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DISSERTATION TITLE

An Investigation On The Role Of Big Data In Managerial Decision Making. A Case Study At Econet Holdings Zimbabwe

A DISSERTATION SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE BACHELOR OF ACCOUNTANCY HONOURS DEGREE OF BINDURA UNIVERSITY OF SCIENCE EDUCATION. FACULTY OF COMMERCE.

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DECLARATION

I, the undersigned, declare that this dissertation entitled *"An investigation on the role of big data in managerial decision making. A case study at ECONET holdings Zimbabwe"* is my original work, submitted in partial fulfilment of the requirements for the degree at Bindura State University. It has not been previously submitted to any other institution of higher learning for any academic award.

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APPROVAL FORM

I certify that the above mentioned student was under my supervision and that l support the submission of this dissertation for marking, as it meets the required academic standards. I further confirm that l provided adequate supervision and that the student has fulfilled all the requirements and expectations set before under my guidance.

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Date:………../……………../………2025

RELEASE FORM

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Dedication

I dedicate this project to my daughter Natalie

Abstract

This study was carried out to establish the role of big data in managerial decision making. The dissertation explores the transformative impact of big data on managerial decision making. This research investigates the role of big data in informing managerial decisions, examining its benefits, challenges and implications for organizational performances. Leveraging advanced analytics and data driven insights, organisations can enhance strategic planning, optimize operations and drive innovation. Through a critical analysis of existing literature and case studies, this study provides insights into the effective integration of big data analytics in decision making process. The findings highlight the potential of big data to revolutionize managerial decision making while also underscoring the need for robust data governance, analytical capabilities and strategic alignment

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Contents

CHAPTER ONE

1.1 INTRODUCTION

The contemporary telecommunications landscape is experiencing unprecedented transformation, driven by the exponential growth of data generation and the increasing complexity of managerial decision-making processes. In an era where organizations generate vast volumes of data from diverse sources including network operations, customer interactions, and market analytics, the ability to harness big data for strategic decision-making has become a critical competitive advantage. This study investigates the role of big data in enhancing managerial decision-making processes at Econet Wireless Zimbabwe, examining how data-driven insights can transform organizational effectiveness, operational efficiency, and strategic positioning in the highly competitive sector.

1.2 BACKGROUND OF THE STUDY

1.2.1 Global Context

The global telecommunications industry faces unprecedented challenges that underscore the critical importance of effective big data utilization in managerial decision-making. Ghasemaghaei and Calic (2020) reveal that more than 80% of organisations are of the opinion that big data will change the competitive landscape, however, an estimation of 25% of them indicate that analytics has changed organizational outcomes considerably. This discrepancy highlights core symptoms that illustrate the inefficiency of employing data for strategic decisions.

Challenges related to cybersecurity are also increasing for telecommunications as for every telco out of two, 53% believe that the cost of a cybersecurity breach will be over US$3mn in 2023, compared to 40% in 2022 (EY Global Cybersecurity Leadership Insights Study, 2024) in the united States. Shamim et al. (2019), and they further report that the inconsistent decision quality is due to the lack of data analytic practices, contributing to more reactive than proactive security approaches. The net neutrality regulation process at the US Federal Communication Commission illustrates decision making complexity, where operators, in an increasing competitive regulatory environment, are balancing regulation compliance with competitive positioning (Deloitte, 2025). To combat of such threats Thompson and Lee (2022) reported that US operators have heavily funded AI-enabled cybersecurity frameworks and predictive analytics systems. Yet breakthrough incidents still occur because operational silos have not been integrated with all available data sources, suggesting that we have the technology but not the organizational decision making.

For the Chinese telecommunications industry, the problems in dealing with strategic decision-making are increasing on account of US-China tech decoupling. According to Chen et al., 2022), the absence of comprehensive big data policies is reflected through fragmented decision-making, as illustrated by bans on Chinese telecommunications technologies and required divestiture of TikTok in which oversight becomes complex in terms of data governance (Carnegie Endowment, 2025). Delayed strategic reaction and contradictory market orientation are also potential symptoms of having insufficient data driven intelligence system according to Wang and Zhang (2021). To address this economic control imbalance, Chinese companies have strived to develop home-grown analytics platforms and adopted “Made in China 2025” strategy that emphasis innovation-driven development; sources: Kumar and Singh, 2023). However, these actions do not act in coherence along government levels and market segments, so that the overall efficacy of technological sovereignty as a unilateral action path seems to not be optimal, and thus a lack of systemic resolution might prevail.

India’s telecom sector is a case in point on critical decision-making challenges even as the country’s subscriber base grows at a fast pace. Patel and Kumar (2023) note that even though Jio acquired 37 million subscribers in 2023, and the number of 5G subscribers in India increased from 10 million to 180 million by 2024, respectively, yet 25% of the users were not satisfied with the network performance (Business Today, 2024). Symptoms manifest in bad allocation decisions, non-coherent service quality delivery, and too late action concerning customer satisfaction challenges by lack of an analytics-based decision framework. Indian operators have deployed customer analytics systems, and networks with AI-driven network optimization solutions, however Martinez and Brown (2022) argue that piecemeal implementations do not result in holistic decision-making benefits. The cut-throat pricing battles between Jio, Airtel, and Vodafone Idea is a testament to how outdated decision-making models cannot reconcile between growth and profitability in data-laden environments. Strategic challenges at Deutsche Telekom in Germany demonstrate how European operators are wrestling with the data-led transformation of the industry. According to Rodriguez et al. (2023) has also proved that slow decision-making processes which continue to apply traditional models do not exploit increasing data user trend and results in that German telecommunication revenues grew only by 1.4% to EUR 19.6 billion in the year 2023 (Deutsche Telekom Annual Report, 2024). The corporation pursues systematic use of accelerators such as AI and global economies of scale as drivers for its strategy, with the expectation of a 4% average annual growth by 2027 (Deutsche Telekom, 2024). However, Jackson et al. (2021) point out, even after spending on technology, European regulatory complexity and market fragmentation impair efficient decision making, in particular as it relates to innovation spending and regulatory cost management.

1.2.2 Regional Context

The East African telecommunications sector presents unique decision-making challenges stemming from infrastructure constraints and regulatory fragmentation. According to Anderson et al. (2021), the region exhibits symptoms of systemic decision making since the inadequate data governance frameworks are prevalent, but it has a positive economic growth prospect, with the region predicted to grow at 5.1% in 2023 and 5.8% in 2024 (African Development Bank 2023). In Kenya, Safaricom's share of 65.7% of the market has not stopped M-PESA from attaining 21.8 million users, whose average monthly P2P sends are worth KSh. 106 billion, there are significant decision-making barriers. Williams and Davies (2023) report symptoms which include poor data governance where Call Detail Records (CDR's) are disseminated to security agencies, with inadequately controlled data analytics and decisions taken in the service weanage impacting on the customer experience. The May 2024 loss of communications after the submarine cable cuts demonstrated a reactive, not predictive, response (Safaricom Wikipedia, 2024). Kenya has introduced digital strategy initiatives M- PESA analytics improvement and technology providers partnerships (Davis and Wilson, 2023), but adoption difficulties remain as regulatory barriers vary widely between such amenities and amongst agencies. Although M-PESA showcases a good example of data-driven financial inclusion, there are still some hurdles in the broader telecommunications decision-making ecosystem regarding the lack of cross-sector coordination. Johnson et al. (2022) record systemic signs of failure of investment planning for infrastructure, the e-Booster Uganda 2023 project suffering from 53 actors faced difficulty due to poor resource allocation to underserved people. Poor decision-making is evident in the ineffective use of the Universal Service Fund and piecemeal roll-out of

Public-Private Partnerships (ResearchGate, 2024). On the other hand, in Uganda, e-Booster initiative run by the Uganda Communications Commission (UCC) funded innovative ICT services for isolated group of people. Garcia & Lopez (2023) however bemoan the coordination failure across stakeholders, arguing that innovative approaches abound but that systematic processes of scaling and sustaining decisions are wanting. Lee and Smith (2021) in Tanzania and Rwanda, for example, point to the problems of conflicting decision-making symptoms around varying data protection frameworks in place among East African countries. As Rwanda posts 8.5% annual GDP growth, mixed telecommunications investment choices curtail regional integration yields (World Bank, 2024). Through the National Broadband Network project, the Rwandan government is providing high speed and affordable internet access, which is a systematic trend reform. Yet Brown et al. (2022) mention the delivery vacuum mainly in cross-border data governance coordination. Tanzania's Personal Data Protection Act establishment indicates regulatory decision-making progress, but differences in scope and detail compared to Kenya's and Rwanda's frameworks continue to hamper regional cooperation and effective data utilization strategies.

1.2.3 National Context

The Zimbabwean telecommunications sector faces distinctive operational challenges that make sophisticated big data utilization crucial for effective managerial decision-making. According to Taylor et al. (2024), Challenges for Zimbabwean telecoms show symptoms of pattern-oriented decision-making failure and the burning in will of this forced fit between lack of economic growth/infrastructure and the ability of data to turn a profit. Symptoms of underevaluation in the Zimbawean telecommunications sector The Zimbabwean telecommunications sector shows some of the symptoms of weak decision making structures. High inflation pressure of 26.5% in December 2023 and unstable currency, the ZiG, introduced in April 2024, leaving the operators in a decision-making paralysis, who have challenges with prices and investments decisions [Miller & Clark (2023)] (Zimbabwe Mail, 2024). Infrastructure decision making shortfalls appear in 19 hours of power outages per day from November 2022, driven by reactive not proactive operations planning (Arum Visuals, 2024). Turner and Harris (2022) show that rational decisions regarding affordability have not been made and, as at October 2024, 11 GB from Econet Wireless was ZWG 242; out of reach for most people in Zimbabwe. The rural-urban digital divide between people (67% of the population lives rural areas without appropriate infrastructure) is a systemic failure in decision making to allocate resources.

But Zimbabwe has introduced several decision-making enhancement measures with varying degrees of success. Evans and Thompson (2024) argue that Econet's network modernization project, which involved the migration of more that 1,012 sites to 4G, is indicative of strategic infrastructure alignment restructuring. The company's operating leases with equipment suppliers illustrate efforts to enhance technology purchase decisions through data-based usage of supplier selection (African Financials, 2024). in the face of such challenge, Econet Wireless Zimbabwe provides a good example of what can be possible as well as what those challenges entailed, data usage grew by 74% and voice usage by 46% for the first quarter in 2024 that showed effective demand management decisions were made (Econet Wireless Zimbabwe, 2024). This is in addition to ZW$ 3.8 trillion (26% of turnover) paid by the company to… government bodies to comply with the regulatory environment, this is indicative of complex regulatory compliance decisions requiring complicated analytics frameworks (African Financials, 2024). Campbell et al. (2023), while technology has offered solutions, fundamental gaps in decision-making frameworks remain. Regulatory decisions made by the Telecommunications Association of Zimbabwe (TOAZ) also seek a good compromise between operator health and consumer welfare, however, Nelson and Parker (2022) note challenges with the operationalisation of traditional decision-making methodologies that fail to integrate big data analytics adequately. The introduction of the ZiG currency and ongoing economic reforms present both challenges and opportunities for implementing more sophisticated data-driven decision-making frameworks in the telecommunications sector.

1.3 PROBLEM STATEMENT

Despite the exponential growth in data generation within the telecommunications sector and the proven potential of big data analytics to enhance decision-making processes, there remains limited empirical understanding of how big data specifically influences managerial decision-making effectiveness at Econet Wireless Zimbabwe. The organization operates in a complex environment characterized by rapid technological advancement, increasing customer expectations, intense competition, and significant operational challenges including currency instability, infrastructure limitations, and regulatory pressures. While Econet has invested substantially in network infrastructure and data capabilities, the extent to which big data analytics is systematically leveraged to improve managerial decision-making quality, speed, and strategic outcomes remains unclear. This knowledge gap hinders the organization's ability to fully capitalize on its data assets and may limit its competitive advantage in an increasingly data-driven telecommunications landscape.

1.4 AIM OF THE STUDY

The aim of this study is to investigate and analyze the role of big data in enhancing managerial decision-making processes at Econet Wireless Zimbabwe.

1.5 OBJECTIVES OF THE STUDY

1. To assess the current level of big data analytics integration in managerial decision-making processes at Econet Wireless Zimbabwe by December 2024.
2. To measure the impact of big data analytics on managerial decision-making quality at Econet Wireless Zimbabwe during the 2023-2024period.
3. To develop specific strategies for optimizing big data utilization in managerial decision-making at Econet Wireless Zimbabwe within a 12-month implementation framework.

1.6 RESEARCH QUESTIONS

1.6.1 Main Research Question

How does big data influence managerial decision-making processes at Econet Wireless Zimbabwe?

1.6.2 Sub-Research Questions

1. What is the current level of big data analytics integration in managerial decision-making processes at Econet Wireless Zimbabwe?
2. How does big data analytics impact the quality of managerial decision-making at Econet Wireless Zimbabwe?
3. What strategies can optimize big data utilization for enhanced managerial decision-making at Econet Wireless Zimbabwe?

1.7 SIGNIFICANCE OF THE STUDY

This study contributes significantly to both theoretical knowledge and practical understanding of big data's role in managerial decision-making within the telecommunications sector. From a theoretical perspective, the research adds to the growing body of literature on big data analytics and organizational decision-making, particularly within the African telecommunications context where limited empirical research exists. The study provides valuable insights into how big data capabilities can be leveraged to address unique challenges faced by telecommunications companies in developing economies.

Practically, the research offers important implications for Econet Wireless Zimbabwe's management by providing evidence-based recommendations for optimizing big data utilization in decision-making processes. The findings will inform strategic decisions regarding technology investments, organizational capabilities development, and competitive positioning. Additionally, the study's insights are valuable for other telecommunications operators in similar markets, policymakers developing digital economy strategies, and technology vendors seeking to understand market needs in emerging economies.

The research also contributes to bridging the gap between big data theory and practical implementation in challenging operational environments, offering lessons for organizations operating under similar constraints of infrastructure limitations, economic volatility, and regulatory complexities.

1.8 STUDY LIMITATIONS

This study acknowledges several limitations that may impact the generalizability and scope of findings. First, the research focuses specifically on Econet Wireless Zimbabwe, which may limit the transferability of findings to other telecommunications companies or different organizational contexts. The unique characteristics of Zimbabwe's economic and regulatory environment may also constrain the applicability of results to other markets.

Second, the study is conducted during a specific timeframe that captures a particular phase of the organization's development and may not reflect long-term trends or future capabilities. The rapidly evolving nature of big data technologies and telecommunications markets means that findings may have limited temporal validity.

Third, access to sensitive organizational data and strategic information may be restricted due to competitive and confidentiality concerns, potentially limiting the depth of analysis. Additionally, the study relies on available data and may not capture all relevant variables or informal decision-making processes that influence outcomes.

Finally, the research methodology employed may have inherent limitations in capturing the full complexity of decision-making processes and their relationship with big data utilization, particularly regarding tacit knowledge and intuitive decision-making elements that are difficult to quantify.

1.9 DEFINITION OF KEY TERMS

1.9.1 Big Data

Big data refers to datasets characterized by high volume, velocity, and variety that exceed the processing capabilities of traditional data management systems and require advanced analytical tools to extract meaningful insights (Chen et al., 2022). According to Wang and Zhang (2021), big data encompasses structured and unstructured information generated at unprecedented speeds from diverse sources including social media, sensors, and transactional systems, necessitating sophisticated storage and processing technologies. Rodriguez et al. (2023) define big data as information assets that demand cost-effective and innovative forms of information processing to enable enhanced insight, decision-making, and process automation across organizational functions.

1.9.2 Managerial Decision Making

Managerial decision making encompasses the systematic cognitive process through which organizational leaders identify problems, gather relevant information, evaluate alternative solutions, and select optimal courses of action to achieve predetermined organizational objectives (Thompson and Lee, 2022). Anderson et al. (2021) conceptualize managerial decision making as a structured approach involving problem recognition, criteria establishment, alternative generation, consequence evaluation, and implementation monitoring within complex organizational environments. Kumar and Singh (2023) describe managerial decision making as the integrative process of utilizing available information, analytical capabilities, and strategic thinking to make choices that optimize organizational performance, resource allocation, and competitive positioning in dynamic business environments.

1.9.3 Telecommunications

Telecommunications refers to the electronic transmission and reception of information, including voice, data, video, and multimedia content, over various distances using wired and wireless communication technologies and infrastructure systems (Martinez and Brown, 2022). Jackson et al. (2021) define telecommunications as the comprehensive industry encompassing network infrastructure, service delivery platforms, and technological solutions that enable real-time communication and data exchange between individuals, organizations, and automated systems across geographical boundaries. Williams and Davies (2023) conceptualize telecommunications as the integrated ecosystem of communication technologies, regulatory frameworks, and business models that facilitate the seamless exchange of information through mobile networks, internet services, satellite systems, and emerging digital communication platforms.

1.10 ORGANIZATION OF THE STUDY

This research study is organized into five comprehensive chapters that systematically address the research objectives and questions:

Chapter One: Introduction - Provides the foundation for the study including the introduction, background at global, regional, and national levels, problem statement, aim and objectives, research questions, significance, limitations, and definition of key terms.

Chapter Two: Literature Review - Presents a comprehensive review of existing literature on big data, managerial decision-making, and telecommunications industry dynamics, establishing theoretical frameworks and identifying research gaps.

Chapter Three: Research Methodology - Outlines the research design, methodology, data collection techniques, sampling procedures, data analysis methods, and ethical considerations guiding the study.

Chapter Four: Data Presentation and Analysis - Presents research findings through systematic data analysis, interpretation of results, and discussion of key discoveries in relation to research objectives.

Chapter Five: Summary, Conclusions, and Recommendations - Provides a comprehensive summary of findings, draws conclusions based on research objectives, and offers practical recommendations for stakeholders.

1.11 CHAPTER SUMMARY

This introductory chapter has established the foundation for investigating the role of big data in managerial decision-making at Econet Wireless Zimbabwe. The chapter demonstrated the critical importance of this research through examination of systematic symptoms of decision-making challenges facing the telecommunications industry at global, regional, and national levels. The background analysis revealed specific problems including inadequate data integration leading to reactive decision-making, fragmented analytics frameworks causing inconsistent strategic responses, and poor resource allocation decisions stemming from insufficient data-driven insights. Despite various solutions attempted across different markets, fundamental gaps persist in effectively leveraging big data for enhanced managerial decision-making. The study aims to bridge this knowledge gap by providing empirical insights into how big data analytics can transform decision-making effectiveness within the unique context of Zimbabwe's telecommunications sector, offering both theoretical contributions and practical recommendations for organizational improvement and strategic positioning. The next chapter is chapter 2.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The strategic utilisation of big data analytics in managerial decision-making processes has emerged as a critical determinant of organisational competitiveness in contemporary telecommunications environments. As companies navigate increasingly complex market dynamics, the ability to harness vast volumes of data for informed decision-making becomes paramount for sustainable competitive advantage. This chapter establishes theoretical foundations through Dynamic Capabilities Theory and Information Processing Theory, providing conceptual frameworks for understanding how organisations develop analytical capabilities and utilise data-driven insights. Subsequently, the literature review systematically examines empirical evidence organised around the study's three primary objectives, providing comprehensive analysis of current knowledge whilst identifying gaps that justify this investigation within Zimbabwe's telecommunications sector.

2.2 Theoretical Framework

2.2.1 Dynamic Capabilities Theory

Dynamic Capabilities Theory, originally developed by Teece et al. (1997) and further refined by Eisenhardt and Martin (2000), provides a robust framework for understanding how organisations develop, integrate, and reconfigure their resource base to address rapidly changing business environments. Dynamic capabilities encompass the organisation's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments, representing higher-order capabilities that enable firms to achieve new forms of competitive advantage (Teece, 2007). Within the context of big data analytics, dynamic capabilities manifest as the organisation's ability to sense market opportunities through data analysis, seize these opportunities by developing appropriate analytical solutions, and transform organisational processes to capitalise on data-driven insights.

The theory's application to this study enables examination of how Econet Wireless Zimbabwe develops and deploys big data analytics capabilities to enhance managerial decision-making processes across different organisational levels and functional areas. Dynamic capabilities theory suggests that successful big data utilisation requires systematic development of analytical competencies, integration of data-driven insights into existing decision-making processes, and continuous refinement of analytical approaches based on performance feedback and environmental changes.

2.2.2 Information Processing Theory

Information Processing Theory, rooted in cognitive psychology and organisational behaviour research, provides essential insights into how individuals and organisations acquire, process, and utilise information for decision-making purposes. The theory, as developed by Galbraith (1973) and later extended by Daft and Lengel (1986), posits that organisations can be viewed as information processing systems that must match their information processing capabilities with the information processing requirements of their tasks and environments. Within the context of big data analytics, Information Processing Theory explains how managers utilise data-driven insights to reduce uncertainty, improve decision quality, and enhance organisational performance outcomes.

The theory's application to this study enables examination of how big data analytics influences information processing capabilities at Econet Wireless Zimbabwe, particularly focusing on how data-driven insights reduce decision-making uncertainty, improve information quality, and enhance managerial confidence in strategic and operational decisions. This theoretical perspective emphasises the importance of information system design, user capabilities, and organisational context in determining the effectiveness of big data analytics for managerial decision-making enhancement.

2.3. Current Level of Big Data Analytics Integration

2.3.1. Infrastructure Development and Technology Adoption

The integration of big data analytics in telecommunications companies requires substantial technological infrastructure encompassing data storage, processing capabilities, and analytical platforms that enable comprehensive data management and analysis.

World's leading telecommunication services companies contributed significant investments in cloud computing infrastructure, big data management systems as well as powerful analytical tools to handle massive datasets from multiple sources and make sense of them on real time basis (Sivarajah et al managerial depth1/provisional1). These technology underpinnings enable the processing of structured and unstructured data from customer-facing interactions, network performance metrics, and market intelligence feeds through powerful Hadoop clusters and machine learning, and cloud-based analytics platforms. Construction of infrastructure generally follows a phased strategy and includes the assessment of existing capabilities, strategic technology planning, and the development of scalable and integrable roll-out approaches (Mikalef et al., 2020; Verma & Bhattacharyya, 2023).

Nevertheless, too much emphasis on enabling technology infrastructure in the absence of addressing needs in readiness of the organization and human capabilities may also lead to underused systems and poor return on investment more particularly in the context of emerging markets, with resource limitations, that may prevent an organization from adopting a full implementation approach (Fosso Wamba et al., 2021). Other viewpoints argue that real-world integration of big data depends on an equal focus on the technology, organisation and people rather than the infrastructure-focused 'technophile' drive characterised by a greater interest in technical capabilities than in practical ease of use and user-centric accessibility. In turn though, digital infrastructure is a prerequisite but not a sufficient condition for deploying big data analytics in ways that lever its full potential to contribute to organisational performance enhancement.

2.3.2 Data Governance and Management Frameworks

Effective big data analytics integration necessitates comprehensive data governance frameworks that ensure data quality, security, and accessibility across organisational boundaries whilst maintaining regulatory compliance and operational efficiency. Successful integration by telecommunications companies often requires systematic data governance and includes data stewardship, quality and assurance processes and security procedures to help maintain integrity in data while simultaneously permitting it to be accessible and analyzable for decision making (Chatterjee et al., 2021). Guidelines such as these set out defined roles and responsibilitieship for data governance, consistent data collection and validation process and secure data methodologies that secure sensitive customer and operational data, whilst ensuring analytical capabilities are supported through the use of fit-for-purpose access control and usage monitoring systems. The operationalisation of governance represents a delicate trade-off between data governance and analytic agility; security and compliance should not become barriers to legitimate analytical activities (Plastino & Purdy, 2021).

Nonetheless, poor data governance is cited as one of the main challenges to big data integration success, with organisations often finding it difficult to keep good data quality and regulatory compliance, and to implement the right access control needed to balance security and usability needs (Wamba & Ngai, 2020; Fosso Wamba et al., 2022). Critics argue over-governance stifles analytic agility and innovation, slows down access to and the use of data – challenges even more acute in dynamic business conditions that demand the ability to rapidly respond with better analytics. The literature on governance proposed that best practices constitute a trade-off between control of data and flexibility in analytics, as risk-based governance focuses on protecting the most important data assets, but also emboldens us to experiment and innovate in the less sensitive parts of the business. Therefore, successful data governance frameworks must strike careful balances between control and accessibility, security and innovation, and standardisation and flexibility to support effective big data analytics integration without constraining organisational agility.

2.3.3 Organisational Analytics Capabilities

The development of organisational analytics capabilities encompasses both technical competencies and analytical thinking skills that enable effective utilisation of big data insights for decision-making enhancement across all organisational levels and functional areas. Telco's have a high level of sophisticated analytics capabilities, generally supporting a centre- of-excellence program, a data-science team and an analytics training program, that teaches people in a formal education setting, then provides them with the opportunity to use that in real life and take on professional development (Chen & Zhang, 2023). These capabilities allow organisations to be able to recognise where the analytical opportunities are and to shape the appropriate approaches to analysis, and to generate the insights informed by data that can drive companies and managers with out-brain insights beyond the purely technical processes and applications of business methodologies. Efforts to build analytic expertise must be characterized by systematic focus on recruiting, training, retention, and knowledge management practices that develop and sustain the wherewithal to succeed (Agarwal & Dhar, 2021).

However, the development of capabilities is hampered by several challenges, such as lack of expertise, difficulty in managing knowledge and barriers in the integration with operational departments (Sivarajah et al., 2021) that may hinder the practical application of analytical insights in the existing organisational structure. Contrastingly, alternative practice positions that it is such distributed statistics models with stresses on citizen data science, and self-service analytics, which are potentially more sustainable than centralised expert-driven models – particularly in those settings with limited access or ability to retain the sort of specialist expertise demanded by some versions of Big Statistics. The capabilities literature suggests that successful capability development involves systematic attention to both specialised analytical knowledge and the more general capacity of an organisation to treat ‘data as assets’ to facilitate collaborative processes between the analytical expert and domain experts. Therefore, while specialised analytics capabilities are necessary technical building blocks, their organisational influence hinges on more general capability development efforts that strengthen the capability of organisations to integrate insights gained through analytics into their existing decision-making and business process landscape.

2.3.4 Performance Measurement and Integration Assessment

Measuring big data analytics integration levels requires comprehensive assessment frameworks that evaluate technological, organisational, and utilisation dimensions of analytical capability development through systematic monitoring and evaluation processes. For mainly telecommunication arenas, balanced score card approaches for infrastructure development, capability building, analytical output generation and the creation of business value have been used to evaluate the integration and to find out the areas of improvements (Kumar & Singh, 2023). Such measurement frameworks integrate technological maturity scores, capability development indexes, and utilising measures reflecting the necessary levels of both analytical sophistication and business impact with covering performance dashboards and an ongoing evaluation process (Zhang & Liu, 2021). The university self-assessment exercise would usually have a number of stakeholder perspectives, introduce both qualitative and quantitative metrics, and be supported by longitudinal reporting that allow us to understand integration trajectories as well as success factors (Chatterjee et al., 2020).

Critics argue that currently methods for measurement frequently focus to a great extent on technical measures at the expense of those that are organisational and strategic impact dimensions-based which are the necessary precursor for the delivery organisations' value (Dubey et al., 2021), especially for complex organisational environments where analytical impact is hard to separate out and accurately measure. Other frameworks emphasize business results related metrics such as decision quality, operational performance, and strategic advantage measures which can describe the value created through analytics in a more holistic view than solely technical oriented performance metrics. The measurement literature indicates that best practices in measures include leading indicators of analytical skills development, and lagging measures of business performance improvement, as the complementary sets to understand the effectiveness of integration. Therefore, whilst technological metrics provide important insights into analytical capability development, comprehensive integration assessment requires balanced attention to capability development processes and business impact outcomes that demonstrate analytical value creation and organisational transformation.

2.4 Impact of Big Data Analytics on Decision-Making Quality

2.4.1 Decision Speed and Responsiveness Enhancement

The net effect is that big data analytics adds tremendous value to managerial decision making speed in the sense of real-time information processing that allows rapid response to evolving market conditions, customer demands, and operational requirements within telecommunications environments. As a result, telcos using sophisticated data analytics platforms realize the significant speed gains in decisioning cycles, such as for customer service resolution times, network issue response times, and competitive strategy flexing times spurted by the fully automated data processing and predictive analytics capabilities (Agarwal & Dhar, 2022). These speed gains can do more than just boost latency, thanks to dashboard-assisted information delivery that grants decision makers timely and relevant insights for quick (and prompt) decision making, allowing them to be more proactive in addressing problems before they grow in scale and take advantage of new possibilities through faster Times to Market. The acceleration is driven by standardisation of mundane analysis tasks as well by creating monitoring systems to detect abnormality in real time (Fosso Wamba et al., 2023) and alerting is applied in cases where the attention of management is required to take timely response.

However, the literature shows that there are potential downsides of making faster decisions such as less time to reflect on the alternatives, higher likelihood of having analytical failures, and possibly erroneous decisions taken with incomplete information or without considering properly the diverse group interests (Mikalef et al., 2021). Opponents such as Sivarajah et al. (2022) argue that by focusing on decision speed, the quality of decisions may be compromised, as complex factors and long-term consequences that need to be carefully thought through or consultation processes with stakeholders may not be adequately considered. The decision-making theory holds that the best approaches are those that optimally trade off between speed and thoroughness by adopting a two-tier approach that enables fast response to operational decisions and more thoughtful consideration of strategic decisions that require deeper examination and faculty engagement. As a result, although big data analytics offers valuable acceleration capabilities in decision-making processes, the effectives of its application is determined by the fit to decision contexts where speed advantages outweigh the potential for the quality of a decision to be compromised owing to the shortened decision time and the narrowing of stakeholder consultation.

2.4.2 Accuracy and Precision Improvements

The integration of big data analytics enhances decision-making accuracy through improved information quality, predictive capabilities, and evidence-based reasoning that reduce uncertainty and subjective bias in managerial judgements across telecommunications operations. . Telecom companies, which leverage advanced analytics, display an improved accuracy in predicting customer behavior, forecasting market trends, and planning for operational performance than organizations that are more dependent on traditional sources of information and intuitive actions (Chatterjee et al., 2022). These enhanced accuracies are driven by full data integration with complex models and structured validation that detects patterns and relationships which are not possible using traditional analysis methodologies, allowing for more accurate forecasting and better strategic planning. The calibration improvement campaign includes systematic data quality control and validation procedures as well as mechanisms for feedback that guarantee robustness and continuous improvement of analytics (Kumar et al., 2022).

However, criticisms remain with respect to the limitation of analytical models, the data quality problem, and interpretation difficulty that could threaten decision accuracy, even with the use of an advanced analysis decision system whenever models are utilized in conditions beyond the scope of original design or when unexpected pattern of the data basis is altered (Zhang & Wang, 2020). Complementary research suggests that the accuracy of analytics is sensitive to data representativeness, model?t, and user interpretation ability and that the differences in sophisticated analysis can translate into the improved decision return in real organisational contexts. The literature on accuracy therefore points to the need for sophisticated analytics to be supported by rigorous validation, user-training and as a result, enforcement of feedback-mechanisms to guarantee accurate analytical insights – as well as valid interpretation by decision-makers. So, although big data analytics offers powerful opportunities to enhance accuracy, reaping these opportunities calls for systematic consideration of data quality, model validation, and user capability development that promotes robust analytical interpretation and application in complex organisational settings.

2.4.3 Strategic Alignment and Coherence

Big data analytics results in the quality of strategic decision-making through in-depth market intelligence, competitiveness analysis and performance monitoring features for strategic alignment and coherence across the organisation levels in telecommunications firms. Firms that are able to use big data to inform strategic decision making report receiving greater alignment between strategy and operations by employing data-informed performance monitoring and strategy development processes that create and maintain both consistency and interconnectedness (Plastino & Purdy, 2022). These alignment advantages are due to linking the operational metrics directly with the strategic measures through integrated analytic frameworks that help managers to measure strategic progress and support the revision of the tactical moves by means of a comprehensive feedback about performance and the market. The alignment process includes: systematic embedding of analytical insights in strategic planning cycles; the establishment of performance dashboards for strategic progress tracking; a review process to ensure that operations activities support the execution of strategic objectives (Wamba & Ngai, 2023)

But research points to difficulties in operationalizing the analytical insights into strategic guidance, especially in making sense of the complex analytical findings and their potential for informing long-term strategic positioning in dynamic competitive settings (Mikalef & Gupta, 2023). Critics say excessive reliance on historical data patterns may limit strategic innovation and adaptation in a discontinuous change environment that should rely upon intuition and creative strategic thought beyond what analytical models can deliver. The literature on strategic alignment similarly implies that best practice requires a fusion of analysis and strategic intuition, and that the creation of holistic strategic understanding represents a synthesis of the best analysis, creative and intuitive thinking, and market wisdom. Therefore, while it is now evident that big data analytics can be an integrative force that enhances the strategizing process by way of information-rich and analysis-rich support it offers, ultimately, the strategic contribution and power of big data analytics is predicated on the extent to which it is inter-woven with human judgment and the creative strategic thinking protocols which encompass analytically-driven and intuitive sides of corporate strategy.

2.4.4 Risk Management

By discovering, exploring and managing benefits of data at an organizational and industrial level, big data analysis also contributes to risk identification, risk assessment and accounting by predictive modelling, scenario analysis and holistic monitoring systems, allowing organizations to proactively manage risks (Zhang & Liu, 2023). Telecommunication SOS DDDD companies adopting advanced analytics for risk management outperform companies that apply traditional risk management practices, which largely rely on historical past experience and expert opinion, in predicting customer churn, preventing network failures, and identifying competitive threats (Sivarajah et al., 2021). These risk management enhancements are enabled by fully integrated data, which facilitate early warning signal systems, predictive models that identify new and fresh risks and scenario building, to help us to understand how much different types of risk, might knock off relative value, tested through an analytical process. Mitigation solution - Improve risk management The risk management improvement consists of the creation of predictive risk models, the set-up of monitoring systems for instant risk indicators, and the deployment of an automated alert solution for a quick reaction to arising risks (Fosso Wamba et al., 2020).

On the other hand, scholars suggest that analytical risk management techniques can actually lead to overconfidence in risk assessment precision and possibly neglect risks that are not represented by the historical data patterns or assumption in analytical models for unprecedented risks without any historical analog in the current decision context (Verma & Bhattacharyya, 2023; Chatterjee et al., 2021). Counterviews argue that risk management is effective when it is a combination of quantitative and qualitative insights and expert judgement; that takes both analytical and decision-making processes into consideration, confirming that everything that can be captured in analytical models is not representation of all the risk we face. The literature on risk management also indicates that the most efficient model is one in which big data analytics enhance the existing traditional risk management, rather than replacing human decision-making with computers altogether, in particular when dealing with strategic risks, for which complex stakeholder dynamics and unique situations reside. Consequently, big data analytics has strong capabilities to identify and assess risks, yet its efficacy is contingent on integration with overarching risk management frameworks that consider both analytical and judgemental aspects of risk through an organised way and by blending quantitative analysis with qualitative judgement and expert opinion.

2.5 Strategies for Optimizing Big Data Utilization

2.5.1 Technology Integration

Effective big data utilization optimisation needs strategic technology integration strategies such as where analytical platforms are aligned to organisational needs, capabilities and strategic goals through systemic and planned implementation processes. Telecom companies who are gaining better configuration outcomes tend to integrate technology layers that include cloud computing environment, machine learning platforms, and real-time processing features, which allow for full analytic flexibility and scalability (Gupta & Sharda, 2023). These integration approaches emphasize on the need for interoperability, scalability and user accessibilities to allow that the information rendered by the technological investments actually turn into analytical power in favor of different decision making needs in organizational contexts at various levels and within different functions. Optimization is a systematic evaluation of current technology infrastructure, opportunities to integrate, and phased implementation approaches to minimize downtime and maximize increased analytical capability (Kumar et al., 2020).

Nonetheless, the adoption of technology can be fraught with challenges, such as the compatibility of technology with legacy systems, the danger of vendor lock-in, and the difficulty of managing complexity, which may impinge on the opportunities for optimisation, especially in well-established firms with existing technological infrastructure and no budget for an extensive system replacement (Mikalef et al., 2021). According to Leskovar et al., (2012) However, sometimes the technological sophistication of solutions is highlighted to the detriment of user needs and business enablers that largely define the fitness of use of a system, leading to the proposal that the practical use outweigh the potential for technical functionality. The literature on technology optimization stresses that effective implementation depends on a balance between technical capabilities and end-user needs and on the use of participatory design processes which ensure that the analytical platforms serve practactical decision-making needs (instead of being primarily driven by their advanced technical capabilities). Hence while technological platforms with advanced capability can serve as critical enablers of big data optimization, the extent to which they are effective will be determined by user-centred design principles that emphasise the practical utility, ease of use and business value creation over technological prowess and sophistication.

2.5.2 Organizational Change Management

Maximizing the potential of big data usage necessitates a structured cultural change that supports data driven decision making, analytic mindsets, and evidence based reasoning at all levels of the organization through well-articulated change management processes. Telecom operators with successful optimization results generally rely on a holistic approach to change management, including programs such as leadership development, cultural change initiatives, and structured training programs on developing analytical skills and a data-driven mindset (Chatterjee et al., 2020). This cultural transition "counsels resistance to change, advocates an Analytical literary, and creates organizational norms that consider evidence based decision making superior to decision making based strictly upon intuition"; through systematic communication, training and reinforcement. The change management process also requires meticulous analysis of the existing organizational culture, identification of the need for change, and systematic change programs covering both formal system and cultural aspects (Wamba & Ngai, 2022).

However, cultural change is an excepted and difficult work due to deep-rooted decision-making routines, reluctance toward data-driven thinking, and it is toughing to prove the value of quant analysis to black-box trusts that using the traditional way to make a decision would be better (Zhang & Wang, 2022). On the other hand, alternative studies indicate that successful cultural change requires piecemeal rollout that proves coverage in terms of analytical value (quick wins) while fostering capability development programs in the long term (technical skills and cultural attitude). The literature on change management also highlights that such organisational cultural change can only be realised when the leadership is committed and structural education and reward systems are in place to reinforce the use of information in the face of cottage industry resistance, which is addressed through education and demonstration. Thus, even if cultural change is a necessary condition for successful big data optimization, such changes that will endure will take place through the sustained focus on and active management of leadership, communication, and reinforcement mechanisms that enable lasting behavioral modifications and organizational learning.

2.5.3 Skills Development and Capability Building

Effective big data utilization optimization necessitates comprehensive skills development programmes that build analytical capabilities across technical, managerial, and operational staff categories through systematic training and development initiatives. Telecom companies reporting better optimization results usually have established structured training schemes that focus on data science skills, reasoning and decision enhancement for ensuring right usage of BDA (Verma & Bhattacharyya, 2022; Mikalef & Gupta, 2021). These capacity building initiatives include dedicated analytical skills as well as data literacy at the organizational level, which facilitate the working relationships between analytics specialists and domain experts by means of structured learning activities and opportunities for hands-on application. Skills development is a process of assessing the existing skills, identifying the skills storm and organizing the relevant training programs to develop technical as well as application oriented skills (Kumar & Singh, 2023).

However, there are substantial constraints to skills development, such as resource constraints, lack of time to train and uncertainty on the rate of learning that could result in restrictive barriers to the diffusion of the programme in multi-staff organisations that have a range of staff backgrounds and competing priorities

(Chatterjee et al., 2022). Critics suggest that traditional teaching methods might not be enough to develop knowledge and skills for complex analytical thinking to use big data in dynamic business environments suitable to adaptive learning and skill building. The ability building literature on the other hand, indicates that the best practices are those, which blend formal learning with practice, mentoring programmes as well as practical applications, for skill acquisition targeted towards real time problem-solving analytical challenges, and peer collaborations (Agarwal & Dhar, 2021).

Thus, whilst systematic skills development provides essential foundations for big data optimization, its effectiveness depends on comprehensive approaches that combine theoretical learning with practical application opportunities, ongoing support systems, and systematic reinforcement through regular practice and feedback mechanisms.

2.5.4 Performance Monitoring and Continuous Improvement

Optimizing sustainable use of big data: Systematic performance measurement and monitoring set the track for analytical effectiveness, business impact, and improvement opportunities using feedback mechanisms and reliable data measurement for continuous improvement. Telecommunications firms leading in the performance of optimization typically adopt a balanced measurement system that utilizes both technical performance measures, utilization-indicators and business metrics to evaluate how analysis is creating value and can be enhanced (Plastino & Purdy, 2022). On the so, and some such runtime adjustment under changing business and technology evolvement may be self-learn as now most of operations need monitoring and inner-control mechanisms and procedures and tools, etc, and performance managing and optimization at running time or as close as possible to the runtime lower air friction at runtime, the runtime itself and not only above the runtime. The monitoring process refers to the creation of performance metrics, introduction of measurement systems and ongoing review processes that measure progress and uncover opportunities for improvement (Gupta & Sharda, 2021).

On the other hand, performance monitoring is faced with: complex measures to perform, difficulty of laboratory testing, changing business dynamics, lack of understanding of what to measure to assess the analytical effectiveness, progress and a myriad of challenges in form of dynamic business outcomes influence analysis effectiveness, progress and inability to optimize it when multiple factors cause business outcomes (Fosso Wamba et al., 2021). Other methods take a qualitative perspective, such as capturing analytical impact through social validation from stakeholders, through case study analysis, or via the long-term monitoring of performance over time that can lead to understanding about optimisation in terms not reducible to metrics. The performance and performance monitoring literatures make it clear that successful measurement has two components: a) a balanced approach: including quantitative metrics and qualitative assessment, in achieving the capture of both the technical performance as well as business-value creation for analytics usage, and b) a holistic evaluation framework (Wamba & Ngai, 2020). Thus, while systematic performance tracking is essential for sustained performance improvement, it is only effective if the performance measurement frameworks are based on the broad view of intuitive performance in reading and identifying its both technical and business aspects for identifying big data utilization optimisation and for having enough malleability to be able to dynamical adopt itself to the changes in organizational requirements and strategic objectives.

2.6 Research Gaps

Existing literature demonstrates that there are major theoretical voids on how the traditional organizational theories are relevant for big data analytics adoption in an emerging market telecommunication context. The existing theoretical background such as Dynamic Capabilities Theory and Information Processing Theory are mainly formulated and tested in western market settings with little extant literature to support their generalization to resource-constrained environments typical of African telcos (Mikalef et al., 2020). Theoretical work does not offer much in the way of a comprehensive framework that encapsulates the unique contextual factors driving adoption in emerging markets such as infrastructure problems, a lack of skills, and regimens that do not quite square with the assumptions of developed markets. What is more, the current theoretical explanation has limitations in consideration of the combined effect of technological capabilities and institutional environment of telecom companies in developing countries, leading to the theoretical blind spot of how organizational theories would be instantiated in reality of developing countries where these telecommunication firms are embedded; thus impairing our understanding of how organizational theories present in the reality of a specific context (Chen & Zhang, 2022).

There are methodological limitations among existing big data analytics research, such as the predominant use of cross-sectional studies, which do not not address the dynamic nature of organizational changes engagements taking place in analytics implementations. The majority of extant studies to date have adopted quantitative methodologies which focus on one point in time measurement of analytics adoption and paid insucient attention to the longitudinal implementation process and the development of evolutionary capability and the adaptation response of organizations contributing to the successful integration of BD (Sivarajah et al., 2022). The methodological literature shows lacking emphasis on mixed methods, which can offer a nuanced understanding of not only the impact on quantitative performance, but also qualitatively how the organization needs to transform in order to be successful with analytics. Furthermore, current research tools do not adequately capture the nature of contextual environment of emerging market telecom operators, such as resource constraints, infrastructure constraints and competitive issues that affect both the intervention strategy adopted and the rigorousness of the design of the evaluation (Gupta & Sharda, 2023).

The literature reflects lack of an in-depth country specific context on big data analytics adoption within African telecommunications markets, despite some of the existing studies being from developed market contexts or Asian emerging markets but not the Sub-Saharan African telecommunications setting. There is virtually no empirical research on Zimbabwean telecommunications firms, and the country's unique economic, technological and regulatory environment is likely to shape patterns of the adoption of analytics and their nature of implementation (Plastino & Purdy, 2022). The contextual literature is found to underwater the importance of local market conditions, regulation, competitive landscape, customer profile and competitive intensity on the efficacy of big data analytics in African telecommunications context. More so, the extant empirical literature provides insufficient evidence as to the relationship between organisational size, market positioning and the success of implementation of analytics in emerging market telcos; knowledge gaps that would hinder practical guidance for telcos embarking on data led transformation projects in resource-stressed environment.

2.7 Chapter Summary

This chapter established comprehensive theoretical foundations through Dynamic Capabilities Theory and Information Processing Theory, providing robust analytical frameworks for understanding organizational capability development and information processing enhancement in telecommunications contexts. The systematic literature review examined empirical evidence across three primary research objectives, revealing substantial opportunities for decision-making enhancement through big data analytics whilst identifying implementation challenges and optimization strategies. The analysis demonstrated significant gaps in current knowledge regarding emerging market telecommunications contexts, particularly within

African markets, justifying this study's focus on examining big data analytics implementation at Econet Wireless Zimbabwe within its specific organizational and market environment.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

This chapter presented the research methodology employed to investigate the role of big data in enhancing managerial decision-making processes at Econet Wireless Zimbabwe. The chapter outlined the research philosophy, approach, design, target population, sampling techniques, data collection methods, and analytical procedures that were utilized to achieve the study objectives. The methodology was designed to ensure the collection of reliable and valid data that could adequately address the research questions and provide meaningful insights into how big data technologies influenced managerial decision-making within the telecommunications sector in Zimbabwe.

3.2 Research Philosophy

Research philosophy is the belief and the assumption of the concept of knowledge formulated that research strategy followed and the method selected (Saunders et al., 2019). This research paper followed positivist view, which considers scientific methods applicable to social phenomena. Underpinning positivism is the belief that reality exists outside of human consciousness, and can be objectively measured through empirical observation and have statistical application. (Bryman & Bell, 2015) In this regard, the positivist philosophy was used to argue for the rationale of the study, as its nature was quantitatively designed to measure and examine the correlation between big data adoption and managerial decision effectives. As Creswell and Creswell(2018) described, positivism is most appropriate for research where the intent is to conduct hypothesis testing and make claims about causal relationships from the use of statistics. The philosophy provided the researcher with a vehicle of ensuring that neutrality and lack of bias was attained when gathering and interpreting numerical data on big data use patterns and decision outcomes at Econet Wireless Zimbabwe.

3.3 Research Approach

The research approach refers to the plan and procedures that guided the research from broad assumptions to detailed methods of data collection and analysis (Creswell, 2014). This study employed a deductive research approach, which involved testing theoretical propositions through empirical investigation. The deductive approach moves from general theories to specific observations, allowing researchers to test existing theories in new contexts (Sekaran & Bougie, 2016).

The deductive approach was appropriate for this study because it enabled the researcher to build upon existing theories of big data analytics and decision-making frameworks to develop hypotheses that were subsequently tested using quantitative data from Econet Wireless Zimbabwe. As argued by Bryman and Bell (2015), the deductive approach is particularly suitable for quantitative research as it allows for the systematic testing of relationships between variables and the generalization of findings to broader populations.

3.4 Research Design

Research design is the overall strategy that integrates the different components of the study in a coherent and logical way, ensuring that the research problem is effectively addressed (Yin, 2018). This study adopted a descriptive survey research design, which enabled the systematic collection of data from a representative sample of managers at Econet Wireless Zimbabwe to describe the current state of big data utilization in managerial decision-making processes.

The descriptive survey design was justified because it allowed for the collection of standardized information from a large number of respondents in a cost-effective manner (Fowler, 2014). This design was particularly suitable for investigating the role of big data in decision-making as it enabled the researcher to gather quantitative data about managers' perceptions, experiences, and practices regarding big data usage. As noted by Malhotra and Dash (2016), survey designs are effective for studies that aim to describe characteristics of a population and examine relationships between variables at a single point in time.

3.5 Target Population

The target population refers to the complete group of individuals or entities that share common characteristics and are of interest to the researcher (Cooper & Schindler, 2014). The target population for this study comprised all managerial staff at Econet Wireless Zimbabwe who were involved in decision-making processes and had exposure to big data analytics tools and systems. This included senior managers, middle managers, and junior managers across various departments such as marketing, operations, finance, customer service, and strategic planning.

The choice of managerial staff as the target population was justified because managers are the primary users of big data analytics for decision-making purposes and possess the knowledge and experience necessary to provide meaningful insights about the role of big data in enhancing decision-making processes (Davenport & Harris, 2017). According to Econet Wireless Zimbabwe's organizational structure, the total managerial population comprised approximately 150 individuals across all levels and departments.

3.6 Sampling and Sampling Techniques

Sampling refers to the process of selecting a subset of individuals from the target population to participate in the research study (Taherdoost, 2016). This study employed stratified random sampling, which involved dividing the target population into homogeneous subgroups (strata) based on management levels and then randomly selecting participants from each stratum.

Stratified random sampling was chosen because it ensured representation from different management levels and departments, thereby enhancing the generalizability of the findings (Kothari, 2004). The population was stratified into three levels: senior managers (15 individuals), middle managers (45 individuals), and junior managers (90 individuals). This sampling technique was justified as it reduced sampling bias and ensured that each subgroup was adequately represented in the sample, as recommended by Sekaran and Bougie (2016).

3.7 Sample Size

Sample size determination is crucial for ensuring that the study has sufficient statistical power to detect meaningful relationships while remaining feasible in terms of time and resources (Hair et al., 2019). This study used Yamane's formula (1967) to calculate the appropriate sample size:

$$\mathbf{n = N / (1 + N(e)^2)}$$

Where:

- n = sample size
- N = population size (150)
- e = margin of error (0.08 or 8%)

Calculation: $n = 150 / (1 + 150(0.08)^2)$ $n = 150 / (1 + 150(0.0064))$ $n = 150 / (1 + 0.96)$ $n = 150 / 1.96$ $n =$ **77 respondents**

To account for potential non-response, the sample size was increased by 15% to 89 respondents. The final sample comprised 89 managers distributed proportionally across the three strata: 8 senior managers, 26 middle managers, and 55 junior managers. This sample size was adequate for conducting meaningful statistical analysis while remaining manageable for data collection purposes, as supported by Cohen et al. (2018).

3.8 Data Collection Method

Data collection techniques refer to the specific methods used to gather information from research participants (Kumar, 2019). This study employed primary data collection through a survey. Primary data collection was chosen because it enabled the researcher to gather specific information directly related to the research objectives and ensured data relevance and currency.

3.8.1 Survey

This study employed the survey method as the primary data collection approach. Fowler (2014) described that survey is a method for collecting data from a portion of the population using standard questionnaires to gather information about their attitudes, opinions, behaviors, attributes, experiences in a structured, consistent, and comparable form. Because survey research has certain unique qualities, which are compatible with the aim of this study and appropriate for its questions, it has been selected as the most appropriate method. The first of these, surveys, utilizes systematic data collection techniques that are maintained across all respondents (Bryman & Bell, 2015). Second, they rely on standardized measurement tools that provide the quantification of variables and statistical analysis (Hair et al., 2019). Third, surveys are a way of collecting data in which samples are taken to represent general populations (Creswell & Creswell, 2018). Fourth, they allowed us to test the relationships between sets of variables at the same time, which was important in exploring the complex relationships between big data usage and managerial decision-making effectiveness (Sekaran & Bougie, 2016).

The method chosen was survey and was well explained as to why by theoretical and practical reasons. In theoretical terms, the positivist philosophy underpinning this study complemented survey research particularly well, because both were predicated on empirical measurement and objective data collection (Kumar, 2019). The deductive research perspective used in this research demanded a methodology, which could meaningfully feed hypotheses generated from the prevailing theories and surveys accorded the provision, structure for testing hypotheses on statistical counts (Malhotra & Dash, 2016).

The survey method had several clear practical advantages for this study. First, it allowed for a quantitative survey to be conducted among a relatively large number of managers (89 respondents), in a cost and time effective way, which was important for the resource constraints of the research project (Cooper & Schindler, 2014). Secondly, surveys aided in standardisation of questions and response formats, which meant that respondents could all be asked the same questions in the same order, thereby improving comparability and reliability of responses between different management levels and departments in Econet Wireless (Fowler, 2014).

Third, the survey was well-suited to assess managers' perceptions, attitudes, and experiences of using big data in decision-making processes, because the survey enabled systematic measurement of subjective constructs via established scales and measurement instruments (Nunnally and Bernstein 1994). Fourth, surveys granted full anonymity and confidentiality and that facilitated honesty regarding the way organizational operations take place and challenges related to decision making that might have been hard to reach using interviews or observation (Bryman & Bell, 2015).

The use of surveying techniques provided the added benefit of data analysis and interpretation. The organised format of survey data allowed for the application of advanced statistical techniques such as descriptive statistics, correlation pattern analysis and multiple regression analysis indispensable for exploring association between big data implementation and effective decision making (Field, 2018). The standardised presentation of data also facilitated data processing and minimized the risk of transcription errors that can be associated with collecting qualitative data (Pallant, 2020).

Additionally, the survey approach was ideal for the type of organization under examination Econet Wireless Zimbabwe, which had managers located in different regions and departments. This procedure enabled the collection of data from all the target respondents at the same time without the inconvenience of prolonged transit or several site visits, hence it was efficient and caused minimal disruption to normal business work (Sue & Ritter, 2012). A survey method was also used so as to be able to uphold the time management schedules of busy managers, as the data was systematically collected throughout the entire sample and the busy managers could complete the questionnaire when it suited them.

3.9 Data Collection Instruments

3.9.1 Structured Questionnaire

The primary data collection instrument was a structured questionnaire consisting of closed-ended questions using Likert scales and multiple-choice formats. The questionnaire was divided into five sections: demographic information, big data awareness and usage, decision-making processes, perceived benefits of big data, and challenges in big data implementation.

The questionnaire was designed based on established scales from previous studies on big data analytics and decision-making, including works by Chen et al. (2012) and McAfee and Brynjolfsson (2012). Likert scales ranging from 1 (strongly disagree) to 5 (strongly agree) were used to measure respondents' attitudes and perceptions. The structured questionnaire format was justified because it facilitated standardized data collection, reduced interviewer bias, and enabled efficient statistical analysis of responses (Fowler, 2014).

3.10 Data Collection Procedures

Data collection procedures outline the systematic steps followed to gather information from research participants (Creswell & Creswell, 2018). The data collection process was conducted over a period of four weeks and involved several stages. First, ethical clearance was obtained from the university and permission was secured from Econet Wireless Zimbabwe management. Second, potential participants were identified using the employee database and contacted via email to explain the study purpose and request participation.

The questionnaires were administered electronically using Google Forms, with reminder emails sent weekly to increase response rates. Follow-up phone calls were made to non-respondents to encourage participation. The electronic administration was justified because it facilitated efficient data collection, reduced transcription errors, and enabled automatic data compilation for analysis (Sue & Ritter, 2012). A response rate of 84% was achieved, with 75 completed questionnaires received from the targeted 89 respondents.

3.11 Reliability and Validity of the Study

Reliability refers to the consistency and stability of measurement instruments, while validity concerns the extent to which instruments measure what they are intended to measure (Hair et al., 2019). To ensure reliability, Cronbach's alpha coefficient was calculated for each scale, with values above 0.7 indicating acceptable internal consistency. The overall reliability coefficient for the questionnaire was 0.89, exceeding the minimum threshold recommended by Nunnally and Bernstein (1994).

Content validity was established through extensive literature review and expert consultation, ensuring that the questionnaire adequately covered all aspects of big data and decision-making. Construct validity was assessed through factor analysis, which confirmed that the items loaded appropriately on their intended constructs. Face validity was ensured by conducting a pilot test with five managers who confirmed that the questions were clear and relevant. These validity measures were crucial for ensuring that the findings accurately reflected the phenomena under investigation, as emphasized by Sekaran and Bougie (2016).

3.12 Data Analysis

Data analysis involves the systematic examination and interpretation of collected data to answer research questions and test hypotheses (Field, 2018). The collected data was analyzed using Statistical Package for Social Sciences (SPSS) version 28.0. Descriptive statistics, including frequencies, percentages, means, and standard deviations, were calculated to summarize the data and describe the characteristics of the sample.

Inferential statistics were employed to test relationships between variables and draw conclusions about the population. Correlation analysis was conducted to examine the strength and direction of relationships between big data usage and decision-making effectiveness. Multiple regression analysis was performed to determine the predictive power of big data variables on decision-making outcomes. The choice of these statistical techniques was justified by the quantitative nature of the data and the research objectives, as recommended by Pallant (2020).

3.13 Ethical Considerations

Ethical considerations are fundamental principles that guide research conduct to protect the rights, dignity, and welfare of research participants (Bryman & Bell, 2015). This study adhered to established ethical guidelines throughout the research process. Informed consent was obtained from all participants, who were provided with detailed information about the study purpose, procedures, potential risks, and benefits before agreeing to participate.

Confidentiality and anonymity were maintained by ensuring that individual responses could not be traced back to specific participants. Data was stored securely and accessed only by the researcher. Participants were informed of their right to withdraw from the study at any time without penalty. The study received ethical approval from the university's research ethics committee, and permission was obtained from Econet Wireless Zimbabwe management. These ethical safeguards were essential for maintaining research integrity and protecting participant welfare, as emphasized by Kumar (2019).

3.14 Chapter Summary

This chapter outlined the comprehensive research methodology employed to investigate the role of big data in enhancing managerial decision-making processes at Econet Wireless Zimbabwe. The study adopted a positivist philosophy with a deductive approach and descriptive survey design, targeting 150 managerial staff and selecting a sample of 89 respondents using stratified random sampling. Data was collected through structured questionnaires and analyzed using SPSS with descriptive and inferential statistics. The methodology ensured reliability and validity through appropriate testing procedures while maintaining ethical standards throughout the research process, providing a robust foundation for addressing the research objectives and generating meaningful insights about big data's impact on managerial decision-making in the telecommunications sector.

CHAPTER 4

DATA PRESENTATION AND ANALYSIS

4.1 Introduction

This chapter presents the analysis of empirical data collected from 75 managerial staff at Econet Wireless Zimbabwe to investigate the role of big data in enhancing managerial decision-making processes. The analysis systematically addresses three research objectives: assessing current big data analytics integration levels, measuring impact on decision-making quality, and developing optimization strategies within a 12-month framework, utilizing SPSS version 28.0 for comprehensive statistical analysis.

4.2 Response Rate

Table 4.1: Response Rate Analysis

Category	Target Sample	Responses Received	Response Rate (%)
Senior Managers	8	7	87.5%
Middle Managers	26	22	84.6%
Junior Managers	55	46	83.6%
Total	**89**	**75**	**84.3%**

The study achieved an exceptional response rate of 84.3%, with 75 completed questionnaires from 89 targeted managers. This high response rate exceeds recommended thresholds and ensures statistical validity across all management levels, with consistent participation ranging from 83.6% to 87.5%, eliminating potential bias from disproportionate representation.

4.3 Demographics

Table 4.2: Demographic Characteristics of Respondents

Variable	Category	Frequency	Percentage
Age	25-35 years	32	42.7%
	36-45 years	28	37.3%

	46-55 years	13	17.3%
	56+ years	2	2.7%
Gender	Male	48	64.0%
	Female	27	36.0%
Education	Bachelor's Degree	45	60.0%
	Master's Degree	26	34.7%
	Professional Cert.	3	4.0%
	Doctoral Degree	1	1.3%
Experience	1-3 years	28	37.3%
	4-7 years	31	41.3%
	8-12 years	12	16.0%
	13+ years	4	5.3%

4.3.1 Age Distribution

The age analysis reveals a predominantly young management workforce, with 80.0% of respondents aged between 25-45 years. The largest group (42.7%) falls within 25-35 years, indicating dynamic, technology-adaptive leadership. This youthful demographic suggests high receptivity to big data analytics adoption and digital transformation initiatives, providing favorable conditions for analytical capability development and organizational change management processes.

4.3.2 Gender Representation

Gender distribution shows male dominance at 64.0% compared to 36.0% female representation, reflecting typical telecommunications industry patterns. While gender imbalance exists, substantial female participation ensures diverse perspectives in analytical adoption assessment. The gender composition provides adequate representation for understanding different approaches to technology adoption and decision-making enhancement across gender demographics within the organizational context.

4.3.3 Educational Qualifications

Educational analysis demonstrates highly qualified management with 94.7% holding university degrees, including 36.0% with advanced qualifications. The predominance of bachelor's degrees (60.0%) indicates solid foundational education, while substantial master's degree representation (34.7%) suggests strong analytical capability potential. This educational foundation creates favorable conditions for big data analytics understanding, adoption, and effective utilization across organizational functions.

4.3.4 Work Experience

Experience distribution shows balanced representation with 78.6% having 1-7 years management experience. The largest group (41.3%) possesses 4-7 years experience, indicating sufficient decision-making exposure while maintaining adaptability to new approaches. This experience profile suggests managers understand traditional decision-making processes while being receptive to analytical enhancement, creating optimal conditions for successful big data implementation and organizational transformation.

4.4 Descriptive Analysis

4.4.1 Current Level of Big Data Analytics Integration

Table 4.3: Big Data Analytics Integration Assessment

Variable	Mean	Std. Dev	Level
Technology Infrastructure	3.42	1.18	Moderate
Analytics Tools Usage	2.87	1.32	Below Average
Data Management Systems	3.65	1.05	Above Average
Staff Analytical Skills	2.93	1.24	Below Average
Strategic Integration	3.15	0.98	Moderate

4.4.1.1 Technology Infrastructure

The technology infrastructure assessment reveals moderate capability levels (M = 3.42, SD = 1.18), indicating that Econet has established foundational technological systems but requires enhancement for comprehensive analytics implementation. Current infrastructure supports basic analytical applications while lacking advanced capabilities for sophisticated analytics. The moderate variation suggests uneven infrastructure development across departments, with some areas achieving higher capability than others. Infrastructure limitations represent primary barriers to analytical expansion, requiring systematic upgrade initiatives to support advanced analytical tools and comprehensive organizational transformation for competitive advantage development.

4.4.1.2 Analytics Tools Usage

Analytics tools utilization demonstrates below-average adoption (M = 2.87, SD = 1.32), indicating limited implementation of available analytical technologies across organizational functions. Current usage focuses on basic reporting and dashboard applications while advanced analytics remain underutilized. The high variation suggests significant differences in tool adoption across departments and management levels, with some areas achieving substantial implementation while others lag considerably. Limited tool usage represents substantial untapped potential for enhanced decision-making support through systematic tool deployment and comprehensive training initiatives.

4.4.1.3 Data Management Systems

Data management systems achieve above-average performance (M = 3.65, SD = 1.05), indicating successful establishment of foundational data collection, storage, and accessibility frameworks. Current systems support routine analytical applications while requiring enhancement for advanced analytics requirements. The moderate variation suggests consistent data management development across organizational areas with some departments achieving higher capability levels. Strong data management foundations provide favorable conditions for analytical expansion while requiring continued development for comprehensive organizational analytical transformation and competitive advantage creation.

4.4.1.4 Staff Analytical Skills

Staff analytical skills demonstrate below-average development (M = 2.93, SD = 1.24), indicating significant capability gaps that limit effective analytical utilization across organizational functions. Current skill levels support basic analytical applications while lacking depth for sophisticated analytical development and implementation. The high variation suggests uneven skill distribution with some individuals possessing advanced capabilities while others require fundamental development. Limited analytical skills represent critical barriers to analytical adoption, requiring comprehensive training programs and capability development initiatives for successful organizational transformation.

4.4.1.4 Strategic Integration

Strategic integration achieves moderate levels (M = 3.15, SD = 0.98), indicating partial incorporation of analytical insights into strategic decision-making processes while revealing substantial enhancement opportunities. Current integration supports tactical applications while lacking comprehensive strategic analytical adoption across organizational planning and development activities. The moderate variation suggests uneven strategic adoption across different management levels and functional areas, with some achieving higher integration than others. Limited strategic integration represents significant opportunities for competitive advantage development through enhanced analytical support for strategic planning and decision-making processes.

4.4.2 Impact on Decision-Making Quality

Table 4.4: Decision-Making Quality Impact Assessment

Variable	**Mean**	**Std. Dev**	**Impact Level**
Decision Speed	3.78	1.05	High
Decision Accuracy	3.65	1.12	High
Problem Solving	3.54	1.08	High
Risk Management	3.42	1.15	Moderate
Strategic Alignment	3.28	1.22	Moderate

4.4.2.1 Decision Speed

Decision speed improvements demonstrate high impact levels (M = 3.78, SD = 1.05), indicating that big data analytics substantially enhances decision-making velocity across organizational functions. Analytical tools enable faster information processing, automated reporting, and real-time monitoring that reduce decision cycle times significantly. The moderate variation suggests consistent speed improvements across different decision contexts and management levels, with most areas experiencing substantial enhancement. Enhanced decision speed provides competitive advantages through faster market response, improved customer service, and more agile operational management that strengthen organizational performance and market positioning.

4.4.2.2 Decision Accuracy

Decision accuracy shows high improvement levels (M = 3.65, SD = 1.12), indicating that analytical tools substantially enhance precision and reliability of managerial decisions across various organizational contexts. Data-driven insights reduce uncertainty, improve forecasting capabilities, and support evidence-based reasoning that minimize decision errors and enhance outcomes. The moderate variation suggests widespread accuracy improvements across different decision types and organizational areas, with most functions experiencing meaningful enhancement. Improved decision accuracy contributes to better resource allocation, enhanced strategic planning, and reduced operational risks that strengthen organizational effectiveness.

4.4.2.3 Problem Solving

Problem solving capabilities achieve high enhancement levels (M = 3.54, SD = 1.08), indicating that analytical tools significantly improve managers' ability to identify, analyze, and resolve complex organizational challenges. Advanced analytics enable pattern recognition, root cause analysis, and systematic problem diagnosis that enhance solution development effectiveness. The moderate variation suggests consistent problem-solving improvements across different organizational areas and management levels, with most functions benefiting from analytical support. Enhanced problem-solving capabilities contribute to operational efficiency, innovation development, and organizational learning that strengthen competitive positioning and performance outcomes.

4.4.2.4 Risk Management

Risk management demonstrates moderate improvement levels (M = 3.42, SD = 1.15), indicating that analytical tools provide meaningful but limited enhancement in risk identification, assessment, and mitigation processes. Current analytical applications support basic risk monitoring and reporting while lacking comprehensive predictive risk modeling capabilities. The higher variation suggests uneven risk management improvements across different organizational areas, with some functions achieving substantial enhancement while others show limited development. Moderate risk management improvement indicates substantial opportunities for advanced analytical development that could provide significant competitive advantages through enhanced organizational resilience.

4.4.2.5 Strategic Alignment

Strategic alignment shows moderate improvement levels (M = 3.28, SD = 1.22), indicating that analytical tools provide limited but meaningful enhancement in connecting operational decisions with strategic objectives and organizational priorities. Current analytical applications support tactical alignment while lacking comprehensive strategic integration across planning and decision-making processes. The high variation suggests significant differences in strategic alignment across management levels and functional areas, with some achieving better integration than others. Limited strategic alignment indicates substantial opportunities for enhanced analytical development that could strengthen organizational coherence and competitive advantage.

4.4.3 Optimization Strategies

Table 4.5: Optimization Strategy Requirements

Variable	Mean	Std. Dev	Priority Level
Infrastructure Upgrade	4.31	0.76	Very High
Training Programs	4.18	0.81	Very High
Data Quality Management	4.05	0.87	High
Tool Implementation	3.92	0.89	High
Process Integration	3.78	0.94	High

4.4.3.1 Infrastructure Upgrade

Infrastructure upgrade achieves very high priority (M = 4.31, SD = 0.76), indicating strong organizational consensus that technological capability enhancement represents the most critical optimization requirement. Current infrastructure limitations constrain analytical adoption and prevent comprehensive organizational transformation, requiring immediate attention and substantial investment. The low variation suggests universal recognition of infrastructure importance across all management levels and functional areas, creating favourable conditions for investment approval and implementation support. Infrastructure upgrade represents the foundation for all other optimization initiatives, requiring systematic planning and phased implementation for maximum organizational benefit and transformation success.

4.4.3.2 Training Programs

Training programs demonstrate very high priority (M = 4.18, SD = 0.81), indicating strong organizational recognition that human capability development represents equally critical optimization requirements alongside technological enhancement. Current skill gaps limit effective analytical utilization and prevent comprehensive organizational adoption of available analytical capabilities. The low variation suggests widespread recognition of training importance across organizational levels and functions, supporting comprehensive capability development initiatives. Training programs must parallel infrastructure development to ensure effective utilization of enhanced technological capabilities and maximize analytical investment returns through systematic human capital development.

4.4.3.3 Data Quality Management

Data quality management shows high priority (M = 4.05, SD = 0.87), indicating strong organizational understanding that reliable, consistent data represents essential foundation for effective analytical applications and decision-making enhancement. Current data quality issues limit analytical reliability and prevent comprehensive adoption of advanced analytical techniques across organizational functions. The moderate variation suggests general recognition of data quality importance while indicating some differences in priority assessment across different organizational areas. Data quality improvements must be integrated into early optimization phases to ensure analytical reliability and effectiveness for sustained organizational transformation.

4.4.3.4 Tool Implementation

Tool implementation demonstrates high priority (M = 3.92, SD = 0.89), indicating organizational recognition that systematic deployment of analytical software and platforms represents important optimization requirements following infrastructure and capability development. Current limited tool utilization prevents comprehensive analytical adoption and constrains organizational transformation potential across functional areas. The moderate variation suggests general agreement on tool importance while indicating some differences in implementation priorities across organizational areas. Tool implementation should be coordinated with infrastructure and training initiatives to ensure effective deployment and utilization for maximum organizational benefit.

4.4.3.5 Process Integration

Process integration shows high priority (M = 3.78, SD = 0.94), indicating organizational understanding that systematic incorporation of analytical insights into decision-making processes represents important but longer-term optimization requirements. Current limited process integration prevents comprehensive analytical value realization and constrains organizational transformation effectiveness across functional areas. The moderate variation suggests varying recognition of process integration importance across different organizational levels and functions, requiring systematic change management and implementation support. Process integration represents essential long-term optimization requirement for sustained analytical transformation and competitive advantage development.

4.5 Inferential Statistical Analysis

4.5.1 Correlation Analysis

Table 4.6: Pearson Correlation Matrix

Variables	**1**	**2**	**3**	**4**	**5**	**6**
1. Integration Level	1.000					
2. Decision Speed	0.742**	1.000				
3. Decision Accuracy	0.698**	0.623**	1.000			
4. Problem Solving	0.634**	0.587**	0.712**	1.000		
5. Risk Management	0.591**	0.554**	0.667**	0.643**	1.000	
6. Strategic Alignment	0.758**	0.832**	0.876**	0.798**	0.723**	1.000

The correlation matrix reveals strong positive relationships between big data integration level and all decision-making quality dimensions, with coefficients ranging from 0.591 to 0.758, all significant at $p < 0.01$. The strongest correlation appears between integration level and strategic alignment ($r = 0.758$), indicating that higher analytical adoption consistently associates with improved organizational coherence and goal alignment. Decision speed shows a strong correlation with integration ($r = 0.742$), suggesting that analytical tools substantially enhance decision-making velocity through automated processing and real-time insights. Decision accuracy demonstrates a strong relationship with integration ($r = 0.698$), confirming that data-driven approaches improve decision precision and reliability. The inter-correlations between decision quality variables (ranging from 0.554 to 0.876) indicate that improvements in one quality dimension typically accompany enhancements in others, suggesting comprehensive analytical benefits across multiple performance areas rather than isolated improvements.

4.5.2 Regression Analysis

Table 4.7: Multiple Regression Analysis - Predicting Decision Quality

Predictor Variables	B	Std. Error	Beta	t	Sig.
(Constant)	0.487	0.234		2.081	0.041
Integration Level	0.623	0.087	0.542	7.161	0.000**
Infrastructure	0.234	0.078	0.231	3.000	0.004**
Skills	0.189	0.065	0.198	2.908	0.005**
Data Quality	0.156	0.072	0.167	2.167	0.033*

The multiple regression model explains 74.3% of variance in decision-making quality ($R^2 = 0.743$), indicating that the identified predictors account for nearly three-quarters of quality improvement outcomes with high statistical significance ($F = 39.832$, $p < 0.001$). Integration level emerges as the strongest predictor ($\beta = 0.542$, $p < 0.001$), confirming that comprehensive analytical adoption has the most substantial direct impact on decision-making enhancement among all measured factors. Infrastructure capability demonstrates significant predictive power ($\beta = 0.231$, $p < 0.01$), indicating that technological foundations represent critical requirements for analytical success and quality improvement. Staff skills show significant influence ($\beta = 0.198$, $p < 0.01$), confirming that human capability development directly contributes to analytical effectiveness and decision-making enhancement. Data quality achieves significant predictive value ($\beta = 0.167$, $p < 0.05$), indicating that reliable, consistent data foundations are essential for analytical applications to generate meaningful decision-making improvements. The model's high explanatory power and significant predictors provide empirical validation for investment priorities in integration, infrastructure, skills, and data quality as key drivers of analytical success.

4.6 Discussion of Findings

4.6.1 Current Integration Level

The moderate integration level (M = 3.15) aligns with Kumar and Singh (2021) findings on telecommunications analytics adoption in emerging markets, indicating typical organizational development patterns. However, Econet demonstrates stronger data management capabilities (M = 3.65) compared to Mikalef et al. (2020) observations of infrastructure-first adoption approaches. The below-average analytics skills (M = 2.93) confirm Chatterjee et al. (2022) assertions about capability gaps in developing economy contexts. The strategic integration level matches Fosso Wamba et al. (2021) predictions about operational-to-strategic adoption progression. These findings indicate that Econet follows established telecommunications analytics adoption patterns while requiring targeted capability development initiatives for comprehensive transformation.

4.6.2 Decision-Making Quality Impact

The high impact on decision speed (M = 3.78) exceeds Chen and Zhang (2022) reported improvements in telecommunications decision-making velocity, indicating exceptional organizational benefits from analytical adoption. Decision accuracy improvements (M = 3.65) align with Verma and Bhattacharyya (2023) findings on analytical enhancement of managerial precision in data-rich industries. The moderate risk management impact (M = 3.42) corresponds with Sivarajah et al. (2021) observations about gradual risk analytics development in telecommunications contexts. Strategic alignment improvements (M = 3.28) match Plastino and Purdy (2022) findings on limited strategic analytical integration in emerging market organizations. These results demonstrate that Econet achieves substantial operational benefits while maintaining significant strategic analytical development opportunities.

4.6.3 Optimization Strategy Requirements

The very high infrastructure priority (M = 4.31) confirms Gupta and Sharda (2023) assertions about technological foundations as primary optimization requirements in emerging market telecommunications. Training program priority (M = 4.18) aligns with Dubey et al. (2021) emphasis on capability development as equally critical success factors. Data quality management importance (M = 4.05) supports Wamba and Ngai (2020) observations about data foundation requirements for analytical reliability. The optimization priority consensus exceeds Zhang and Wang (2022) reported organizational alignment levels, indicating strong transformation readiness. These findings suggest that Econet demonstrates exceptional organizational consensus on optimization requirements while following established best practices for analytical capability development.

4.7 Chapter Summary

This chapter presented comprehensive analysis of data collected from managerial staff at Econet Wireless Zimbabwe to investigate big data analytics adoption and decision-making enhancement. The analysis demonstrated strong response rates across management levels, with demographics revealing a young, well-educated workforce. Descriptive analysis addressed all research objectives, showing moderate analytical integration with significant enhancement opportunities, substantial decision-making quality improvements particularly in speed and accuracy, and organizational consensus on infrastructure and training as optimization priorities. Inferential statistics confirmed strong relationships between integration levels and quality outcomes while identifying key success predictors. The findings provide empirical foundations for understanding analytics adoption patterns and developing targeted optimization strategies within telecommunications contexts.

CHAPTER 5: SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

5.1 Introduction

This final chapter synthesizes the research findings to provide definitive conclusions about the role of big data analytics in enhancing managerial decision-making processes at Econet Wireless Zimbabwe. The chapter integrates empirical evidence from the quantitative analysis with theoretical frameworks to develop practical recommendations and strategic guidance for organizational transformation. The synthesis addresses each research objective while providing broader insights applicable to telecommunications organizations in emerging market contexts, progressing from research summary through specific conclusions, actionable recommendations, and identification of future research opportunities that can advance understanding of big data analytics adoption and organizational transformation.

5.2 Summary of Key Findings

5.2.1 Current Level of Big Data Analytics Integration at Econet Wireless Zimbabwe

The research reveals that Econet Wireless Zimbabwe has achieved moderate levels of big data analytics integration in managerial decision-making processes, with an overall integration score of 3.15 indicating substantial progress while revealing significant enhancement opportunities. The integration pattern demonstrates clear hierarchical and functional variations, with senior managers achieving higher analytical adoption compared to junior managers, and operational functions outperforming strategic planning areas. Technology adoption shows selective implementation patterns, with traditional business intelligence tools achieving high usage rates while advanced analytical technologies remain underutilized. Data management systems demonstrate above-average performance, providing strong foundations for analytical expansion, though staff analytical skills require substantial development. The findings indicate successful foundational implementation that creates favorable conditions for comprehensive analytical transformation and competitive advantage development.

5.2.2. Impact on Decision-Making Quality

The empirical analysis demonstrates substantial positive impact of big data analytics on decision-making quality across multiple performance dimensions, with overall improvement scores representing high performance levels and significant enhancement from pre-analytics baselines. Decision-making speed shows exceptional improvements, with analytical tools enabling faster information processing and real-time monitoring that dramatically reduce decision cycle times while maintaining quality standards. Decision accuracy and problem-solving capabilities achieve high enhancement levels, indicating that data-driven approaches improve precision, reliability, and systematic analytical reasoning across organizational functions. Risk management capabilities demonstrate moderate improvements with opportunities for advanced development, while strategic alignment shows limited but meaningful enhancement. The quality improvements provide compelling evidence that analytical investments generate substantial organizational value through enhanced managerial effectiveness and operational performance across diverse decision-making contexts.

5.2.3 Optimization Strategies and Implementation Requirements

The comprehensive analysis identifies technical infrastructure limitations as the most severe barrier to optimal big data utilization, requiring immediate attention and substantial investment for organizational transformation success. Skills and training gaps emerge as equally critical challenges that cannot be addressed through technological improvements alone, necessitating comprehensive capability development initiatives parallel to infrastructure enhancement. Optimization priorities reveal strong organizational consensus on immediate requirements, with infrastructure upgrade and training programs achieving very high priority scores, followed by data quality management and analytics tool implementation. The implementation framework indicates that infrastructure development requires high resource investment with reasonable timelines and high success probability, while capability building demands sustained commitment over extended periods. The findings provide clear guidance for resource allocation and implementation sequencing that addresses critical organizational constraints while maximizing analytical investment returns and transformation effectiveness.

5.3 Conclusions

5.3.1 Current Level of Big Data Analytics Integration at Econet Wireless Zimbabwe

Based on the data the conclusions at Econet Wireless Zimbabwe demonstrates moderate big data analytics integration with significant enhancement potential, indicating that the organization has successfully established foundational analytical capabilities while requiring systematic development for comprehensive transformation. The moderate integration level of 3.15 reveals that analytical adoption has progressed beyond basic implementation but remains substantially below optimal utilization levels. Senior managers achieve higher integration levels than junior managers, indicating that analytical adoption increases with organizational responsibility and decision complexity. The selective technology adoption pattern shows successful implementation of traditional business intelligence tools while advanced analytics remain underutilized, creating substantial opportunities for sophisticated analytical capability development and competitive advantage creation.

5.3.2 Impact on Decision-Making Quality

Big data analytics implementation generates substantial decision-making quality improvements across multiple performance dimensions, with particularly strong enhancements in speed and accuracy that provide measurable organizational benefits. Decision speed improvements of 43.5% demonstrate that analytical tools dramatically reduce information processing time and enable faster organizational responses to market changes and operational challenges. Decision accuracy enhancements indicate that data-driven approaches significantly improve managerial precision and reduce decision errors across organizational functions. The strong correlations between integration levels and quality outcomes confirm that higher analytical adoption consistently associates with better decision-making performance, providing compelling justification for continued analytical investment and capability development initiatives.

5.3.3 Optimization Strategies and Implementation Requirements

Critical optimization requirements center on infrastructure development and capability building as immediate priorities, followed by systematic tool implementation and process integration for comprehensive organizational transformation. Infrastructure limitations represent the primary barrier to analytical advancement, requiring substantial technological investment to support advanced analytical applications and organizational expansion. Skills gaps constitute equally important challenges that demand comprehensive training programs and capability development initiatives to ensure effective analytical utilization. The strong organizational consensus on optimization priorities provides favorable conditions for transformation success, with clear agreement on infrastructure upgrade and training program importance. The 12-month implementation framework requires significant resource commitment but offers high success probability for achieving substantial analytical enhancement and competitive advantage development.

5.4 Recommendations

Econet Wireless Zimbabwe should immediately prioritize comprehensive technical infrastructure development and systematic staff training programs to address the most critical barriers to analytical optimization and organizational transformation. The infrastructure enhancement should include cloud computing platforms, advanced data storage systems, and analytical software deployment that provides foundations for sophisticated analytical applications. Simultaneously, comprehensive training programs should target analytical skills development across all management levels, focusing on technical competencies, data interpretation capabilities, and analytical decision-making approaches. These parallel initiatives should be supported by systematic data quality management implementation and quick-win project identification that demonstrates analytical value while building organizational confidence and transformation momentum.

Following foundational development, Econet should focus on advanced analytics tool deployment and strategic planning integration that leverages established capabilities for competitive advantage creation and organizational enhancement. The advanced tool implementation should prioritize predictive modeling, machine learning applications, and sophisticated business intelligence platforms that provide distinctive analytical capabilities beyond basic reporting and monitoring. Strategic integration should systematically incorporate analytical insights into planning processes, competitive analysis, and long-term decision-making frameworks that enhance organizational coherence and strategic effectiveness. These initiatives should be supported by cross-functional analytics center of excellence establishment and performance measurement system development that ensures analytical consistency and continuous improvement across organizational functions.

Long-term organizational transformation should emphasize culture change initiatives, innovation development, and industry leadership positioning that creates sustained competitive advantages through analytical excellence and market differentiation. The culture transformation should promote data-driven decision-making, analytical thinking, and evidence-based reasoning across all organizational levels through systematic communication, reinforcement, and leadership modeling. Innovation development should leverage analytical capabilities for new product creation, service optimization, and business model enhancement that generates revenue opportunities and market advantages. Industry leadership positioning should establish Econet as analytical excellence exemplar through thought leadership, best practice sharing, and competitive differentiation that creates sustained market advantages and organizational reputation enhancement in the telecommunications sector.

5.5 Areas for Further Studies

- Future research should conduct longitudinal studies tracking big data analytics implementation progress over extended periods to understand capability development trajectories, organizational learning processes, and long-term performance outcomes that current cross-sectional research cannot capture
- Researchers should examine big data analytics adoption across different industries within emerging market contexts to understand sector-specific success factors, implementation challenges, and optimization strategies that determine analytical transformation effectiveness.
- Future research should investigate the integration of machine learning, artificial intelligence, and advanced predictive analytics in emerging market telecommunications organizations to understand implementation requirements, success factors, and organizational impact of cutting-edge analytical applications.

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