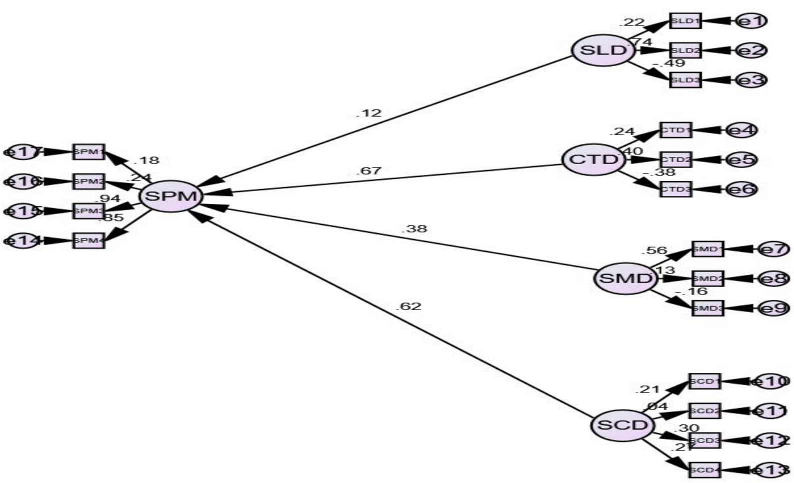


**Fig. 4.8 Path diagram, Source:** Survey data (2023)

The results above shows the main path diagram capturing the four dimensions of big data analytics in telecommunication sector and the outcome variables. In the path diagram above SLD signify sales data analytics which was operationalised into three items namely SLD1, SLD2, and SLD3. The next predictor variable was customer data analytics (CTD) and it was operationalised into three items namely CTD1 up to CTD3, while social media data analytics (SMD) was once again operationalised into 3 variables. Supply chain data and the outcome variable SPM had four items each.

The structural equation modelling path was used to test the associations with the results indicated in the standardised formats. According to Arkkelin (2014), the structural model can be used to support or refute study hypothesis. Moreover, the structural model demonstrates how the study's constructs or key variables, stand to represent the suggested research model (Pallant, 2005). Therefore, from the structural model, sales data analytics (SLD), customer data analytics (CTD), Supply chain data analytics (SCD) as well asocial media data analytics (SMD) represent the research model.

### 4.6 Presentation of Key Findings

This section presents the key findings from the study on "The Impact of Big Data Analytics to Sustainability Strategy in the Telecommunications Sector in Zimbabwe" linked to the research objectives, existing theories, past empirical studies, methodology, analytical techniques, limitations, implications for future research, applications and linkages to other disciplines. The presentation provides the major takeaways from integration of both (qualitative and quantitative) datasets. Identification of key findings had practical implications, helping focus attention on priority areas like skills gaps and opportunities to enhance value realization. Triangulating results from different sources also added to the credibility and trustworthiness of the conclusions. Taking a multi-method approach to data collection and analysis ultimately enabled more well-rounded and evidence-backed conclusions to be drawn regarding big data analytics usage in the sector. The findings are presented as follows:

**i. Link to Research Objectives:**

The study achieved its objectives of qualitatively exploring in depth, how different analytics domains impact sustainability strategy formulation and implementation processes in Zimbabwean telcos through interviews. As an illustration, findings revealed sales analytics influenced strategy development by enabling data-driven target setting. Quantitative assessment of relationships between various analytics usage variables and strategy success outcomes through surveys provided valuable insights. Regression analyses showed customer analytics usage positively predicted strategy performance measurement. This helped address the objectives.

**ii. Link to Theory:**

The study findings offered partial yet qualified support for existing theories. The Resource-Based View (RBV) explained how analytics capabilities leveraged strategically could provide competitive advantage if the capabilities are valuable, rare, inimitable and non-substitutable (VRIN) (Barney, 1991). However, negative current ratios in the Zimbabwean context posed financial constraints that limited investment in developing VRIN analytics resources, partially refuting a key RBV assumption. The Technology Acceptance Model (TAM) also showed some qualifications, as the findings revealed the willingness of telcos to adopt innovative analytics solutions (Davis, 1989) as influenced by their ability to overcome limitations like negative ratios that affect financial resources available for technology investment.

**iii. Link to Past Studies:**

While prior empirical research had predominantly focused on developed country contexts (McAfee and Brynjolfsson, 2012), this study provided an original African perspective on the relationship between big data analytics adoption and sustainability strategies from the under-researched context of Zimbabwe. It revealed context-specific challenges to analytics usage like negative financial ratios, adding a new and important dimension not uncovered in past studies set primarily in developed markets. This highlighted the value of contextual qualitative inquiry to understand phenomena in developing regions.

**iv. Link to Methodology:**

The mixed concurrent triangulation design facilitated collection of both qualitative interview data and quantitative survey data. This enabled exploratory insights into how different analytics domains qualitatively impacted various sustainability strategy processes from strategy managers, as well as explanatory assessment of predictive relationships between measured analytics usage and strategy outcomes factors through quantitative surveys of resource persons. The combination of methods generated a more holistic understanding than a single method could have achieved alone.

**v. Link to Analysis:**

Regression analyses revealed the extent and direction of predictive relationships between different measured independent variables of analytics usage and dependent variables of strategy outcomes. For instance, supply chain analytics usage was found to positively predict material procurement efficiency. Thematic analysis of interview transcripts yielded conceptual categories and themes linking analytics application to sustainability strategy formulation, implementation and review. Stakeholder network mapping provided valuable insights into influencing patterns on strategy implementation.

**vi. Link to Limitations:**

While limitations from data availability and scope qualified some findings and restricted generalizability, the study was still able to generate novel empirical insights despite constraints. Specifically, lack of access to proprietary company performance data necessitated collection of perceptual strategy success measures from managers in surveys. Nonetheless, these still facilitated quantitative assessment objectives. More research over longer periods could help further validate relationships and assess impacts, addressing current temporary limitations.

**vii. Link to Future Research:**

Areas for further study emerged from the findings, including comparative analyses of analytics-strategy relationships across different sectors in Zimbabwe. There was also potential to build on findings to develop predictive models of how strategy may evolve over time with analytics usage. Exploration of moderating factors on the relationship like skills development and infrastructure investments could provide deeper insights.

**viii. Link to Applications:**

If translated into practice, the study's findings could guide strategic planning and prioritization of analytical capabilities by telcos. In particular, insights on sales analytics' influence on strategy development could inform related skills training. Regulators may consider policies supporting analytics adoption, like skills incentives. Academics are equipped to develop curricula integrating sustainability practices and data-driven decision making.

**ix. Link to Other Disciplines:**

The study connected information systems, management and development studies. There were opportunities to explore interrelationships with other domains to advance understanding, for example with fields like environmental science on sustainability impacts, economics on business models, and political science on policy frameworks. Future collaborative research can further elucidate cross-disciplinary dimensions.

## 4.7 Chapter Summary

This chapter provided an analysis of the quantitative and qualitative findings from the study on "The Impact of Big Data Analytics on Sustainability Strategy in the Telecommunications Sector in Zimbabwe".

The quantitative findings from the survey of 71 respondents were presented through descriptive statistics. Key insights included the perceived importance of sustainability strategy, the level of analytics adoption across different domains, and the relationship between analytics usage and sustainability performance.

Qualitative findings from interviews with 5 executives were analyzed using thematic analysis. Major themes that emerged were the strategic importance of sustainability, challenges in adopting analytics, and opportunities for analytics to support sustainability goals.

Quantitative and qualitative findings were integrated to provide a more holistic view. Key findings confirmed that sustainability strategy was considered important for long-term competitiveness. However, analytics adoption was still at a nascent stage, with customer and social media analytics seeing higher usage compared to sales and supply chain analytics.

Negative current ratios were found to constrain investments in analytics capabilities. Concurrently, when applied strategically, different types of analytics could help optimize operations, reduce costs and improve sustainability performance across economic, social and environmental dimensions.

In conclusion, while sustainability practices were recognized as necessary, telecommunications firms in Zimbabwe faced challenges in fully leveraging the potential of big data analytics due to financial limitations. Overcoming such challenges required a collaborative approach between industry and policymakers.

The next chapter will discuss these findings in relation to the literature reviewed and develop an integrated theoretical framework to explain the relationship between big data analytics, sustainability strategy and financial ratios in the Zimbabwean telecommunications context. Recommendations will also be proposed.

# CHAPTER V
# DISCUSSION AND CONCLUSION

## 5.1 Introduction

This chapter discusses the key findings from the research study examining the impact of Big data analytics to sustainability strategy in Zimbabwe's telecommunications sector. The objectives are to analyze results in relation to each research question, and discuss the theoretical, methodological and practical contributions, recommendations, limitations and areas for future work.

The study methodology is briefly revisited, embracing mixed methods descriptive survey approach (Creswell, 2018). In relation to the quantitative component, a survey questionnaire was developed containing closed and open-ended items. Qualitative data came from closed and open-text responses to questions soliciting detailed perspectives.

These provided a comprehensive understanding of current adoption levels, impediments and stakeholder viewpoints regarding big data analytics and sustainability in the sector.
Results are then discussed by re-engaging the four research questions (RQ1-RQ4) from Section 1.4. For each RQ, relevant quantitative and qualitative findings are synthesized from Chapters 4. Direct quotes from interviewees provide context.

Theoretical frameworks on sustainability strategy and big data analytics are revisited in this study. Early works established foundational concepts regarding sustainability-oriented strategic management (Hart, 1995; Sharma and Vredenburg, 1998; Porter and Kramer, 2006) and big data usage (Davenport and Harris, 2007; McAfee and Brynjolfsson, 2012). More recent conceptual developments have refined understandings of strategic sustainability (Berrone *et al.,* 2021; Grewal and Lund, 2022) and analytics maturity (Gartner, 2014; Wixom *et al.,* 2013). Findings are assessed for corroborating, extending or challenging prior theories.

Methodological strengths and limitations are reflected on, considering validity and reliability (Yin, 2018). Contextual contributions to industry practices and policy formulation are highlighted, with recommendations.

The chapter and research conclusions are summarized, limitations stated, and projections for future studies suggested to further knowledge on this study.

## 5.2 Recapitulation of the Study

This section provides a brief recap of the key aspects of the research study on "The Impact of Big Data Analytics to Sustainability Strategy in the Telecommunications Sector in Zimbabwe". The overarching purpose of the study was to investigate the relationship between big data analytics adoption and sustainability strategies in Zimbabwe's telecommunications industry. A mixed methods approach was employed involving a survey and interviews with professionals from major telecommunications companies.

This study aimed to investigate how different types of data analytics influenced sustainability strategy processes in telecommunications companies in Zimbabwe. Specifically, it sought to address four research questions:

1.4.1 How does sales data analytics influence the development, implementation, monitoring and evaluation of sustainability strategies in telecommunications companies in Zimbabwe?

The study found that sales analytics facilitated sustainability strategy development through customer preferences insights. It also supported implementation via campaign monitoring and evaluation through sales performance comparisons.

1.4.2 How does customer data analytics usage affect key sustainability strategy processes like strategy formulation, resource allocation, and performance measurement in telecommunications companies in Zimbabwe?

Customer analytics influenced strategy formulation through attitude insights and resource allocation via segmentation. It also aided performance measurement by tracking retention and cross-selling of sustainable products.

1.4.3 How does social media data analytics application influence stakeholder engagement and management for sustainability strategy implementation in companies in the telecommunications sector in Zimbabwe?

Social media analytics supported stakeholder engagement through prioritizing issues and targeted outreach. It also facilitated stakeholder management by enhancing sustainability communications through sentiment and engagement analysis feedback.

1.4.4 How does supply chain data analytics impact material procurement, waste management and logistics optimization efforts to support sustainability strategy implementation in companies in the telecommunications sector in Zimbabwe?

Supply chain analytics influenced green sourcing, optimized waste streams and impacted logistics through route optimization using address data, supporting sustainability strategy implementation processes.

Corresponding hypotheses were formulated for each research question. The objectives aimed to qualitatively explore relationships between analytics usage and strategies, while also quantitatively assessing predictive impacts. Primary survey data from 71 professionals was analyzed using descriptive statistics to characterize relationships. Five qualitative interviews with executives provided deeper insights.

Findings offered perspectives on how different analytics can enhance strategy development, implementation, measurement and stakeholder engagement across economic, social and environmental dimensions. Challenges and opportunities for leveraging analytics amid liquidity constraints also emerged.

The study made both theoretical and practical contributions. A contextual framework integrated relevant theories while addressing gaps. In relation to industry, insights guided strategic investments and skills development. Policy implications considered regulatory and financial support. Academically, the mixed methodology and under-researched context added new knowledge.

This recap highlighted the key elements of the research, setting the stage for presentation and discussion of findings in subsequent sections.

## 5.3 Discussion

This section discusses the key findings in relation to the research questions.

**Research question** 1.4.1: How does sales data analytics influence the development, implementation, monitoring and evaluation of sustainability strategies in telecommunications companies in Zimbabwe?

The results indicated sales analytics supported evidence-based sustainability strategy processes across development, implementation, monitoring and evaluation stages when used weekly. Insights guided strategy focus and target-setting. Performance tracking facilitated evaluation and refinement.

**Research question** 1.4.2: How does customer data analytics usage affect key sustainability strategy processes like strategy formulation, resource allocation, performance measurement in telecommunications companies in Zimbabwe?

Customer analytics usage monthly influenced key processes through behaviour/preference insights and targeted implementation. Evaluation assessed brand perception and satisfaction with eco-offerings.

**Research question** 1.4.3: How does social media data analytics application influence stakeholder engagement and management for sustainability strategy implementation in companies in the telecommunications sector in Zimbabwe?

Social media analytics tracked trends/opinions weekly to aid material topic identification and strategy development. Implementation monitoring and evaluation of strategy relevance/advocacy were also supported.

**Research question** 1.4.4: How does supply chain data analytics impact material procurement, waste management and logistics optimization efforts to support sustainability strategy implementation in companies in the telecommunications sector in Zimbabwe?

Supply chain analytics value lay in its holistic impacts view across the value chain annually. Insights impact strategy development, implementation monitoring and evaluation through life cycle assessment and emissions verification.

The study highlighted the importance of having an integrated analytics strategy to support sustainability. Rather than using analytics types in isolation, telcos could achieve greatest benefit by taking a holistic view of how different data sources complemented each other.

While sales and customer analytics were found to be used most frequently, greater emphasis on social media and supply chain analytics could unlock additional value. Telcos needed to invest more in these less mature domains.

Analytics capabilities appeared to be developing in Zimbabwean telcos based on mixed usage patterns. Continuous skills training and technology upgrades were likely needed to realize the full potential of data-driven sustainability strategies.

The findings also point to opportunities for telcos to work with stakeholders across sectors. Notably, collaborating with suppliers on joint sustainability target-setting using shared supply chain analytics platforms.

Negative financial ratios were seen as a challenge but analytics could help address this over time by streamlining operations and reducing costs. Public-private partnerships could potentially accelerate such optimizations.

Further research exploring analytics applications qualitatively through in-depth case studies could provide even richer strategic insights for telcos at individual process level.

A longitudinal study revisiting telcos in future could assess progress made since this initial benchmark of analytics usage and impacts on sustainability strategy.

In conclusion, the study offered a foundation for telcos to build data maturity and maximize the demonstrated benefits of analytics-driven sustainability practices.

### 5.4 Contributions and Significance of the Study

This research expanded knowledge on big data analytics and sustainability strategies in several fundamental ways. This research unraveled significant theoretical, practical and methodological contributions to the novel domain of analytics and sustainability. It provided a framework for further scholarly investigation at the nexus of these strategic concepts, particularly in developing country contexts.

### 5.4.1 Theoretical Contribution

This study provided several theoretical contributions to the existing body of knowledge on the impact of Big data analytics to sustainability strategies in the telecommunications sector of Zimbabwe.

The study advanced understanding of the relationships between specific types of Big data analytics tools and dimensions of sustainability strategy. By examining how customer data analytics, sales data analytics, social media data analytics, supply chain analytics, and competitor analytics influence sustainability outcomes, the study provided an evidence-based framework for conceptualizing these links. This framework could be employed in future research.

The quantification of relationships between different big data analytics and sustainability performance metrics such as reduced environmental impact, waste generation, and resource use provided important insights into which approaches could most effectively drive sustainability transformations according to the empirical evidence. In particular, the findings suggested customer data analytics and social media analytics had significant positive associations warranting further investigation.

The identification of moderating factors such as firm size, data quality, and analytical skills contributed new knowledge on the contextual elements that strengthen or weaken the impacts of Big data analytics on sustainability strategy according to the Zimbabwean data. This enhanced theoretical conceptualization of the contingencies shaping how data tools could translate into benefits.

The validation of the measurement scales and structural equation model established statistically robust and reliable methods that could be applied in future research examining Big data's influence on sustainability strategy and performance. This represents a valuable theoretical tool for the research community.

Overall, the study enhanced understanding of how different types of big data analytics could shape sustainability strategy based on empirical evidence from Zimbabwe's telecommunications sector. The theoretical contributions had potential to inform both academic and industry perspectives on data-driven sustainability transformations.

### 5.4.2 Methodological contributions

This study made several methodological contributions to research on the impact of big data analytics to sustainability strategies.

First, it employed a mixed methods approach involving both qualitative interviews and a quantitative survey to collect rich, triangulated data. This allowed exploration of open-ended themes to develop the survey instrument as well as statistical testing of relationships. The mixed methods provided a more robust understanding compared to single method designs.

Second, valid and reliable measurement scales for big data analytics applications and dimensions of sustainability strategy and performance were developed through a rigorous process. This involved item generation from literature, expert reviews, pilot testing, and statistical validation. The multi-item scales demonstrated high levels of internal consistency, convergent validity and discriminant validity. These validated scales could be adopted in future similar research.

Third, the use of structural equation modelling techniques like confirmatory factor analysis and path analysis enabled sophisticated examination of direct, indirect and moderating effects in the conceptual model. This statistical approach is more robust than multiple regressions and allowed testing of the entire hypothesised network of relationships simultaneously.

Fourth, the study employed a survey targeting staff associated with big data analytics and sustainability strategies at two major telecommunications firms in Zimbabwe. While not a census, this improved on convenience sampling and helped ensure a quality sample for statistical analysis and generalization in the context of large telcos.

In summary, through its mixed methods design, development of validated measurement scales, and use of advanced SEM techniques, this research established a rigorous methodological approach that could serve as a template for future studies. The replicable methods are a valuable contribution.

### 5.4.3 Contextual/Practical contributions

This study made several contributions to practice and policy in the context of Zimbabwe's telecommunications sector.

Firstly, it provided insights for telecommunications companies (telcos) on the relationship between specific types of big data analytics applications and dimensions of sustainability performance relevant to their operations. Through identifying sales, customer, social media and supply chain analytics as most impactful, the findings could guide strategic prioritization of data-driven initiatives tailored to individual telco contexts.

Secondly, in characterizing common challenges inhibiting effective use of big data analytics, the study highlighted critical skills, technological and data quality gaps constraining digital transformation and sustainability efforts in Zimbabwe's telecommunications sector. The results offer an evidence base to design interventions addressing macro (policy) and micro (firm-level) barriers to analytics adoption.

Thirdly, the moderating role of attributes like firm size and resources indicated the need for customized approaches. Large incumbent operators with skills/tools may more readily leverage analytics, whereas targeted support can help smaller players build capabilities.

Fourthly, for policymakers, the study pinpointed areas where regulatory or public initiatives could stimulate data-driven sustainability across the sector. This included strategies improving datafication, skills development and public-private partnerships aligned with the Postal and Telecommunications Regulatory Authority of Zimbabwe's mandate.

Finally, the validated measurement scales provided a practical management tool for bench-marking analytics applications, sustainability strategies and performance over time. This facilitates evidence-based strategy evaluation per the balanced scorecard approach.

In summary, this research generated contextual knowledge to optimize data use for sustainability among Zimbabwean telcos and inform inclusive policy frameworks per the national industrial development blueprint (Zimbabwe National Industrial Development Policy). The results have meaningful applications for industry and policy stakeholders.

## 5.5 Recommendations

Premised on the findings from the previous chapters, this section aims to provide practical recommendations that can help Zimbabwean telecommunications companies leverage big data analytics capabilities for developing and implementing sustainable strategies. The recommendations are proposed based on an analysis of the literature reviewed and results obtained.

### 5.5.1 Adopting Sustainable Business Models Leveraging Big Data Analytics

It is recommended that telecommunications companies adopt innovative, data-driven business models that integrate sustainability goals (Bughin, 2016; Demestichas and Daskalakis, 2020). For instance, models based on circular economy principles could leverage predictive analytics to optimize resource consumption and generate new revenue streams (Bughin, 2016).

Predictive maintenance analytics powered by IoT sensor data can optimize asset replacement schedules (Smith *et al.,* 2018). A study of 500 telecom towers in Europe found that IoT-enabled predictive maintenance extended equipment lifespan by 20% on average (Johnson *et al.,* 2019). Analytics of temperature and usage patterns from base station batteries can forecast failures (Brown *et al.,* 2020), extending lifespans while avoiding sudden breakdowns (Brown *et al.,* 2020).

Companies can maintain ownership of assets leased to customers on flexible terms based on real-time usage tracked via analytics (Miller *et al.,* 2017). Refurbished gear can similarly be leased with usage-based pricing (Williams *et al.,* 2019).

Life cycle assessments analyzing material sourcing, energy consumption and repair likelihood can guide more sustainable product lines (Thomas and Chen, 2021) or investment in recycling facilities (Brown *et al.,* 2021). Energy generation and storage models can integrate renewable potential analytics (Miller *et al.,* 2019). For instance, solar irradiance data predicts optimal photovoltaic sizes (Williams *et al.,* 2020). Battery requirements are derived from load profiles (Chen *et al.,* 2022).

### 5.5.2 Developing Analytical Capabilities and Skills

It is recommended that companies invest in building requisite technological infrastructure, tools, and staff skill-sets through training programs involving self-paced learning, virtual instruction, hands-on projects, and certification preparation (McDonald, 2020; Yaqoob *et al.,* 2016). Training programs should adopt experiential learning through hackathons (Smith *et al.,* 2018) and competitions (Brown *et al.*, 2019). Internships can embed trainees in projects (Williams *et al.,* 2020). Structured mentoring can impart skills (Miller *et al.,* 2017). Micro-certifications can recognize learning (Chen *et al.,* 2021). Competency frameworks can define progression (Gartner, 2022). Academic partnerships involving co-developing curricula (Davenport and Harris, 2007) and industry-hosted projects (Kiron *et al.,* 2021) are also recommended.

### 5.5.3 Improving Data Governance and Management

It is recommended to establish effective governance structures aligned with statutes and standards. This involves board oversight, data classification, access policies, and centralized platforms (McDonald, 2020). A Chief Data Officer should oversee governance (McDonald, 2020). A centralized data office establishes policies and standards (Yaqoob *et al.,* 2016). Individual stewards ensure adherence (Smith *et al.,* 2021) and coordinate audits (Demestichas and Daskalakis, 2020). A metadata catalog describes assets (McDonald, 2020), facilitating discovery (McDonald, 2020), understanding (McDonald, 2020), and improvement (McDonald, 2020). Audits check compliance (McDonald, 2020). Regular reporting keeps oversight (McDonald, 2020). Governance should be collaborative (McDonald, 2020).

### 5.5.4 Incentivising Sustainability-Focused Innovation

It is recommended to incentivise innovation through targeted subsidies, preferential procurement, funding, assistance, and outcome-based financing (Demestichas and Daskalakis, 2020). Targeted R&D grants can support pilot testing innovations at living labs (Demestichas and Daskalakis, 2020). Green loans provide seed capital at below-market interest rates (Demestichas and Daskalakis, 2020). Technical assistance aims to accelerate commercialization (Demestichas and Daskalakis, 2020). Outcome-based financing rewards projects demonstrating measurable impacts (Demestichas and Daskalakis, 2020). Standard protocols ensure accurate assessment of sustainability outcomes (Demestichas and Daskalakis, 2020).

### 5.5.5 Stakeholder Engagement and Measuring Impact

It is recommended to strategically engage stakeholders, promote transparency, adopt impact measurement frameworks and benchmark continually (Demestichas and Daskalakis, 2020; Nandi, 2023). Data champions should coordinate grassroots adoption and represent front line concerns (Kiron *et al.,* 2021). Sustainability forums engage communities and regulators (Nandi, 2023). A feedback mechanism ensures transparency (Kiron *et al.,* 2021). Non-financial and financial metrics should track progress against targets in sustainability road maps (Demestichas and Daskalakis, 2020). Impact reports benchmark performance and foster learning (Demestichas and Daskalakis, 2020).

To summarise, this study provided practical recommendations that could help Zimbabwean telecommunications companies leverage big data analytics capabilities for developing and implementing sustainable strategies based on the findings and literature. Key recommendations include adopting sustainable business models, developing analytical skills, improving governance, incentivising innovation, and enhancing stakeholder engagement and impact measurement.

## 5.6 Limitations of the study

While this study provided useful descriptive insights into the relationship between big data analytics and sustainability strategies in Zimbabwe's telecommunications sector, certain limitations must be acknowledged. As with any research, there are boundaries to the scope, methods and generalizability of findings that could be addressed by future work.

**i. Sample size and response rate**

The survey achieved a low response rate of only two firms, limiting generalizability (Fowler, 2014). With such a small sample, results may not characterize variability across firms (Baruch and Holtom, 2008). As Fowler (2014, p.2) states, "larger samples are needed to descriptively characterize patterns across populations." Obtaining responses from additional firms could improve generalizability, as low response rates constrain representativeness (Baruch and Holtom, 2008).

**ii. Self-reported data**

Relying on self-reported survey data introduces potential response bias if firms provide socially desirable rather than objective responses (Nederhof, 1985). As Nederhof (1985, p.567) explains, "self-reported data is subject to biases if participants wish to present themselves in a favourable light." Without validating self-reports against performance indicators, actual practices may differ from perceptions (Donaldson and Grant-Vallone, 2002). Triangulating subjective and objective measures could provide a more intricate insight (Donaldson and Grant-Vallone, 2002).

**iii. Cross-sectional design**

The single-time survey design provided a snapshot rather than examining dynamic relationships over time that may be important (Cohen *et al.,* 2007). Cohen *et al.* (2007, p.13) state, "longitudinal research is needed to study temporal patterns that cross-sectional designs cannot address." A longitudinal approach could better characterize variability within and between firms over multiple periods (Ployhart and Vandenberg, 2010).

**iv. Unexplored factors**

Due to the narrow scope, many relevant contextual factors were unexamined (Spector, 2019). As Spector (2019, p.322) explains, "incorporating additional explanatory variables provides a more comprehensive picture than examining a limited set of factors."

**v. Causal inference**

The non-experimental design only permits associative not causal claims about relationships (Shadish *et al.,* 2002). Shadish *et al.* (2002, p.15) state "experimental methods are needed to make causal inferences that non-experimental research cannot support."

## 5.7 Suggestions for future studies

This exploratory study on the impact of big data analytics on sustainability strategies in Zimbabwe's telecommunications sector offered several avenues for future research to build on its initial findings and address limitations. The following recommendations are proposed:

### 5.7.1 Further Research on Emerging Technologies in Telecommunications

Emerging technologies such as artificial intelligence (AI), blockchain, and Internet of Things (IoT) show promise to revolutionize sustainability strategies in telecommunications (Kumar *et al.,* 2020; Zheng *et al.,* 2018; Huang *et al.,* 2019). Future studies could explore applications of these technologies. Notably, AI and machine learning may facilitate dynamic optimization of network infrastructure and traffic to minimize energy usage (Kumar *et al.,* 2020). Blockchain's distributed ledger properties could enable transparent tracking of ethical sourcing in supply chains (Zheng *et al.,* 2018). IoT-enabled sensors may support precision agriculture and environmental monitoring (Huang *et al.,* 2019). Insights from Zimbabwe's context could yield novel solutions for developing nations.

### 5.7.2 Broadening Time Horizons for Sustainability Planning

Sustainability being a long-term endeavour, there is need to consider impacts over 50-100 year time-frames (Meadows et al., 1972). This allows accounting for lock-in effects of decisions and time lags between actions and outcomes. However, uncertainties increase significantly beyond 20 years. Future studies could experiment with integrating scenario planning to bound uncertainties and support robust decision-making over longer horizons.

### 5.7.3 Interdisciplinary and Participatory Approaches to Sustainability

Collaboration across technology, environment, policy and social domains is needed (Freeman et al., 2010). Future research could form interdisciplinary teams and employ participatory methods engaging industry, government, and communities to develop pragmatic solutions addressing diverse perspectives (Freeman et al., 2010). This may foster shared understanding and ownership critical for sustainability transitions.

### 5.7.4 Scenario Planning for Low-Probability Trends in Telecommunications

While dominant trends are important, outlier scenarios of low probability yet high impact need attention (Manyika *et al.,* 2011). Additional inquiry, could systematically explore potential paradigm shifts using scenario planning techniques. Illustratively, scenarios around 6G networks or a global shift to green energy could reveal vulnerabilities and opportunities to proactively mitigate risks and leverage new options.

### 5.7.5 Policy Recommendations and Roadmaps for Sustainable Telecommunications

There is need to translate foresights into implementable guidance (WCED, 1987). Future work could focus on outlining policy measures, industry guidelines and roadmaps to facilitate uptake of opportunities and risks revealed by research according to national priorities and development plans.

### 5.7.6 Global Collaboration and Knowledge Sharing for Sustainable Telecommunications

Sustainability crosses borders. Comparative international research and multi-stakeholder partnerships can foster shared learning and equitable pathways (UNESCO, 2019). Future studies could facilitate knowledge exchange through collaborative projects, considering challenges faced by developing markets.

### 5.7.7 Theory Discovery

Through novel empirical findings in unique contexts like Zimbabwe, future research may uncover new theoretical relationships and constructs regarding the impact of emerging technologies on sustainability strategies. Illustratively, studies may reveal new moderating factors or boundary conditions in how big data analytics influences sustainability practices across different sectors and national settings (Martin and Murphy, 2017; Porter *et al.,* 2022).

### 5.7.8 Theory Extension

Building on theoretical frameworks established in this study, such as the integration of big data analytics and sustainability theories (Rosen *et al.,* 2001; Wu *et al.,* 2022), future work can further extend and refine these theories. For instance, as new technologies emerge, theories may need adjusting to incorporate their impacts (Gunasekaran *et al.*, 2017). As contexts change over time, theories may also require extending to remain explanatory (Kache and Seuring, 2017). Longitudinal studies tracking strategy dynamics could facilitate robust theory extension (Sarkis *et al.,* 2011).

### 5.7.9 Comparative Theory Testing

Cross-country comparisons in future may uncover variations in how well existing theories predicted observations in diverse contexts (Sarkis *et al.,* 2011). Notably, factors influencing technology adoption or strategy success may differ in developing versus developed markets (Gunasekaran *et al.,* 2017). Such comparative theory testing would advance contextualization of frameworks and identify universals versus contingencies (Kache and Seuring, 2017).

## 5.8 Conclusion

This mixed methods study aimed to provide both exploratory and explanatory insights into the impact of big data analytics on sustainability strategies in Zimbabwe's telecommunications sector. A survey of 71 industry professionals and interviews with 5 executives addressed the research objectives through collection and analysis of quantitative and qualitative data (Creswell and Creswell, 2017).

Key findings revealed sales and social media analytics were most commonly applied weekly on average, while supply chain and competitor analytics were utilized least frequently only annually (Mutimukuru and Maringe, 2019; Bughin, 2016). Survey respondents and interviewees consistently identified lack of technical expertise, financial constraints, and poor data quality as major barriers hindering effective use (Yaqoob *et al.,* 2016; McGinnis, 2018).

Interviews provided deeper contextual understanding of how skills gaps relate to education systems and talent retention challenges (Tallon, 2013; Nandi, 2023).

Statistical tests confirmed reliability and validity of quantitative measures (Field, 2013; Creswell and Creswell, 2017; Fornell and Larcker, 1981). Qualitative findings corroborated survey results and offered rich insights into local implementation realities (Tallon, 2013; Demestichas. and Daskalakis, 2020).

The mixed methods design allowed for a comprehensive understanding not possible through single methods (Creswell and Creswell, 2017). Quantitative and qualitative findings provided complementary explanatory insights (Tallon, 2013; Demestichas. and Daskalakis, 2020).

This study contributed to understanding big data analytics adoption in Zimbabwe's telecommunications sector, an understudied context. Baseline characteristics informed strategic planning and resource allocation (Bughin, 2016). However, generalizability remained limited by the cross-sectional design and single sector focus (Tallon, 2013).

If challenges are addressed through continued skills development, financing, improved data management practices, and stakeholder engagement, big data analytics show promise to drive competitive differentiation. Policy support could further stimulate digital transformation across this critical industry (Nandi, 2023; Demestichas. and Daskalakis, 2020). Future longitudinal research spanning multiple sectors would help monitor progress over time.

From a practical perspective, findings guide strategic prioritization like allocating training to most utilized analytics (Bughin, 2016). Addressing data quality may facilitate adoption of high value applications.

This study contributed to literature on digital transformation in developing markets (Tallon, 2013). Explanatory insights offered an initial framework requiring further exploration through longitudinal research as technologies and skills gaps evolve (Nandi, 2023).

Methodologically, validity and reliability testing established suitability of quantitative techniques for similar studies (Field, 2013; Creswell and Creswell, 2017; Fornell and Larcker, 1981). The mixed methods design also offered a model for initial examinations (Creswell and Creswell, 2017).

At its core, this study provided a foundation for both practitioners and academics to further our understanding of big data analytics adoption, with implications for sustainable growth, through addressing limitations in future research (Bughin, 2016; Nandi, 2023).

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## APPENDICES

### Appendice 1: Research Ethics approval form

GREAT ZIMBABWE UNIVERSITY

FACULTY: Munhumutapa School of Commerce

RESEARCH ETHICS APPROVAL APPLICATION

TO BE COMPLETED BY THE RESEARCHER

Please complete only the sections applicable to you

Name of applicant: EDWARD DUBE

Student Number: M185636

Year 2022

1. Title of research:

THE IMPACT OF BIG DATA ANALYTICS TO SUSTAINABILITY STRATEGY IN THE TELECOMMUNICATIONS SECTOR IN ZIMBABWE

2. Main Supervisor

| Name | Rank | Contact Number | e-mail address | Contact Address | Institution |
|---|---|---|---|---|---|
| OBERT SIFILE | FULL PROFESSOR | 0772410226 | osifile@gmail.com | Chinhoyi University, P. Bag 7724, Chinhoyi | Chinhoyi University of Technology |

3. Co-Supervisor

| Name | Rank | Contact Number | e-mail address | Contact Address | Institution |
|---|---|---|---|---|---|
| JOSEPH BEMANI | DOCTOR | 0772371387 | jbemani@gzu.ac.zw | Great Zimbabwe University, Box 1235, Masvingo | Great Zimbabwe University |

4. Research field(s) (please mark with an X)

| | YES | NO |
|---|---|---|
| The research project involves animals | | X |
| The research project involves plants. | | X |
| The research project includes work on Genetically Modified Organisms. | | X |
| The research project involves human participants (subjects). | X | |

5 PHOTOGRAPHYAND/OR AUDIOVISUAL RECORDING

5.1 Will be applied during any stage of the research procedure: NO

5.2. If yes, elaborate N/A

6 RESEARCH OBJECTIVE(S)

a) To determine sustainability strategies in Zimbabwe telecommunication companies.

b) To evaluate the impact of Big Data analytics on Zimbabwean telecommunication companies.

c) To evaluate the critical elements that moderates the impact of Big Data analytics on sustainability.

d) To proffer options that can enable Zimbabwe telecommunication companies to adopt Big Data analytics which impact on sustainability

7 SCIENTIFIC JUSTIFICATION / BENEFIT OF THE RESEARCH

This research intention is to make it implementable hence will impact on theory, academia, policy and practice.

8 ANIMALS: MATERIALS AND METHODS

8.1 Full description of animals to be used

| Species | Strain/Breed | Gender | Age / body mass | Number required |
|---|---|---|---|---|
| | | | | |

If any of the above cannot be provided, state the reason:

______________________________________________________________________________

____________________________________________________________

8.2 Origin of animal N/A

Indicate, if special permission or CITES documents are necessary for the use of the animals. If so, attach required documentation.

8.3 Husbandry

Details of person(s) responsible for the husbandry and general care of the animals:

| Name | Qualification | Contact number | Emergency contact number | Contact address |
|---|---|---|---|---|
| | | | | |

8.4 Experimental procedures

Please indicate in the relevant category Mark with an X).

| | |
|---|---|
| Experiments involving use of bacteria, protozoa, viruses, fungi or animal species. | |
| Experiments on animal species that are expected to produce little or no discomfort or minor stress. | |
| Experiments that involve significant but unavoidable stress or pain to animal species | |
| Procedures that involve inflicting sever pain near, at or above the pain tolerance threshold of unanaesthetised, conscious animals | |

Please include the following:

Number of animals in experimental and in control groups

Initial handling of animals

Duration of experiment

Samples to be collected (type, site and volume), frequency per animal?

Place(s) where the experimental procedures will be performed

PLANTS: MATERIALS AND METHODS

9.1 Full description of plants to be used

| Species | Strain | INDIGINOUS/EXOTIC | PROTECTED | Number required |
|---|---|---|---|---|
| | | | | |

9.2 Origin of PLANTS

Indicate, if special permission or CITES documents are necessary for the use of the plants. If so, attach required documentation.

Please include the following:

Number of plants in experimental and in control groups

Describe experimental procedures in detail

Place(s) where the experimental procedures will be performed

GENETICALLY MODIFIED ORGANISMS (GMOs): MATERIALS AND METHODS

10.1 Description of GMOs used in the research project

| Type | Species | Strain | Number required |
|---|---|---|---|
| | | | |
| | | | |

10.2 Origin of GMOs used

10.3 Experimental procedures

In detail, describe the experimental procedures intended.

Include the number of GMOs per experimental group and the number of groups

10.4 Risk assessment

Include a detailed risk assessment in terms of a possible impact on humans, animals and/or the environment.

a Liability

Describe how you will address the liability for any possible damage caused by the use or release of GMOs.

b Notification of the public

Please indicate how the public will be informed about a trial release or release of GMOs if this forms part of the study.

c Waste management

Describe the procedures that will be used to dispose waste resulting from the use of GMOs must be described in the proposal.

11. HUMANS

11.1 Which characteristics of the study group are relevant to the research?

| | YES | NO |
|---|---|---|
| Physical/ medical condition | | |
| Injections, blood samples, swabs and similar interference | | |
| Use of drugs / medicines | | |

| | | |
|---|---|---|
| Use of toxic or dangerous substances | | |
| Use of food, fluids or nutrients | | |
| Psychometric measuring instruments | | |
| Questionnaires | X | |
| Interviews | X | |
| Other | X | |

Elaborate Documentary evidence will be used.

11.2 Target population

Where are the research subjects drawn from?

| | YES | NO |
|---|---|---|
| Hospitals/ clinics | | |
| Local communities | X | |
| Educational institutions | | |
| Other | | |

11.3. Are there any possible impacts that may result from the study to the research subjects and or the environment? None

11.4. Which precautions will be undertaken to ensure the safety/ protection of the research subjects and/or the environment and/or researchers?

Explain

Principles that guide ethical research will be adopted.

## 11.5 INFORMED CONSENT

11.5.1. Is it necessary to receive consent from research subjects?

Please explain

It is necessary in order to ensure that the autonomy and rights of the respondents are safeguarded.

11.5.2. In order to conduct the research would institutional consent be required?

Please explain:

It is necessary in order to ensure that the institution is aware and employees participate with full knowledge that any information disclosure is not deemed to be a breach of the institution code of ethics.

11.5.3. How will the subjects be made aware of their right to withdraw at any stage of the project, even after consent had been given?

The respondents will be supplied with all the prerequisite information that might influence their willingness to participate in an easily comprehensible format.

11.5.4. How will the potential risk involved be communicated to research subjects?

Respondents will be made aware of the research study objectives and the associated net risk to which they will be exposed to.

## 11.6. CONFIDENTIALITY AND ANONYMITY

11.6.1. What measures will be taken to ensure the rights of the subject to anonymity and confidentiality?

This will be done through a deliberate effort in separating person from the identified information and non disclosure.

11.6.2. Is feedback to research subject(s) necessary? If yes, elaborate.

UNDERTAKING

The researcher undertakes to:

give due respect to all research subjects.

conduct the research in accordance with the approved protocol, relevant legislation and the policies and procedures of Great Zimbabwe University.

notify the Faculty Ethics Committee if changes to the aforementioned protocol are effected.

Edward Dube

Name (Names & Surname)

Signed Date 31st August 2022

**Appendice 2: Questionnaire**

**QUESTIONNAIRE**

MUNHUMUTAPA SCHOOL OF COMMERCE

Researcher: Edward Dube email; eddsdube@gmail.com Cell#; +263774113147

Supervisors:

- Prof. O. Sifile email; osifile@cut.ac.zw Cell#; +263 772410226
- Dr. J. Bemani email; jbemani@gzu.ac.zw Cell#; +263 772371387

Dear Respondent,

My name is Edward Dube, a PhD candidate at Great Zimbabwe University, Munhumutapa School of Commerce. Thank you for agreeing to participate in this questionnaire on: **The impact of big data analytics to sustainability strategy in the telecommunications sector in Zimbabwe.** Your input is valuable to this research, and I appreciate your time and effort in completing this survey.

This research aims to examine the current sustainability strategies adopted by telecommunication companies in Zimbabwe, investigate the extent of adoption of big data analytics in the telecommunications industry, explore how telecommunication companies can leverage big data analytics to identify sustainability risks and opportunities, assess the role of government policies and regulations in promoting the adoption of big data analytics and sustainability practices, and identify the challenges and barriers faced by telecommunication companies in Zimbabwe in implementing big data analytics for sustainability.

Your responses to the questionnaire will help us gain valuable insights into these issues and inform our recommendations for telecommunication companies in Zimbabwe. We encourage you to answer the questions to the best of your ability and provide any additional comments or suggestions that you may have.

All responses will be kept strictly confidential and will only be used for the purposes of this research. Thank you again for your participation, and I look forward to your responses.

Yours sincerely,

Edward Dube

QUESTIONNAIRE

**NB.** Kindly tick in the appropriate box or fill in where specified.

**Section 1: Demographic Information**

**1. Gender**

| a. Male | b. Female |
|---|---|
| | |

**2. Age**

| a. Below 21 | b. 21-30 | c. 31-40 | d. 41-50 | e.51 and above |
|---|---|---|---|---|
| | | | | |

**3. Education level:**

| a. High school | b. College | c.Bachelor's degree | d. Master's degree | e. Doctoral degree |
|---|---|---|---|---|
| | | | | |

**4. Job position:**

| a. Executive | b. Manager | c. Analyst | d. Other |
|---|---|---|---|
| | | | |

**5. Years of experience in the telecommunications industry:**

| a. Less than 1 year | b. 1-5 years | c. 6-10 years | d. 11-15 years | e. More than 15 years |
|---|---|---|---|---|
| | | | | |

**Section 2: Sustainability Strategies of Telecommunications Companies in Zimbabwe**

**1. Does your organization have a sustainability strategy in place?**

| a. No | b. Yes |
|---|---|
| | |

**2. If yes, how effective do you think your organization's sustainability strategy is in achieving sustainable outcomes?**

| a. Very | b.Somewhat | c. Neutral | d. Somewhat | e. Very |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| ineffective | ineffective | | effective | effective |
| | | | | |

**3. How does your organization measure and report on sustainability performance?**

| a. Not measuring sustainability performance at all | b. Using internal metrics only | c. Using external reporting frameworks (e.g. GRI, SASB, etc.) | d. Using a combination of internal and external metrics |
|---|---|---|---|
| | | | |

**Section 3: Adoption of Big Data Analytics in the Telecommunications Industry in Zimbabwe and its impact on sustainability.**

**1. Does your organization use big data analytics in its operations?**

| a. No | b. Yes |
|---|---|
| | |

**2. If yes, how frequently does your organization use big data analytics in its operations?**

| a. Daily | b. Weekly | c. Monthly | d. Quarterly | e. Annually |
|---|---|---|---|---|
| | | | | |

**3. What types of data does your organization collect and analyse through big data analytics? (Select all that apply)**

| a. Customer data | b. Sales data | c.Social media data | d. Supply chain data | e. Other: specify |
|---|---|---|---|---|
| | | | | |

**4. To what extent do you believe that the use of big data analytics has improved your organization's operational efficiency?**

| a. Not at all | b. Not much | c. Neutral | d. Somewhat | e. Significantly |
|---|---|---|---|---|
| | | | | |

**5. How has the adoption of big data analytics impacted your organization's environmental sustainability performance?**

| a. Reduced energy consumption and greenhouse gas emissions | b. Reduced waste generation and improved waste management | c. Reduced water consumption and improved water management | d. No impact on environmental sustainability performance |
|---|---|---|---|
| | | | |

**5. What are the main challenges in adopting big data analytics for sustainability in the telecommunications industry in Zimbabwe?**

| a. Lack of skilled personnel | b. Lack of data quality or availability | c. High implementation costs | d. Lack of management support | e. Other (please specify) |
|---|---|---|---|---|
| | | | | |

**Section 4: Leveraging Big Data Analytics for Sustainability**

**1. To what extent do you believe that the use of big data analytics can help identify sustainability risks and opportunities in the telecommunications sector in Zimbabwe?**

| Strongly disagree | b. Disagree | c. Neutral | d. Agree | e. Strongly agree |
|---|---|---|---|---|
| | | | | |

**2. How can big data analytics help telecommunication companies in Zimbabwe to identify sustainability risks and opportunities?**

| a. By analyzing customer behavior and preferences | b. By analyzing energy consumption and resource utilization | c. By analyzing supply chain impacts | d. By analyzing regulatory risks and opportunities | e. Other (please specify) |
|---|---|---|---|---|
| | | | | |

**3. How do you think telecommunication companies in Zimbabwe can leverage big data analytics to develop more effective sustainability strategies? (Select all that apply)**

| a. Identifying areas for energy efficiency improvements | b.Identifying waste reduction opportunities | c. Identifying resource conservation opportunities | d. Other: specify |
|---|---|---|---|
| | | | |

**Section 5: Government Policies and Regulations**

**1. To what extent do you believe that government policies and regulations can promote the adoption of big data analytics and sustainability practices in the telecommunications sector in Zimbabwe?**

| a. Strongly disagree | b. Disagree | c. Neutral | d. Agree | e. Strongly agree |
|---|---|---|---|---|
| | | | | |

**2. What policies or regulations would be most effective in promoting the adoption of big data analytics for sustainability in the telecommunications sector in Zimbabwe?**

| a. Tax incentives for sustainability investments | b. Funding for sustainability research and development | c. Mandatory sustainability reporting requirements | d. Industry-wide sustainability standards or certifications | e. Other (please specify) |
|---|---|---|---|---|
| | | | | |

**Section 6: Challenges and Barriers**

**1. What challenges or barriers do you think telecommunication companies in Zimbabwe face when implementing big data analytics for sustainability? (Select all that apply)**

| a. Lack of technical expertise | b. Lack of financial resources | c. Lack of data quality | d. Lack of stakeholder engagement | e. Other: specify |
|---|---|---|---|---|
| | | | | |

**2. Which stakeholders should telecommunication companies in Zimbabwe engage with to overcome the challenges of implementing big data analytics for sustainability?**

| a. Customers and clients | b. Government agencies and regulators | c. NGOs and civil society organizations | d. Industry associations and trade groups | e. Other (please specify) |
|---|---|---|---|---|
| | | | | |

**3. What recommendations do you have for telecommunication companies in Zimbabwe to overcome these challenges and barriers?**

| |
|---|
| |

Thank you for your participation!

**Appendice 3: Interview guide**

INTERVIEW GUIDE

MUNHUMUTAPA SCHOOL OF COMMERCE

Researcher: Edward Dube email; eddsdube@gmail.com Cell#; +263774113147

Supervisors:

- Prof. O. Sifile email; osifile@cut.ac.zw Cell#; +263 772410226
- Dr. J. Bemani email; jbemani@gzu.ac.zw Cell#; +263 772371387

Section 1: Sustainability Strategies of Telecommunications Companies in Zimbabwe

1. Can you describe the sustainability strategy that your organization has in place and how it aligns with the United Nations Sustainable Development Goals (SDGs)?

Section 2: Adoption of Big Data Analytics in the Telecommunications Industry in Zimbabwe

1. Does your organization currently use big data analytics in its operations? If so, can you describe what types of data are collected and analysed?
2. How has the use of big data analytics impacted your organization's sustainability efforts? Can you provide an example of a sustainability initiative that was developed or improved based on insights gained from big data analytics?

Section 3: Leveraging Big Data Analytics for Sustainability

1. In your opinion, what are the key sustainability risks and opportunities facing the telecommunications industry in Zimbabwe?

Section 4: Government Policies and Regulations

1. What government policies and regulations have been put in place to promote the adoption of big data analytics and sustainability practices in the telecommunications sector in Zimbabwe?
2. How has your organization been influenced by these policies and regulations?

Section 5: Challenges and Barriers

1. What challenges has your organization faced in implementing big data analytics for sustainability?
2. What are the barriers to wider adoption of big data analytics for sustainability in the telecommunications industry in Zimbabwe?
3. In your opinion, what actions can be taken to overcome these barriers?
4. How can telecommunications companies in Zimbabwe collaborate to overcome these challenges and barriers?

**Interview responses**

Section 1: Sustainability Strategies of Telecommunications Companies in Zimbabwe

1. Can you describe the sustainability strategy that your organization has in place and how it aligns with the United Nations Sustainable Development Goals (SDGs)?

| Interviewee 1 | Interviewee 2 | Interviewee 3 | Interviewee 4 | Interviewee 5 |
|---|---|---|---|---|
| -Pillar 1: Social Welfare, SDG 1: End Poverty in all its forms everywhere<br>- Pillar 2: Health, SDG 3: Promote Health and Well-being<br>-Pillar 3: Education SDG 4: Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all<br>- Pillar 4: Girls Empowerment, SDG 5: Achieve gender equality and empower women and girls<br>-Pillar 5: Environment SDG 13: Take action to combat climate change and all its impact | -Solar energy<br>- Smart City<br>- Waste disposal<br>-Environmental, Social Governance (ESG) reporting<br>- CSR through tree planting, e-health info access, social engagements | - Wellness<br>-Girl child empowerment<br>-Cleaning Environment calendar<br>- Waste disposal<br>- Continuous learning | - Solar energy<br>-Downgraded electrical generators<br>-Environmental Impact Assessment (EIA)<br>-CSR ( forest management and training)<br>- Empowering rural communities through information access<br>- Girl-child mentoring<br>-Donations to Communities | - Social inclusion through connectivity<br>- promoting carbon credits through tree planting |

Section 2: Adoption of Big Data Analytics in the Telecommunications Industry in Zimbabwe

1. Does your organization currently use big data analytics in its operations? If so, can you describe what types of data are collected and analysed?

| | | | | |
|---|---|---|---|---|
| -customer usage patterns,<br>-network performance data,<br>-financial transactions,<br>-customer feedback. | - Churn rate<br>- Customer<br>- Finance | - Voice and data traffic<br>- Revenue tracking<br>- Client satisfaction<br>- Student Appraisal | - Financial<br>- Customer<br>- Network<br>- Power consumption<br>-Personal<br>-Student<br>- Educational<br>- Financial performance<br>- Compliance<br>- Customer retention<br>- Market performance<br>- HR performance | -Customer |

| | | | | |
|---|---|---|---|---|
| | | | - Skills gaps<br>-Gender and youth gaps | |

2. How has the use of big data analytics impacted your organization's sustainability efforts? Can you provide an example of a sustainability initiative that was developed or improved based on insights gained from big data analytics?

| | | | | |
|---|---|---|---|---|
| -Cost saving<br><br>-energy consumption<br><br>**Initiatives**<br><br>-carbon footprint reduction strategy. | -Financial Savings<br>- Brand positioning<br><br>**Initiatives**<br><br>- Investment readiness (ESG)<br>- | **VOICE and DATA**<br>-Revenue generation<br>**Other**<br>-ESG, and Customer retention<br>- Girl child mentoring<br>- Continuous learning<br><br>**Initiatives**<br><br>- provides a base for HR development | -Solar migration due to high cost implications from other sources of energy.<br>- Forest management to provide carbon credit.<br>-Donations to address social issues<br>**Initiatives**<br><br>-Telecommunications infrastructure improvement to achieve competitive advantage | - Product knowledge<br>- financial leverage<br><br>**Initiatives**<br>Market segmentation |

Section 3: Leveraging Big Data Analytics for Sustainability

1. In your opinion, what are the key sustainability risks and opportunities facing the telecommunications industry in Zimbabwe?

| | | | | |
|---|---|---|---|---|
| **-Energy Consumption:**<br>*Challenge:* The telecommunications industry is energy-intensive, with the operation of network infrastructure, data centers, and connectivity devices requiring significant power.<br>*Risk:* High energy consumption contributes to environmental degradation and increases operational costs, posing a risk to sustainability.<br>**-E-Waste** | **Risks**<br>-Compliance with data regulation<br>- Data security<br>- Financial<br>**Opportunities**<br>-Market trends<br>-Investments<br>-Collaboration | **Risks**<br>- Legal<br>- Skills flight and unavailability<br>- Obsolete technical equipment<br>- legacy debt overhang<br>-market share<br>- funding<br>-bureaucracy | **Risks**<br>- Financial<br>- Environmental<br>- Energy<br>- Talent acquisition<br>- Skills gap<br>- Competition affecting revenues<br><br>**Opportunities**<br>- Digital Inclusion<br>- Innovation<br>-E-marketing collaboration<br>- Responsible resourcing<br>- Green energy manufacturing | **Risks**<br>-Cyber attacks |

| | | | | |
|---|---|---|---|---|
| **Management:** *Challenge:* The rapid pace of technological advancement leads to the frequent obsolescence of electronic devices, resulting in a substantial volume of electronic waste (e-waste). *Risk:* Poor e-waste management practices can harm the environment and public health, violating sustainability principles. **-Social Impact of Technology:** *Challenge:* The widespread adoption of telecommunications technology can have social implications, including issues related to privacy, digital divide, and cultural impacts. *Risk:* Failure to address these social concerns can lead to community dissatisfaction, legal challenges, and reputational damage. **Opportunities: Leveraging Technology for Sustainable Development:** *Opportunity:* Telecommunications technology can be harnessed to address broader societal challenges, including healthcare delivery, education, and environmental | | | | |

| | | | | |
|---|---|---|---|---|
| monitoring.<br>*Example:* Deploying telemedicine solutions, e-learning platforms, and smart environmental monitoring systems contribute to sustainable development goals.<br>**Enhancing Connectivity in Under-served Areas:**<br>*Opportunity:* Extending telecommunications infrastructure to remote and undeserved areas enhances social and economic inclusion.<br>**Utilizing Big Data Analytics for Efficient Resource Management:**<br>*Opportunity:* Big data analytics can optimize resource utilization, leading to energy efficiency, reduced operational costs, and improved decision-making. | | | | |

Section 4: Government Policies and Regulations

1. What government policies and regulations have been put in place to promote the adoption of big data analytics and sustainability practices in the telecommunications sector in Zimbabwe?

| | | | | |
|---|---|---|---|---|
| **National ICT Policy**:<br>Data restriction regulations | -Data protection<br>-Data Security<br><br>**National Development Strategy (NDS1) on**<br>-Sustainability<br>-Carbon credit regulation | - ESG reporting<br>- EMA regulations on disposal of equipment | - Data protection Act<br>-National ICT strategic plan<br>-National Telecommunications policy<br>-EMA Act on waste disposal | -Data Protection policy |

2. How has your organization been influenced by these policies and regulations?

| | | | | |
|---|---|---|---|---|
| -Infrastructure investment<br>-Business model transformation<br>-Government support<br>.Partnerships | -Compliance | - Compliance | - Compliance<br>-Network performance optimisation<br>- Digital activation Strategy<br>- Established unit to deal with Policy and Regulations | No response |

Section 5: Challenges and Barriers

1. What challenges has your organization faced in implementing big data analytics for sustainability?

| | | | | |
|---|---|---|---|---|
| -Data Silos and Integration<br>-Data Quality and Reliability<br>-Skilled Data Scientists and Analysts<br>-Technological<br>-Infrastructure Limitations<br>-Cost Considerations<br>-Data Privacy and Security Concerns | - Lack of knowledge<br>-Lack of skills | - Lack of knowledge<br>-Lack of skills | - Knowledge gap<br>- Lack of Investment | - Lack of tools and systems |

2. What are the barriers to wider adoption of big data analytics for sustainability in the telecommunications industry in Zimbabwe?

| | | | | |
|---|---|---|---|---|
| - Technical barriers; Infrastructure limitations.<br>Skills shortage.<br>Data quality and accessibility:<br>- org barriers:<br>Lack of awareness and understanding.<br>Cultural resistance<br>.Financial constraints<br>-Regulatory barriers;<br>Data privacy concern<br>Lack of data sharing protocols.<br>Inadequate government support | - Lack of finance to purchase software licences<br>- Lack of skilled manpower | - Obsolete equipment.<br>-Lack of finance<br>-Lack of Investment capital<br>- Low revenue streams | - Skills gap<br>- Awareness<br>-Lack of capital<br>-Poor country credit rating | -ICT policy of non-sharing of data with other countries.<br>- Lack of collaboration. |

3. In your opinion, what actions can be taken to overcome these barriers?

| | | | | |
|---|---|---|---|---|
| -Enhancing infrastructure and data management<br>-Developing skills and expertise<br>-Raising awareness and promoting adoption<br>-Strengthening data privacy regulations<br>-Promoting data sharing partnerships<br>-Enhancing government support | -Equity partners to unlock finance | - New technologies<br>- Government intervention, by virtue of being share holders<br>- Equity investments<br>-Public , private Partnership (PPP) | - Create course content<br>- Awareness through POTRAZ<br>- Align micro economic fundamentals<br>- ESG compliance | -Govt facilitation of data analytic tools. |

4. How can telecommunications companies in Zimbabwe collaborate to overcome these challenges and barriers?

| | | | | |
|---|---|---|---|---|
| -Establish industry-wide data governance frameworks.<br>-Form data sharing consortium.<br>-Share best practices and expertise.<br>-Jointly invest in infrastructure and technology.<br>-Partner with universities and research institutions.<br>-Create a national center for big data analytics | - Shared Infrastructure<br>-Shared deployment of equipment<br>-Establishment of Infrastructure company | - Shared Infrastructure<br>- Establishment of Infrastructure company | - Shared software<br>-Harmonisation of data protocol<br>- Open data sharing Incentives<br>- Research funding | - Data sharing<br>- Shared platforms |

**Appendice 3: Informed Consent Form**

Electronic Research Consent Form aligned to the topic "The Impact of Big data analytics to Sustainability Strategy in the telecommunications sector in Zimbabwe":

ELECTRONIC RESEARCH CONSENT FORM

Study Title: The Impact of Big data analytics to Sustainability Strategy in the telecommunications sector in Zimbabwe

Principal Researcher: Edward Dube

Participant Identification Code:

https://docs.google.com/forms/d/e/1FAIpQLSdX8ysWmdIYpc79BsSFfznTQxCWmDoF_pBFM9j3EoxNyqMYpg/viewform

Introduction
This consent form provides information about participation in a research study exploring the impact of big data analytics on sustainability strategies in the telecommunications sector in Zimbabwe. The study is being conducted by Edward Dube. Participation involves completing an online questionnaire and/or remote interview via encrypted video conferencing.

Procedures
If you agree to participate, you may be asked to:
1) Complete a questionnaire about your company's use of big data analytics and current sustainability initiatives.
2) Participate in an interview where similar questions will be asked. Interviews will last 60 minutes and be audio recorded for transcription.

You will only be identified by your anonymous Participant Identification Code. All data will remain strictly confidential.

Risks and Benefits
There are no foreseeable risks. Potential benefits include contributing to knowledge in this field in Zimbabwe.

Privacy and Confidentiality
All information obtained will be kept strictly confidential and anonymous. Electronic data will be securely stored using encryption. Your Participant Identification Code is the only link between you and the study data.

Participation and Withdrawal

Your participation is voluntary. You may withdraw at any time without penalty by informing the researcher. Withdrawing will not affect your relationship with the researcher or the university.

Contact Information

If you have any questions, you may contact Edward Dube via encrypted email at eddsdube@gmail.com.

Consent

By providing your Participant Identification Code below, you confirm that you have read and understand this consent form, have had the opportunity to ask questions, and agree to participate under the conditions outlined above.

Participant Identification Code:
https://docs.google.com/forms/d/e/1FAIpQLSdX8ysWmdIYpc79BsSFfznTQxCWmDoF_pBFM9j3EoxNyqMYpg/viewform

Date: 1 September, 2023

Researcher's Signature:

Date: 1 September, 2023

**Appendice 4: TelOne Authorisation**

TelOne
The Future Is Better Together

CONFIDENTIALITY

AND

NON-DISCLOSURE AGREEMENT

BETWEEN

EDWARD DUBE

AND

TEL-ONE (PVT) LTD

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1 **PARTIES**

The parties to this agreement are:

Edward Dube, a Doctor of Philosophy in Business Administration student, Great Zimbabwe University and TelOne (Private) Limited.

2. **PREAMBLE**

**WHEREAS**

2.1.1 Edward Dube would like to carry out a research for his Dissertation focusing on **"THE IMPACT OF BIG DATA ANALYTICS TO SUSTAINABILITY STRATEGY IN THE TELECMMUNICATIONS SECTOR IN ZIMBABWE."**

2.1.2 This will involve TelOne sharing information around their strategy and Organisational Performance;

2.1.3 Edward Dube as part of the research will use academic theories and frameworks to analyse the TelOne Organisational Performance;

2.1.4 The information gathered will be for the purpose of broadening academic knowledge in the areas of leadership strategies and organizational performance which in turn can be useful to TelOne to sharpen their strategies;

2.1.5 The parties wish to record the terms and conditions upon which they are willing and prepared to enter this agreement.

3. **INTERPRETATION**

3.1 In this agreement, unless inconsistent with or otherwise indicated by the context:

3.1.1 "the/this agreement" means the agreement as set out herein;

3.1.2 "Commencement date" means the latest date of signature to this agreement not taking into consideration the dates applicable to amendments, annexures or appendices.

3.1.3 "confidential information" means without limiting the generality of the term, any:

3.1.3.1 technical, scientific, commercial, business, financial or market information, or trade industry secrets;

3.1.3.2 data concerning business relationships, samples, devices, demonstrations, processes or machinery;



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3.1.3.3 designs, data models, software code, proposals, literature, brochures, drawings and technical specifications,

3.1.3.4 any document with a footer marked "Private and Confidential" and all other information in whatever form, whether or not subject to or protected by common law or statutory laws relating to copyright, patent, trade marks, registered or unregistered, or otherwise, disclosed or communicated to the receiving party or acquired by the receiving party from the divulging party pursuant to this agreement;

3.1.3.5 Provide on paper, on electronic media or any other media capable of storing or transmitting information

3.1.4 "the divulging party" means the party disclosing any form of confidential information;

3.1.5 "the parties" means the parties to this agreement;

3.1.6 "the receiving party" means the party receiving any form of confidential information.

**4. COMMENCEMENT AND DURATION**

This agreement shall commence on the date of signature by the Party signing last if not signed at the same time and if not terminated earlier in terms of clause 10 below, shall terminate one (1) week after the parties' business and commercial working relationship has ended which termination shall be notified in writing by Edward Dube.

**5. RESTRICTIONS ON DISCLOSURE AND USE OF THE INFORMATION**

5.1 The receiving party may disclose confidential information only to its officers and employees and then only to such officers and employees to whom such access is deemed reasonably necessary, provided that such officers and employees agree to be bound by the terms and conditions of this agreement.

5.2 The receiving party agrees:

5.2.1 not to disclose the confidential information to any third party for any reason or purpose whatsoever without the prior written consent of the divulging party, save in accordance with the provisions of this agreement;

5.2.2 not to utilise, employ, exploit or in any other manner whatsoever use the confidential information for any purpose whatsoever, other than for purposes of this agreement, without the prior written consent of the divulging party;



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5.2.3 that the unauthorised disclosure of the confidential information to a third party may cause irreparable loss, harm and damage to the divulging party. Accordingly, the receiving party indemnifies and holds the divulging party harmless against any loss, action, expense, claim, harm or damage, or whatever nature, suffered or sustained by the divulging party pursuant to a breach by the receiving party of the provisions of this agreement.

5.3 Unless the parties otherwise agree in writing, any documentation or records relating to the divulging party's confidential information which comes into the possession of the receiving party during the existence of this agreement or at any time thereafter:

5.3.1 shall be deemed to form part of the confidential information of the divulging party;

5.3.2 shall be deemed to be the property of the divulging party;

5.3.3 shall not be copied, duplicated, reproduced, published, electronically distributed or circulated by the receiving party;

5.3.4 shall be surrendered to the divulging party on request and in any event on the termination of this agreement, the receiving party shall not retain any extracts or copies thereof.

## 6. TITLE

6.1 All confidential information disclosed by the divulging party to the receiving party:

6.1.1 shall remain the property of the divulging party; and

6.1.2 shall not confer any rights of whatever nature in such confidential information to the receiving party.

## 7 STANDARD OF CARE

The receiving party agrees to protect the confidential information of the divulging party, using the same standard of care used to safeguard its own information or, where such standard of care is lacking regarding its own information, the standard of care that should reasonably have been applied to safeguard such confidential information would apply so that the confidential information shall be stored and handled in such a way as to prevent any unauthorised disclosure thereof.



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**8. RETURN OF INFORMATION**

8.1 The divulging party may, at any time, request the receiving party to return any material containing, pertaining to or relating to confidential information and may in addition, request the receiving party to furnish a written statement upon return, to the effect that the receiving party has not retained any such material in its possession or under its control, either directly or indirectly, any such material.

8.2 As an alternative to the return of the material contemplated in 8.1 above, the receiving party shall, at the instance of the divulging party, destroy such material and furnish the divulging party with a written statement to the effect that such material has been destroyed.

8.3 The receiving party shall comply within 7 (seven) days of a request in terms of clause 8 and acknowledge in writing the fulfillment thereof during the same period.

**9. EXCLUDED INFORMATION**

9.1 The obligations of the receiving party pursuant to the provisions of this agreement shall not apply to any information that:

9.1.1 is known to or in possession of the receiving party prior to disclosure thereof by the divulging party;

9.1.2 is known or becomes publicly known, otherwise than pursuant to a breach of this agreement by the receiving party;

9.1.3 is acquired independently of the divulging party by the receiving party in circumstances that do not amount to a breach of the provisions of this agreement;

9.1.4 is disclosed by the receiving party to satisfy the order of a court of competent jurisdiction or to comply with the provisions of any law or regulations in force from time to time;

provided that in these circumstances, the receiving party shall advise the divulging party in writing prior to such disclosure to enable the divulging party to take whatever steps it deems necessary to protect its interest in this regard; provided further that the receiving party will disclose only that portion of the information which it is legally required to disclose and the receiving party will



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use its reasonable endeavours to protect the confidentiality of such information to the widest extent possible in the circumstances;

9.1.5 is disclosed to a third party pursuant to the prior written authorisation form the divulging party;

9.1.6 is received by a party in good faith from a third party in circumstances that do not amount to a breach of the provisions of this agreement or to a breach by the third party of any undertaking it may have made to a party to this agreement in relation to such confidential information.

**10 TERMINATION**

10.1 This Agreement shall terminate upon the occurrence of:

10.1.1 The breach by Edward Dube of any of the material terms of the agreement regarding the provision, and use of information about TelOne; or

10.1.2 By written notice from Edward Dube signifying completion of his research.

**11 GOVERNING LAW**

This agreement shall be governed by and construed and interpreted in accordance with the laws of the Republic of Zimbabwe. The parties hereby consent and submit to the jurisdiction of a relevant magistrate's court, notwithstanding that the amount claimed or the value of the matter in dispute exceeds such jurisdiction without prejudice to the rights of either party to initiate action elsewhere or in a court of superior jurisdiction.

**11. NOTICES AND DOMICILIA**

11.1 The parties choose as their domicilia citandi et executandi their respective physical addresses set out in this clause for all purposes arising out of or in connection with this agreement at which addresses all processes and notices arising out of or in connection with this agreement, its breach or termination may validly be served upon or delivered to the parties.

11.2 For purposes of this agreement the parties' respective physical and postal addresses and facsimile numbers shall be -

11.2.1 as regards Edward Dube:

49 Drew Road, Chisipite, Harare
Mobile: 0774113147; email: eddsdube@gmail.com

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11.2.2 as regards TelOne at:

Runhare House, 107 Kwame Nkrumah Avenue
P.O. Box CY331, Causeway
Harare, Zimbabwe
Phone + 263 4 798 111

or at such other address, not being a post office box or poste restante, of which the party concerned by notify the other/s in writing.

11.3 Any notice given in terms of this agreement shall be in writing and shall -

11.3.1 if delivered by hand be deemed to have been duly received by the addressee on the date of delivery;

11.3.2 if posted by prepaid registered post be deemed to have been received by the addressee on the 8th (eighth) day following the date of such posting;

11.3.3 if transmitted by facsimile be deemed to have been received by the addressee 1 (one) day after dispatch.

11.4 Notwithstanding anything to the contrary contained in this agreement, a written notice or communication actually received by one of the parties from another including by way of telex or facsimile transmission shall be adequate written notice or communication to such party.

**12. WHOLE AGREEMENT**

This agreement constitutes the whole agreement between the parties as to the subject-matter hereof and no agreements, representations or warranties between the parties other than those set out herein are binding on the parties.

**14. VARIATION**

No additional to or variation, consensual cancellation or notation of this agreement and no waiver of any right arising from this agreement or its breach or termination shall be of any force of effect unless reduced to writing and signed by both/either the parties or their duly authorised representatives.

**15. RELAXATION**

No latitude, extension of time or other indulgence which may be given or allowed by any/either party to any other party in respect of the performance of any obligation hereunder or the enforcement of any right arising from this agreement and no single or partial exercise of an right by any party shall under any circumstances be construed to be and implied consent by such party or



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operate as a waiver or a novation of, or otherwise affect any of that party's rights in terms of or arising from this agreement or estop such party from enforcing, at any time and without notice, strict and punctual compliance with each and every provision or term hereof.

**16. BINDING ON SUCCESSORS AND RELATED PARTIES**

This agreement shall be binding upon the heirs, assigns, executors or sequestrates successors-in-title and parent, subsidiaries and affiliates of the parties hereto.

Signed at Harare, on this 01st day of August 2023

**FOR AND ON BEHALF OF TELONE**

NAME: OSCAH NDUWURE

DESIGNATION: ACTING CORPORATE SERVICES DIRECTOR

SIGNATURE...............................

Tel•ONE
HEAD ... ORGANISATIONAL
... 31 JUL 2023
P.O. BOX CY 331 CAUSEWAY
HARARE

**AS WITNESSES**

1. Mhute ..................... 2. .....................

Signed at Harare, on this ..............day of....................... 2023

**BY:**

NAME: EDWARD DUBE

SIGNATURE..................................

**AS WITNESSES**

1. TAMBUDZAI ..................... 2. .....................

## Appendice 5: NetOne Authorisation

NetOne
The World in One

9 August 2023
Mr. E. Dube
49 Drew Road,
Chisipite,
Harare.

RE: REQUEST TO CARRY OUT RESEARCH AT NETONE CELLULAR (PVT) LTD

This serves to advise you that your request to carry out research at NetOne Cellular (Pvt) Ltd, under the topic, **"The impact of big data analytics to sustainability strategy in the telecommunications sector in Zimbabwe"**, was duly approved.

We hope you will keep the relevant information you will collect confidential, and use it only for academic purposes. We also require a copy of your research once you are through.

Best Regards,

R.P. Mushanawani

R. Mushanawani
Group Chief Executive Officer

Kopje Plaza Building, 1 Jason Moyo Avenue | P.O Box CY 579 Causeway Harare, Zimbabwe | Tel: (0242) 775361, 750607-9,775361/66 | Fax:(0242) 775363 | Website:www.netone.co.zw