

**A comprehensive framework for big data analytics capabilities and competitive
advantage in South Africa**

by

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DECLARATION

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I declare that the above thesis is my own work and that all the sources that I have used or quoted have been indicated and acknowledged by means of complete references.

I further declare that I submitted the thesis to originality checking software and that it falls within the accepted requirements for originality.

I further declare that I have not previously submitted this work, or part of it, for examination at Unisa for another qualification or at any other higher education institution.

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TO MY LATE MUM AND MY LOVING FAMILY

PUBLICATIONS EMANATING FROM THIS STUDY

The following publications emanated from this research:

Subramoney, S., and Dagada, R. (2025). The big data analytics capabilities and competitive advantage in South Africa: Perspectives from a qualitative study. In R. Dagada (Ed.), *Research in Southern African digital business* (Vol. V). Mercury Books.

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ABSTRACT

This study examines the contribution of big data analytics capabilities to gaining competitive advantage in South African businesses. The study is underpinned by the resource-based theory and dynamic capabilities theory and develops and tests a conceptual model that positions big data analytics capabilities as a multidimensional construct comprising tangible, human, and intangible resources. The study also examines the mediating role of dynamic and operational capabilities in linking big data analytics capabilities to improve competitive advantage.

An exploratory sequential mixed method design was employed. The qualitative phase employed semi-structured interviews with high-level executives from various industries to determine the contextual challenges and success factors for implementing big data analytics in South Africa. The outcomes of this phase guided the application of a survey instrument in the quantitative phase where feedback was collected from 110 business leaders. The results were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM).

The findings reveal that big data analytics capabilities have a significant positive effect on dynamic capabilities, which in turn have a substantial impact on competitive advantage. However, operational capabilities revealed no impact on competitive advantage. The study also highlights context-specific challenges such as skills shortages, infrastructure constraints, organisational readiness, and regulatory requirements impacting the adoption of big data analytics capabilities in South Africa.

This research contributes to practice as well as theory by applying big data analytics capabilities literature to a developing market context, confirming dynamic capabilities as a driver of competitive advantage. The research also provides business leaders with practical insights into how to develop and deploy big data analytics capabilities. The study also offers a conceptually rich framework and proposes directions for further study to improve the understanding of big data analytics in dynamic and constrained environments.

In addition, the study recommends that South African businesses invest in developing dynamic capabilities, talent, and data-driven cultures, while policymakers prioritise digital infrastructure, funding incentives, and regulatory frameworks to support adoption. Limitations include the cross-sectional design, reliance on self-reported data, focus on medium-to-large firms, and restriction to the South African context, which limit generalisability but open avenues for longitudinal and cross-sectoral research.

Keywords: Big data, big data analytics, big data analytics capabilities; dynamic capabilities; competitive advantage; operational capabilities; resource-based theory; dynamic capabilities theory; data-driven culture; mixed methods; PLS-SEM; South Africa.

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LIST OF ABBREVIATIONS

Abbreviation	Full Term
4IR	Fourth Industrial Revolution
AI	Artificial Intelligence
AVE	Average Variance Extracted
AWS	Amazon Web Services
CRM	Customer Relationship Management
DCT	Dynamic Capabilities Theory
EFA	Exploratory Factor Analysis
ERP	Enterprise Resource Planning
ETL	Extract–Transform–Load
GDPR	General Data Protection Regulation
GPS	Global Positioning System
HTMT	Heterotrait–Monotrait Ratio
ICT	Information and Communication Technology
IoT	Internet of Things
IT	Information Technology
KBT	Knowledge-Based Theory
KMO	Kaiser–Meyer–Olkin
ML	Machine Learning
NLP	Neural Language Processing
PLS-SEM	Partial Least Squares Structural Equation Modelling
POPIA	Protection of Personal Information Act
RBT	Resource-Based Theory
RDT	Resource Dependency Theory
RPA	Robotic Process Automation
RQ	Research Question
SEI	Software Engineering Institute
SEM	Structural Equation Modelling
SME	Small and Medium Enterprises
SNT	Social Network Theory
UNISA	University of South Africa
VRIN	Valuable, Rare, inimitable, Non-Substitutable
VUCA	Volatility, Uncertainty, Complexity, and Ambiguity
WEF	World Economic Forum

CHAPTER 1: NATURE AND SCOPE OF THE STUDY

1.1 CHAPTER OVERVIEW

This chapter introduces the nature and scope of the study, focusing on how big data analytics capabilities influence competitive advantage in South African businesses. It outlines the contextual and theoretical basis informing this investigation, relating to the increasingly strategic positioning of data in the Fourth Industrial Revolution (4IR) and continued challenges relevant to organisational development in developing economies.

Within this context, big data analytics capabilities are increasingly considered a critical organisational resource that enables innovation, agility, and performance (Wamba, Akter, Edwards, Chopin and Gnanzou, 2015; van de Wetering, Mikalef and Dennehy, 2022). However, South African businesses often face systemic barriers such as infrastructural limitations, skills shortages, and regulatory constraints that hinder the full realisation of analytics-driven competitiveness (Calitz, Poisat, and Cullen, 2017; Maharaj and Pillay, 2023).

To frame this investigation, the chapter draws on two complementary theoretical lenses; the resource-based theory and the dynamic capabilities theory, to explain how businesses can develop and transform their data and technological resources into sustainable competitive advantage. The resource-based theory provides the foundation for understanding big data analytics capabilities as valuable, rare, inimitable, and non-substitutable (VRIN) resources (Barney, 1991). The dynamic capabilities theory extends this view by emphasising an organisation's ability to sense opportunities, seize them, and transform resources in response to change (Teece, 2007). These theories collectively anchor the study in both strategic management and information systems literature to ensure that the exploration of resources not only includes what matters but also how they are effectively deployed in complex and resource-constrained environments.

The chapter provides a definition of the problem, followed by the justification of why the research was conducted, and the purpose, objectives, and questions that were

used to drive the study. The justification indicates both theoretical and practical reasons for understanding the function of big data analytics capabilities within South Africa's dynamic business environment. This study further outlines the contributions of the research to academic literature, organisational strategy, and to South Africa's national policy, especially in improving data-driven competitiveness and digital transformation in the context of developing countries (OECD, 2021; World Bank, 2020).

In addition, this chapter outlines the exploratory sequential mixed methods research design used in the study. This design integrates qualitative insights from interviews with business leaders and quantitative validation using PLS-SEM. The significance of such a methodological approach lies in its ability to provide a detailed understanding of the development, implementation, and leveraging of big data analytics capabilities within South African businesses by combining both depth of exploration and statistical rigour (Creswell and Plano Clark, 2018). Finally, the chapter outlines the structure of the study by mapping how the research progresses from the conceptual grounding through to the empirical findings, culminating in theoretical contributions and practical recommendations. Figure 1 illustrates this structure, showing how the research develops from the background and theoretical framing to the presentation of results, conclusions, and implications for both organisational leaders and policymakers.

In summary, this chapter sets the scene for the study by outlining its conceptual foundations, theoretical orientation, and methodological direction. The next section highlights the broader context of the study, discussing big data analytics in the Fourth Industrial Revolution and explaining why it is critical to understand its strategic value for South African businesses.

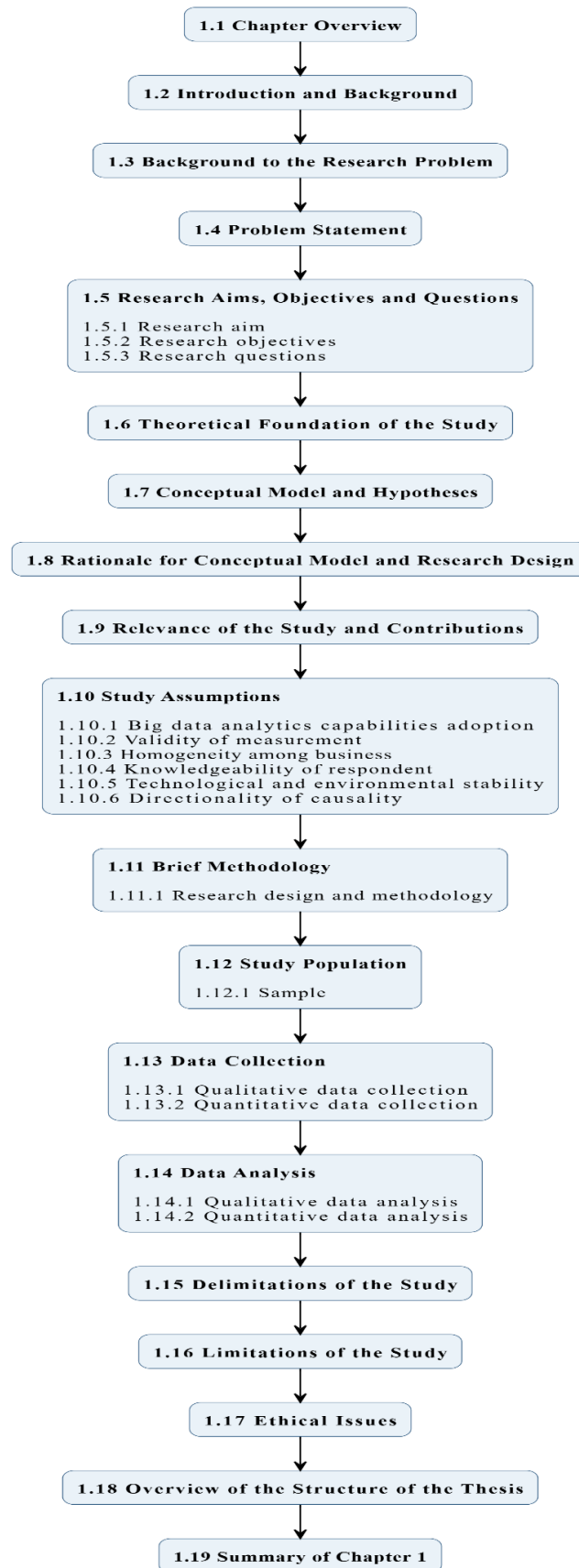


Figure 1: Overview of Chapter 1

Source: Author

1.2 INTRODUCTION AND BACKGROUND

Global statistics have revealed that the average person generates 1.7 MB of data per second (Stengel, 2021). By the year 2020, 64.7 zettabytes of data were created, consumed, and stored, and by 2025, this number is expected to grow to 180 zettabytes (Statista, 2021). Yet, many businesses continue to struggle in translating these vast volumes into actual value, as the effective use of data rather than its possession drives outcomes (Walker, 2015).

As today's businesses rely more on digital platforms and technological advancements, the ability to analyse large volumes of data has become crucial. This explosion of data is known as big data, and it is defined by characteristics such as volume, velocity, and veracity of structured, unstructured, and semi-structured data (Kache and Seuring, 2017; Shah, Peristeras and Magnisalis, 2021). Numerous scholars and business leaders have hailed big data as the new oil of the 21st century, while others proclaim it as a technological Revolution that will transform our daily lives (Frey and Osborne, 2017). However, the characteristics of big data make it fundamentally different from other forms of data, and traditional information technology (IT) systems are unable to cope with interpreting it effectively to derive value (Pathak, Mohapatra and Rath, 2018).

Big data analytics provide organisations with the means to extract actionable insights from complex datasets, enabling better decision-making, more agile operations, and improved competitiveness. Many businesses have therefore made substantial investments in big data analytics technologies and tools in the hope of deriving value from their data (Fabijan, Holmström Olsson, Pantić, and Bosch, 2017; Nguyen, Li, Spiegler, and Lin, 2018).

The value of big data analytics in driving business decisions has been a strategic focus for business leaders over the past decade (Hämäläinen and Inkinen, 2019; Kwon, Lee and Shin, 2014; Lioutas and Charatsari, 2020; Mikalef and Pateli, 2017). Many academics and scholars agree that big data analytics can create opportunities that lead to competitive advantage (George, Haas, and Pentland, 2014; Wilson and Cong, 2021).

However, despite rapid investment in big data analytics, many leading business executives and decision-makers still lack the necessary skills to manage and extract value from such projects (Baottong, Baharuddin, Sasmita and Salam, 2025). This gap has led to several failures in big data implementation. Proponents of big data analytics, therefore, emphasise the need to hire data analysts and scientists (Alharthi, Krotov and Bowman, 2017; Davenport and Patil, 2012; Galbraith, 2014).

Globally, however, there is a shortage of such skill sets, and these professionals demand exorbitant salaries that many businesses cannot afford (Corea, 2019; Alharthi et al., 2017). Although researchers like Dremel, Herterich, Wulf and Vom Brocke (2020) and Kache and Seuring (2017) have focused on the technical side of big data analytics, there is still limited real-world research showing how these capabilities contribute to gaining a competitive edge. In practice, many business leaders are still unsure about how to embed analytics into the parts of their organisation that create value (Dremel et al., 2020; Kache and Seuring, 2017; Mikalef and Pateli, 2017).

Nevertheless, a research framework developed by Mikalef, Pappas, Krogstie and Giannakos (2018) highlights six thematic areas that link big data and competitive advantage. The authors argue that the connection between big data and competitive advantage is understudied and requires focused empirical research to assist businesses realise value. These findings were supported in the New Vantage Partners (2020) survey, which revealed that despite increased investment in big data technologies and tools, many businesses still struggle to achieve competitive advantage (New Vantage Partners, 2020). Davenport and Bean (2018) therefore concluded that businesses that manage their big data analytics capabilities strategically will outperform businesses that merely invest in technology (Aftab and Siddiqui, 2018; Davenport and Bean, 2018).

Big data analytics capabilities are defined as a business's potential to use its technological resources and talent to retrieve, record, store, and analyse data to provide meaningful insights (Akter, Haque and Jahan, 2022; Gupta and George, 2016; Kiron, Prentice and Ferguson, 2014). Gupta and George (2016), and Mikalef, Krogstie, Pappas and Pavlou (2021) applied resource-based theory to explain how combining

and reconfiguring tangible, intangible, and human skill resources could improve advantage and drive competitive advantage.

However, it is argued that resources are contextual, easily imitable, and subject to rapid change making them insufficient for sustained competitive advantage (Braganza, Brooks, Nepelski, Ali and Moro, 2017). Hence, the resource-based theory may not fully explain how big data analytics capabilities lead to competitive advantage (Kshetri, 2022). Although many scholars support the holistic adoption of big data across their business functions, there still is a limited understanding of how these resources are transformed into sustained strategic advantage.

A further challenge in contemporary business environments is how organisations mobilise big data capabilities under conditions of market volatility. Aligning analytics with strategy remains difficult amid rapid technological change, evolving consumer behaviour, and uncertainty. As highlighted by Liberatore, Pollack-Johnson and Clain, 2017, many firms struggle to translate big data insights into actionable strategies that enable them to sense and respond effectively to change. Consequently, businesses often underutilise their analytical potential, missing opportunities for agility and competitive renewal (Liberatore, Pollack-Johnson and Clain, 2017).

The dynamic capabilities theory, proposed by Teece (2007), provides a more robust lens for exploring how big data analytics capabilities may support competitive advantage in such environments. Several authors reinforce the view that dynamic capabilities, such as sensing, seizing, and transforming enable organisations to continuously realign and adapt their competencies to maintain a competitive edge (Mikalef et al., 2018; Eisenhardt and Martin, 2017; Kraaijenbrink, Spender and Groen, 2010; and Mikalef et al. 2018) However, research indicates that big data analytics capabilities often influence performance indirectly through business model innovation (Jenkison, Chiba, Mthombeni and Verachia, 2024).

In South Africa, businesses face unique challenges: economic instability, poor infrastructure, high inequality, and skills shortages. Despite being part of global networks such as BRICS, South African businesses are slower in adopting big data technologies due to limited resources, poor ICT alignment, and high demand for

scarce skills (Ayankoya, Calitz and Greyling, 2016; McKinsey, 2016; UNCTAD, 2021). Moreover, as highlighted by Dagada (2024), regulatory overreach and poorly conceived public policies often constrain South Africa's digital transformation, which directly impacts the pace of adopting big data analytics capabilities. Despite these disadvantages, recent evidence from South African retailers further confirms that tangible, human, and intangible big data analytics positively affect organisational performance (Welbotha and van den Berg, 2024).

The World Economic Forum (2024) further notes that many African businesses lack strategic clarity and infrastructure to implement data-driven transformation effectively (WEF, 2024). On the other hand, these challenges also create opportunities. As the COVID-19 pandemic and global digitalisation accelerated data flows and transformation efforts, South African businesses are increasingly recognising the value of agility and responsiveness (Nguyen, Ngo, Ruël, and Ruël, 2021). Yet, despite these opportunities, implementation failures persist due to weak alignment, insufficient skills, and lack of organisational readiness (Chen, Chiang and Storey, 2012). A recent study in the South African manufacturing sector confirms that big data analytics capability maturity can be modelled as higher-order formative–reflective constructs (Kanniah and Pelser, 2024).

By combining insights from resource-based theory and dynamic capabilities theory, the study identifies the pathways through which big data analytics capabilities can drive and sustain competitive advantage in South Africa's turbulent business environment. It further provides both a theoretical and practical understanding of how businesses in South Africa can develop and align big data capabilities to generate value. It also seeks to identify the key resource inputs and capabilities pathways required for effective implementation, thus offering a roadmap for business navigating rapid transformation in the digital economy. To guide the study the conceptual model illustrated in Figure 2 below was used.

1.3 BACKGROUND TO THE RESEARCH PROBLEM

The fourth industrial revolution (4IR) has ushered in an era where data is increasingly considered to be a strategic resource (Schwab, 2016; Wamba, Gunasekaran, Akter,

Ren, Dubey and Childe, 2017). However, most South African organisations have not been able to secure full value from big data analytics capabilities because of infrastructural, skills-related, and strategic constraints (Calitz et al., 2017). Although several studies globally emphasise the importance of big data analytics capabilities in terms of competitiveness (Mikalef et al., 2022), few studies have been conducted in a systematic fashion to assess how those capabilities convert to competitive advantages in developing markets (Maharaj and Pillay, 2023).

Earlier studies, such as Akter et al. (2022), Gupta and George (2016), and Mikalef and Pateli (2017), emphasised the importance of big data analytics capabilities. Nevertheless, they often failed to consider the challenges faced by the developing market business environments, including infrastructural limitations, skills shortages, and regulatory uncertainty (Destefanis, Neirotti, Paolucci and Raguseo, 2021; Subramoney and Dagada, 2024).

For example, there is a scarcity of empirical studies that have examined how dynamic and operational capabilities mediate the relationship between big data analytics capability and competitive advantage (Saide and Sheng, 2020; Fosso Wamba, 2017). These capabilities represent the essential means to explain how organisations transform analytics resources into strategic value (Mikalef et al., 2022). This study addresses this by developing a refined and context-sensitive understanding of analytics deployment in South African businesses and examining the role of dynamic and operational capabilities as intermediaries between big data analytics capabilities and competitive advantage.

This research also answers calls for more empirical evidence emanating from developing markets (Wamba, Ngai, Riggins and Akter, 2017) and bridges the gap between the theoretical value of big data analytics and its practical realisation in resource-constrained environments. A literature review of a critical nature was first conducted to consolidate and synthesise insights into key components of big data analytics capabilities. These components include data integration, predictive modelling, real-time analytics, and data visualisation, that enable organisational agility, informed decision-making, and long-term performance (Antunes, Pino and Tate, 2020).

Building on this, the study utilised an integrated mixed-method approach entailing qualitative interviews with business leaders and quantitative analysis through PLS-SEM. Such a combination allowed for both depth of exploration and statistical validation in assessing the mechanisms through which big data analytics capabilities generate sustainable competitive advantage in resource-scarce environments. By combining the resource-based and dynamic capabilities theories, the study linked the academic perspective to practical application for business leaders, policymakers, and researchers.

1.4 PROBLEM STATEMENT

Big data analytics capabilities are increasingly applied in business environments globally (Mikalef et al., 2019). However, South African businesses find it difficult to leverage such capabilities towards long-term competitive advantage due to infrastructural, capabilities, and strategic constraints (Nunu, 2019). Existing literature predominantly addresses big data analytics capabilities as a strategic asset but does not consider the mediating processes by which businesses can translate data into competitive advantage outcomes, namely, the dynamic capabilities (sensing, seizing, and transforming opportunities) and operational capabilities (marketing and technological execution) that are used (Teece, 2017).

However, in resource-constrained contexts such as South Africa, the link between big data analytics capabilities- driven operational capabilities and competitive advantage may be weaker or inconsistent. This is because businesses often face infrastructural limitations, skills shortages, and budgetary constraints that hinder the full translation of operational capabilities into competitive advantage. Moreover, South African businesses experience complex and sometimes fragile infrastructural constraints, regulatory uncertainty, and shortage of skills (Maharaj and Pillay, 2023; Van Zyl, 2022). These contextual conditions raise fundamental questions about whether, and under what conditions, big data analytics capabilities explain competitive advantage in the local context, given the existence of appropriate dynamic and operational capabilities.

These challenges are further shaped by broader environmental and contextual factors, including market dynamism, technological infrastructure, regulatory conditions, and

organisational readiness. Such factors influence how effectively organisations can develop and leverage big data analytics capabilities, particularly in resource-constrained environments such as South Africa.

Global studies recognise the facilitating role of business capabilities in amplifying the impact of big data analytics capabilities (Gupta and George, 2016; Wamba, Akter, Trinchera and De-Bourmont, 2021). However, empirical evidence on how these relationships function in developing markets remains limited (Dagada, 2025a; Maluleka and Dagada, 2024; Subramoney and Dagada, 2024). This gap creates a strategic imperative to investigate how various components of big data analytics capabilities, such as tangible resources, intangible resources, and human skills, interact with business capabilities to shape competitive advantage in the South African context.

Despite the increasing use of big data analytics capabilities, many South African businesses still struggle to translate analytical capabilities into tangible strategic outcomes. The literature also provides only limited guidance on the business configurations that make big data analytics capabilities effective under contextual constraints. There is also a lack of empirical testing of comprehensive models that link big data analytics capabilities into dynamic and operational capabilities, and to competitive advantage. This study addresses this gap by validating and adapting an existing model to the South African context, providing a structured investigation into how big data analytics capabilities translate into competitive advantage.

1.5 RESEARCH AIMS, OBJECTIVES AND QUESTIONS

This section outlines the overall aim of the study, followed by the specific objectives and research questions that guided the investigation.

1.5.1 Research aim

The aim of this research was to examine the extent to which big data analytics capabilities contribute to competitive advantage in South African businesses, with a specific focus on the mediating roles of dynamic and operational capabilities. The study sought to develop a practical and empirically grounded framework for understanding how businesses can build, integrate, and leverage big data analytics

capabilities to improve strategic outcomes, particularly in resource-constrained environments.

1.5.2 Research objectives

In pursuit of achieving this aim, the following objectives were established:

1. To identify and validate the key dimensions of big data analytics capabilities, tangible resources, human skills, and intangible resources, in the South African business context.
2. To assess the relationship between big data analytics capabilities and dynamic capabilities.
3. To assess the relationship between big data analytics capabilities and operational capabilities (marketing and technological).
4. To evaluate the influence of dynamic capabilities on competitive advantage.
5. To evaluate the influence of operational capabilities on competitive advantage.
6. To develop a contextually relevant framework that integrates big data analytics capabilities with broader organisational strategy for sustainable competitive advantage.

1.5.3 Research questions

This research was guided by the following questions:

RQ1: How do big data analytics capabilities contribute to competitive advantage in South African businesses?

RQ2: What roles do dynamic capabilities play in mediating the relationship between big data analytics capabilities and competitive advantage?

RQ3: What roles do operational capabilities play in mediating the relationship between big data analytics capabilities and competitive advantage?

RQ4: What contextual factors influence the effectiveness of big data analytics capabilities in achieving competitive advantage?

To ensure conceptual consistency and methodological coherence, the research objectives, questions, and hypotheses were aligned. Table 1 illustrates this alignment demonstrating how each objective is linked to a corresponding research question and hypothesis, thereby providing a structured roadmap for the empirical testing and framework development undertaken in this study.

Table 1: Alignment of research objectives, research questions, and hypotheses
Source: Author

Research objective	Research question	Hypothesis
1. To identify and validate the key dimensions of big data analytics capabilities, tangible resources, human skills, and intangible resources in the South African business context.	RQ1: How do big data analytics capabilities contribute to competitive advantage in South African businesses?	No direct hypothesis was formulated for this objective. This objective was addressed through the literature review, qualitative findings and the measurement model validation.
2. To assess the relationship between big data analytics capabilities and dynamic capabilities.	RQ2: What roles do dynamic capabilities play in mediating the relationship between big data analytics capabilities and competitive advantage?	H1: Big data analytics capabilities positively influence dynamic capabilities.
3. To evaluate the influence of dynamic capabilities on competitive advantage.	RQ2: What roles do dynamic capabilities play in mediating the relationship between big data analytics capabilities and competitive advantage?	H2: Dynamic capabilities positively influence competitive advantage.
4. To assess the relationship between big data analytics capabilities and operational capabilities (marketing and technological).	RQ3: What roles do operational capabilities play in mediating the relationship between big data analytics capabilities	H3: Big data analytics capabilities positively influence operational capabilities.

	and competitive advantage?	
5. To evaluate the influence of operational capabilities on competitive advantage.	RQ3: What roles do operational capabilities play in mediating the relationship between big data analytics capabilities and competitive advantage?	H4: Operational capabilities positively influence competitive advantage.
6. To develop a contextually relevant framework integrating big data analytics capabilities with broader organisational strategy for sustainable competitive advantage.	RQ4: What contextual factors influence the effectiveness of big data analytics capabilities in achieving competitive advantage?	No direct hypothesis was formulated for this objective, as it was addressed through the qualitative findings, interpretation of the quantitative findings and the framework development.

1.6 THEORETICAL FOUNDATION OF THE STUDY

This study is grounded in two key theoretical perspectives, namely the resource-based theory and dynamic capabilities theory. Resource-based theory emphasises the role of firm-specific resources, including data, technology, and human skills, as sources of competitive advantage. However, in dynamic environments, these resources must be continuously adapted. Dynamic capabilities theory extends this perspective by focusing on the organisation's ability to sense opportunities, seize them, and transform resources accordingly. Together, these theories provide a complementary lens for understanding both the resource base of big data analytics capabilities and the mechanisms through which these resources are transformed into competitive advantage.

1.7 CONCEPTUAL MODEL AND HYPOTHESES

Building on the theoretical foundations outlined above this study develops a conceptual model grounded in the literature on big data analytics capabilities, the resource-based theory, and the dynamic capabilities theory (Subramoney and Dagada, 2025a). Prior research has shown that three big data analytics dimensions, tangible resources, human skills, and intangible resources enable businesses to sense, seize, and transform opportunities in dynamic environments (Gupta and George, 2016).

To contextualise this model for South African businesses, the current study incorporated additional environmental variables such as market complexity, dynamism, and hostility and revalidates the relationships through both qualitative and quantitative phases. These variables, while not directly hypothesised, informed the qualitative research design and interpretation. The model investigated the influence of big data analytics capabilities on competitive advantage through two key mediators: dynamic capabilities and operational capabilities.

Drawing on the resource-based and dynamic capabilities theory, big data analytics capabilities are expected to enhance organisational responsiveness and strategic adaptability. These capabilities enable businesses to process complex information, identify opportunities, and respond effectively in dynamic environments. In this context, dynamic capabilities are expected to play a central mediating role, while operational capabilities support execution and efficiency.

The conceptual model illustrated in [Figure 2](#) below presents the following hypothesised relationships.

While the conceptual model focuses on the direct and mediated relationships between big data analytics capabilities, dynamic capabilities, operational capabilities, and competitive advantage, these relationships are embedded within broader environmental and contextual conditions. Factors such as market dynamism, technological infrastructure, regulatory conditions, and organisational readiness may shape the effectiveness of these capabilities, particularly in emerging market contexts such as South Africa (Gupta and George, 2016; Mikalef et al., 2018; Teece, 2007; Wamba et al., 2021). However, consistent with prior research that treats such

contextual factors as contingent rather than structural variables, these factors are not explicitly modelled as moderating variables in the quantitative phase of this study. Instead, they are explored in the qualitative phase to provide deeper insight into the conditions under which big data analytics capabilities contribute to competitive advantage.

Big data analytics capabilities encompass a range of analytical approaches, commonly categorised into descriptive, diagnostic, predictive, and prescriptive analytics. While descriptive and diagnostic analytics focus on understanding historical performance and identifying underlying causes, and prescriptive analytics emphasises decision optimisation, this study specifically focuses on predictive analytics. This emphasis is appropriate as predictive analytics enables organisations to anticipate future trends, identify emerging opportunities, and support proactive strategic decision-making. In the context of this study, predictive analytics is therefore most closely aligned with the development of dynamic capabilities and the pursuit of competitive advantage in South African businesses.

H1: Big data analytics capabilities positively influence dynamic capabilities.

Big data analytics capabilities represent a combination of data, technology, and human expertise that enable organisations to generate actionable insights. According to the resource-based theory, valuable and rare resources form the foundation for capability development. Dynamic capabilities theory extends this view by emphasising the organisation's ability to sense opportunities, seize them, and reconfigure resources accordingly. Empirical studies (e.g., Mikalef et al., 2018; Gupta and George, 2016) suggest that organisations with strong analytics capabilities are better positioned to enhance these adaptive processes. In the South African context, where firms operate under resource constraints and uncertainty, the ability to leverage analytics for strategic responsiveness becomes particularly important.

H2: Dynamic capabilities positively influence competitive advantage.

Dynamic capabilities play a critical role in translating organisational resources into sustained performance outcomes. Unlike operational capabilities, which focus on efficiency, dynamic capabilities enable organisations to adapt to changing environments through sensing, seizing, and transforming activities (Teece, 2007).

Prior research (Eisenhardt and Martin, 2017; Mikalef et al., 2021) demonstrates that firms with stronger dynamic capabilities are more likely to achieve competitive advantage, particularly in volatile environments. In emerging markets such as South Africa, where external uncertainty is high, dynamic capabilities are expected to be a key driver of competitive positioning.

H3: Big data analytics capabilities positively influence operational capabilities.

Big data analytics capabilities also contribute to the enhancement of operational capabilities by improving efficiency, decision-making, and process optimisation. From a resource-based perspective, the integration of data and technology supports better execution of routine organisational activities. Studies have shown that analytics capabilities can improve marketing effectiveness, customer targeting, and technological performance (Dubey, Gunasekaran, Bryde, Dwivedi and Papadopoulos, 2020; Gupta and George, 2016). In the South African context, these improvements are particularly relevant for organisations seeking to optimise performance under constrained conditions.

H4: Operational capabilities positively influence competitive advantage.

Operational capabilities are traditionally associated with the efficient execution of business processes, including marketing and technological implementation. While these capabilities contribute to improved performance, their ability to generate sustained competitive advantage is debated. Some scholars argue that operational capabilities enhance performance outcomes (Porter, 2008), while others suggest that they are insufficient without the support of dynamic capabilities (Teece, 2017). In developing contexts such as South Africa, operational capabilities may contribute to competitive advantage, but their impact is likely to be more limited compared to dynamic capabilities. This study therefore tests their direct influence empirically.

The conceptual model, grounded in the resource-based and dynamic capabilities theories, informed the hypotheses and guided the methodological design of both the qualitative and quantitative processes. It offers a framework for how big data analytics capabilities as multi-dimensional capabilities inform strategic renewal as well as competitive advantage outcomes in complex settings (Akter et al., 2022)

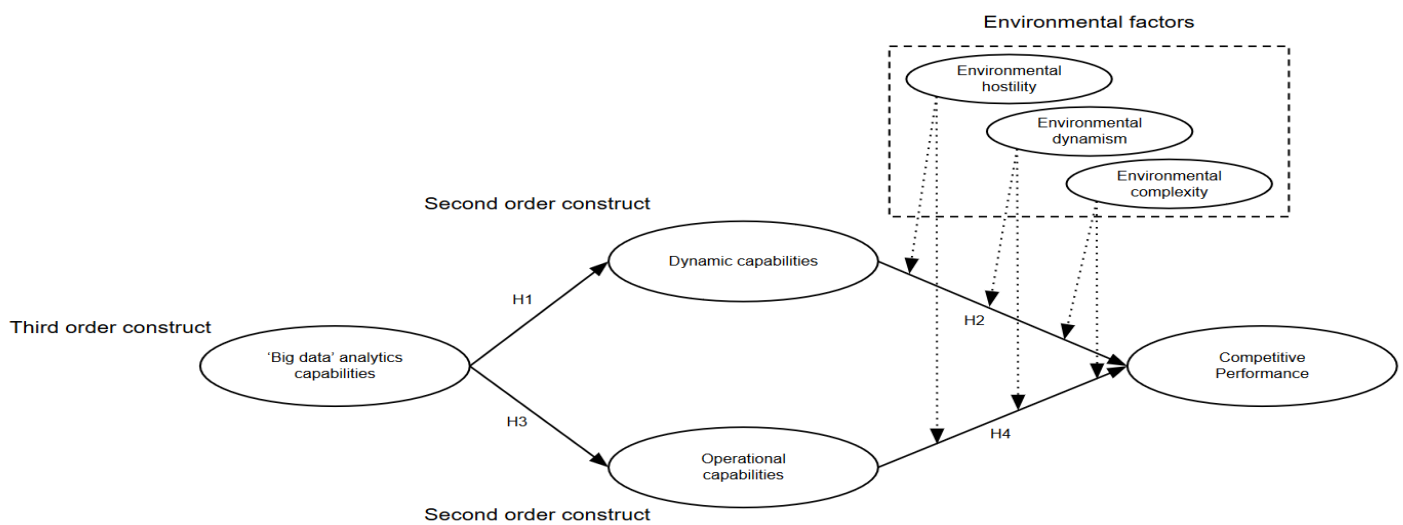


Figure 2: Conceptual Model

Source: Adapted from Framnes and Danielsen, 2017

Dynamic capabilities are proposed as the key mediator that influences big data analytics to achieve competitive advantage (Mikalef et al., 2021; Teece, 2007). Operational capabilities, although explored, have a lesser effect on competitive advantage in developing economies such as South Africa (Dubey et al., 2020). The theoretical model guided the development of the interview questions and the survey instrument to maintain consistency between theory, qualitative information, and quantitative measurement (Creswell and Plano Clark, 2018).

1.8 RATIONALE FOR THE CONCEPTUAL MODEL AND RESEARCH DESIGN

The study applied a conceptual model developed from the existing literature. It drew on prior work by scholars such as Gupta and George (2016) who explored the relationship between big data analytics and organisational advantage through dynamic and operational capabilities. These studies offered a comprehensive structure for linking tangible, human, and intangible resources to capabilities that drive competitive advantage (Gupta and George, 2016; Mikalef, Boura, Lekakos and Krogstie, 2019).

Much of this prior work was tested and validated in developed world contexts, particularly in countries with advanced economies and high digital maturity. Therefore, the strength of the model derived from the literature is its combination of resource-

based and dynamic capabilities theories, which offers a theoretically grounded approach to understanding how big data analytics capabilities contribute to competitive advantage.

This research investigates the extent to which this model applies within the context of a developing economy such as South Africa. South African businesses face context-specific challenges such as infrastructural limitations, low ICT literacy levels and organisational cultures that may not yet be fully data-oriented. These environmental and institutional differences are likely to affect how big data analytics capabilities are adopted and leveraged for competitive advantage. To address these contextual factors, the study used a qualitative phase involving in-depth interviews with South African business leaders to uncover local insights into the enablers and inhibitors of big data analytics adoption. These findings were then used to refine the quantitative survey instrument to improve its contextual sensitivity. The study subsequently tests these relationships using PLS-SEM, with results discussed in the later chapters.

1.9 RELEVANCE OF THE STUDY AND CONTRIBUTIONS

This research holds both theoretical and practical significance, particularly as it explores the comparatively under-researched convergence between big data analytics capabilities and competitive advantage within the South African business environment. From a theoretical standpoint, the study contributes to the evolving literature on big data analytics capabilities by employing the resource-based and the dynamic capabilities theories to examine how South African businesses utilise big data analytics capabilities to achieve and sustain competitive advantage in dynamic and resource-constrained settings (Barney, 1991; Mikalef et al., 2021).

The study improves the current understanding of big data analytics capabilities and competitive advantage by considering dynamic and operational capabilities as mediators between big data analytics capabilities and competitive advantage, thus exploring a wider framework (Gupta and George, 2016; Wamba, Akter, Trinchera et al., 2021).

This study also addresses a current gap in the literature by big data analytics capabilities competitiveness in a developing economy, thereby broadening the global applicability of big data analytics capabilities theory frameworks (Calitz et al, 2017; Mothibi and Venter, 2020). This provides a meaningful Global South contribution to big data analytics capabilities research. It demonstrates that, although frameworks developed in the global north are useful, research scholars need to be aware of how the findings from these studies are considered for implementation in developing countries, especially due to the difference in business capacity, infrastructure, skillset, and culture. It identifies key enablers and inhibitors specific to the South African context, such as skill shortages, limited infrastructure, and regulatory challenges, which can inform targeted capacity development initiatives and public–private partnerships (Calitz et al., 2017; Mikalef et al., 2018). The research provides guidance in a framework to business leaders in South Africa on where and how to invest in and develop big data analytics capabilities strategically for long-term competitiveness. Furthermore, the findings present evidence-based principles to support data strategies aimed at enhancing business agility, innovation, and responsiveness to evolving market conditions (Wamba et al., 2017). The findings also have policy implications for the government in terms of digitalisation. Government support for data literacy, IT infrastructure, and the digitalisation of SMEs will be critical to enable the broader adoption of big data analytics capabilities tools (OECD, 2021; World Bank, 2020).

The study also contributes theoretically and practically. Theoretically, it extends existing big data analytics capabilities models by testing and applying them in the setting of a developing economy and including environmental contingencies. Practically, it results in a refined model and framework which offer strategic guidance for South African businesses intending to leverage data analytics. It also specifies capabilities areas that require investment for increased competitiveness.

1.10 STUDY ASSUMPTIONS

There are certain assumptions in this study that are employed in the use of the conceptual framework and the interpretation of the results. These assumptions (discussed below) frame the research methodology and assist in ensuring that big data analytics capabilities, dynamic capabilities and operational capabilities are meaningfully assessed. They also align with the theoretical lens adopted in this study,

namely the resource-based theory (Barney, 1991) and the dynamic capabilities theory (Teece, 2007), both of which emphasise the role of internal resources and capabilities in achieving competitive advantage.

1.10.1 Big data analytics capabilities adoption

It is assumed that the businesses surveyed have adopted or are in the process of adopting big data analytics capabilities in some way, to allow meaningful assessment of big data analytics capabilities (Mikalef et al., 2021; Wamba, Gunasekaran et al., 2017).

1.10.2 Validity of measurement

It is believed that the measures used within the survey truly captured the dimensions of big data analytics capabilities, dynamic capabilities, operational capabilities, and competitive advantage, based on established constructs in the literature (Gupta and George, 2016; Mikalef et al., 2022). This is an assumption consistent with the theoretical frameworks, namely the resource-based and the dynamic capabilities theories (Barney, 1991; Teece, 2017).

1.10.3 Homogeneity among businesses

Even though the sample was drawn from a mix of businesses in South Africa, this study hypothesises that their processes linking big data analytics capabilities and competitive advantage were homogenous enough to ensure generalisability within the South African business context (Calitz, et al., 2017; Nunu, 2019).

1.10.4 Knowledgeability of respondent

The study assumed that the respondents knew about their business data practices, capabilities, and strategic implications, and therefore could provide accurate and representative answers (Wamba, Akter, Trinchera et al., 2021).

1.10.5 Technological and environmental stability

This research assumed a stable technological environment throughout the data collection period, and that businesses could run their big data analytics capabilities and systems without significant interruption (Mikalef et al., 2018).

1.10.6 Directionality of causality

This study assumed a direct causal relationship between big data analytics capabilities, dynamic capabilities and operational capabilities, which in turn influence competitive advantage (Mikalef et al., 2018). Having established this alignment, the section below outlines the methodological approach adopted in the study. A brief overview is presented, with detailed discussion of the design, sampling, and analysis procedures provided later in Chapter 4. This ensures that the research process was transparent, and that the chosen mixed-methods design was justified, considering the study's objectives.

1.11 BRIEF METHODOLOGY

This research used a mixed-methods approach, with qualitative and quantitative methods to investigate how big data analytics capabilities lead to competitive advantage (Creswell and Plano Clark, 2018; Mikalef et al., 2019; Wamba, Queiroz, Trinchera, 2021). The use of the mixed-methods approach is elaborated further in Chapter 4 of this research.

According to Ahmed, Pereira and Jane (2024), combining qualitative and quantitative approaches provides windows into business research problems. Therefore, integrating qualitative and quantitative approaches in most instances produces more advanced and richly textured results than depending on a solitary method. Furthermore, each methodology has certain advantages and can counterbalance the limitations of the other (Ahmed et al., 2024). Through a combination of both datasets, this research facilitated triangulation and sound hypothesis testing (Bryman, 2016). Structural Equation Modelling (SEM) was used to specify the measurement and relationship paths in the conceptual framework proposed (Sarstedt, Ringle and Hair, 2021). PLSSEM was selected due to its suitability for exploratory research, complex models and relatively small sample size (Hair, Risher, Sarstedt and Ringle, 2019).

1.11.1 Research design and methodology

An exploratory sequential mixed-methods design was used (Creswell and Plano Clark, 2018). The research began with qualitative interviews to explore how big data analytics capabilities is experienced in practice and to inform the survey instrument. Themes derived from interviews were used to refine the conceptual model. A quantitative

survey followed, with 110 valid responses analysed using PLS-SEM. This approach ensured a strong link between theory, context, and empirical validation.

1.12 STUDY POPULATION

Thacker (2020) defines a population as a group of individuals or cases with the same characteristics which the researcher can identify and study. The study population of this research was the business decision-makers and leaders who were involved in big data and analytics functions across businesses in South Africa. These participants were working in the roles of data scientists, IT managers, analytics consultants, business analysts, and strategic managers. This group was selected because of their positions as business leaders and their ability to make decisions in their use of big data (Fosso Wamba, 2017). Their inclusion was based on their designated status identified on their LinkedIn profiles. Participants were purposively chosen because of their senior positions, experience, and direct involvement with data-driven strategy within their businesses.

1.12.1 Sample

Collecting data from every person in the population is impossible. Instead, a sample must be selected. A sample is the group of individuals who are targeted or selected to take part in a particular study (McCombes, 2025). A purposive sampling technique was deliberately used for this study so that similar or related participants could provide information to this study and purposefully inform an undertaking dealing with the study's research problem (Creswell, 2017).

The qualitative part of the research focused on senior professionals and specialists who had hands-on experience with big data strategy and implementation. A sample of ten participants from various industries in South Africa was chosen to participate in the interviews. Their input helped to uncover the practical challenges and enabling conditions surrounding the use of big data analytics capabilities in the South African business environment.

The quantitative phase applied both purposive and stratified, as well as snowball sampling methods to identify business leaders involved in data-driven decision-making and big data project work. Out of the 118 completed surveys, 110 were found

to be usable for the study. The respondents came from a wide range of industries, including finance, telecoms, retail, healthcare, manufacturing, and government services (Dubey et al., 2020). Calculating the appropriate sample size was dependent on several factors (Sachdeva, 2009), and such are outlined in detail in Chapter 4 of this study.

1.13 DATA COLLECTION

To address the research questions and test the proposed hypotheses, this study used an exploratory sequential mixed-methods design where the qualitative findings from the first phase were used to inform and shape the broader quantitative phase (Creswell and Plano Clark, 2018).

1.13.1 Qualitative data collection

The first phase consisted of semi-structured interviews which explored key concepts such as big data usage in businesses, dynamic capabilities (sensing, seizing, transforming), operational capabilities, and competitive advantage. These interviews were conducted via Zoom and Microsoft Teams, allowing flexibility while maintaining consistency across participants. With informed participant consent, interviews were recorded to ensure accurate capture of responses. Participants were assured of confidentiality and anonymity, and participation was voluntary. All data were securely stored and used solely for academic purposes. Participants were selected using purposive sampling, targeting individuals with experience in data-driven decision-making and strategic management within South African organisations. A total of 10 participants were interviewed, which was deemed sufficient to achieve data saturation (Saunders, Lewis and Thornhill, 2023).

1.13.2 Quantitative data collection

The framework was tested during this phase including investigation of the relationships between big data analytics capabilities, dynamic capabilities, operational capabilities, and competitive advantage. This phase used the literature and qualitative findings to refine the survey that was used (Framnes and Danielsen, 2017; Dangale and Dagada, 2024; Subramoney and Dagada, 2025a). Reflective and formative indicators were included in the instrument and covered key constructs including tangible resources, human skills, intangible resources, dynamic capabilities (sensing, seizing,

transforming), operational capabilities (marketing, technology), and competitive advantage. Items were rated using a five-point Likert scale from "Strongly Disagree" to "Strongly Agree."

LinkedIn was used to distribute the survey, and thereafter snowball sampling was used to distribute the survey to other participants. The respondents included senior managers, data analysts, IT personnel, and decision-makers of big data analytics capabilities in South African businesses. A total of 118 responses were received. After removing participants who indicated that they were not directly involved in the use of big data, 110 responses were retained for analysis.

For the quantitative phase, a non-probability sampling approach, combining purposive and convenience sampling, was employed due to the targeted nature of the study and the need to access respondents with relevant expertise in analytics and strategic decision making.

1.14 DATA ANALYSIS

The data analysis was carried out in two stages, consistent with the exploratory sequential mixed-methods design, where qualitative findings informed the development of the quantitative phase and subsequent hypotheses testing (Creswell and Plano Clark, 2018).

1.14.1 Qualitative data analysis

The qualitative component of the study explored how South African business leaders apply big data analytics capabilities in their strategic environments. The qualitative data analysis adhered to a thematic analysis approach as outlined by Braun and Clarke (2008) to unveil insights concerning how South African business leaders perceive and implement big data analytics capabilities in practice. Microsoft Excel was used as a data management and coding tool to systematically code and organise the qualitative data. This analysis informed the refinement of the conceptual framework and contributed directly to the development of the quantitative instrument (Duan, Cao and Edwards, 2020; Wamba, Queiroz et al., 2021). This approach is widely used in exploratory research to identify patterns and relationships with complex organisational contexts (Nowell, Norris, White and Moules, 2017).

The analysis followed five key processes:

- 1. Familiarisation with the data** – Transcripts were reviewed in detail to identify initial ideas and observations.
- 2. Coding** – The data segments were coded based on the recurring concepts, expressions, and themes raised by participants.
- 3. Theme development** – The codes were grouped into themes based on the conceptual framework, which is the tangible and intangible resources, human capabilities, dynamic capabilities (sense, seize, transform), and operating capabilities.
- 4. Reviewing themes** – The themes were cross-checked with the coded data and with literature expectations.
- 5. Interpretation** – Narrative summaries were constructed to describe how qualitative findings supplement or vary from quantitative results.

This qualitative component provided rich, contextual information on the way big data analytics capabilities have expression in South African businesses and informed the process of creating the survey instrument for the quantitative study. Themes from the qualitative data were also employed for triangulation and explanation of the results presented in Chapters 5 and 6.

1.14.2 Quantitative data analysis

Quantitative data were captured onto Microsoft Excel and exported to the SmartPLS software to evaluate the postulated relationships among constructs. PLSSEM is widely recommended for exploratory research involving complex models and latent constructs, particularly where sample sizes are small (Hair et al., 2019).

The approach was selected for its ability to manage complex frameworks involving formative and reflective constructs, and for its suitability in exploratory research as well as with small to medium-sized samples (Dangale and Dagada, 2024).

The final dataset consisted of 110 valid responses, following the removal of incomplete or unreliable entries. The descriptive statistics were compiled in Excel format, and the main SEM analysis was conducted in two phases with the first phase, measurement framework assessment, testing the validity and reliability of the constructs. Measurements included Cronbach's alpha, (composite reliability), convergent validity

(average variance extracted – AVE), discriminant validity (Fornell-Larcker criterion, Heterotrait-Monotrait ratio – HTMT), and outer loadings and weights for the formative indicators, and multicollinearity (variance inflation factor).

The second phase, the structural framework assessment, confirmed the hypothesised relationships via path coefficient analysis and bootstrapped significance testing, R^2 and f^2 statistics to evaluate framework fit and effect size, and testing mediating effects for dynamic and operational capabilities. The analysis verified that the measurement structure fulfilled critical validity criteria. Other hypothesised structural relationships, primarily the impact of dynamic capabilities on competitive advantage were also supported. Mediating effects were assessed using bootstrapping procedures, examining indirect effects and their statistical significance. The complete results are presented in Chapter 5, with interpretation and discussion provided in Chapter 6.

1.15 DELIMITATIONS FOR THE STUDY

Delimitations allow the researcher to make choices as to what to include or exclude from the study. They help to set boundaries so that the scope of the study is not too broad and to ensure that the study remains focused on answering the research problem. Unlike limitations, which are outside the researcher's control, delimitations are within their control and ensure that the study is manageable regarding time, budget, and resources (Creswell and Creswell 2017).

This research was delimited by certain factors that were purposefully defined to guide the scope and enable depth in the analysis; for example, it was limited to South African businesses. While implications from the results could be generalised to other emerging economies, they were described specifically in the context of the South African business environment. The study mostly included medium to large businesses, with a limited number of smaller businesses responding due to lower adoption rates of analytics tools and infrastructure. The study addressed three big data analytics capabilities resources; tangible, intangible, and human skills, and how they are aligned with dynamic and operational capabilities. It did not explore any other software tools or specific technologies that could impact big data analytics capabilities.

The research was also conducted in a specific timeframe and may not reflect changes in big data analytics capabilities practices or market conditions outside of that period.

Although the study applied a mixed-methods approach, the qualitative phase was primarily used to guide the design of the quantitative instrument. The emphasis was placed on the quantitative findings, with the qualitative data providing context and support. These parameters were established to keep the research focused and feasible while still yielding meaningful insights. They also served as a foundation for future studies that may explore these areas in more detail (Dagada, 2025a).

1.16 LIMITATIONS OF THE STUDY

Limitations affect the understanding of certain parts of the research and help to explain why the results should be interpreted carefully (Creswell and Creswell, 2017). For example, this study was conducted within a specific timeframe, which limited its ability to observe changes over time or to establish causality. In addition, the use of self-reported data in both interviews and surveys may have introduced response bias, as participants could have provided socially desirable answers or omitted certain details due to recall bias (Podsakoff, Mackenzie, Lee and Podsakoff, 2003). The sample primarily comprised leaders from medium to large businesses, meaning that the perspectives of smaller businesses, such as startups, were underrepresented because of low response rates.

Furthermore, the focus on South African companies limits the generalisability of the findings to other geographic contexts or economic conditions. The research model included big data analytics capabilities, dynamic and operational capabilities, and competitive advantage but did not consider other potentially relevant factors such as leadership style, organisational culture, or external market forces. Future studies may benefit from incorporating these constructs to provide a more holistic understanding. Despite these limitations, the study provides valuable insights and lay the groundwork for further research across broader contexts.

1.17 ETHICAL ISSUES

The study adhered to ethical research guidelines during both the qualitative and quantitative phases. Ethics approval was provided by the UNISA Research Ethics Committee prior to the collection of data and is attached as per annexure G. Key ethical processes adhered to included informed consent, where participants were informed of the study's purpose, methodology, potential risks, and their rights, with written consent obtained prior to participation. Anonymity and confidentiality were

ensured by anonymising and coding all identifiable information before analysis. Voluntary participation was emphasised, with participants informed that they could withdraw from the study at any time without consequences. Risk was mitigated by designing the study to avoid psychological or social harm, and no harmful interactions occurred during data collection. Transparency was maintained by providing researcher and UNISA ethics board contact details in case of concerns or complaints. These ethical measures ensured the integrity of the research and compliance with both institutional and academic standards. Participants were assured of confidentiality and anonymity, and participation was voluntary. Ethical considerations were adhered to throughout the research process, with data securely stored and used solely for academic purposes.

1.18 OVERVIEW OF THE STRUCTURE OF THE THESIS

Table 2 provides a structured overview of the study's layout, showing how each chapter was built on the previous one to form a coherent progression from background and theory to methodology, findings, and conclusions. This structured flow ensured that the research questions and objectives were consistently addressed, while also clarifying the logical sequence of argumentation and analysis.

Table 2: Overview of the structure of the thesis

Source: Author

Chapter	Title	Description
Chapter 1	Nature and scope of the study	Introduces the study by presenting the background, problem statement, research questions, aims and objectives. It also includes the assumptions, delimitations, limitations, and the significance of the study. It outlines the context of big data analytics capabilities in South African businesses and highlights the research gap.

Chapter 2	Literature review	Offers a review of the latest academic and practitioner literature for big data analytics capabilities, dynamic capabilities, operational capabilities, and competitive advantage. The underlying theory and the current empirical evidence are examined critically.
Chapter 3	Theoretical and conceptual framework	Presents the theoretical and conceptual framework of the study. It explains the key theories, defines the constructs, clarifies the relationships between big data analytics capabilities, operational capabilities and competitive advantage, and develops the study hypotheses.
Chapter 4	Research methodology	Describes the research design, mixed methods approach, sampling, data collection instruments, procedures, and analysis for both qualitative and quantitative phases.
Chapter 5	Qualitative results and discussion	Presents and interprets the results from the qualitative phase of the study based on interviews with ten business leaders. Thematic analysis identifies overarching themes that are used for refining the design of the quantitative instrument.
Chapter 6	Quantitative results and hypothesis testing	Displays the quantitative phase results, including descriptive statistics, measurement framework fit, and structural framework analysis using PLS-SEM. The hypotheses are tested, and the relationships between big data analytics capabilities, dynamic capabilities, operational capabilities, and competitive advantage are discussed.

Chapter 7	Discussion, conclusions, and recommendations	Synthesises the outputs of both research phases, connects them with theory, and responds to the research questions. It also offers concluding remarks, policy and practical implications, study limitations, and recommendations for future studies.

The chapter concludes with the study structure outlined above and a summary of the key elements presented in Chapter 1. This recap reinforces the motivation, objectives, and scope of the study, while also positioning the research within the South African context of big data analytics capabilities and competitive advantage. It sets the stage for Chapter 2, which reviews the relevant literature and theoretical foundations that underpin the study.

1.19 SUMMARY OF CHAPTER 1

Chapter 1 grounds the study by establishing context and background to investigate how big data analytics capabilities can be leveraged to provide competitive advantage in South African businesses. The chapter presents the background and motivation for the study, and the increasing prominence of data-driven approaches in turbulent and evolving environments. The research question, problem, and sub-questions are articulated, followed by a clear set of objectives. The chapter establishes principal assumptions, namely, that big data analytics capabilities, when strategically aligned and supported by dynamic and operational capabilities, can significantly contribute to competitive advantage. Delimitations helped determine the limits of the study and restrict it to only those South African businesses with current or emerging large data initiatives. The delimitations have been acknowledged, particularly in terms of generalisability as well as accessibility of detailed business-level data. The chapter also describes the mixed-methods approach to research, with qualitative and quantitative research approaches being explained in more detail in Chapter 4.

Finally, it sets out an outline of the subsequent chapters, beginning the literature review and empirical investigation on a clear path.

CHAPTER 2: LITERATURE REVIEW

2.1 CHAPTER OVERVIEW AND INTRODUCTION

Chapter 1 introduced this study by outlining the research problem, objectives, and gaps in existing literature. Building on that foundation, this chapter critically reviews the main academic work relevant to the study, focusing on big data, big data analytics, big data analytics capabilities, dynamic capabilities, operational capabilities, and competitive advantage. The purpose is to provide the theoretical grounding necessary for building the study's conceptual framework.

In today's increasingly digital business landscape, big data analytics is recognised as a key driver of innovation and competitiveness. While it offers opportunities for proactive insights and data-driven decision making, businesses face significant challenges due to the volume, speed, and complexity of data (Gressel, 2019). Realising value from big data therefore requires more than technology investment; it demands the strategic development of capabilities that allow firms to extract value, adapt to change, and align analytics with core business objectives.

The tables presented in this chapter represent a synthesis of key constructs and relationships identified in the literature, developed to provide a structured overview of big data analytics capabilities and their associated organisational outcomes.

This chapter also situates these debates in the South African context, where economic, institutional, and technological constraints shape the adoption and effectiveness of big data analytics capabilities. By reviewing and synthesising existing knowledge, the chapter highlights how these competencies contribute to competitive advantage, identifies internal and external determinants that influence this relationship, and outlines the gaps in current scholarship. This review provides the theoretical grounding for the study and supports the development of a conceptual framework.

2.2 THE CONCEPT OF BIG DATA ANALYTICS CAPABILITIES

To fulfil the research gap specified in the problem statement, a conceptual model depicted in Chapter 1, Figure 2 was proposed. The model provided a theoretical foundation and a systematic view of the most significant variables and their interdependencies. This conceptual model was based on the one proposed by Framnes and Danielsen (2017) that describes big data analytics capabilities as a third-order construct of three core resources: tangible, human, and intangible. These resources flow through two distinct pathways, dynamic and operational capabilities, which play a role in determining a business's ability to achieve competitive advantage.

The key components of the conceptual model include big data analytics capabilities, which enable businesses to make fact-based decisions and comprise tangible resources such as technology infrastructure and investment, human skills including technical and managerial capabilities, and intangible resources such as organisational learning and a data-driven culture (Davenport and Bean, 2018).

Dynamic capabilities involve the business's capacity to sense, seize, and transform in response to changes in the environment. They serve as intermediaries for the impact of big data analytics capabilities on competitive advantage by enabling strategic renewal and agility. Dynamic capabilities are particularly critical for enabling technological agility, which is the business's ability to integrate, adopt, and adapt to new technologies in rapidly evolving markets.

In the context of big data analytics, these capabilities allow businesses to sense emerging technological trends such as artificial intelligence, cloud computing, and automation; seize opportunities through rapid experimentation and investment; and transform organisational processes to sustain competitive advantage. Internationally, businesses that excel in these dynamic processes, such as Amazon, Netflix, and Alibaba have demonstrated superior innovation speed and market responsiveness (Teece, 2018; Warner and Wäger, 2019).

In South Africa, similar patterns are emerging, where businesses that exhibit strong sensing and seizing capacities, such as in the financial and telecommunications sectors, show greater agility in adopting digital solutions despite infrastructural and

resource limitations (Calitz et al., 2017). This technological agility enables faster innovation cycles, improved customer responsiveness, and better alignment between data insights and strategic execution. Firms that successfully embed these dynamic capabilities consistently record stronger operational performance and sustainable competitive positions, both locally and globally (Teece, 2018). Thus, dynamic capabilities not only mediate the relationship between big data analytics and performance outcomes but also serve as the organisational mechanism that converts technological turbulence into strategic opportunity. Operational capabilities describe day-to-day execution skills in areas such as marketing and technology. Though important, they are posited to play a secondary mediating role in achieving advantage outcomes. Finally, competitive advantage indicates the ability of the business to outperform its competitors through enhanced resource capabilities that align with strategic agility.

The conceptual model lays the foundation for the development of the hypotheses, methodology, and data collection of this study. The model provides an end-to-end framework of analysis that explains how big data analytics capabilities affect continuous competitive advantage, particularly in the context of South Africa's fast-moving, resource-constrained business environment.

Before examining the role of big data analytics capabilities, it is important to first establish a clear understanding of the foundation on which they rest, big data itself. The following section therefore defines big data, tracing how its meaning has evolved across disciplines, and highlighting the characteristics that make it both an opportunity and a challenge for businesses. This conceptual grounding sets the stage for exploring how big data analytics capabilities are built and applied.

2.3 BIG DATA

To develop a deeper understanding of how big data analytics capabilities are conceptualised, it is first necessary to clarify the meaning of big data itself.

2.3.1 Defining big data.

The term big data has emerged as a central term in both academic and business settings. However, being an evolving and interdisciplinary phenomenon, it has been delineated in many divergent ways across computer science, data science, information systems, and management research. Over the last twenty years, the meaning of big data has shifted. Initially, big data was recognised for its size and speed of data processing (Provost and Fawcett, 2013). Recently, big data included characteristics such as its value, complexity, and the conditions needed to use it effectively (Shah et al., 2021). Table 3 below summarises selected definitions of big data from key academic and practitioner sources. It illustrates how the concept has expanded and matured over time, from a purely technological challenge to a strategic business resource that can drive competitive advantage.

Table 3: Definitions of big data

Source: Laney, 2001; McKinsey Global Institute, 2016; Kitchin, 2014b; De Mauro, Grecco and Grimaldi, 2016; Wamba, Gunasekaran et al., 2017; Zicari, 2014

Author(s)	Year	Definition
Laney (Gartner)	2001	Defined big data in terms of the “3Vs”: Volume, Velocity, Variety, large volumes of data generated at high velocity and in diverse formats.
Manyika, Chui, Brown, Bughin, Dobbs, Roxburgh and Hung Byers (McKinsey Global Institute)	2016	Datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyse.
Kitchin	2014b	Big data is not just about size; it is also about complexity, relationality, exhaustiveness, and scalability of data.
De Mauro, Greco and Grimaldi	2016	Big data refers to the information assets characterised by such a high volume, velocity, and variety that require specific technology and analytical methods.

Wamba, Gunasekaran et al.	2017	A holistic approach to managing, processing, and analysing 5Vs, Volume, Velocity, Variety, Veracity, Value to generate actionable insights.
Zicari	2014	Big data can be seen as an ecosystem of technologies, data, analytics, and human decision-making that create value from large, fast, and diverse data.

Laney (2001), credited with originating the widely adopted 3Vs framework, identified volume, velocity, and variety as key technical challenges faced by businesses in managing data, a definition that laid the foundation for subsequent conceptual developments. Manyika et al. (2011) observed the limitations of traditional database technologies to handle datasets of this scale and hence the necessity to devise new data architectures and tools.

Kitchin (2014b) responded further that big data was not only a question of scale but also one of complexity, exhaustiveness, and scalability, recognising the relational and structural character of data environments in modern times. De Mauro, Greco and Grimaldi (2016) returned to the 3Vs, highlighting that big data's defining characteristic is the fact that it requires specialised technologies and advanced analytic techniques.

Further definitions by Wamba, Akter, Trinchera et al. (2017) and Zicari (2014) enhance this view. Wamba, Akter, Trinchera et al. (2017) expanded the original framework by adding two more dimensions, veracity and value, emphasising the importance of accuracy and usefulness in a business context. Zicari (2014) described big data as a broader system that brings together data, technology, analytics, and human judgment to create value (Wamba, Akter, Trinchera et al., 2017; Zicari, 2014).

Taken together, these definitions illustrate the evolution of big data (Lee, 2017), from a purely technical challenge to a strategic organisational capability. In contemporary business environments, big data is now understood not merely as large or fast data, but as an integrated set of resources and capabilities that drive innovation, agility, and

competitive advantage (Wamba, Akter, Trinchera et al., 2017; Zicari, 2014; Shah et al., 2021). In this study, big data is thus conceptualised as an organisational capability involving the management of complex, high-volume data, supported by analytics tools, an enabling culture, and human expertise, with the goal of creating business value and sustaining competitive advantage in dynamic markets.

2.3.2 Big data evolution and business importance

The evolution of big data has shown its growing role as a transformational business resource (Kache and Seuring, 2017; Mikalef et al., 2021). Often referred to as the new oil of the 21st century, big data has attracted considerable attention (Gandomi and Haider, 2015), prompting many businesses to invest in analytics tools to uncover its value (Lioutas and Charatsari, 2020). Big data, when applied correctly, helps businesses make better decisions and improve their ability to compete (Frey and Osborne, 2017; Hämäläinen and Inkinen, 2019). As a result, many businesses have started to review their strategies, day-to-day operations, and ways of interacting with customers (Delton and Robertson, 2016).

Businesses such as finance, healthcare, marketing, and manufacturing have adopted big data tools to access timely information and enhance operational effectiveness (Agnihotri, Dingus, Hu and Krush, 2023). Studies also indicate that big data supports quicker business responses to market changes and improves adaptability in business processes. The ability to adapt faster to environmental shifts are critical for business survival especially in the current competitive business landscape, since customer preferences and technological advancements are constantly changing. Hence, more businesses in emerging markets are utilising big data to improve their competitive advantage (Agnihotri et al., 2023)

2.3.3 Challenges and strategic considerations

While the possibility of transformation through big data is widely acknowledged, its application is far from being free of serious issues. For example, businesses are faced with challenges related to data privacy, ethics, integrating heterogeneous data sources, and the accuracy and quality of big data (Antonetti and Rosengren, 2022a; Shah, et al., 2021). One of the key challenges in using big data is data governance and assuring its quality. Due to its unstructured nature and size, businesses need a

complete system that can provide accuracy, consistency, and integrity (Fabijan et al., 2017; Hämäläinen and Inkinen, 2019). Without strong governance, businesses risk making decisions based on inaccurate or incomplete data, which can negatively impact competitive advantage and damage customer trust.

Beyond quality, ethical issues have also become more prominent. Privacy infringement, misuse of personal data, and algorithmic bias are now part of mainstream debates and academic research (Kitchin 2014b; Agnihotri et al., 2023). Businesses must therefore adopt clear ethical codes and comply with legal frameworks such as the European Union's General Data Protection Regulation (GDPR) (EU, 2016), and South Africa's Protection of Personal Information Act (POPIA). These require major changes in how data is collected, stored, and processed (Custers and Ursic, 2016).

The integration of unstructured and semi-structured data also presents technical and organisational hurdles. Many businesses still rely on outdated data management systems that are not equipped for big data leading to the need for significant investments in updated technologies and infrastructure (Aftab and Siddiqui, 2018). Another important challenge lies in the shortage of people with the right skills. There are not enough professionals who can work with big data, especially those who know how to handle, manage, and analyse large and complex datasets (Corea, 2019; Hämäläinen and Inkinen, 2019). In countries like South Africa, this problem is more serious, and training institutions have not produced enough graduates with the skills that businesses need (Calitz et al., 2017; McKinsey, 2016). It is also expensive for businesses to hire and keep such skilled staff.

To resolve these challenges, most companies are starting to employ machinery such as machine learning and artificial intelligence (AI) (Raisch and Krakowski, 2021). These machineries can take large data and convert it into useful patterns and information (Frey and Osborne, 2017; Aftab and Siddiqui, 2018). However, there are excessive costs associated with these machineries, and businesses must invest in proper systems and train staff members to use them to their fullest potential. It is also becoming more necessary to create a working culture where decisions are based on data.

Finally, achieving proper use of big data does not just entail buying new hardware or software. It entails bringing in qualified personnel, proper systems, and a clear strategy. Companies that want to benefit from big data need to balance investment in the right technologies with resolving key issues like data privacy, ethical usage, and regulatory compliance (Mikalef et al., 2021).

2.3.4 Definition and strategic purpose of big data analytics

Over the past few decades, big data analytics has become a critical area of interest in both academic research and business practice, mainly because of its ability to extract meaningful insights from large and complex datasets. Scholars have explored various aspects of big data analytics including definitions, applications, benefits, and challenges, to build a clearer understanding of this fast-developing field (Wamba, Queiroz, Wu and Sivaraj 2023; Mikalef et al., 2021). Big data analytics has been defined as the systematic analysis of large and sophisticated data to uncover patterns, trends, and insightful information for better decision-making and strategic planning needs (Kwon et al., 2014; McAfee, Brynjolfsson, Davenport, and Patil, 2012; Chen, Preston and Swink, 2016). By doing this, business leaders seek to produce useful information that enhances their ability to act on facts, reduce uncertainty, and create long-term value (Wilson and Cong, 2021).

As Davenport and Patil (2012) assert, big data analytics helps businesses not only to better understand their operations but also to develop good capabilities for sustaining improved business results. Research has indicated that through proper application, big data analytics facilitates cost savings, revenue increases, process improvement, and faster response to market changes (Erevelles, Fukawa and Swayne, 2016, Kwon, et al. 2014; Mikalef et al., 2021). The importance of big data analytics is reflected in the increasing global investment in related technologies and in developing skilled professionals. However, applying big data analytics successfully requires a clear understanding of its technical and organisational challenges. At the centre of these challenges are the four core characteristics which are, volume, variety, velocity, and veracity, which define the complexity of the data environment (Framnes and Danielsen, 2017; Shah et al., 2021).

2.4 THE FOUR VS OF BIG DATA ANALYTICS: CHALLENGES AND CONSIDERATIONS

The concept of big data is commonly characterised by four key dimensions, volume, variety, velocity, and veracity with each presenting unique challenges and considerations that influence how businesses extract value from data.

2.4.1 Volume

The volume of big data refers to the massive amount of information generated from diverse sources such as transactional data, customer activity records, sensors, and social media platforms (Wang and Hajli, 2017). While businesses have improved their storage and computing capabilities to handle large datasets, the major challenge lies in how to derive maximum strategic value from this data (Framnes and Danielsen, 2017). Managing large data volumes requires scalable infrastructure, advanced data warehousing, and analytical tools that enable efficient extraction, transformation, and analysis in real time. However, many organisations, particularly in developing economies, still struggle to harness these data volumes effectively due to limitations in infrastructure, cost, and analytics maturity (Mikalef et al., 2021).

2.4.2 Variety

Variety refers to the diversity of data types and formats, structured, semi-structured, and unstructured that must be integrated and analysed to inform business decisions. The ability to manage and interpret multiple formats such as text, audio, video, and sensor data is central to the value creation potential of big data analytics (Delen and Demirkan, 2013; Wamba, Queiroz et al., 2021).

However, managing data variety is particularly problematic in emerging markets, where legacy systems, technological heterogeneity, and skills shortages constrain integration across departments (Mikalef et al., 2021). Businesses therefore require flexible analytics tools and data integration frameworks capable of bridging disparate data environments.

Beyond the technical challenges, variety introduces semantic and contextual complexity. Different systems often use inconsistent definitions, taxonomies, and metadata structures, resulting in misaligned data streams. Consequently, harmonising

diverse datasets into a unified analytics ecosystem demands both technological sophistication and robust governance oversight.

2.4.3 Velocity

Velocity captures the speed and frequency with which data is generated, transmitted, and processed. The proliferation of Internet of Things (IoT) devices, mobile applications, and digital transactions has exponentially increased the pace of data generation (Framnes and Danielsen, 2017). For modern businesses, the ability to process and respond to data in real or near-real time has become a source of competitive advantage (Wamba, Akter, Trinchera et al., 2017). High-velocity data supports predictive analytics, real-time monitoring, and agile decision-making. However, rapid data flow also places significant strain on network infrastructure, storage capacity, and analytical responsiveness. In South Africa and other developing economies, factors such as unstable connectivity, limited bandwidth, and inconsistent system interoperability often inhibit the ability to exploit high-velocity data streams effectively. Consequently, achieving true data velocity requires not only technological readiness but also agile organisational processes capable of converting fast data into fast action.

2.4.4 Veracity

Veracity refers to the accuracy, reliability, and trustworthiness of data, ensuring that information used for analysis is complete, unbiased, and free from noise or distortion. High-veracity data provides a credible foundation for analytics-driven decision-making. However, in many organisations, maintaining veracity remains one of the most persistent barriers to effective big data analytics (Wamba, Gunasekaran et al., 2017).

Beyond the technical dimension, veracity is a multidimensional issue encompassing managerial, ethical, and cultural challenges. According to Kache and Seuring (2017), achieving veracity requires coordinated organisational action, including cross-departmental accountability for data quality, well-defined data ownership, and transparent governance structures. In many firms, fragmented data ownership leads to inconsistencies and duplication, resulting in reduced reliability and trust in analytical outcomes. Ensuring veracity is therefore not only about maintaining data accuracy but also about preserving integrity and traceability. Data must retain its provenance and

context throughout the analytics process so that insights can be verified and trusted in decision-making. However, Kache and Seuring (2017) highlight that many of these veracity challenges stem from implementation barriers such as disconnected data systems, lack of standardised data quality protocols, and poor coordination between IT and business units. These practical constraints make it difficult to translate governance policies into consistent, organisation-wide practices.

Shah et al. (2021) further argue that veracity challenges are both technical and cultural. On the technical side, organisations must deploy rigorous validation systems, metadata management tools, and automated cleansing mechanisms to detect and correct errors in real time. On the cultural side, veracity depends on cultivating ethical awareness, stewardship, and accountability among employees. A data-driven culture must be nurtured, where users understand the significance of accuracy, avoid manipulation or selective interpretation, and uphold privacy and ethical standards in analytics practice. These implementation challenges reveal that veracity is not purely a data-engineering concern, but a comprehensive organisational capability requiring leadership oversight, ethical governance, and continuous investment in human and technological systems. As Wilson and Cong (2021) emphasise, successful organisations invest simultaneously in technology, governance, and people to overcome the veracity barrier.

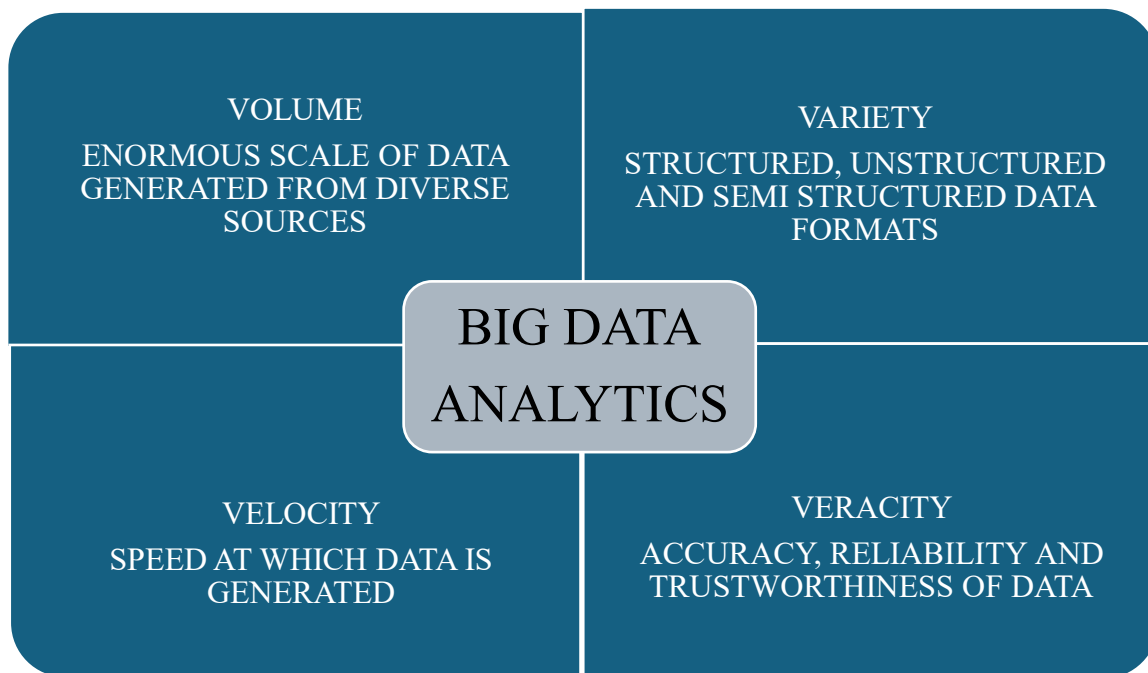


Figure 3: The 4V's of big data

Source: Author

Addressing these four characteristics of big data is crucial to realising its value. Without strong capabilities in data management, analytics skills, and governance, businesses risk generating misleading or incomplete insights (Mikalef et al., 2021). In today's fast-evolving business environment, businesses must invest in advanced technologies, build appropriate data-driven cultures, and foster human capabilities to overcome these barriers (Wilson and Cong, 2021). Although big data analytics offers immense value, the literature indicates a need to balance its advantages with a pragmatic understanding of its implementation issues (Kache and Seuring, 2017; Shah et al., 2021). Overcoming the challenges of the four V's is critical to unearthing its full value to sustain competitive advantage (Mikalef et al., 2021). As this research transitions to big data analytics capabilities, it is evident that organisational capabilities to leverage big data analytics are complex and multidimensional. The following section hence examines the concept of big data analytics capabilities, offering an in-depth insight into organisational ability to build and execute these capabilities for strategic benefit.

2.5 BIG DATA ANALYTICS CAPABILITIES

In this section, the focus is on what big data analytics capabilities means and the different dimensions that make up big data analytics capabilities.

2.5.1 Definitions and dimensions of big data analytics capabilities

The emergence of big data analytics capabilities has brought a significant shift in how businesses leverage their data resources to improve business advantage (Framnes and Danielsen, 2017; Wamba, Queiroz et al., 2021). Big data analytics capabilities refer to an organisation's ability to coordinate and utilise data-related resources. These include technology, skilled people, and supportive culture, to produce insights that inform decision-making and improve competitiveness (Gupta and George, 2016; Mikalef et al., 2021).

At its core, big data analytics capabilities comprises three primary dimensions, tangible resources, such as data infrastructure, storage, and processing capabilities, human skills, including technical and managerial expertise. These are required to analyse data and translate insights into strategy and intangible resources, such as organisational learning, leadership commitment, and a culture that embraces data-driven decision-making (Gupta and George, 2016; Wamba, Gunasekaran et al., 2017).

Human skills in big data analytics capabilities therefore extend beyond technical expertise to include higher-order interpretive and communication capabilities. This includes the ability to translate analytic outputs into meaningful insights for decision making. This is often referred to as data storytelling, which involves translating complex analytical outputs into clear, actionable insights for decision-makers. Organisational learning scholars such as Rhodes, Argyris and Schön, 1996; Senge, 2006, emphasise the importance of interpretation, shared understanding, and communication in enabling effective organisational responses to data (Rhodes, Argyris and Schön, 1996; Senge, 2006). In this context, data storytelling supports the transformation of analytical outputs into strategic decisions, thereby strengthening the link between big data analytics capabilities and competitive advantage.

This broader view reflects that big data analytics capabilities is not just a technical function but a strategic organisational capability. It brings together data use with the

ability to embed insights across business operations, decision processes, and innovation efforts (Mikalef et al., 2021). Researchers also point out that big data analytics capabilities require businesses to build dynamic capabilities, allowing them to adjust their data use as business environments change (Teece, 2018; Fosso Wamba, Gunasekaran, Akter, Ren, Dubey and Childe, 2020).

In today's context where data is seen as a key business asset, big data analytics capabilities increasingly recognised as a critical factor in achieving innovation and competitive advantage (Agnihotri et al., 2023). For South African businesses in particular, the activation of big data analytics capabilities offers a means to overcome challenges such as volatile markets, infrastructural limitations and skills shortage with a view to rendering them competitive in both the global and domestic markets (Calitz et al., 2017; Mikalef et al., 2021).

2.5.2 Evolution and drivers of big data analytics capabilities

The evolution of big data analytics capabilities have been credited to advances in computing power, data storage capacity, and information management technology (Kache and Seuring, 2017). Early big data technologies such as Hadoop supported large-scale storage and processing of data, whereas cloud computing was cost-effective and accessible with their maturity (Wamba, Gunasekaran et al., 2017; Mikalef et al., 2021).

At the same time, advancements in artificial intelligence (AI) and machine learning have enhanced the ability to derive value from large and complex datasets (Framnes and Danielsen, 2017; Agnihotri et al., 2023). Businesses have therefore now reviewed their data collection methods to manage and analyse their data more efficiently. Whereas choices under traditional decision-making processes relied on tiny samples and individual judgment, the capacity to obtain big data analytics currently empowers businesses to make data-driven decisions using whole, up-to-date information (Delton, 2020). Businesses are increasingly likely to leverage big data analytics to find market trends, monitor customer behaviour, and fix operational inefficiencies, resulting in more informed and responsive decision processes (Davenport and Patil, 2012; Mikalef et al., 2021).

In parallel, the rise of machine learning and artificial intelligence (AI) techniques has enabled businesses to extract insights from data sources that were previously too large or complex to analyse effectively (Agnihotri et al., 2023; Framnes and Danielsen, 2017). Business leaders seeking to use data as a strategic resource to improve customer experience, streamline operations, and create new revenue streams (Agnihotri et al., 2023; Wilson and Cong, 2021). This drive to extract business value from data is one of the main reasons for the growing importance of big data analytics capabilities across businesses and within developing economies such as South Africa (Calitz et al., 2017; McKinsey, 2016).

However, the literature shows that businesses still face challenges in developing big data analytics capabilities. Beyond the financial investment required, many businesses struggle with data integration, handling unstructured data, attracting, and retaining analytics talent, and obtaining consistent support from senior leadership (Gupta and George, 2016; Vidgen, Shaw and Grant, 2017). The shortage of data science and analytics professionals is a global concern, and it is particularly pressing in emerging markets (Agnihotri et al., 2023; Corea, 2019). In South Africa, while universities and training institutions have introduced data-related programmes, the demand for skilled workers continues to exceed supply (Calitz et al., 2017).

To overcome these barriers, researchers recommend a strategic and integrated approach to building big data analytics capabilities. This involves combining technical infrastructure with skilled personnel and fostering a data-driven organisational culture (Gupta and George, 2016; Mikalef et al., 2021). Efforts to build big data analytic capabilities should include continuous training, leadership support, and a commitment to organisational learning (Framnes and Danielsen, 2017; Wamba, Queiroz et al., 2021). Building on the drivers and evolution of big data analytics capabilities, it is essential to understand the key components that make up these capabilities, as these elements collectively determine how effectively an organisation can convert data into strategic value.

2.5.3 Key components of big data analytics capabilities

Big data analytics capabilities are comprised of several interrelated elements integrated to enable businesses to harness strategic value from data. According to

Gupta and George (2016) and Mikalef et al. (2021), big data analytics capabilities is dependent not only on technological resources, but also on human skills, process alignment, as well as analytics platforms that enable data to be transformed into useful insights (Gupta and George, 2016; Mikalef et al.,2021).

Four core components consistently emerge in the literature as critical to big data analytics capabilities. These are data integration, predictive modelling, real-time analytics, and data visualisation as depicted in the Figure 4 below (Framnes and Danielsen, 2017; Wamba, Queiroz et al., 2021).

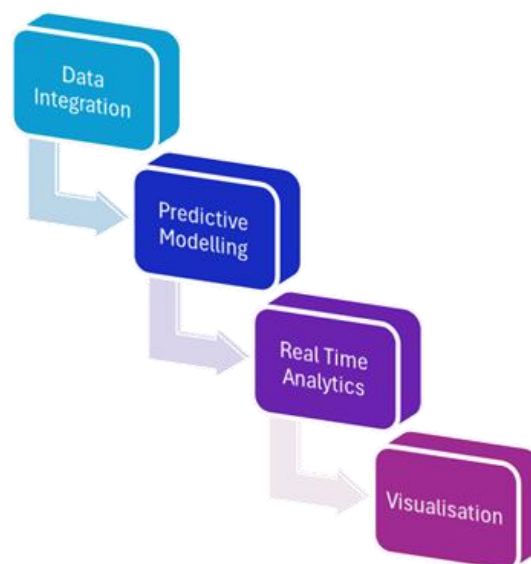


Figure 4: Flowchart illustrating the components of big data analytics
Source: Author

The following subsections discuss each of these components in detail, beginning with data integration, which provides the foundation for consolidating diverse data sources into consistent and usable datasets.

2.5.3.1 Data integration

Data integration provides the foundation for bringing together market data into consistent datasets that are ready to be analysed (Framnes and Danielsen, 2017).

This includes data from disparate sources both internal (ERP, CRM, operational systems) and external (social media, IoT devices, market data), (Hoffman and Novak, 2018). New integration technologies such as Apache Kafka, Informatica, and Talend are enabling businesses to overcome fragmentation and silos. As a result, they can potentially achieve maximum value from their data assets (Manyika et al., 2011; Mikalef et al., 2021). However, data integration, in the case of South Africa, remains a contentious issue, with legacy systems and fragmented information and technology (IT) architectures usually being a hindrance to businesses' ability to create end-to-end views of data (Calitz et al., 2017). An innovative approach, coupled with an unprecedented data governance structure to deliver uniformity, quality, and usability, is required to break these obstacles (Wamba, Queiroz, Wu et al., 2023).

2.5.3.2 Predictive modelling

Predictive modelling uses statistical techniques and machine learning processes for forecasting trends, and outcomes, and enabling forward-looking decision-making (Oladuji, Akintobi, Nwangde and Ajuwon; 2023). Regression analysis which includes classification, neural networks, and ensemble learning are suitable techniques to model the behaviour of consumers, estimate their risk profiles and enhancing the optimisation of business processes (Ciacchi and Penco, 2024; Wilson and Cong, 2021).

Predictive modelling represents one of four key types of analytics, namely descriptive, diagnostic, predictive, and prescriptive analytics. While descriptive and diagnostic analytics focus on understanding past performance and identifying underlying causes, and prescriptive analytics focus on recommending optimal actions, this study specifically emphasises predictive modelling. This focus is justified as predictive modelling is most closely aligned with the forward-looking, decision-support capabilities required for competitive advantage. In the context of big data analytics capabilities, predictive modelling enables organisations to anticipate trends, respond proactively to environmental changes, and support strategic decision-making. Therefore, although all four types of analytics are recognised, predictive modelling is prioritised in this study due to its direct relevance to dynamic capabilities and competitive advantage.

In South African businesses such as those in telecommunications, finance and in the retail sector, predictive models are increasingly being used to forecast customer appetite and retention, minimise price strategies, and inform credit risk decisions (Oladuji et al; 2023). However, building and deploying predictive models requires incredibly talented human capital and significant investment in analytics infrastructure (Agnihotri et al., 2023).

2.5.3.3 Real-time analytics

Real-time analytics enables businesses to process and examine information immediately, forming the foundation of direct decision making in dynamic environments (Framnes and Danielsen, 2017). Systems such as Apache Flink, Spark Streaming, and cloud-based applications enable businesses to detect emerging trends, monitor operations in real time, and respond ahead of competitors and opportunities (McAfee et al., 2012). For fraud prevention, dynamic pricing, and customer experience personalisation, real-time analytics has proven to be a competitive necessity (Wamba, Akter, Trinchera et al., 2021). South African banks, for instance, increasingly leverage real-time data streaming to detect fraud and build individualised credit offers for customers (Green, 2025).

2.5.3.4 Data visualisation

Data visualisation technologies have the key role of ensuring that challenging data and analysis outputs are effectively communicated with decision-makers (Danielsen, Olsen and Framnes, 2021). Data driven analytic tools and technologies like Tableau, Power BI, and open-source libraries allow businesses to transform their data into interactive dashboards. In addition, simple-to-use visual formats allow for enhanced interpretation and informed decision making (Mikalef et al., 2021).

In South African businesses, where analytics maturity is not well developed, visualisation has a crucial role to play in bridging the difference between technical expertise and business users. Visualisation through well-designed dashboards helps organisational agility by allowing executives and managers to monitor key metrics and respond quickly to evolving scenarios (Hussinki, Ritala, Vanhala, Kianto and Mero; 2025). While these components form the foundation of big data analytics capabilities, their true value lies in the tangible benefits they bring to competitive advantage. The

following section outlines both the advantages and ongoing challenges associated with implementing big data analytics capabilities in practice.

2.5.4 Benefits and challenges of big data analytics capabilities

The implementation of big data analytics capabilities offers significant potential benefits to businesses across sectors. By transforming large and complex datasets into actionable insights, big data analytics capabilities enable businesses to enhance decision-making quality, improve operational efficiency, personalise customer experiences, and achieve sustained competitive advantage (Davenport and Patil, 2012; Mikalef et al., 2021). The most cited advantages of big data analytics capabilities include improved decision-making, where evidence-based information reduces uncertainty and supports informed strategic choices grounded in robust data. Such benefits lead to increased operational efficiency, driven by predictive analytics that facilitate proactive process optimisation such as predictive maintenance and demand forecasting (Fowowe and Adedapo, 2025). Furthermore, enhanced customer experience through personalised marketing, dynamic pricing, and tailored product offerings; and boosted innovation and responsiveness, as real-time analytics provide the agility needed to perform in fast-changing environments.

However, despite these advantages, businesses continue to face recurring challenges when utilising the capabilities of big data analytics technologies and tools. Key challenges identified in the literature include data silos, fragmented technology, the high costs of implementing big data tools and infrastructure, and persistent skills shortages. Further issues involve concerns related to data quality, governance, and ethics (Corea, 2019; Gupta and George, 2016; Vidgen et al., 2017). Table 4 summarises these capabilities alongside their associated benefits and typical challenges.

Table 4: Matrix summarising key big data analytics capabilities, their associated benefits, and typical challenges

Source: Author's own compilation based on Akter et al., 2017; Gupta and George, 2016; Mikalef et al., 2019 and Wamba et al., 2021).

Capability	Benefits	Challenges
Data integration	Unified data sources	Data quality issues; legacy systems
Predictive modelling	Enhanced forecasting accuracy	Shortages of skilled talent
Real-time analytics	Immediate, proactive decision-making	Handling data silos; system complexity
Data visualisation	Improved communication of insights	User resistance; limited analytics culture

As shown in Table 4, each capability brings clear strategic benefits but also introduces persistent obstacles that must be managed. In the South African context, development of big data analytics capabilities is also compromised by infrastructure constraints, regulatory requirements (e.g., POPIA), and high cost of advanced analytics software (Africa Data Revolution Report, 2016; Calitz et al., 2017; Mikalef et al., 2021). Moreover, as big data analytics practices become increasingly reliant on AI-driven models, concerns related to algorithmic bias, transparency, and privacy are rising in prominence (Agnihotri et al., 2023).

Addressing these barriers requires a holistic organisational approach one that combines investments in technology, talent development, and change management, supported by a strong data governance framework and leadership commitment (Gupta and George, 2016; Mikalef et al., 2021). These challenges are not simply a matter of acquiring new tools but requires a coordinated and well-supported approach across the organisation. This includes aligning investments in infrastructure with efforts to build internal skills, establish clear data governance protocols, and ensure leadership drives the adoption of data-driven practices (Gupta and George, 2016; Mikalef et al., 2021). In this context, it becomes essential to examine the foundational resources that enable the development of big data analytics capabilities. Figure 5 provides an

overview of these resources, highlighting the strategic inputs required for organisations to build effective analytics capabilities.

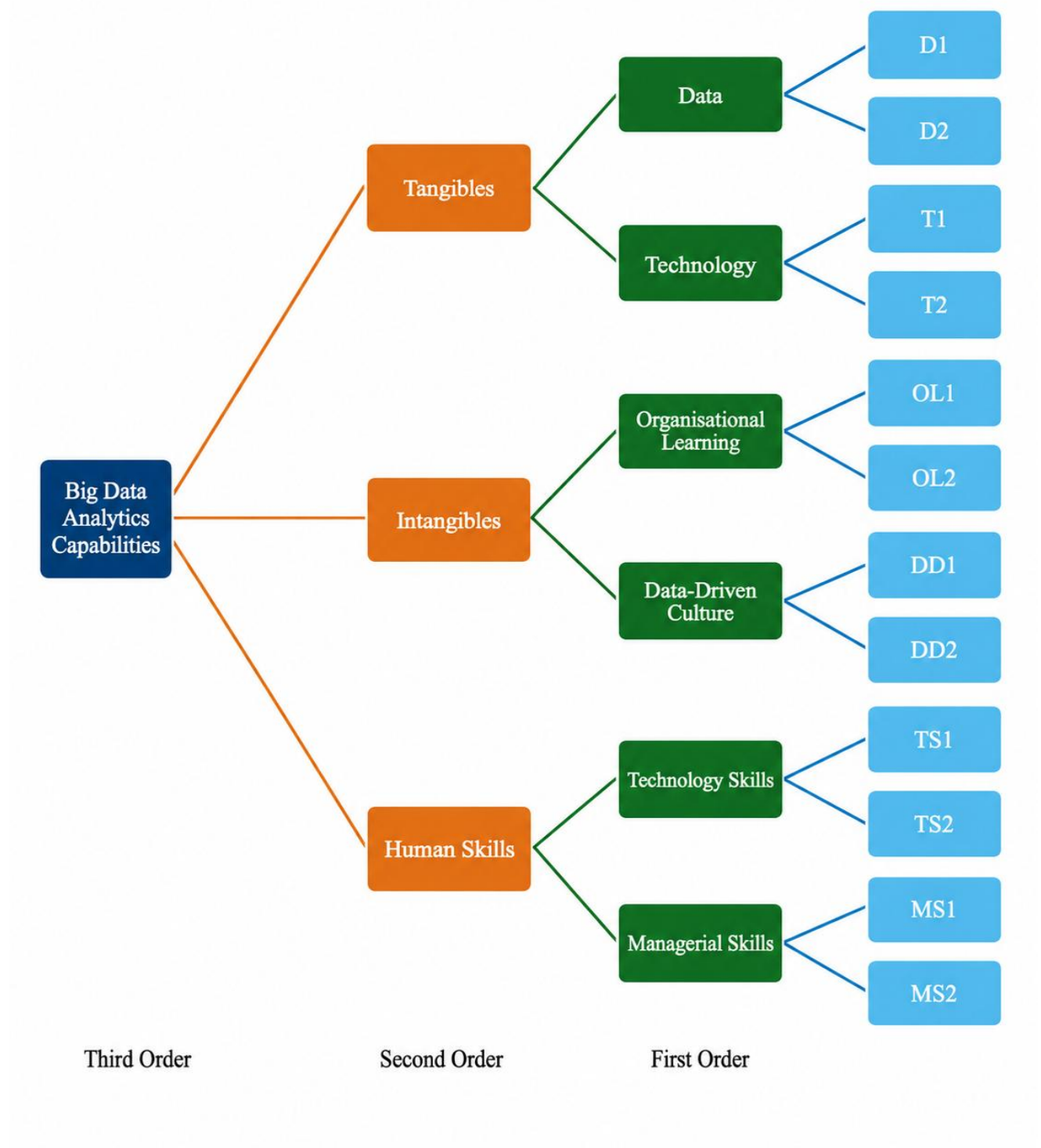


Figure 5: Resources for developing big data analytics capabilities.

Source: Author

As shown in Figure 5, the development of big data analytics capabilities relies on a combination of resources that extend beyond technology alone. The next section discusses these resources in greater detail, focusing on four interdependent dimensions; data infrastructure, technology, human skills, and organisational processes that collectively shape the ability of firms to extract strategic value from big data.

2.5.5 Resources for developing big data analytics capabilities.

At the core of advancing big data analytics capabilities lie the strategic resources that enable businesses to convert data into actionable insights. The literature consistently highlights four key dimensions that underpin the development of big data analytics capabilities, data infrastructure, technology, human skills, and organisational processes (Mikalef et al., 2021). These dimensions are interdependent and collectively shape an organisation's ability to extract value from big data.

2.5.5.1 Data infrastructure

The foundation of effective big data analytics capabilities is a strong and scalable data infrastructure, one capable of managing the volume, velocity, and variety of contemporary data streams (Agnihotri, 2023). Technologies such as cloud computing, data lakes, distributed file systems, and hybrid architectures are increasingly used to support the storage, management, and accessibility of complex and unstructured datasets (Wamba, Queiroz et al., 2021).

2.5.5.2 Technology

Technological tools, such as advanced algorithms, natural language processing, and predictive modelling, are key enablers of big data analytics capabilities (Delton, 2020c). When seamlessly integrated with capable data infrastructure, these tools support high-speed processing, advanced analytics, and the visualisation of actionable insights (Mikalef et al., 2021). However, as the technology landscape continues to rapidly evolve, businesses must routinely assess and upgrade their data toolsets to maintain analytical competitiveness (Agnihotri et al., 2023).

2.5.5.3 Human skills

Human skills are a cornerstone of effective big data analytics capabilities, as they enable businesses to translate technical potential into actionable business value. Professionals such as data scientists, analysts, engineers, and subject-matter experts bring the technical expertise needed to design, develop, and implement data analytics solutions (Corea, 2019; Gupta and George, 2016; Maluleka and Dagada, 2024). However, having technical skills alone is not enough. Businesses also need managers and leaders who can understand analytics and connect the results to the business's goals. These strategic and managerial skills help ensure that the insights gained from data are used in real decision-making and planning (Davenport and Patil, 2012).

In South Africa, one of the main challenges to building strong big data analytics capabilities is the shortage of people with the right skills. While more universities and training institutions are now offering data science programmes, there are still not enough qualified professionals to meet industry demand (Calitz et al., 2017). This shortage calls for investment in education, practical training, and long-term recruitment and retention efforts of analytics talent by businesses and policymakers.

2.5.5.4 Organisational processes

To enable big data analytics capabilities to provide real value to a business, the internal processes and systems of the business must be supportive. This includes efficiency in managing data, setting clear procedures and standards, and ensuring the correct tools are used in the business operations. When these are in place, data insights can effectively and rapidly be put into action across all organisational areas.

In addition, strong data governance is important. This refers to the rules and systems that ensure data is accurate, secure, and used responsibly. For South African businesses, this also includes meeting legal requirements such as those set out in the Protection of Personal Information Act (POPIA) (Agnihotri et al., 2023). A good governance system helps protect the business and builds trust in how data is used. Without such sound governance structures, businesses risk undermining the reliability and ethical use of their data resources.

Equally important is the cultivation of a strong data-driven organisational culture. The integration of a data-driven mindset in daily decision-making enables adaptability, accountability, and continuous learning. A culture that is sensitive to data, makes all levels of the business's employees interact with analytics, thereby enhancing their responsiveness and effectiveness in using big data analytics in the business (Framnes and Danielsen, 2017; Mikalef et al., 2021). The interconnectedness of resources, the people, technology, and organisational learning, is therefore central to the development of effective big data analytics capabilities. Each element strengthens the others, and competitive advantage depends on maintaining this balance over time.

2.5.5.5 The interconnected nature of resources

One of the main conclusions reached in the literature is that these human skills, technology, and organisational learning are not separate factors, but reinforcing and inter-linked (Framnes and Danielsen, 2017; Wamba, Queiroz et al., 2021). Technology with no skilled staff to extract meaning from its output is useless; likewise, skilled analysts require current tools to perform optimally. Moreover, a culture of learning produces the long-term development of human skills, which in turn encourages workers to accept new methods of analysis and technology. High-end technologies can also enable learning by making knowledge-sharing spaces and shared analytics platforms possible (Agnihotri et al., 2023).

Furthermore, this complementary combination advances over time. As technologies evolve, the demands of competencies change, and with that, the necessity to keep investing in talent development and cultural transformation (Gupta and George, 2016). The cyclical interchange among these factors is imperative in sustaining big data analytics capabilities in turbulent environments (Mikalef et al., 2021). Under shifting business environments, adaptability and innovation across these dimensions are critical to tapping into the full potential of big data analytics (Schubert and Barrett, 2024). Having discussed these basic resources, the following section now addresses the tangible resources, beginning with data as a core resource that enables the development of big data analytics capabilities.

2.6 TANGIBLE RESOURCES

In the literature, the development of big data analytics capabilities is underpinned by three categories of tangible resources, data, technology, and basic resources (Agnihotri, 2023; Gupta and George, 2016). These resources are the foundational building blocks that enable businesses to process and transform data into actionable insights that can enhance competitive advantage (Dagada, 2025b; Dangale and Dagada, 2024).

2.6.1 Data

Data has emerged as one of the most valuable resources of the digital economy and is central to the physical resources needed for big data analytics capabilities (Framnes and Danielsen, 2017; Gupta and George, 2016). Data is often referred to as the new oil, acting as the raw material that fuels the entire analytics value chain (Brynjolfsson and McElheran, 2016).

2.6.1.1 Internal and external sources of information

Big data information is derived from internal as well as external sources. Internal sources of data are operational, transactional, and customer data from within the company's systems. External data can be sourced from public data sets, commercial suppliers, social media, and collaborative networks (Agnihotri et al., 2023; Mikalef et al., 2021).

2.6.1.2 The value of timeliness

Access to data in a timely fashion is paramount. Streams of real-time or near-real-time streams of data flows, facilitated through streaming architectures, are crucial for providing fast, responsive decision-making in dynamic markets (Framnes and Danielsen, 2017).

2.6.1.3 Challenges of data as a resource

Businesses continue to face data privacy, quality, governance, and integration issues, particularly when it comes to heterogeneous data from various sources (GDPR, POPIA; Custers and Ursic, 2016). Robust data management frameworks as depicted in the Figure 6 below, are required to ensure precision, consistency, and data conformity (Framnes and Danielsen, 2017; Mikalef et al., 2021).

Data Definition Framework

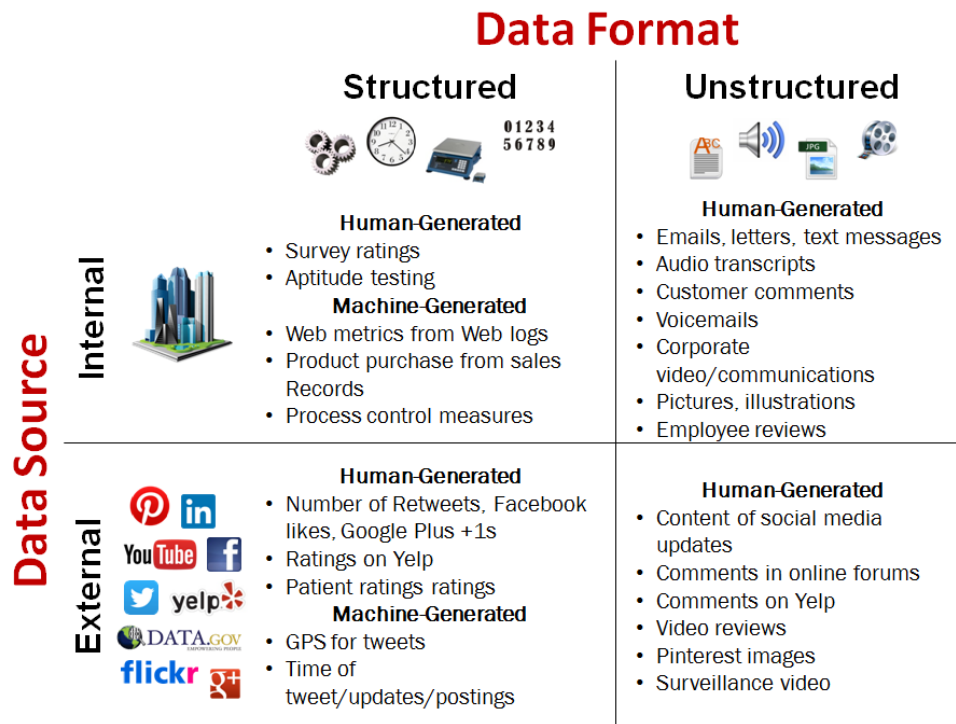


Figure 6: Data sources as core inputs to big data analytics capabilities

Source: Hayes (2014)

Figure 6 is an illustration of the broad categories of data sources that serve as core inputs to big data analytics capabilities. Building on this overview, Table 5 provides a more detailed breakdown of these sources, distinguishing between internal and external data, as well as between structured and unstructured formats, to demonstrate how both human- and machine-generated data contribute to the analytics process.

Table 5: Data sources

Source: Authors own compilation based on (Eisenhardt and Martin, 2017; Teece, 2018; Wamba et al., 2021)

Data source	Structured	Unstructured
Internal	Human-generated	Human-generated

	Survey ratings and customer satisfaction forms	Internal emails, reports, memos
	HR testing data (advantage reviews, skills)	Meeting transcripts (Teams, Zoom recordings)
	Customer loyalty databases (CRM)	Employee feedback (focus groups, open-ended surveys)
	Machine-Generated	Machine-Generated
	ERP transactions: sales, procurement, finance	Video surveillance (CCTV)
	Web traffic logs and clickstream (internal apps)	IoT sensor streams (Industrial equipment, smart buildings)
	Supply chain data (inventory, lead times)	Social media text/images from internal campaigns
	Process control data from manufacturing	
External	Human-generated	Human-generated
	Social media engagement metrics (likes, shares, retweets)	Social media posts (Twitter, Facebook, Instagram)
	Ratings on platforms (Google, Yelp, Hello Peter)	Public comments in news media and forums
	Industry benchmarking surveys	YouTube videos, customer video reviews
	Government reports and open datasets	Blogs, influencer content
	Machine-generated	Machine-generated
	Public web clickstream data	GPS/location metadata from mobile apps
	Smart device sensor data (external partnerships)	Live feeds from external systems (e.g., logistics, telco networks)
	Government open data portals (e.g., Data.gov.za, SA Stats)	

As shown in the above Table 5 and the Figure 6, big data analytics capabilities draw upon a rich and diverse set of data sources categorised along two main dimensions: internal versus external origin, and structured versus unstructured format (Gupta and George, 2016; Mikalef et al., 2021; Wamba, Queiroz et al., 2023). Systematised internal information like enterprise resource planning (ERP) transactional data, human resources databases, and customer satisfaction scores constitute the indispensable foundation for descriptive and predictive analytics. Unstructured information like voice calls, emails, meeting transcripts, social media posts, and internet of things (IoT) sensor streams require advanced analytical methods to extract its business value (Framnes and Danielsen, 2017).

External data sources offer another level of insight. Customer-generated content, open government data sets, competitor intelligence, and live sensor feeds all contain context and environmental sensitivity particularly valuable in rapidly changing markets such as in South Africa (Agnihotri et al., 2023; Dangale and Dagada, 2024; Maluleka and Dagada, 2024). The ability to integrate these scattered sources of information both in format and organisational terms is therefore a core skill.

Leading businesses invest in building sophisticated data architectures and extract-transform-load (ETL) pipelines that support comprehensive, real-time analytics. In South Africa, such integration is often complicated by legacy systems, fragmented data ownership, and infrastructure constraints (Calitz et al., 2017). Yet it is essential for unlocking the full potential of big data analytics capabilities driving competitive advantage. The next resource that will be discussed is technology.

2.6.2 Technology

Technology is the foundation of big data analytics capabilities, through which businesses can handle complex, large, and high-velocity data sets and conduct complex analytics (Wamba, Queiroz et al., 2021). Technology provides businesses with technological capacity and computational power to transform raw data into meaningful information that enables competitive advantage (Framnes and Danielsen, 2017). This section examines key components of technology as a tangible resource for big data analytics capabilities, including technological infrastructure, management

of unstructured data, big data ecosystems, scalability, cloud computing, and integration with organisational processes.

2.6.2.1 Technological infrastructure

Modern big data analytics capabilities rely on distributed storage technology (HDFS), distributed processing environments (Apache Spark), and cloud-based scalable platforms that accommodate real-time processing of structured and unstructured data (Agnihotri et al., 2023). As businesses generate more volumes and varieties of data, the traditional relational database cannot suffice (Framnes and Danielsen, 2017).

2.6.2.2 Unstructured data handling

One of the greatest challenges with big data systems is that up to 80% of enterprise information is unstructured, social media, sensor data, video, audio, and text (Gupta and George, 2016; Mikalef et al., 2021). Such data requires advanced analytic tools and technologies to unearth the value from these complex datasets, as conventional databases are insufficient to handle the complexity of this data. (Wamba, Queiroz et al., 2021). Businesses therefore need to adopt big data infrastructure that can cope with huge volumes of unstructured and semi-structured data (Mikalef et al., 2021).

2.6.2.3 Hadoop and big data ecosystem

Hadoop remains a key component in the modern big data ecosystem. It provides an open-source framework for distributed storage and parallel processing of large datasets (Gupta and George, 2016). The Hadoop ecosystem, including Hive, Pig, Spark, Kafka, and HBase, enables businesses to build comprehensive analytics platforms that integrate storage, processing, streaming analytics, and real-time visualisation (Framnes and Danielsen, 2017).

Yet, several pitfalls and limitations have been identified in research and practice alike. Hadoop is difficult to deploy and maintain due to its complex configuration and requirement of a steep learning curve, especially in cases where organisations lack substantial in-house data-engineering expertise (Warren and Marz, 2015). Managing distributed clusters requires advanced skills in systems administration and programming; this usually points to extremely high costs regarding training and operation. Moreover, whereas Hadoop was designed for batch-oriented workloads, it

is less efficient at real-time analytics and low-latency applications. Although frameworks such as Spark and Kafka have mitigated this limitation to a great degree, integrating them introduces additional architectural complexity.

Data security and governance are persisting concerns. The distributed nature of Hadoop environments increases exposure to privacy and access-control vulnerabilities; thus, very thorough security protocols must be implemented, a concern quite critical under regulatory frameworks such as POPIA and GDPR (Wamba, Akter et al., 2021). The system's reliance on commodity hardware can introduce performance variability and maintenance overheads, with node failures and data replication processes affecting efficiency. In developing contexts such as South Africa, infrastructure instability, intermittent power supply, and bandwidth constraints heighten these challenges, often limiting the scalability and sustainability of Hadoop deployments (Calitz et al., 2017). Finally, organisations often face integration and cost issues when aligning Hadoop with legacy enterprise systems or proprietary databases. Migrating data from traditional platforms to Hadoop clusters can be resource-intensive and time-consuming, with uncertain return on investment unless accompanied by clear analytics strategies.

Even though Hadoop and all the associated parts of the ecosystem are powerful at their core for large-scale analytics, their effective utilisation intrinsically requires technical expertise, governance maturity, and infrastructure readiness. Understanding these constraints is essential for designing realistic big data strategies that align with organisational capacity and the broader technological environment. While Hadoop addresses issues to do with storage and scalability, it lacks support for real-time processing and requires specialised skills and hence has a limited scope of use in resource-constrained firms.

2.6.2.4 Scalability and cloud computing

As data volumes grow exponentially, scalability becomes a critical requirement for sustaining big data analytics capabilities. Cloud computing platforms such as Amazon Web Services (AWS), Microsoft Azure, and Google Cloud Platform enable businesses to flexibly expand storage and processing capabilities without incurring the fixed costs of on-premises infrastructure (Agnihotri et al., 2023; Kache and Seuring, 2017). Cloud

platforms also offer advanced machine learning services, data lakes, and real-time analytics, which are essential for building competitive advantage (Mikalef et al., 2021). Nevertheless, case evidence from a South African retail bank demonstrates the risks and opportunities that come along with the migration of applications into cloud data infrastructures (Dagada, 2025b).

Cloud computing has become a cornerstone of modern big data analytics by offering on-demand access to scalable computing power, storage, and analytical tools through virtualized environments (Hashem, Yaqoob, Anuar, Mokhtar, Gani and Khan, 2015). It helps organise stores and process large datasets on cloud platforms, such as AWS, Microsoft Azure, and Google Cloud, without investing in expensive on-premise infrastructure. Cloud-based analytics allows flexible scaling, pay-per-use models, and fast deployment of machine-learning and visualisation services (Wamba, Queiroz et al., 2021).

Alongside this, edge analytics brings computation close to data sources, such as sensors, IoT devices, and local gateways in a decentralized model. This reduces latency and network congestion by processing data in near real time before sending aggregated insights to the cloud (Shi and Dustdar, 2016). As cloud and edge analytics converge, the functionality will let organisations benefit from both centralized scalability and localized responsiveness. Despite these advantages, several implementation challenges and limitations accompany cloud- and edge-based analytics solutions.

Data security and privacy remain the foremost concern. Storing and transferring sensitive data across multiple cloud or edge nodes exposes organisations to heightened cybersecurity and compliance risks. Jurisdictions such as South Africa's Protection of Personal Information Act (POPIA) and the European GDPR require strict controls over cross-border data flows, encryption, and user consent management (Calitz et al., 2017). Dependence on network reliability is another constraint. Limited or unstable broadband connectivity, particularly in developing regions, can degrade system performance, disrupt real-time analytics, and increase operational downtime (Mikalef et al., 2021).

Cost management also continues to be difficult. While cloud services reduce capital expenditures, on the operational side there is a tendency for costs to increase in the longer run. As volumes of data increase, continuous processing takes place, and firms have a dependency on specific services provided by vendors. Many businesses do not recognise data transfer and storage fees, leading to “hidden” costs that cut into projected savings. Vendor lock-in and interoperability issues can also impede flexibility. Each provider uses proprietary APIs, architecture, and security models, raising the complexity of migration or integration of services across multiple platforms.

Edge-computing limitations include constrained computational capacity, energy consumption at the device level, and the need for sophisticated orchestration between edge and cloud layers. Managing distributed analytics across heterogeneous devices requires advanced technical expertise and standardised governance mechanisms (Shi and Dustdar, 2016). This is exacerbated in the South African context by infrastructure inequality, power instability, and limited domestic data-centre capacity. Each of these limits the diffusion of the cloud or push dependence upon foreign cloud providers, which also creates sovereignty and compliance concerns in a country like South Africa. Collectively, cloud and edge analytics bring potentially transformative capabilities in terms of scalability, flexibility, and responsiveness, but their actual delivery is contingent on robust data governance, network reliability, cost management, and human skills. Organisations should thus adopt cloud and edge in a strategic manner that aligns technological choices with business objectives and local regulatory realities to sustainably develop big data capabilities. Organisations must therefore approach cloud and edge adoption strategically, aligning technological choices with business objectives and local regulatory realities to ensure sustainable big data capability development.

2.6.2.5 Integration with organisational processes

Technology does not operate in silos. To deliver maximum utility for big data analytics capabilities, businesses should integrate technology within organisational processes, data governance structures, leadership agendas, as well as human capabilities (Gupta and George, 2016; Mikalef et al., 2021). Without proper alignment, even the most advanced technologies are ineffective. Cross-functional integration is necessary, as it

enables a data-driven culture where teams collaborate across business functions to embed analytics into core processes (Wamba, Queiroz et al., 2021). This entails dismantling silos among business units, data science, and IT, and fostering collaborative flows where analytics informs marketing, supply chain, HR, finance, and executive decision-making.

Increasingly, research highlights the reality that big data analytics capabilities maturity relies on the capacity of businesses to leverage technology capabilities and convert them into valuable knowledge embedded in key business processes (Framnes and Danielsen, 2017). These processes include embedding data and analytics as key strategic business objectives (Teece, 2018), supported by tone at the top and management sponsorship to implement data-driven transformation (Mikalef et al., 2021). They also involve embedding big data analytics capabilities in management systems to promote innovation and drive a data culture (Ye, Yu and Zheng, 2022), as well as developing governance models for ensuring data quality, privacy, security, and compliance (Agnihotri et al., 2023). This is consistent with findings that ICT governance remains a critical enabler for integrating big data systems in South African corporates (Dagada, 2025b). In addition, these processes require must support fact-based decision-making at all organisational levels (Gupta and George, 2016).

Integration, however, in South Africa remains a challenge, as older legacy systems, geographically dispersed data sources, and ineffective cross-functional integration continue to exist (Calitz et al., 2017). These are constraints that must be overcome to reap the full benefit of big data analytics capabilities in addressing market volatility, regulatory challenges, and socio-economic uncertainty. The strongest businesses integrate their technology strategy into business objectives, leadership vision, and organisational culture (Wamba, Queiroz et al., 2021). This ensures that big data analytics capabilities are not treated as a stand-alone technical function but as an integral engine of business advantage.

To translate big data analytics capabilities into strategic value, businesses must also rely on a robust technological foundation. Table 6 outlines the technological stack that enables the integration of analytics with organisational processes, illustrating how

different layers; from data sources to business applications, collectively support effective analytics adoption.

Table 6: Technological stack enabling big data analytics capabilities integration with organisational processes

Source: Authors own compilation based on, Mikalef et al., 2019)

Layer	Example components	Integration focus
Business applications	CRM, ERP, supply chain, marketing automation, finance	Embedded in business functions
Analytics and AI	Machine learning, predictive modelling, NLP, optimisation	Strategic decision support
Data processing	ETL pipelines, real-time streaming (Kafka, Spark)	Timely delivery of insights
Data storage	Data lakes, cloud storage, relational databases	Unified and governed data layer
Data sources	Internal systems, IoT, external APIs, public data	Comprehensive data acquisition

As shown in Table 6, technology is the backbone of big data analytics capabilities, but its utilisation depends on whether it is integrated within the larger organisation. Businesses that develop scalable, flexible, and interlinked technology foundations that support strategic goals, and human capital will be best positioned to derive value from big data and remain competitive (Agnihotri et al., 2023).

2.6.2.6 Artificial Intelligence and Machine Learning in Big Data Analytics

In big data environments, Artificial intelligence (AI) and Machine learning (ML) have been applied in several areas such as predictive maintenance, customer segmentation, fraud detection, and risk modelling (Mikalef et al., 2021). AI and ML integration in big data systems is a critical enabler when it comes to driving data-driven innovation. Machine-learning algorithms, including deep neural networks, random forests, and gradient boosting, are employed in the discovery of hidden relationships across big datasets. AI techniques such as Neural Language Processing (NLP) and computer vision further enable unstructured data like text, audio, and images to be

analysed in real time (Wamba, Queirozet al., 2021). These technologies ensure intelligent automation and continuous organisational learning when combined with scalable architectures such as Hadoop and cloud computing.

However, with the increased use of artificial intelligence (AI) and machine learning (ML) for big data projects, many challenges and limitations arise. For example, data quality and bias continue to be significant challenges. AI models are only as good as the data that trains them, therefore, inadequate, incomplete, or biased data may result in skewed results that could indicate errors and create misleading outcomes (Shah et al., 2021). Algorithmic transparency and interpretability are additional challenges to adoption, especially in high-consequence fields such as finance and healthcare. Most AI models, particularly those depending on deep-learning approaches, remain black-box systems, which prevent a decision-maker from tracing how the output is obtained. This aspect is likely to jeopardise managerial trust in such algorithms and even regulatory compliance (Doshi-Velez and Kim, 2017). Skills and talent shortages also impede widespread adoption. Advanced analytics requires data scientists, machine-learning engineers, and domain experts who can translate model results into business strategy. In South Africa, limited access to such specialised skills slows progress toward AI maturity. This is compounded by talent migration to global markets, (Calitz et al., 2017).

Computational and infrastructure constraints also limit performance. Training large ML models requires high processing power and high storage bandwidth. These resource demands create significant cost and scalability barriers for many organisations, especially those in developing economies. Ethical and regulatory concerns have further emerged as AI becomes more pervasive, and issues such as privacy, accountability, and misuse of predictive algorithms have come to the attention of regulators and the public. Compliance with frameworks like POPIA and GDPR further complicates the governance of AI-based analytics systems (Maharaj and Pillay, 2023). Integration with existing systems poses another challenge. Many firms operate legacy databases or incompatible software architectures that prevent seamless deployment of AI and ML pipelines. Successful implementation therefore requires re-engineering of both technology and process workflows.

Despite these constraints, the possible benefits of AI and ML in big data analytics are large. Where carried out responsibly, these technologies help an organisation move from descriptive analytics, that is, what occurred to predictive and prescriptive analytics. that is, what will happen and what should be done. This capability accelerates decision-making, enhances customer experience, and offers a sustained competitive advantage in local and global markets. AI and ML adoption is increasing in the South African setting, especially in areas of high value such as financial services, telecommunications, and public administration.

However, genuinely sustained value creation from these technologies depends on governance, skills, and ethical challenges that currently prevent scalability of their deployments. In all, Artificial Intelligence and Machine Learning are the transformational extensions of big data analytics, but their effectiveness depends on high-quality data, transparent governance, adequate infrastructure, and continuous human capacity development. Organisations that invest strategically in these enablers are better positioned to transform data into intelligence and intelligence into sustainable competitive advantage.

2.6.2.7 Data Governance and Ethical Considerations

Data governance is the structural and procedural framework that defines how data is managed, protected, and utilised across its lifecycle. It encompasses policies, standards, and accountability mechanisms that ensure data quality, integrity, security, and ethical use (Fosso Wamba et al., 2020). Effective governance allows organisations to correctly align data assets with strategic objectives while meeting the legal and regulatory frameworks of a country, such as POPIA in South Africa and the GDPR in Europe. On matters of big data analytics, strong data governance cannot be compromised but must instil confidence and transparency in analytical outputs. It ensures that data collected from diverse sources, often at high velocity and volume, is accurate, secure, and used in ways that respect both individual rights and organisational accountability (Mikalef et al., 2021). Ethical data management practices reinforce confidence among stakeholders and are increasingly viewed as a source of competitive differentiation.

Despite these benefits, significant challenges and ethical dilemmas accompany the implementation of data governance frameworks. The variety and volume of data sourced from IoT devices, social media, customer transactions, and third-party vendors complicates the creation of uniform governance structures. Many businesses lack centralised oversight or clear data ownership, thus causing fragmented accountability and inconsistent standards (Kache and Seuring, 2017). Businesses must also consider overlapping domestic and international data-protection laws.

In South Africa, POPIA requires stringent conditions for consent, data processing, and cross-border transfer. Multinational organisations operating locally also face simultaneous compliance with GDPR, creating high administrative and legal burdens (Maharaj and Pillay, 2023). With greater autonomy in analytics and AI systems, ethical risks such as data misuse, profiling, and discrimination have increased. Algorithmic decisions can replicate biases in society that are embedded in historical data or favour certain user groups, thus resulting in ethical and reputational risks (Shah et al., 2021).

Moreover, breaches, unauthorised access, and cyber threats are persistent concerns, especially in distributed and cloud environments. Poorly managed encryption and access controls can compromise data integrity, erode public trust, and result in severe regulatory penalties. Governance also involves changing employee behaviour and leadership mindsets. Many organisations struggle to embed data ethics into daily operations, relying instead on compliance checklists rather than genuine ethical awareness (Mikalef et al., 2021). Building a data stewardship culture where employees understand their ethical obligations therefore remains a major capability gap. Effective governance further requires qualified data officers, privacy specialists, and legal experts, roles that are still scarce in developing economies. Smaller organisations in particular face difficulty balancing compliance obligations with limited human and financial resources (Calitz, Poisat and Cullen, 2016).

In the South African context, governance challenges are compounded by uneven institutional capacity, limited data literacy, and fragmented digital infrastructure. Many public-sector entities in South Africa are still struggling at the early stage of formalizing their governance frameworks, often narrowly focused on compliance and not necessarily on strategic value creation from data.

Private and public organisations will need to embed governance principles within larger digital-transformation agendas, supported by the active leadership of executives and coordination across functions. From an ethical point of view, sustainable analytics relies on responsible data practices that protect privacy, ensure fairness, and advance societal benefit. International research underlines the fact that ethics need to be inbuilt throughout the data lifecycle, from collection and storage to algorithmic processing and dissemination (Floridi and Cowls, 2019).

This approach transforms ethics from a reactive compliance task into a proactive strategic capability that enhances long-term organisational legitimacy. In summary, data governance and ethics form the backbone of trustworthy big data analytics ecosystems. Effective governance combines legal compliance with moral responsibility, ensuring that analytics practices align with societal expectations and regulatory norms. Organisations that invest in building these capabilities, through leadership commitment, continuous education, and transparent accountability, are better equipped to manage risk and sustain competitive advantage in a data-driven economy. Having established the technological dimension of big data analytics capabilities, the following section explores basic resources, including time and financial investment that are essential considerations for businesses leaders seeking to build sustainable capabilities.

2.6.3 Basic Resources

The development of big data analytics capabilities relies heavily on basic resources such as financial investment, time, strategic budgeting, and infrastructural support. These foundational elements create the platform upon which more advanced capabilities can be built. However, they also present unique challenges, particularly in the South African context where businesses often operate under conditions of economic uncertainty, infrastructure constraints, and skills shortages.

2.6.3.1 Financial Investment and Time

Time and financial investment are required to develop big data analytics capabilities. Without proper funding and sufficient time, it becomes difficult for businesses to build

the necessary infrastructure, develop skills, and change internal operations (Gupta and George, 2016). Building effective big data analytics capabilities involves far more than the procurement of software or hardware. It requires continuous organisational investment in experimentation, skills development, knowledge creation, and the gradual embedding of analytics into decision-making processes.

The benefits of big data analytics capabilities are therefore not immediate. Businesses need time to move from basic data collection and technology acquisition towards more mature forms of analytics use. Early stages often involve pilot projects, fragmented insights, and learning through trial and error. Over time, these efforts can develop into stronger organisational routines, better data governance, improved analytical literacy, and more informed decision-making.

Longitudinal studies show that initial big data analytics capability initiatives often experience setbacks due to immature data infrastructure, skills shortages, organisational resistance, and low analytic literacy among managers (Calitz et al., 2017). Businesses that treat big data analytics capabilities as short-term information technology projects often fail to achieve meaningful impact. In contrast, those with a long-term strategic focus, typically over a three-to-five-year period, are better positioned to build sustainable analytics competencies (Mikalef et al., 2021).

2.6.3.2 Strategic Budgeting and Differentiation from Information Technology

Strategic budgeting is important because big data analytics capabilities require a different form of investment from traditional information technology projects. While traditional information technology investments often focus on system stability, efficiency, automation, and operational support, big data analytics investments are directed towards insight generation, innovation, experimentation, and strategic responsiveness.

For this reason, Framnes and Danielsen (2017) argue that big data investments should be allocated separate budgets from other technology projects because their strategic purposes differ. Big data investments help businesses uncover insights, identify patterns, improve decision-making, and respond more flexibly to changing market conditions. Traditional information technology projects, by comparison, often

aim to improve efficiency and maintain stability, which are important but may not, on their own, create long-term competitiveness.

A separate budgeting approach allows businesses to accommodate the uncertain and experimental nature of big data analytics projects. It also protects core information technology functions from disruption while giving analytics initiatives the flexibility to evolve through testing, learning, and refinement. This is particularly important because returns from big data analytics investments are not always immediate or guaranteed in the same way as traditional information technology projects.

Organisational adaptation is therefore central to the development of big data analytics capabilities. It is not sufficient for businesses to invest in modern technologies or hire skilled data professionals. Meaningful transformation requires changes in how work is done, how decisions are made, and how different parts of the business collaborate. This includes rethinking established processes, reshaping decision-making norms, aligning leadership priorities with data-driven goals, and encouraging stronger cooperation across departments (Framnes and Danielsen, 2017).

2.6.3.3 Barriers in Developing Economies and the South African Context

In developing economies, the development of big data analytics capabilities is often more complex because businesses face structural and resource-related constraints. In South Africa, many businesses still operate with outdated infrastructure, fragmented data systems, and inconsistent levels of digital readiness across sectors. These conditions make it more difficult to establish integrated and adaptable analytics capabilities (Calitz et al., 2017).

Similar challenges are reflected in South Africa's broader industrialisation debates, where shortages of skilled labour and rigid macroeconomic conditions may hinder technological advancement (Dagada and Lekaba, 2024). Businesses also face economic uncertainty, limited access to specialised data skills, and pressure to justify investments that may only produce visible returns over time. These conditions make sustained commitment especially important.

The South African context therefore requires executive and board-level direction. Leadership must understand that big data analytics capability development is not a once-off technology purchase, but a long-term organisational capability-building process. It requires phased investment, patience, and the willingness to learn from early setbacks. In environments where infrastructure and talent gaps remain significant, businesses need to build maturity gradually rather than expecting immediate competitive returns (Calitz et al., 2017; Srinivasan and Swink, 2018).

Literature consistently indicates that big data analytics capability development is a long-term goal and entails more than financial investment. It requires vision, commitment, and effective leadership (Gupta and George, 2016; Mikalef et al., 2021). While technological tools and systems are essential, they do not guarantee success on their own. The effectiveness of big data analytics capabilities depends on skilled individuals who can interpret complex data, extract valuable insights, and apply those insights in ways that support organisational goals. Without these human skills, the potential of big data cannot be fully realised, and even the best tools may fail to produce meaningful value (Gupta and George, 2016; Mikalef et al., 2021).

2.6.3.4 Investment Horizon for Big Data Analytics Capabilities Development

Developing big data analytics capabilities requires sustained financial and strategic commitment over time. In contexts such as South Africa, where infrastructure and talent challenges persist, investments need to be phased so that organisations can build maturity gradually (Dagada, 2025a; Subramoney and Dagada, 2025). Table 7 illustrates a typical investment horizon, showing how short, medium, and long-term efforts translate into organisational outcomes.

Table 7: Investment horizon for big data analytics capabilities development

Source: Authors own compilation based on Barney, 1991; Gupta and George, 2016; Porter, 2008; Wamba et al., 2021)

Time horizon	Key focus areas	Typical outcomes
Short-term (0–12 months)	Technology acquisition, initial data integration, pilot analytics projects	Isolated insights, proof-of-concept, learning phase

Medium-term (1–3 years)	Skills development, organisational process redesign, building data governance	Embedded analytics in core functions, early advantage gains
Long-term (3–5 years)	Strategic integration, advanced analytics, dynamic capabilities, cultural transformation	Sustained competitive advantage, agility, innovation

As reflected in Table 7, the competitive value of big data analytics capabilities does not materialise immediately but develop over a multi-year trajectory. Short-term efforts often produce isolated insights and learning opportunities. Medium-term investments begin to embed analytics into organisational functions, while long-term commitment enables analytics to support sustained competitive advantage, agility, and innovation.

This investment horizon is particularly relevant to South African businesses, where economic volatility, talent shortages, and infrastructure gaps may slow the development of analytics maturity. These challenges do not mean that big data analytics capabilities are unattainable. Rather, they suggest that organisations need phased investment, strong leadership, and strategic persistence to realise value over time.

2.6.3.5 Summary of Basic Resources

This section has shown that basic resources form an essential foundation for the development of big data analytics capabilities. Financial investment, time, strategic budgeting, and infrastructure provide the conditions required for businesses to acquire technology, develop skills, improve data systems, and embed analytics into organisational routines.

The discussion also highlighted that big data analytics investments should not be treated as ordinary information technology projects. Unlike traditional information technology investments, which often focus on stability and operational efficiency, big data analytics investments are more closely linked to experimentation, learning, innovation, and strategic decision-making. For this reason, they require dedicated budgets, long-term planning, and sustained leadership support.

In the South African context, the development of big data analytics capabilities is further complicated by economic uncertainty, skills shortages, fragmented infrastructure, and uneven digital readiness. These barriers make it necessary for businesses to adopt a phased and patient approach to capability development. The value of big data analytics capabilities is therefore likely to emerge gradually, with competitive benefits becoming clearer only after sustained investment and organisational learning. Building on this foundation, the next section examines human skills as another critical pillar in the development of big data analytics capabilities.

2.6.3.6 Summary of tangible resources

Tangible resources which are data, technology, and basic resources are foundational to building effective big data analytics capabilities. However, their strategic value is realised only when these resources are combined with skilled human resources and an enabling organisational culture. These tangible resources form the foundational infrastructure that enables the deployment of big data analytics capabilities, facilitating the development of dynamic capabilities (H1) and operational capabilities (H3). The following sections therefore examine human skills and intangible resources as additional pillars of big data analytics capabilities development.

2.6.4 Human skills

Skilled professionals, including data analysts, data scientists, engineers, and domain experts provide the technical expertise needed to transform raw data into actionable intelligence (Corea, 2019). Equally important are managerial skills, which ensure that analytics outputs are aligned with organisational strategy and drive business impact (Davenport and Patil, 2012). In South Africa there is a shortage of analytics skills in the technical and managerial space thus presenting significant barriers to big data analytics capabilities development (McKinsey, 2016). The following sections discuss these skills:

2.6.4.1 Technical skills

Technical skills form the operational backbone of big data analytics capabilities, enabling businesses to design, develop, and deploy analytics processes and systems (Corea, 2019). These skills typically include data engineering and architecture, data analysis and statistical modelling, machine learning (ML) and artificial intelligence (AI)

techniques, visualisation and reporting tools, as well as data governance and quality management (Framnes and Danielsen, 2017).

2.6.4.1.1 Core technical competencies

Technical personnel including data scientists, analysts, engineers, and machine learning experts enable businesses to transform large, complex datasets into meaningful insights (Mikalef et al., 2021). Therefore, technical skills in programming languages such as Python, R, and SQL, distributed platforms such as Hadoop and Spark, and cloud services are now vital (Agnihotri et al., 2023).

2.6.4.1.2 The talent shortage challenge

A global shortage of these advanced technical skills is one of the most cited obstacles to big data analytics capabilities (Corea, 2019). In developing markets like South Africa, talent shortages prevail, with universities not producing enough skills to match the demand especially in the data analytics and data science fields (Calitz et al., 2017). To fill these gaps businesses are developing their employees in online digital skills with access to online learning platforms such as Udemy, Coursera and edX (Sultana, Akter and Kyriazis, 2024). Additionally, employers are investing in local and blended training comprising both technical and practical skills for their employees (Ubara, 2025). Furthermore, they are also investing in technical and practical data training and upskilling journeyman data professionals so as to develop greater collaboration across the workforce. These skills enable a greater level of data literacy across organisations.

2.6.4.1.3 The dynamic nature of technology skills

Given the fast-evolving nature of big data technologies (e.g., explainable AI, edge computing), technical skills must be constantly updated (Wamba, Queiroz et al., 2021). Businesses that cultivate continuous learning cultures among technical teams are better positioned to maintain competitive advantage (Ubara, 2025).

2.6.4.2 Managerial skills

According to Akter (2016), managers can be grouped into technology and strategic managers. Both types discussed below are essential to deriving competitive value from big data analytics capabilities.

2.6.4.2.1 Technology managers

Technology managers focus on architecture and platform integration (Akter, 2016). Recent studies show that managerial capabilities, especially tacit knowledge and leadership experience, form a difficult-to-imitate source of sustained competitive advantage (Gupta and George, 2016; Ubara, 2025). While technical competence powers the big data analytics infrastructure, managerial competences determine how data insights are interpreted, communicated, and used for strategic advantage (Framnes and Danielsen, 2017; Gupta and George, 2016). Managerial competences are experienced-based and context-specific, driven by industry expertise, leadership experience, and strategic vision (Janssen, van der Voort and Wahyudi, 2017).

2.6.4.2.2 Strategic managers

The development and use of big data analytics capabilities relies heavily on a set of core competencies that go beyond technical expertise. These include the ability to strategically align analytics initiatives with broader business priorities, ensuring that data efforts are not operating in isolation but are instead contributing directly to organisational goals. To achieve this alignment, there must be constant coordination between the management and analytics teams to ensure a mutual understanding of the strategic goals, with analytics as the enabler. Additionally, data-driven innovation is essential to drive business goals. This can be possible through recognising new areas to target for better or new market opportunities, such as new products or customers (Arthur, 2013). Being able to translate data signals into practical innovation opportunities separates mature data-driven businesses from those merely experimenting.

The role of strategic managers is therefore key in businesses that are building big data analytics capabilities. Strategic managers are the link between the analytics specialists who focus on data processing, modelling, and technical reports and top business executives, who make strategic and operational choices. The role of strategic managers is thus not a role of coordination, but translation, alignment, and integration.

Managers in this field are responsible for making sure that the findings of analytics teams are not just technically valid but also strategically relevant. For example, data might reveal changes in customer behaviour or operating limitations, however without

the guidance of a strategy, this type of information can remain undeveloped. The manager channels the analytics output into significant areas like product development by identifying customer needs that shape new features or services. Through this, analytics is made a significant driver of innovation. Managers also contribute to improving operational efficiency. This can involve using analytics to improve supply chains, strengthen areas of cost savings, or improve resource allocation. By ensuring that such insights are acted upon, managers help drive data into tangible operational advantages.

Another significant field is market responsiveness. Strategic managers facilitate their businesses to be more responsive and faster at reacting to changes in the market, using trends in data for informing pricing, customer engagement, or competition positioning strategies. This type of responsiveness is even more important in rapid-changing business environments where delayed decisions can lead to lost opportunities or strategic mishaps. Finally, these managers reinforce big data analytics to drive business needs and make informed decisions that create competitive advantage and growth (Gupta and George, 2016; Sultana et al., 2024).

2.6.4.2.3 Communication and collaboration

One of the key managerial skills is the ability to effectively communicate analytics insights to non-analytical stakeholders (Hussinki et al., 2025). Managers create cross-functional teams through which analytics are incorporated into daily business decisions (Framnes and Danielsen, 2017). Cross-functional leadership is also crucial to ensure collaboration and that data silos are broken down as the information flows through the business units. Leaders must lead in the field of data by talking the data language and translating the language to their juniors. Setting the data tone at the top is necessary to drive a data-driven workforce. Embracing the big data concept is of crucial importance when establishing a data culture. Decisions that are data-driven must be encouraged at all levels to improve the tone within the organisation. Strong data culture facilitates improved use of insights, decision-making with greater confidence, and value creation in the long term (Akter, 2016; Schubert and Barrett, 2024).

2.6.4.3 Summary of human skills

Both managerial and technical skills are essential for big data analytics capabilities success. As technical professionals develop the analytic ability to handle intricate data, managerial leaders ensure that strategic relevance is maintained in insights, that they are communicated appropriately, and they are embedded within decision-making processes. The degree to which a business can build such supportive capabilities through continuous learning, inter-unit collaboration, and leadership commitment will define its ability for using big data analytics capabilities into sustainable competitive advantage (Framnes and Danielsen, 2017). These human skills directly support the agility and adaptability required in dynamic capabilities (H1), while also enhancing the efficiency of operational capabilities (H3) such as marketing and technology functions. Notably, while human ability makes businesses capable of managing and performing big data processes, these efforts are subject to the organisation's internal environment, more broadly, its learning ability and commitment to a data-focused culture. Intangible but incredibly powerful, these resources (discussed below) become the foundation for the development of long-term capabilities and innovation.

2.6.5 Intangible resources

In addition to human and physical assets, organisational learning and data driven culture are also envisioned in the literature as central to big data analytics capabilities formation (Framnes and Danielsen, 2017; Mikalef et al., 2021). These assets define the extent to which an organisation can adopt data analytics into its functional and strategic framework (Subramoney and Dagada, 2024; Dagada, 2025b). Businesses that have ongoing learning resources and a strong data-centric culture are likely to achieve long-term value from their data assets, be adaptive to evolving environments, and achieve competitive advantage (Agnihotri et al., 2023). One of the critical pillars in this category is organisational learning, discussed below.

2.6.5.1 Organisational learning

Organisational learning refers to ongoing ability to transform and improve analysis practices (tools, workflows, and processes), according to shifting markets and the development of modern technology (Teece, Pisano and Shuen, 1997). It further facilitates big data analytics capabilities, for businesses to learn, innovate, and remain competitive in high-data environments (Mikalef et al., 2021). It is also key to

embedding big data analytics capabilities into the everyday workings of the business rather than keeping it confined to isolated projects. This ongoing integration allows data insights to inform decisions across departments, helping businesses respond more effectively to change and build resilience over time (Orero-Blat, Leal Rodríguez, & Palacios-Marqués, 2025)).

Following the dynamic capabilities theory (Teece, 2018), organisational learning allows the continuous development of a business's internal resources such as personnel, processes, and information systems based on knowledge gained from data (Mikalef et al., 2021). However, analytics alone does not provide useful outcomes, as value is generated when external data is set in the context of a business's experience and knowledge. It is this combination of data-driven knowledge with institutional knowledge that helps businesses make superior, more strategic decisions. Businesses that combine these elements effectively can make better decisions and respond more strategically to change (Gupta and George, 2016; Janssen et al., 2017; Teece, 2018). At its core, organisational learning provides the flexibility that big data analytics capabilities need to thrive. It supports the realignment of people and processes, helps connect analytics to real-world experience, and embeds data thinking into everyday work. These elements together create a foundation for continuous adaptation and long-term strategic benefit (Mikalef et al 2021).

2.6.5.2 Data driven culture

The next intangible resource is data-driven culture. A sound data-driven culture (DDC) supports the development of big data analytics capabilities. It shapes the use of data, how much people trust the results, and whether insights are applied across the organisation (Gupta and George, 2016). When people trust the quality of data and believe the analysis is fair, they are more likely to use it. In businesses with a strong data-driven culture, staff rely on data rather than guesswork, which reduces the influence of opinion and encourages more consistent decision-making (Schubert and Barrett, 2024).

Being clear about how data is collected and interpreted builds confidence. If employees understand the process behind the data, they are more likely to trust the

results and take responsibility for the decisions they make. Openness in reporting and explaining outcomes also improves internal accountability (Alaskar, Mezghani and Alsadi, 2021). Therefore, a culture that encourages learning helps employees to become comfortable when working with data. Training sessions, mentoring, and internal discussions make it easier for staff to use analytics in their work. As more employees improve their data skills, the benefits of big data analytics capabilities can be spread more widely across the organisation (Gupta and George, 2016; Mikalef et al., 2021).

Moreover, for analytics to be effective, the work done by data teams must be connected to real business priorities. A strong data-driven culture supports this by keeping data projects focused on solving practical problems and achieving outcomes that matter to the organisation (Schubert and Barrett, 2024). Using data responsibly is also essential. In South Africa, the Protection of Personal Information Act (POPIA) sets out rules for how companies should collect, store, and use personal information. These laws are like Europe's GDPR and are designed to protect people's rights (Custers and Ursic, 2016). Failing to follow these laws can cause serious problems such as legal action, fines, reputational damage, and a loss of customer trust. Ethical concerns are also growing. For example, if data systems are built on biased information, they can make unfair decisions that affect specific groups (Hussinki et. al., 2025).

To avoid this, businesses need clear rules about how data is handled. They also need to make fairness, honesty, and transparency a normal part of how they work with data. This helps protect both the business and the people it serves (Mikalef et al., 2021). In South Africa, issues around inequality are prevalent, making it vital to ensure that the digital divide is not worsened and that disadvantaged and vulnerable groups are not excluded from data uptake. By using data in fair and inclusive ways, long-term value can be supported. In summary, a strong data culture helps businesses make the most of their analytics by building trust in data, supporting objective decisions, encouraging openness and responsibility, improving data skills across the business, and keeping data work aligned with company goals. Without this kind of culture, even the best technology and skilled staff may not lead to meaningful results (Alaskar et al., 2021). For this reason, building a culture that supports data use is a key task for leadership.

It also prepares the organisation to take on more advanced capabilities, as discussed in the next section.

2.6.5.3 Summary of intangible resources

Together, organisational learning and a data-driven culture are essential for realising the full potential of big data analytics capabilities. They impact on how physical and human resources are utilised to drive analytic capabilities to achieve sustainable competitive advantage for strategic and operational efficiencies. Businesses that invest in these abstract resources obtain dynamic capabilities that underpin long-term competitive advantage particularly in dynamic environments such as South Africa (Schubert and Barrett, 2024). Organisational Learning and Data-Driven Culture are together essential pillars that enable businesses to fully unleash the potential of their big data analytics capabilities. These two intangible resources affect not only the way tangible and human resources are leveraged, but also the way analytics capabilities evolve and settle in the strategic and operational fabric of an organisation (Framnes and Danielsen, 2017; Mikalef et al., 2021).

Organisational learning provides businesses with the dynamic ability to continuously absorb new knowledge, adapt to emerging technologies, and reconfigure resources in line with market shifts and evolving customer needs (Gupta and George, 2016; Teece, 2017). A strong learning orientation enables businesses to move beyond isolated analytics projects fostering an integrated, business-wide capabilities that supports innovation, agility, and resilience. Similarly, a data-driven culture lays the social and behavioural foundations that drive widespread adoption of data-based decision-making (Mikalef et al., 2021). Data driven culture ensures data insights are trusted, valued, and acted upon by all employees thereby closing the gap between analytics output and business results (Alaskar et al., 2021).

Interestingly, organisational learning and a data driven culture complement each other. A data driven culture is enabled by organisational learning through promoting ongoing analytics training and literacy (Framnes and Danielsen, 2017). A well-established data driven culture, in contrast, facilitates organisational learning by embracing new data-derived ideas and a culture of ongoing improvement (Gupta and George, 2016). Businesses that continually invest in such forms of intangible resources will tend

to have stronger dynamic capabilities i.e. the sensing, seizing, and transforming, which lie at the centre of sustainable competitive advantage, particularly in turbulent, resource-constrained economies such as South Africa (Schubert and Barrett, 2024).

Without those intangible resources, even advanced data infrastructure and technical abilities can remain incapable of providing impact, with insights going unrealised, siloed, or not linked to central decision-making streams (Wamba, Queirozet al., 2021). Thus, organisational learning and data driven culture are force multipliers for big data analytics capabilities as they accelerate their strategic value, raise their alignment with business agendas, and repair long-term competitive advantage. These intangible resources strengthen the business's ability to sense and respond to market changes, thereby enhancing dynamic capabilities (H1) and indirectly contributing to competitive advantage (H2).

2.6.6 Summary of resources for big data analytics capabilities

In summary, the literature clearly demonstrates that effective big data analytics capabilities are built upon a combination of tangible, human, and intangible resources. Visible assets like data, technology, and core investment of finance and time provide the infrastructure support to handle advanced analytics. Technical and managerial human capabilities enable businesses to convert data into insights and infuse analytics in decision-making. Invisible assets like organisational learning and data culture enable adaptability, ongoing improvement, and strategy alignment, required to sustain big data analytics capabilities overall (Maluleka and Dagada, 2024). Significantly, these resource categories are highly reinforcing and interdependent with each other. Businesses that can synergistically integrate and manage these resources' dimensions are in a better position to construct the dynamic and operational capabilities driving competitive advantage. The subsequent section now discusses these strategic pathways in more detail.

2.6.7 Strategic pathways linking big data analytics capabilities to competitive advantage.

The literature provides evidence that big data analytics capabilities achieve competitive advantage through two mediating mechanisms: dynamic capabilities (sensing, seizing, transforming) and operational capabilities (marketing and

technological capabilities) (Teece, 2018; Wamba et al., 2023). Existing studies identify three key outcomes through which big data analytics capabilities contribute to competitive advantage. The first is operational agility, which enables businesses to respond effectively to market changes and external disruptions. The second is informed decision-making, where data-driven insights guide both strategic and tactical choices. The third is enhanced customer insight, which supports more individualised and focused customer engagement.

In this study, big data analytics capabilities are hypothesised to comprise three dimensions: tangible resources (foundational resources, information, technology), human skills (technical and managerial), and intangible resources (data culture and organisational learning). These resources enable businesses to build both dynamic and operational capabilities that drive sustainable competitive advantage, a relationship particularly applicable in dynamic and resource-constrained settings such as South Africa (Wamba et al., 2023). The competitive edge of big data analytics capabilities lies not only in its ability to process and analyse data, but also in the pathways it creates for agility, informed decision-making, and customer-focused value creation (Mikalef et al., 2021). Through these mechanisms, big data analytics capabilities strengthen both dynamic capabilities and operational excellence in marketing and technology, providing businesses with superior adaptability, innovation, and customer value creation in competitive markets. The following sub-sections examine these two key capability pathways in greater depth.

2.6.8 Dynamic capabilities

Dynamic capabilities are defined as “the business’s ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments” (Teece, et al., 1997). In the context of big data analytics capabilities, dynamic capabilities enable businesses to continually sense new opportunities, seize them through resource reallocation, and transform existing routines and processes to maintain competitive advantage (Teece, 2018). This is especially important in data-driven, dynamic markets such as South Africa, where agility and innovation are essential for sustained advantage (Mikalef et al., 2021).

2.6.8.1 Theoretical foundations

Dynamic capabilities theory emerged to address limitations in the resource-based view, which was criticised for its static orientation and lack of attention to how businesses adapt resources in dynamic environments (Helfat and Peteraf, 2003; Pitelis and Wang, 2023). Dynamic capabilities provide a template for understanding how businesses generate, renew, and recreate resources in three basic activities: sensing, seizing, and transforming (Ertl, Setzke, Böhm and Krcmar, 2020). In this study, dynamic capabilities were conceptualised as mediators between big data analytics capabilities and competitive advantage, as outlined in Hypotheses 1 and 2 (Teece, et al., 1997; Teece, 2007).

2.6.8.2 Sensing

Sensing is central to dynamic capabilities, that is, the ability of an organisation to sense, interpret, and anticipate emergent opportunities and threats (Teece, 2007). Big data analytics capabilities enhance sensing capabilities through real-time analytics, environmental scanning, and predictive insights (Agnihotri et al., 2023). Businesses with strong sensing capabilities use big data analytics capabilities tools such as artificial intelligence (AI), machine learning, and neural processing language to monitor shifting customer preferences, market trends, and competitor moves (Mikalef and Pateli, 2017). For instance, South African retailers are increasingly using big data to detect new consumer demand patterns and adjust offerings accordingly (Dritsas and Trigka, 2025). However, sensing is not purely technological. It requires organisational-wide participation where employees at all levels contribute to environmental awareness and insight generation (Ertl et.al., 2020).

2.6.8.3 Seizing

Seizing refers to an organisation's ability to mobilise resources and implement strategies that capture new opportunities (Teece, 2018). Big data analytics capabilities support seizing by providing intelligence that guides resource allocation, product development, and market entry decisions (Mikalef et al., 2021; Wamba, Queirozet al., 2021). Building such capabilities carries with it some level of risk and haste especially in the unstable South African context where companies need to be agile but not in a random manner (Calitz et al., 2017). Banks, for instance, are using big data analytics capabilities to identify untapped markets and develop customer-led propositions

(Akter, Wamba, Gunasekaran, Dubey and Childe, 2016). In manufacturing, predictive analytics leads transformation toward predictive maintenance that boosts productivity (Teece 2018). Seizing requires marketplace legitimation, whereby companies must make sure that the products match customer demands and deliver value (Hussinki et. al., 2025).

2.6.8.4 Transforming

Transforming involves the ongoing reconfiguration of a business's resource base, operational routines, and capabilities (Teece et al., 1997; Wilden, Gudergan, Nielsen and Lings, 2013). Big data analytics capabilities provide critical inputs to this process by informing strategic adjustments and organisational renewal. Transformation is continuous; and in today's data-driven economy, businesses must adapt business models, technologies, and customer experiences on an ongoing basis (Framnes and Danielsen, 2017). Furthermore, while dynamic capabilities such as transforming emphasise how organisations renew and adapt their strategic direction, they must be complemented by the ability to deliver consistent performance in everyday operations. This is where operational capabilities become essential. They translate strategic insights and adaptive capacity into efficient processes and reliable outputs, ensuring that the benefits of big data analytics are embedded in the organisation's daily functioning.

2.6.9 Operational capabilities

Operational capabilities represent an organisation's ability to perform its day-to-day business activities effectively and efficiently (Wilden, et al., 2013). Whilst dynamic capabilities focus on adaptability and strategic renewal, operational capabilities enable the delivery of high-quality, cost-effective, and timely outputs forming the executorial cornerstone of big data analytics capabilities-driven strategies (Teece, 2017). Operational capabilities, such as marketing and technological functions, differ from dynamic capabilities in that they focus on performing existing activities efficiently rather than reconfiguring them to adapt to change (Winter, 2003). Therefore, while dynamic capabilities are about strategic renewal, operational capabilities are about routine execution.

There are two categories of operational capabilities in big data analytics studies: marketing capabilities and technological capabilities (Gupta and George, 2016; Mikalef et al., 2021). The capacities enable businesses to convert big data analysis into operational efficiency and customer value. One of the facilitators of operational capabilities is information technology (IT). Advanced analytics, enterprise resource planning (ERP) systems, and AI software enhance operational processes by enhancing coordination, speed, and decision-making with data (Ye, Yu and Zheng, 2022). IT-enabled operational capabilities provide near-term advantage gain and, if embedded with unique tacit knowledge, more sustainable competitive advantages (Framnes and Danielsen, 2017).

However, empirical evidence in emerging and resource-constrained contexts suggests that the link between operational capabilities and sustained competitive advantage is not always consistent. Factors such as infrastructure limitations, skills shortages, and volatile market conditions can restrict the extent to which operational efficiencies translate into long-term advantage gains (Calitz et al., 2017; Mikalef et al., 2021). This potential variability is particularly relevant in the South African context and is reflected in the study's examination of Hypothesis 4. In this study, operational capabilities, specifically marketing and technological capabilities are hypothesised to be influenced by big data analytics capabilities(H3) and to impact competitive advantage (H4).

2.6.9.1 Marketing capabilities

Marketing capabilities involve using data-driven insights to optimise market segmentation, customer targeting, relationship marketing, and brand management (Wamba, Queiroz et al., 2021). Big data analytics capabilities support marketing capabilities by enabling precise market segmentation through advanced customer analytics (Framnes and Danielsen, 2017). They enhance, the creation of personalised customer experiences tailored through predictive models, real-time customer engagement via omnichannel platforms, and the optimisation of marketing campaigns that leverage behavioural data and conversion metrics (Agnihotri et al., 2023). In South Africa's competitive retail and financial sectors, big data analytics driven marketing capabilities are helping businesses achieve differentiation and customer loyalty by creating highly tailored offerings (Mikalef et al., 2021).

2.6.9.2 Technological capabilities

Technological capabilities refer to a business's ability to integrate emerging technologies and boost operational workflows (Mikalef et al., 2021). These capabilities encompass process optimisation, such as using predictive analytics for inventory management, supply chain efficiency, and dynamic pricing, cost efficiency through the automation of repetitive tasks and improved resource allocation. They enhance service delivery achieved by real-time operational adjustments that improve speed and quality (Framnes and Danielsen, 2017). For example, South African hospitals use big data analytics capabilities to optimise patient flow and resource utilisation, while e-commerce businesses apply big data to improve order fulfilment and logistics (Mikalef et al., 2021). Technological capabilities are cumulative, evolving through experience, learning-by-doing, and embedded organisational knowledge (Wu et al., 2010). Businesses with superior technological operational capabilities integrate big data analytics insights into core workflows, ensuring alignment between data-driven intelligence and operational execution.

2.6.9.3 Integrating operational and dynamic capabilities.

Operational and dynamic capabilities complement each other (Teece, 2018). Dynamic capabilities initiate strategic change, while operational capabilities enable efficient implementation. For example, resellers that identify a shift towards sustainable goods use their operational capabilities to adjust sourcing and delivery processes, while manufacturing businesses apply operational capabilities to implement predictive maintenance practices informed by sensing new technology trends. In South Africa's uncertain business environment, this convergence is especially crucial, as businesses must utilise big data analytics both to predict change through dynamic capabilities and to execute with operational excellence. This is particularly important given constraints such as human resource shortages and infrastructure deficits (Calitz et al., 2017; Mikalef et al., 2021).

While both capabilities contribute to competitive advantage, they represent distinct pathways. In this study, **H1** proposes that big data analytics capabilities and dynamic capabilities are positively correlated, while **H2** states that dynamic capabilities and competitive advantage are positively correlated. Similarly, **H3** suggests that big data analytics capabilities and operational capabilities are positively correlated, and **H4**

argues that operational capabilities and competitive advantage have a positive relationship.

2.6.10 Summary of strategic pathways

Big data analytics capabilities channel competitive advantage through two strategic processes: dynamic capabilities and operational capabilities. These channels, in combination, dictate the extent to which businesses can adapt to change, innovate, and sustain superior advantage. Dynamic capabilities involve sensing, seizing, and transforming, enabling businesses to detect emerging opportunities and threats in real-time (Teece, 2018). They mobilise resources to act on those opportunities and continuously adjust business models and processes to remain competitive (Framnes and Danielsen, 2017; Ertl et al., 2020). Operational capabilities, which include marketing and technological capabilities, ensure the efficient and effective execution of strategies informed by big data analytics, the creation of enhanced customer value through personalised marketing and superior service delivery (Agnihotri et al., 2023). They further ensure the streamlining of internal processes through cost efficiency and technology-driven innovation (Kach and Seuring, 2022).

Critically, the relationship between dynamic and operational capabilities is cyclical. Dynamic capabilities offer strategic renewal, while operational capabilities drive effective execution. At the same time, insights generated through operational capabilities (via big data analytics) provide feedback to dynamic capabilities, enabling more informed sensing and seizing (Wilden, et al., 2013). For South African businesses operating within resource-scarce and volatile markets, this integration is particularly essential. Companies that invest continuously in big data analytics capabilities, supported by both dynamic and operational capabilities, are more likely to achieve agility, innovation, and sustainable competitive advantage (Calitz, et.al 2017). This interaction in turn affects organisational advantage (Framnes and Danielsen, 2017). Against the historic research background of advantage measurement, various methods and frameworks have been established to evaluate organisational outcomes.

2.6.11 Competitive advantage

This section critically examines the most important dimensions of advantage, particularly competitive advantage as the end goal of leveraging big data analytics capabilities. Advantage is a fertile, multi-faceted construct. Scholarship addresses it differently, as greater efficacy and efficiency, marketplace success, innovation achievement, or profitability frequently benchmarked against historical baselines as well as against industry counterparts (Chang and Gurbaxani, 2012; Pavlou and El Sawy, 2011). Scholars make use of both financial indicators, such as profitability, return on assets, and revenue growth, and non-financial indicators, such as customer satisfaction, brand value, process effectiveness, and innovation capabilities.

Of particular interest is the concept of competitive advantage, involving a business's ability to surpass its rivals through more favourable market positioning, and profitability, growth, and innovation (Dangale and Dagada, 2024; Ferrier, Smith and Grimm, 1999; Lu and Ramamurthy, 2011). A sustained competitive advantage is characterised not only by capturing market share but also by defending it against imitation through superior capabilities, agility, or customer value (Teece, 2007). Importantly, competitive advantage is dynamic rather than static. Businesses must constantly adapt to shifts in customer expectations, competitor moves, technological change, and regulatory environments (Drnevich and Kriauciunas, 2011). This highlights the importance of capabilities, especially dynamic capabilities that enable sensing, seizing, and transforming during market turbulence (Mikalef, Gupta, Pappas and Krogstie, 2023).

A long-term view is essential in competitive advantage measurement. While many studies rely on quarterly or annual results, longer multi-year investigations reveal ongoing trends. This is particularly relevant to investments in big data analytics capabilities and capability development, which may have a lagged effect (Wilden, et al., 2013). Businesses are therefore forced to balance short-term benefits against strategic capability development for long-term advantage. It is also important to note that businesses may possess asymmetric capabilities, excelling in some dimensions (such as product innovation) while lagging in others (such as cost efficiency or supply chain responsiveness). For example, a company might achieve greater customer loyalty via personalisation facilitated by big data analytics capabilities yet possess

inefficient internal processes that undermine margins (Drnevich and Kriauciunas, 2011). A composite advantage metric must therefore account for such trade-offs and complexity.

Scholars argue that the measurement of competitive advantage is best approached through a balanced framework that incorporates financial outcomes such as profitability, growth, and return on investment; market outcomes such as market share and brand strength. This structure should also include operational outcomes such as efficiency, speed, and cost control; innovation results such as new products, services, and organisational flexibility; and customer consequences such as satisfaction, loyalty, and overall experience. Relative benchmarking against key competitors remains a requisite point of reference for assessing advantage, since markets are competitive arenas (Rai and Tang, 2010). In the specific instance of big data analytics capabilities, the measurement of competitive advantage is subtler. It requires attention to how dynamic and operational capabilities integrate to create benefit, for instance, how real-time analytics (operational capabilities) drive agility (dynamic capabilities), or how big data analytics capabilities underpin both. Additionally, the rapid pace of technological evolution and market change implies that companies need to watch and adapt continually, as static advantage structures do not function in a digital, data-driven context (Mikalef et al., 2021).

The integration of big data analytics capabilities, dynamic capabilities, operational capabilities, and competitive advantage is summarised in Table 8, which provides a consolidated view of the constructs and their roles within the study.

Table 8: Integrated Conceptual Framework Linking BDAC, Capabilities and Competitive Advantage

Source: Author's own synthesis based on Teece (2007; 2018); Gupta and George (2016); Mikalef et al. (2019); Wamba et al. (2021); Akter et al. (2016); Porter (2008); Barney (1991).

COMPONENT	CONSTRUCT	KEY ELEMENTS	ROLE IN THE STUDY	SUPPORTING LITERATURE
Big Data Analytics Capabilities (BDAC)	Tangible Resources	Data, technology, infrastructure	Enable data acquisition, storage, and processing	Gupta and George (2016); Mikalef et al. (2019); Wamba et al. (2021)

	Human Skills	Technical skills, managerial skills	Enable data analysis, interpretation, and decision-making	Mikalef et al. (2019); Akter et al. (2016)
	Intangible Resources	Data-driven culture, organisational learning	Support strategic use of analytics and knowledge sharing	Gupta and George (2016); Wamba et al. (2021)
Dynamic Capabilities	Sensing	Identifying opportunities and threats	Enables organisations to detect changes in the environment	Teece (2007); Teece (2018)
	Seizing	Mobilising resources to capture opportunities	Supports strategic decision-making and investment choices	Teece (2007); Eisenhardt and Martin (2017)
	Transforming	Reconfiguring resources and processes	Enables adaptation and long-term competitiveness	Teece (2007); Wamba et al. (2021)
Operational Capabilities	Marketing Capabilities	Customer insight, segmentation, positioning	Supports market responsiveness and value delivery	Morgan (2014)
	Technological Capabilities	IT systems, innovation capability	Supports implementation of analytics and operations	Mikalef et al. (2019)
	Competitive Advantage	Performance, efficiency, strategic positioning	Reflects improved firm performance and sustained advantage	Porter (2008); Barney (1991); Wamba et al. (2021)

Finally, environmental contingencies in the form of dynamism, complexity, and hostility are key moderators of the relationship between big data analytics capabilities and competitive advantage (Schilke, 2014). The ability to manage turbulent environments through superior dynamic capabilities is increasingly a key driver of sustainable advantage. In the next section, these environmental contingencies are examined in greater depth.

2.6.12 Environmental factors moderating big data analytics and competitive advantage

The relationship between big data analytics capabilities and competitive advantage is not linear or automatic but is instead influenced by a sequence of external environmental drivers. These mediate the extent to which big data analytics capabilities, dynamic capabilities, and operational capabilities are translated into superior advantage (Chen, Wang, Nevo, Jin, Wang and Chow, 2017). Both the resource-based view and dynamic capabilities theory emphasise that the environment plays a critical role in determining how internal capabilities and resources contribute to advantage outcomes (Chen et al., 2014). In this regard, businesses must not only develop big data analytics capabilities internally but also remain sensitive to external conditions that affect the efficacy of these capabilities.

The literature commonly cites three environmental dimensions as moderators of the impact of big data analytics capabilities: environmental complexity, environmental dynamism, and environmental hostility (Lin, Wu, S and Luo, 2025). These dimensions reflect the volatility and uncertainty of external variables that South African businesses must constantly address to realise the full value of their data-driven investments.

2.6.12.1 Environmental complexity

Environmental complexity is understood in terms of the range, heterogeneity, and interdependence of external forces, markets, technologies, regulatory institutions, and stakeholder expectations, that a business must contend with (Chen et al., 2014; Pavlou and El Sawy, 2011). In complex environments, big data analytics capabilities help businesses make sense of large volumes of diverse data, ambiguous signals, and integrating structured and unstructured data from multiple sources like customers, regulators, and competitors (Wilden, 2013). Studies show that in these environments',

dynamic and big data analytics capabilities have more advantage effects because they facilitate effective sense-making (Pavlou and El Sawy, 2011; Wilden and Gudergan, 2013). In less variable environments, operational excellence may suffice, and big data analytics capabilities is a less important advantage differentiator (Chen et al., 2015). In the South African context, the financial services, telecommunication, and healthcare markets have complex and dynamic regulatory landscapes (e.g., POPIA), fragmented consumer bases, and socio-political forces. In such contexts, advanced big data analytics capabilities offer a critical competence for managing such complexity and building adaptive strategies (Ye, Yu and Zheng, 2022).

2.6.12.2 Environmental dynamism

Environmental dynamism refers to the rate and unpredictability of change in markets, customer behaviours, technologies, and competitive actions (Pavlou and El Sawy, 2011; Teece, 2018). In dynamic environments, big data analytics capabilities enhance organisational agility by enabling real-time sensing of trends and market changes, supporting predictive modelling and scenario planning, and providing a foundation for rapid resource reconfiguration and innovation (Mikalef et al., 2021). In the South African context, businesses undergoing digital transformation in sectors such as retail, e-commerce, fintech, and media operate in fast-evolving consumer and competitive landscapes. Companies with well-developed big data analytics capabilities can quickly adjust products, services, and customer experiences in response to these shifts (Agnihotri et al., 2023). At the same time, the rapid advancement of Fourth Industrial Revolution (4IR) technologies has heightened exposure to cyberattacks, further complicating the data environment (Dagada, 2025b). However, dynamism also shortens the lifespan of competitive advantages, which must be constantly renewed through ongoing capability development to keep pace with adaptive competitors (Framnes and Danielsen, 2017).

2.6.12.3 Environmental hostility

Environmental hostility refers to the extent of threat, uncertainty, and competitive pressure in the external environment, including factors such as economic turbulence, regulatory complexity, talent shortages, hostile market competition, and infrastructure vulnerabilities. In hostile settings, big data analytics capabilities assist businesses in

identifying risks, strengthening operational resilience, and uncovering new opportunities even under adverse conditions (Lin et al., 2025). Dynamic capabilities and big data analytics capabilities must therefore work in tandem to manage resource scarcity and volatile market conditions (Framnes and Danielsen, 2017). In the South African context, many sectors face challenges such as socio-economic uncertainty, load-shedding, policy shifts, skills gaps, and intense market competition. Within such hostile environments, big data analytics capabilities provide a pathway to greater organisational resilience and strategic foresight, which are critical for sustaining advantage under adversity (Agnihotri et al., 2023).

2.6.12.4 Summary of environmental moderators

Complexity, dynamism, and hostility of environmental factors measure the degree to which big data analytics capabilities drive competitive excellence. Those businesses that can connect big data analytics capabilities with these external factors through the lens of continuous scanning, capabilities tuning, and strategy agility are likely to achieve sustained advantage (Pavlou and El Sawy, 2011; Wilden et al., 2013). This is particularly important for South African businesses, whose markets demonstrate structural complexity, volatility, and resource constraints (Calitz et al., 2017). Success therefore depends not only on internal big data analytics capabilities resources but also on adaptive alignment with external forces. As this section shows, environmental awareness and agility are essential complements to big data analytics capabilities, helping businesses to thrive in today's unpredictable business landscape.

2.7 SUMMARY OF CHAPTER 2

The literature review has synthesised the complex interdependencies between big data analytics capabilities, core organisational resources, dynamic and operational capabilities, external environmental drivers, and their combined influence on competitive advantage (Framnes and Danielsen, 2017). The study confirms that big data analytics capabilities alone are not necessarily identical to superior advantage. Rather, competitive advantage results from the strategic alignment of big data analytics capabilities with physical and intangible assets, human capabilities, dynamic capabilities, and operational execution. These must be coupled with responding suitably to complexity, hostility, and dynamism moderation effects (Chen et al., 2014).

As the digital economy continues to develop further, businesses must undertake an interdisciplinary approach, developing big data analytics capabilities alongside organisational learning. They should establish a data culture, and continuously enhance their sensing, seizing, and transforming capacities to remain competitive in increasingly uncertain markets (Janssen et al., 2017; West et al., 2022).

Future research should consider the implications of emerging technologies such as artificial intelligence, cloud-based analytics, and real-time data streams, and explore new organisational processes that enable agility and innovation in data-driven environments (Wamba, Queiroz et al., 2023). There also exists a necessity for greater insights into how businesses in South Africa, can overcome structural constraints to leverage big data analytics capabilities maximally for sustainable competitive advantage (Calitz et al., 2017; Subramoney and Dagada, 2025).

This chapter has established the literature-based foundation for the conceptual model of this research. The following chapter elaborates further on the theoretical framework and central conceptual models from which this research draws including resource-based theory, dynamic capabilities theory, knowledge-based theory, the capabilities maturity model, and value chain analysis which together form the conceptual framework and hypotheses of the study.

CHAPTER 3: THEORETICAL AND CONCEPTUAL FRAMEWORK

3.1 CHAPTER OVERVIEW AND INTRODUCTION

This chapter establishes the theoretical foundations of the research. Based on the literature review presented in Chapter 2, it places the research within established theories and models that explain how big data analytics capabilities create and sustain competitive advantage. The discussion begins with the most relevant theories which are the resource-based theory and the dynamic capabilities theory, followed by the supporting perspectives and critically evaluates a range of suitable theoretical models, such as the capability maturity model, the value chain analysis model, knowledge-based theory, social network theory, resource dependency theory, information processing theory, and ambidexterity theory.

Each of these theories and models offers unique lenses to view how big data analytics capabilities can be interpreted, constructed, and leveraged for competitive advantage. In this study, the resource-based and dynamic capabilities theories are applied (Subramoney and Dagada, 2025). Resource-based theory focuses on physical, intellectual, and human assets as the foundation of big data analytics capabilities, while dynamic capabilities theory builds on this by specifying how firms dynamically sense, seize, and reconfigure capabilities to adapt in chaotic environments. However, a combination of these models drove the conceptual model of this study.

This chapter develops the conceptual model outlined in Chapter 1 and elaborates further on the theoretical justification for its employment and application within this study. It describes how big data analytics capabilities influence competitive advantage through two intervening mechanisms: dynamic capabilities and operational capabilities. These theories, as discussed below, inform the development of the research model, influence the formulation of the hypotheses, and define the analytical framework that the study employed in investigating the strategic value that big data analytics capabilities add to South African businesses. By doing this, it acts as the intellectual bridge between the literature review and methodological design that follows in Chapter 4.

The chapter structure is shown in Figure 7 below:

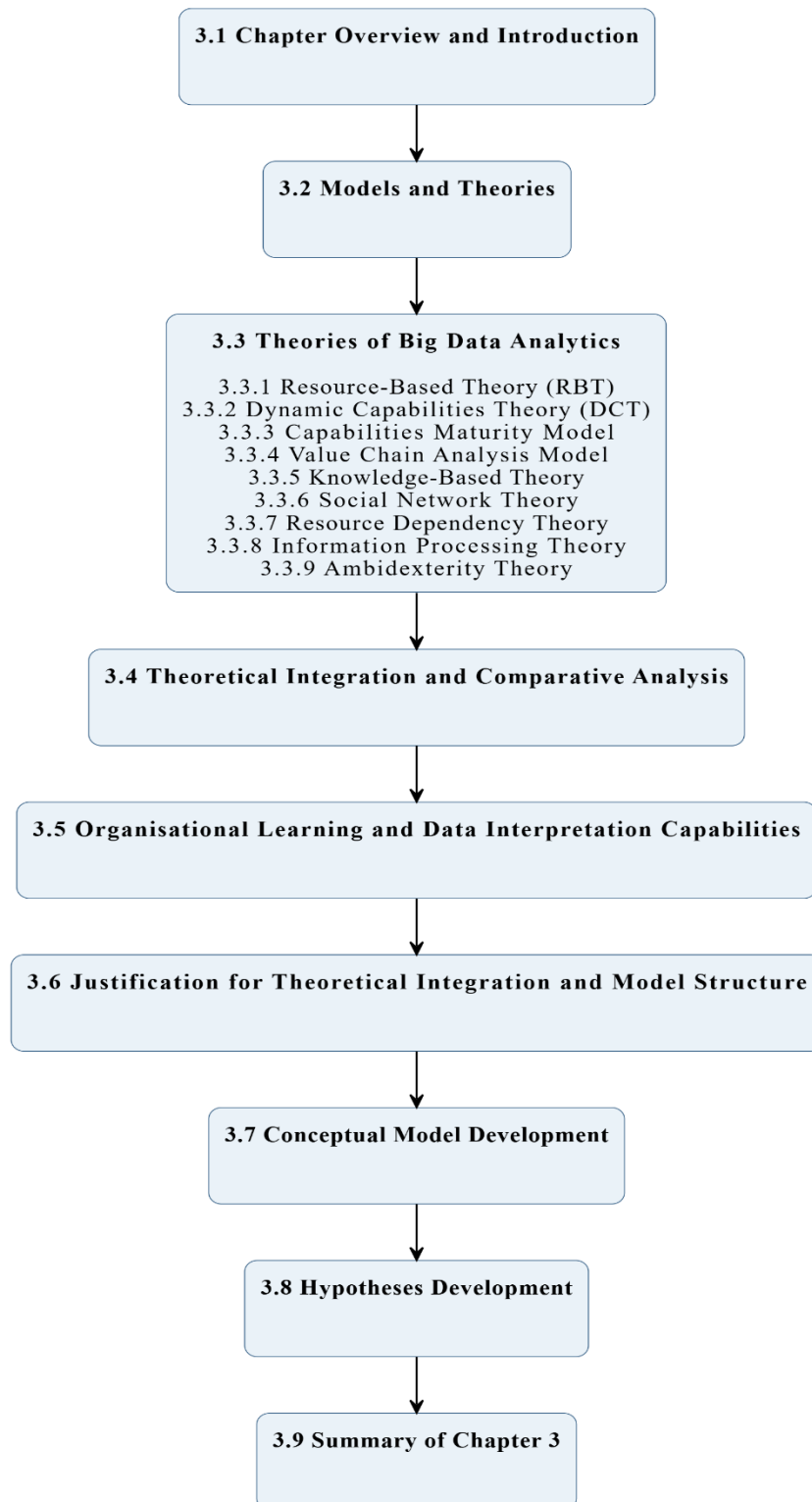


Figure 7: Overview of Chapter 3 – Theoretical and Conceptual Frameworks

Source: Author

3.2 MODELS AND THEORIES

Models and theories play a critical role in various fields of study, including science, social sciences, economics, psychology, and others (Fleck, 2016). They provide a framework for understanding complex phenomena, explaining observed phenomena, and predicting future events (Newman et al., 2021). Additionally, they guide decision-making, inform policies, and develop strategies for solving problems (Muthukrishna and Hendrich, 2019). In scientific research, models and theories help to organise and structure empirical observations into coherent explanations (Popper, 2014). Researchers use such models to simplify reality by capturing the essential features of a system, while theories are sets of related assumptions and hypotheses that explain how and why a phenomenon occurs (Muthukrishna and Hendrich, 2019). By using models and theories, researchers can make testable predictions about them, and evaluate their accuracy, leading to discoveries and advancements in various fields (Friedman, 1994; Kuhn, 1997; Newman, Obschonka, Moeller and Chandan, 2021).

In the context of analytical modelling, four categories are commonly recognised, namely descriptive, diagnostic, predictive, and prescriptive modelling (Wamba et al., 2017). Descriptive modelling focuses on summarising historical data to understand what has happened, while diagnostic modelling explains why certain outcomes occurred. Predictive modelling uses statistical and analytical techniques to forecast future outcomes, and prescriptive modelling provides recommendations on possible actions based on these predictions. While all four modelling approaches are relevant in the broader field of data analytics, this study primarily focuses on predictive modelling, as it aligns with the objective of examining and testing the relationships between big data analytics capabilities, dynamic capabilities, operational capabilities, and competitive advantage.

Several models and theories can be useful in studying big data analytic capabilities and competitive advantage. For example, the resource-based theory provides a framework for understanding how businesses can achieve competitive advantage by leveraging their internal resources and capabilities, including their data analytic capabilities (Barney, 1991).

The dynamic capabilities theory can also be useful for understanding how a company can continuously adapt and improve its data analytic capabilities to maintain their competitive advantage in a rapidly changing business environment (Teece, 2007). Other models and theories that can be useful for studying big data analytic capabilities and competitive advantage include the capabilities maturity model, which can be used to assess the level of maturity of a company's data analytic capabilities (Paulk, Curtis, Chrissis and Weber, 1993). The value chain analysis can be used to identify how data analytic capabilities can create value for customers and stakeholders (Porter, 2008). By discussing different models and theories in the research, this study demonstrated a deep understanding of the theoretical foundations of the research and the broader implications of the research findings. This also positioned the research within existing literature and identify potential areas for future research.

3.3 THEORIES OF BIG DATA ANALYTICS

In recent years, various theoretical perspectives have emerged to explain how organisations can develop, integrate, and exploit big data analytics capabilities to create value. While technical advances in analytics tools and data infrastructure are essential, it is now widely recognised that organisational, strategic, and capability-related factors determine whether businesses can achieve sustained competitive advantage through big data (Mikalef et al., 2022).

Moreover, theories in the big data domain provide insights into how businesses evolve their analytics maturity through structured capability development, how big data enables the reconfiguration of value chains, and the role of knowledge creation and sharing in data-driven organisations. They also highlight the importance of building networks and partnerships to enhance big data analytics capabilities, as well as the contribution of dynamic and ambidextrous organisational structures in fostering adaptability within volatile environments (Eisenhardt and Martin, 2017).

The following sections critically analyse the most relevant theories and models that explain the link between big data analytics capabilities and competitive advantage.

3.3.1 Resource-Based Theory

The resource-based theory originated from the original work of Edith Penrose, who contended that the capacity of a firm to expand and survive is a function of its ability to develop and realise its internal resources (Penrose, 2009). Richard Rumelt further expanded this concept by introducing the notion of strategic assets, referring to a company's resources that are challenging to duplicate or imitate (Rumelt, 1984).

This influential management framework highlights a company's internal resources and capabilities as the primary wellspring of competitive advantage. It attempts to explain why certain businesses outperform others, asserting that businesses achieve competitive advantage because they possess resources that are valuable, rare, inimitable, and non-substitutable (VRIN) (Barney, 1991). Extending Barney's work, the VRIN framework has developed into a foundation of the resource-based theory to emphasise the necessity of resources that are valuable, rare, inimitable, and non-substitutable in achieving and maintaining superior advantage. It has become one of the most popular theories across strategic management, offering insights into what drives exceptional advantage among businesses.

The theory highlights the need to invest in resources and capabilities building to achieve a long-term competitive advantage (Barney, 1991). It classifies a business's resources as tangible and intangible, and focuses on the value, rarity, imitability, and non-substitutability tests of a resource to create a competitive advantage. Successful application of the theory means that companies can achieve a sustainable competitive advantage by acquiring and maintaining valuable, rare, inimitable, and non-substitutable resources (Dagada, 2023; Subramoney and Dagada, 2024). Uniquely scarce resources that are difficult to imitate and substitute can create sustained competitive advantage. Businesses can create inimitable data analytics competence by leveraging this internally through investment in cutting-edge technologies, recruitment of skilled data scientists and analysts, robust data infrastructure, and a data-driven culture.

This model suggests that big data analytical competence can be an asset when trying to gain a competitive edge. With the utilisation of data analytics applications, business companies can reveal distinctive insights, enhance decision-making, and improve

advantage. Utilising data analytics functionality can help businesses make sound decisions, gain knowledge on customer activity, and enhance operational advantage.

The VRIN framework highlights that resources must fulfil four criteria to be considered a source of competitive advantage. They must be valuable so that they can enable a firm to capitalise on opportunities or minimise threats in its external environment. They must also be rare, such that their limited quantity in the industry gives an edge. Resources must be inimitable, meaning they are difficult for competitors to replicate, and they must be non-substitutable, with no other equally effective alternatives in the marketplace.

The theory is, however, faulted in its capacity to identify valuable, rare, inimitable, and non-substitutable resources, particularly regarding big data analytics competencies (Peteraf, 1993). The theory cannot also capture all the value of intangible assets, such as human capital and analytic capabilities, which are vital in big data analytics (Teece, 2018). Even extrinsic factors like market forces, regulatory environments, and technological innovations can significantly determine a business's competitive advantage in leveraging big data analytics capacity (Chen et al., 2015). Therefore, the theory overlooks, to some extent, the role of extrinsic drivers like market forces, industry composition, and customer requirements, which also influence the competitive advantage of a firm.

To depict the foundations of this perspective, Figure 8 presents the resource-based theory, which positions firm-specific resources and capabilities as the cornerstone of sustainable competitive advantage.

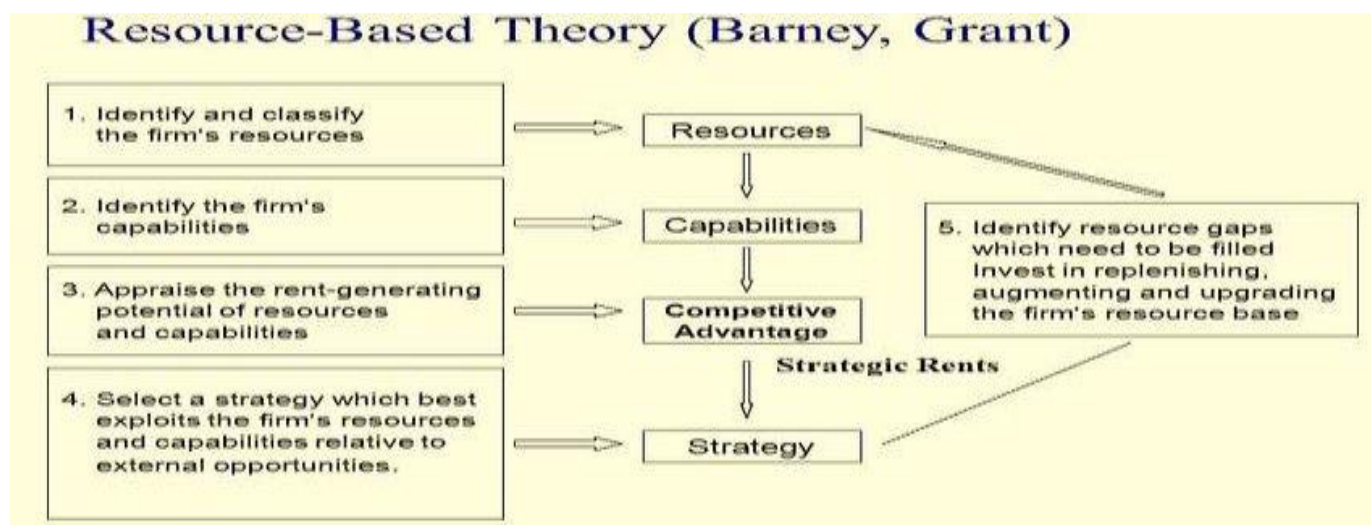


Figure 8: Resource-based theory

Source: Barney (1991)

3.3.2 Dynamic Capabilities Theory

The dynamic capabilities theory is distinct from the resource-based theory because it emphasises businesses' internal processes and capabilities as key drivers of competitive advantage. Dynamic capabilities theory brings out the importance of businesses having the capabilities to sense the changing environment, capture new opportunities, and recombine their resources and capabilities in response to shifting conditions (Teece et al., 1997). This system of management emphasises the significant role of a company's capabilities in innovating and responding to changes in the market. This suggests the need for speedy development and deployment of new data analytics capabilities for the purpose of reacting to evolving customer demands (Teece et al., 1997). It provides an integrated conceptual basis for comprehending the dynamic nature of big data analytics capabilities and their potential contribution to the creation of competitive advantage (Teece, 2007).

According to the dynamic capabilities theory perspective, businesses can gain a competitive advantage through the creation of the capacity to adapt and respond to changing market situations. In the case of big data analysis, such capabilities are fluid assets enabling businesses to process high volumes of data in a timely manner and make sound decisions (Teece et al., 1997).

One of the limitations of the dynamic capabilities theory is that it might ignore the role of stable resources and capabilities as a basis for adaptation and innovation. Specifically, big data analytics capabilities require stable assets such as a company's data infrastructure, data quality, and data management processes to effectively use big data analytics capabilities. Another criticism of the dynamic capabilities theory framework is its inability to completely account for the role of the external environment, including technological developments or changes in regulations. These may have a substantial impact on the adaptability and reaction of a firm to changing market circumstances. Public policy weaknesses are noted in South Africa's failed industrialisation and macroeconomic efforts (Dagada and Lekaba, 2024). These highlight the importance of analysing big data analytics capabilities through a contextual lens that includes national-level enablers (Dagada and Lekaba, 2024).

Although dynamic capabilities theory gives prominence to a business's capabilities to sense, seize, and reconfigure, it does not necessarily consider other factors like strategic positioning and the external environment, which can also help a firm achieve sustainable competitive advantage (Kane, Alavi, Labianca and Borgatti, 2014). Dynamic capabilities theory also does not provide a clear line on how businesses can build and create their dynamic capabilities. While it highlights the role of sensing, seizing, and reconfiguring, it does not entirely prescriptively inform how to develop such abilities or introduce new ones. More significantly, it could overlook the role of internal determinants like organisational culture and leadership in creating and sustaining dynamic capabilities. Having a learning and innovation culture to establish robust big data analytics capabilities can be difficult without strong leadership and organisational support. Even without this, the dynamic capabilities theory still offers an informative framework for understanding how businesses can adapt to environmental changes and build a sustainable competitive advantage. By prioritising the development of dynamic data analysis skills, businesses can tap data as a critical asset to gain competitive advantage and succeed in the long term.

To illustrate this perspective, Figure 9 presents a model of the dynamic capabilities theory, which highlights how firms sense opportunities, seize them, and transform their resources to remain competitive in rapidly changing environments.

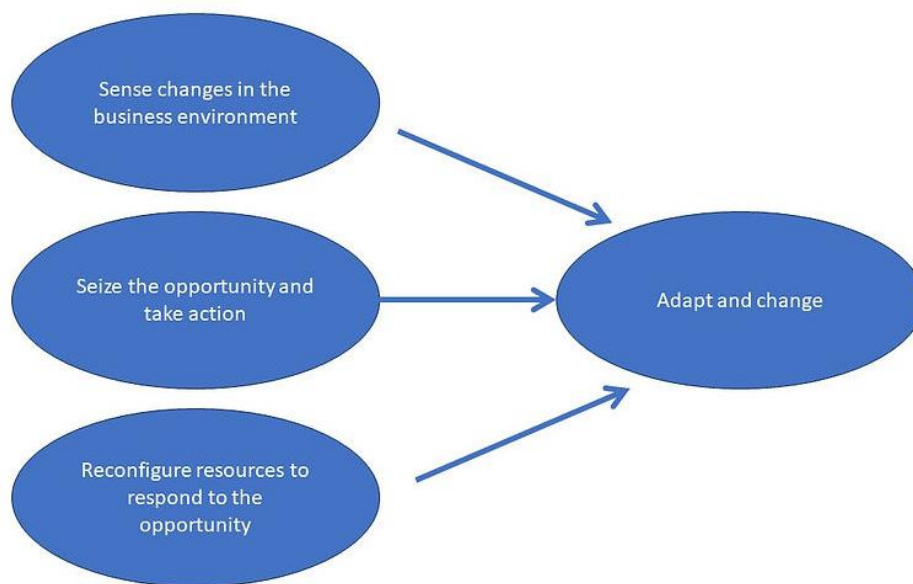


Figure 9: Dynamic capabilities theory

Source: Author

The above model demonstrates how competitive advantage is influenced by the business's dynamic capabilities. These enable it to sense and seize opportunities, as well as to transform its resources and capabilities to adapt to changing market conditions (Saar and Dagada, 2024; Subramoney and Dagada, 2025).

Dynamic capabilities are three interrelated processes:

Sensing opportunities: the ability to identify and sense changes and opportunities in the external environment. It is the process of ongoing monitoring and collection of intelligence about market trends, customer needs, technology advances, and competitive activities.

Seizing opportunities: the ability to make strategic decisions and take timely actions to exploit identified opportunities. This includes the business's capacity to allocate resources, mobilise teams, and execute initiatives that leverage the identified opportunities.

Transforming: the ability to reshape and transform the business's resources, processes, and capabilities to accommodate new market conditions. It involves structural transformation, putting in place new systems, reworking business models,

and fostering organisational learning and innovation (Aversa, Haeffliger and Reza, 2017).

Learning capabilities refer to the capacity of a company to gain, integrate, and implement novel knowledge and skills. This includes individual learning at the employee level as well as collective learning at the organisational level. Learning capabilities help the firm stay updated with industry trends, technological advancements, and customer preferences.

Innovation capabilities refer to the company's capacity to generate and implement novel ideas, products, services, or business models. These establish an environment of innovation, fostering creativity, regulating the innovation process, and converting innovative solutions into successful commercialisation.

The dynamic capabilities theory was thus considered suitable for this study because of the following:

This study attempted to explore how capabilities in digital analytics translate to competitive advantage. Dynamic capabilities theory emphasises constructing and applying capabilities to deal with dynamic and uncertain environments, which is similarly consistent with learning the impact of big data analytics capabilities on competitive advantage. The theory recognises that there is a need for adaptability, agility, and ongoing learning. Big data analytics capabilities require organisations to repeatedly acquire, analyse, and leverage data in new terms. Dynamic capabilities allow businesses to capture effective responses to variances in the market, industry, and customer demands, thus gaining competitiveness.

Dynamic capabilities theory requires reconfiguring resources and competences to respond to external variance. Big data analytics capabilities usually require organisations to align various resources, such as data storage infrastructure, analytical tools, and technical personnel. Dynamic capabilities theory provides a framework for reorganisation and allocation of resources in a strategic manner to enhance their big data analytics capabilities. Dynamic capabilities theory allows strategic decision-making regarding resource allocation, strategic alliances, and organisational design. Therefore, when deciding on big data analytics capabilities, informed decisions about

investing in technology, hiring talent, partnerships, and data governance must be made (Naudé and Nagler, 2021). Dynamic capabilities theory offers insights into how to make strategic choices to develop and leverage big data analytics capabilities to the greatest advantage. Dynamic capabilities theory promotes the effectiveness of dynamic capabilities in varying ways across organisational contexts and industries. This is relevant when analysing their impact on competitive advantage, as different organisations will face different challenges and opportunities in leveraging data analytics. Thus, it is necessary to understand the organisational context in determining the relationship between big data analytics capabilities and competitive advantage.

Dynamic capabilities theory was applicable to this research because it specifically examines an organisation's ability to sense and respond to changes and opportunities external to it, which is what big data analytics capabilities lead to competitive advantage.

3.3.3 Capabilities Maturity Model

The capabilities maturity model is a process improvement framework that helps organisations improve their processes, achieve their business objectives, and which assesses and measures organisational maturity. This model was first introduced by the Software Engineering Institute (SEI) in the 1980s and has since been widely used in software development and other industries (Paulk et al., 1993). Although widely used to evaluate and improve software development processes, it can be employed for other areas of application as well, for instance, big data analytic capabilities (Mikalef et al., 2022).

The Capabilities maturity model consists of five levels of maturity, each representing a different stage of process capability and organisational development (Paulk et al., 1993). In big data analytics, businesses typically pass through several maturity levels. At **Level 1: Initial or ad-hoc**, no regular processes are adopted within the organisation. Processes are unstructured, reactive, and outputs are unpredictable. At **Level 2: Repeatable or developing**, basic project management processes are established, and organisations begin to introduce control and consistency, ensuring that similar projects are handled in a standardised manner.

At **Level 3: Defined**, processes are standardised, documented, and well understood, with clear knowledge of successful execution.

At **Level 4: Managed**, the organisation manages its processes quantitatively, using metrics and measurements to control and monitor performance.

Finally, at **Level 5: Optimising**, organisations continuously improve and optimise their processes by leveraging lessons learned and identifying innovative ways to enhance their capabilities (Mikalef et al., 2022).

By advancing through the levels, organisations can enhance big data analytic capabilities, which will lead to greater competitive advantage in utilising data effectively and in making data-driven decisions (Cervone, 2017).

Regarding big data analytics capabilities and competitive advantage, the Capabilities maturity model can be applied to help businesses improve how they analyse and manage data. By achieving higher maturity levels for such processes, they can develop unique information-based capabilities that bring competitive advantage in the marketplace. For example, at level two, organisations can implement common data management and analysis processes that are stable and reproducible. This can help ensure that data are collected and analysed in a structured and efficient manner, which can improve the quality and relevance of the resulting insights. At level three, organisations can develop a documented and consistently applied data management and analysis process. At higher levels of maturity, organisations can develop a quantitative and measured process for data management and analysis. Finally, at level five, they can optimise their data management and analysis process for maximum efficiency and effectiveness, which can enable them to leverage their unique information-based capabilities to gain a competitive advantage in the marketplace (Ferraris, Santoro and Scuotto, 2020).

Businesses with higher maturity levels demonstrate superior ability to integrate analytics into decision-making, align big data analytics with strategic objectives, and evolve their capabilities in response to environmental change. Despite its potential benefits the Capabilities maturity model framework, also has some potential drawbacks and limitations that must be considered. For example, the Capabilities maturity model framework may require significant investment in terms of time,

resources, and expertise to implement and maintain. Additionally, the framework may not apply to all industries or business contexts, and other resources, such as human capital and technology infrastructure, and may be more critical for effective innovation and decision-making.

In summary, the Capabilities maturity model provides a valuable conceptual framework for understanding how organisations can improve their data management and analysis processes. However, while it offers useful insights into process improvement and staged development, it was not directly applied in this study. The present research rather adopted the resource-based and dynamic capabilities theories as its primary theoretical foundations, as these were considered more appropriate for examining how big data analytics capabilities contribute to competitive advantage. The Capabilities maturity model has been therefore discussed here as a complementary perspective that helps illustrate the progressive nature of capability development. To illustrate this perspective, Figure 10 presents the Capabilities maturity model, which outlines the progressive stages through which organisations enhance their processes and develop stronger information-based capabilities.

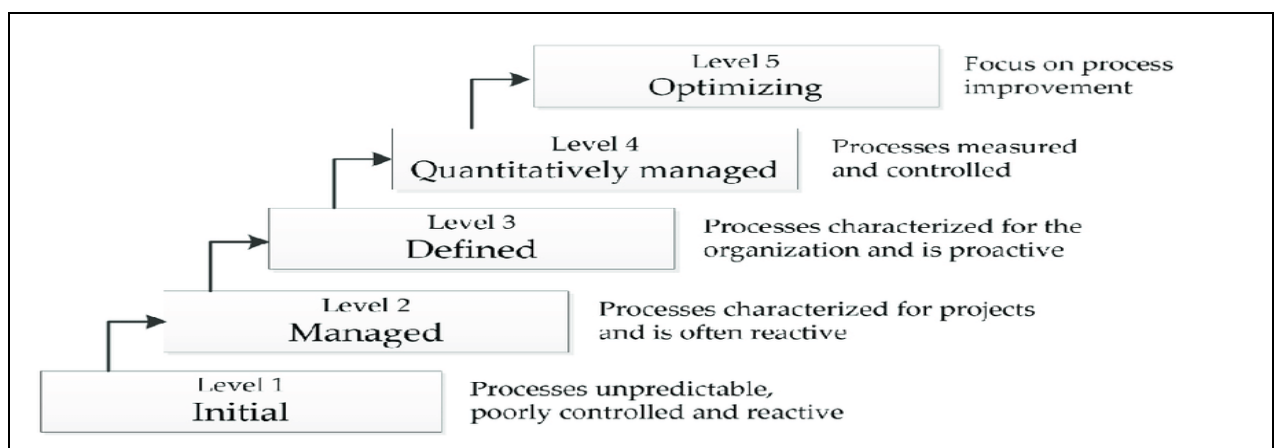


Figure 10: Capabilities maturity model

Source: Adapted from : <https://www.6sigma.us>

3.3.4 Value Chain Analysis Model

Following the discussion of the capabilities maturity model, which focuses on process improvement and maturity, the value chain analysis model provides another useful perspective for understanding how organisations create value through their

internal activities. This model, initially created by Michael Porter (2008) in his book *Competitive Advantage: Creating and Sustaining Superior Advantage*, is a handy tool for the dissection of the internal operations that bring value to a company products or services. The model establishes primary activities involved in production and service delivery and supportive activities that facilitate primary functions.

Primary activities are inbound logistics, operations, outbound logistics, marketing and sales, and service activities. Supporting complementary activities are procurement, technology development, human resource management, and infrastructure activities such as management, planning, finance, legal, and quality control. These activities contribute to the total value creation process of the organisation. It describes how each phase influences others and contributes value to the overall product. Through effective coordination of such relationships, companies can optimise processes, reduce costs, enhance quality, and generate improved customer value.

Application of the value chain analysis varies across industries and organisations. For instance, in the setting of big data analytics capabilities, the model can be applied to identify areas in which data analytics can create value for a company's operations. Analysing data sets such as inbound logistics, marketing and sales, and service data can enable businesses to optimise supply chains, personalise marketing, and improve customer service (Dubey et al., 2020). Moreover, value chain analysis assists in informing investment strategy in big data analytics capabilities. Technology development activity analysis will reveal the areas for investment in data infrastructure and analytics solutions, while human resource management activity analysis will highlight training needs to constitute an effective team that can leverage data analytics.

One should however realise the constraints of the value chain analysis model, particularly relating to external issues and data privacy. For example, while the model is coordinated with internal operations, it may ignore certain external problems impacting a business's competitive advantage, such as market pressures and regulatory problems. The model also does not directly deal with data safety and privacy issues, which are significant concerns when dealing with sensitive information.

However, this model does not directly address the relationship between big data analytics capabilities and competitive advantage. The model was therefore considered unsuitable for use in this study, which adopted the resource-based and dynamic capabilities theories as its main theoretical foundations. To illustrate how businesses identify and prioritise areas where analytics can create value, Figure 11 presents Porter's value chain model, a widely used framework for mapping organisational activities and locating opportunities for efficiency and differentiation.

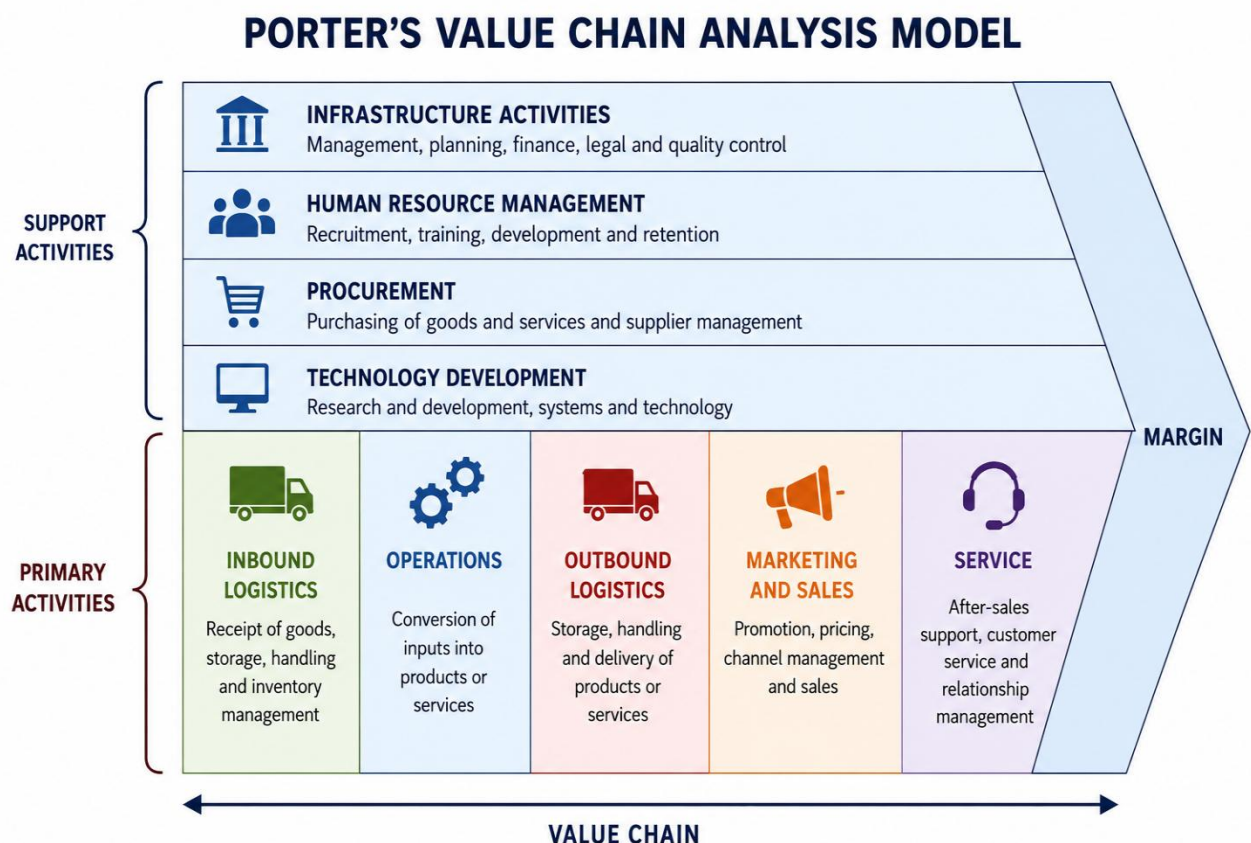


Figure 11: Porter's Value Chain Analysis model

Source: Adapted from Porter, (2008)

As shown in Figure 11, the Value Chain model highlights how big data analytics can support value creation by strengthening both primary and support activities. However, while useful for investment prioritisation, the model does not adequately explain the deeper relationship between big data analytics capabilities and competitive advantage. To address this gap, the following section turns to the knowledge-based

theory, which provides a more comprehensive lens by emphasising knowledge, learning, and organisational culture as drivers of sustainable advantage.

3.3.5 Knowledge-Based Theory

The knowledge-based theory provides a critical framework for knowledge management in organisations, as well as a construction of learning and knowledge-sharing culture to facilitate innovation, decision-making, and overall advantage (Zack, 1999). According to knowledge-based theory, knowledge is critical in the development and sustenance of competitive edge, since it entails an organisation's idiosyncratic knowledge, culture, skills, and processes difficult for competitors to replicate (Saeed, Adiguzel, Shafique, Kalyar and Abrudan, 2023). Studies have indicated that the acquisition, transfer, and utilisation of knowledge can lead to significant competitive strengths (Grant, 1996a).

The knowledge-based theory includes organisational knowledge, personal knowledge, and external knowledge as primary components. These can be utilised by organisations to create a competitive advantage through technical knowledge, expertise, industry knowledge, and experience. The knowledge-based theory emphasises the importance of knowledge creation, sharing, and leveraging within organisations for building capabilities, decision-making, innovation, and sustainable competitive advantage in the contemporary knowledge economy (Intezari and Gressel, 2017).

Organisational knowledge is the aggregation of current knowledge, expertise, and capabilities within the business. It encapsulates both explicit and implicit knowledge created, transferred, and produced by organisational processes and interactions. Organisational knowledge includes intellectual capital, best practices, processes, routines, and intellectual property that form its' competitive advantage. It is influenced by individual and external knowledge, in which individual knowledge is acquired through employees' skills and experiences, and external knowledge is obtained from outside sources and environments (Chatterjee, Rana and Dwivedi, 2024).

Individual knowledge is possessed by the organisation's employees, such as their experience, skills, expertise, and intuition. It is either tacit or explicit, where tacit knowledge is rooted in the people's personal experience and skills and explicit

knowledge is formally documented information. Employees' knowledge contributes to organisational knowledge and its competitive advantage. It consists of technical skills, domain knowledge, and knowledge of tools, technology, and methods relevant to the organisation's business area. Technical knowledge and expertise allows individuals to do their job effectively and contribute to organisational success.

External knowledge refers to knowledge external to the organisation such as information, data, market trends, industry, customer, and technological developments that are relevant to the operations and strategies of the organisation. Gaining and leveraging external knowledge through partnerships, collaborations, research, and market intelligence can render an organisation competitive. In the instance of big data analytics capabilities, knowledge-based theory places the value of human capital in knowledge management central to the position. Businesses can invest in hiring and training staff with expert data science, machine learning, and related skills for proper analysis of huge and complex sets of data.

However, knowledge-based theory has limitations and faults. As much as it recognises the importance of knowledge in gaining competitive edge through big data analysis, it ignores outside constituents such as market conditions and customer tastes that could affect a business's competitive edge. Besides, quantifying and measuring knowledge can be arduous and subjective, thereby making it challenging to assess the effectiveness of knowledge-based theory in practice (Grant, 1996b). Efficient use and management of knowledge assets in complex organisations may therefore be challenging. Additionally, knowledge-based theory may not be translatable to all business environments or industries, since other assets may be more central to creating and sustaining competitive advantage (Davenport and Dyche, 2013).

The theory may overlook the contribution of other aspects such as technology infrastructure and human capital, the keys to improved innovation and decision-making (Zack, 1999). Finally, knowledge-based theory may not discuss the contribution of technical expertise and technology infrastructure sufficiently required for quality big data analytics, laying greater emphasis on intangible aspects of knowledge.

To visualise the core principles of this perspective, Figure 12 illustrates the knowledge-based theory framework, which emphasises how organisations leverage knowledge as a strategic asset to build and sustain competitive advantage.

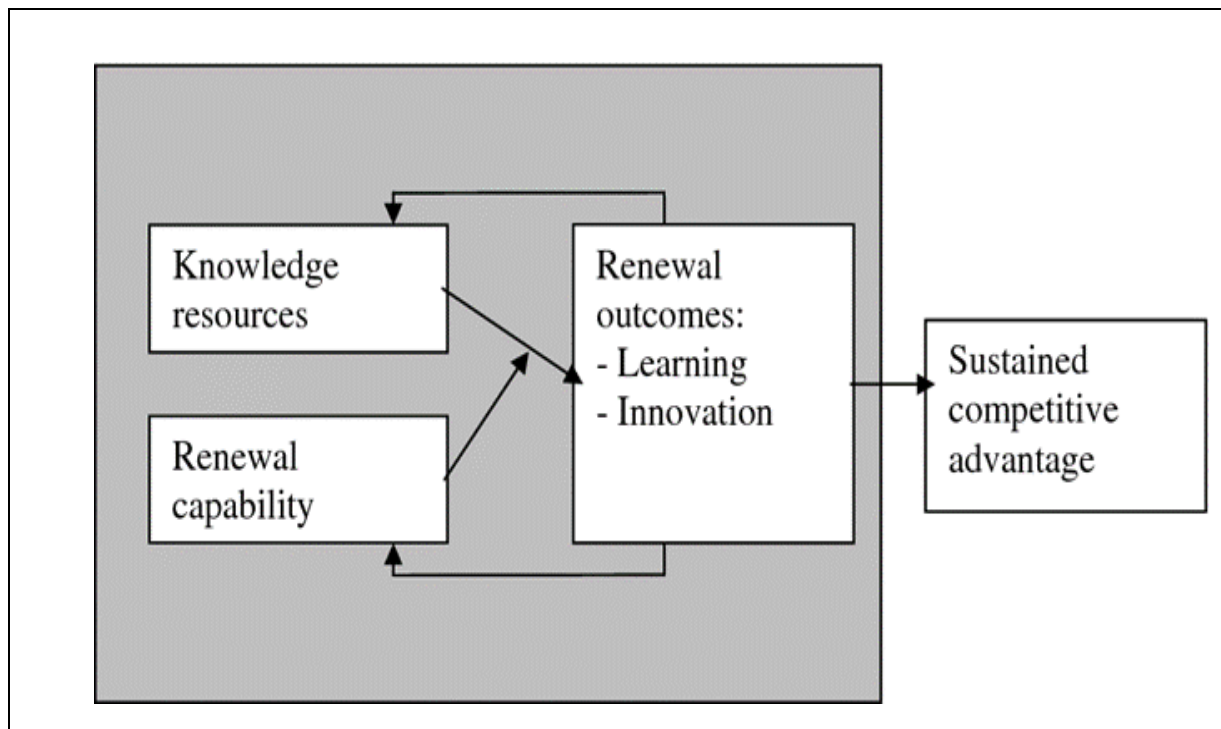


Figure 12: Knowledge-based theory

Source: Pöyhönen, (2004)

As shown in Figure 12, while knowledge is valuable, the focus of this study is on big data analytics capabilities and their impact on competitive advantage. The knowledge-based theory does not directly address this relationship and was therefore unsuitable for use in this study. Given this limitation, the study turns to the social network theory, which extends the discussion by focusing on the relational and network dimensions of value creation and capability development.

3.3.6 Social Network Theory

Social network theory is a management framework that explains how relationships between individuals, groups and organisations can create access to valuable information, resources and knowledge (Krackhardt, Nohria and Eccles, 2003). The theory argues that social relationships may become a source of competitive advantage because they are difficult for competitors to imitate (Burt, 2005). Through strong

relationships with suppliers, partners, customers and other stakeholders, organisations may gain access to knowledge, market intelligence and collaborative opportunities that support strategic decision-making (Koka, Madhavan and Prescott, 2006).

The main components of social network theory are network structure, network content and network governance (Krackhardt et al., 2003). Network structure refers to the pattern of relationships between individuals, groups and organisations, and helps identify key actors and connections within a network (Borgatti and Halgin, 2011). Network content refers to the information, knowledge and resources exchanged through these relationships (Hansen, Podolny and Pfeffer, 2001). Network governance refers to the rules, norms and systems that guide behaviour and coordination within networks (Brass, Butterfield and Skaggs, 1998; Gulati, Nohria and Zaheer, 2000).

In the context of big data analytics capabilities, social network theory is useful because it highlights the role of partnerships, information-sharing and stakeholder relationships in supporting access to data, expertise and technological resources. For example, organisations may rely on relationships with data providers, technology vendors, consultants, universities or industry partners to strengthen their analytics capabilities (Li, 2020). These networks may support innovation, knowledge sharing and the development of data-driven practices.

However, social network theory has limitations in relation to this study. The theory focuses mainly on relationships and social structures, rather than on the internal organisational resources, analytical capabilities and dynamic capabilities required to convert big data into competitive advantage. It may also understate the role of technology infrastructure, data quality, human skills and organisational learning. In addition, social networks can be difficult to measure and may vary significantly across industries and organisational contexts (Borgatti and Halgin, 2011).

Figure 13 presents an example of a social network model based on information ties, showing how relationships between actors can shape the flow of information within an organisation.

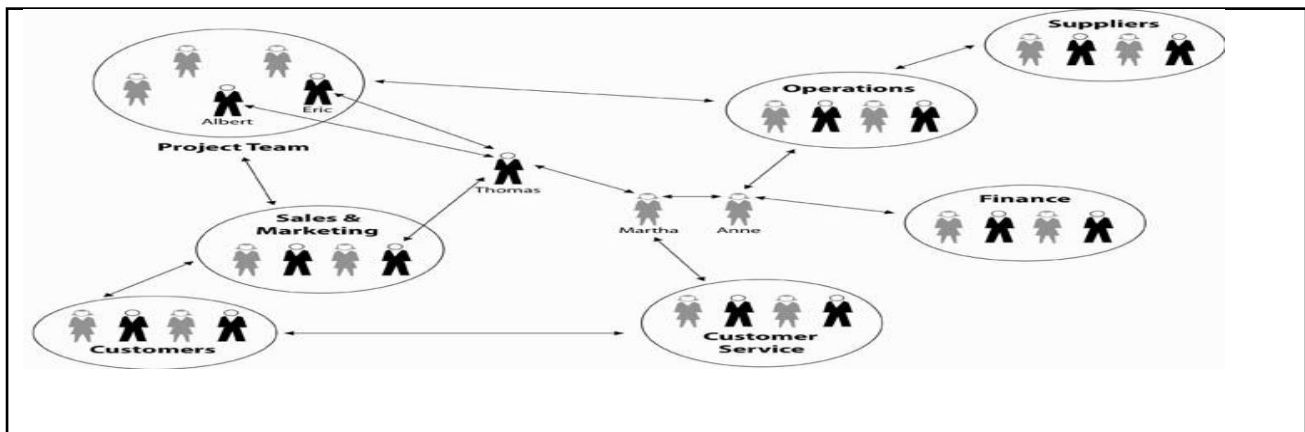


Figure 13: Social network theory

Source: https://saylordotorg.github.io/text_principles-of-management-v1.1/s13-02-an-introduction-to-the-lexicon.html

However, social network theory does not directly explain how big data analytics capabilities contribute to competitive advantage. Since this study focuses on the role of data, technology, human skills, intangible resources and dynamic capabilities, social network theory was not selected as the main theoretical foundation. The following section examines resource dependency theory, which provides a lens for understanding how organisations manage external resources and dependencies to support stability and advantage.

3.3.7 Resource Dependency Theory

The resource dependency theory explains how organisations rely on external resources and how the control of those resources can influence their behaviour and advantage (Pfeffer, 2003). Resource dependency theory categorises resource dependencies into three types: supply, demand, and institutional dependencies (Pfeffer, 2003). Organisations may seek to control their resource dependencies to reduce uncertainty, increase stability, and gain a competitive advantage by forming strategic alliances, acquiring resources, or developing their resources (Pfeffer, 2003).

In the context of big data analytics capabilities and competitive advantage, Resource dependency theory offers a valuable framework for understanding how organisations can manage their data analytics capabilities to reduce uncertainty and gain a

competitive edge (Nambisan, Wright and Feldman, 2019). Organisations can accomplish this by investing in data analytics tools and infrastructure, establishing partnerships and alliances with external data suppliers, or by acquiring data analytics business (Nambisan et al., 2019).

Critics of resource dependency theory propose that it overemphasises the role of outside factors in organisational advantage at the cost of downplaying the significance of in-house factors such as culture, leadership, and organisational design (Hillman and Hitt, 1999). In addition, resource dependency theory oversimplifies inter-organisational relations, which are based on control over strategic resources (Hillman and Hitt, 1999; Shamim, Cang, Yu and Li, 2016). The limited scope of analysis in resource dependency theory can overlook the social and political factors that influence resource dependencies (Hillman and Hitt, 1999).

Resource dependency theory's emphasis on control and stability may overlook the importance of flexibility and adaptation in response to changing market conditions (Hillman and Hitt, 1999). Although the resource dependency theory has given interesting insights into the interdependence between organisations and the external environment, it is vital to consider applying resource dependency theory in combination with alternative theoretical models and empirical data to view the organisational behaviour and advantage more holistically (Hillman and Hitt, 1999).

This is particularly relevant in South Africa, where digital commerce governance frameworks shape how firms depend on external resources for analytics adoption (Dagada, 2023). To capture this perspective, Figure 14 illustrates the resource dependency theory, which shows how organisations interact with and depend on external resources to maintain stability and advantage.

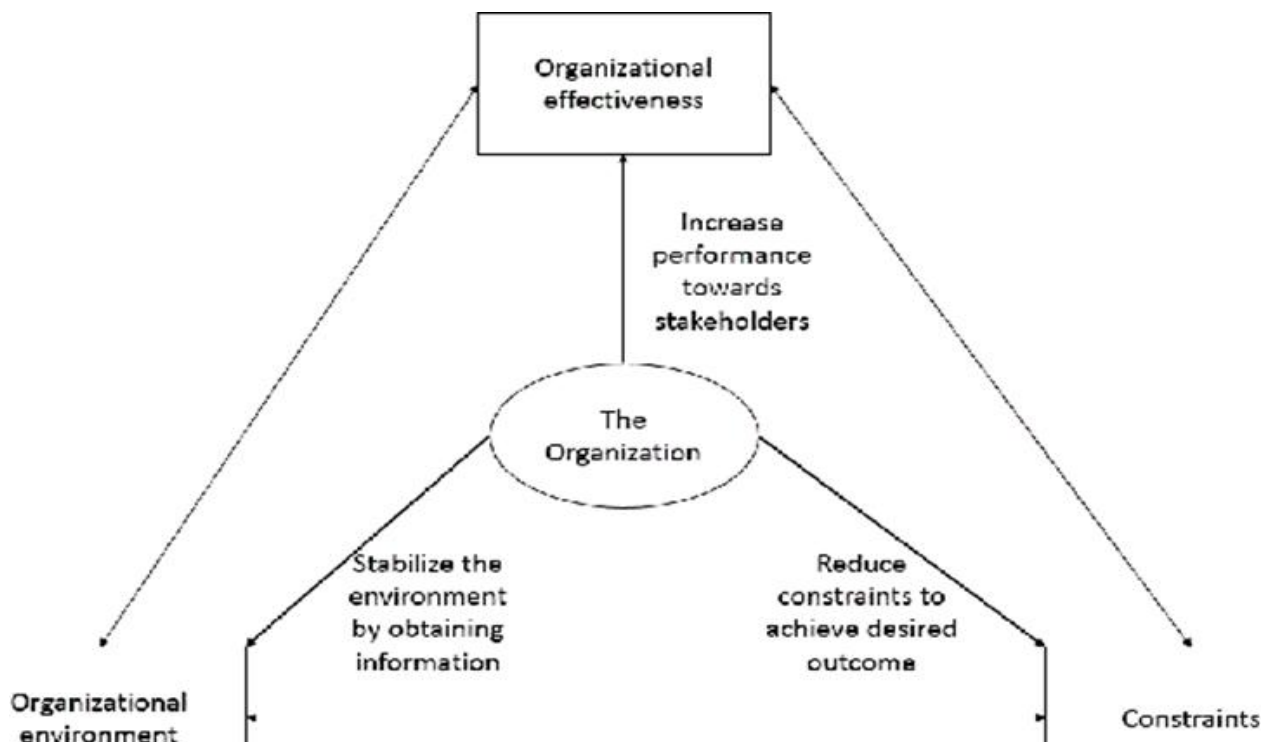


Figure 14: Resource dependency theory

Source: Delke (2015)

As seen in Figure 14, the resource dependency theory highlights the influence of external resources and interdependencies on organisational behaviour. However, while relevant to understanding vulnerabilities and dependencies, it does not directly explain the role of big data analytics capabilities in driving competitive advantage. To extend the discussion toward information handling and decision-making, the following section introduces the information processing theory, which emphasises how organisations acquire, interpret, and use information to improve performance and competitiveness.

3.3.8 Information Processing Theory

The information processing theory highlights how organisations acquire, process, and apply information in decision-making processes as well as gaining a competitive advantage. In the case of big data analytics, the theory is centred on the importance of effective information processing capacity for harnessing the maximum potential of large volumes of information (Atkinson and Shiffrin, 1968).

The theory mandates that organisations with advanced big data analytics capacity can efficiently draw meaning from disparate data sources, screen and interpret the pertinent data, and use it to back up decision-making processes (Atkinson and Shiffrin, 1968). By maximising information processing efficiency, precision, and appropriateness, organisations will acquire greater competitive advantage through better-informed strategic decisions, improved operations advantage, and greater customer satisfaction (Atkinson and Shiffrin, 1968).

However, the information processing theory may not represent the complexity and complications of processing and examination of volumes of data. Big data analytics is more than processing unstructured and structured information, but also involves data quality challenges, bringing data together, and the need for sophisticated analytics techniques (Chen et al., 2012). The theory could benefit from addressing these technical aspects to provide a more comprehensive understanding of the pathway to competitive advantage in big data analytics (Chen et al., 2012).

Information processing capabilities are the organisation's ability to manage and process information effectively (Chen et al., 2012). It entails several things such as the gathering of data, storing, retrieval, analysis, interpretation, and dissemination. These capabilities enable the organisation to have insights, identify patterns, make effective decisions, and take proper actions from the processed information. Effective information processing mechanisms are the technologies, systems, and processes that enable efficient information processing. This includes data gathering techniques and tools, storage, retrieval, integration, analytics, visualisation, and reporting. Organisational structures and processes that facilitate smooth information flow, collaboration, knowledge sharing, and decision-making are also included (Chen et al., 2012).

The input stage is the reception of information from the environment by way of senses; the processing stage involves various mental processes that restructure and process the information received at the input stage. The output stage is the responses, actions, decisions, or behaviours that are yielded by virtue of information processing (Atkinson and Shiffrin, 1968).

To demonstrate the principles of this approach, Figure 15 presents the basic information-processing model of memory, which illustrates how information is received, stored, and retrieved through cognitive processes.

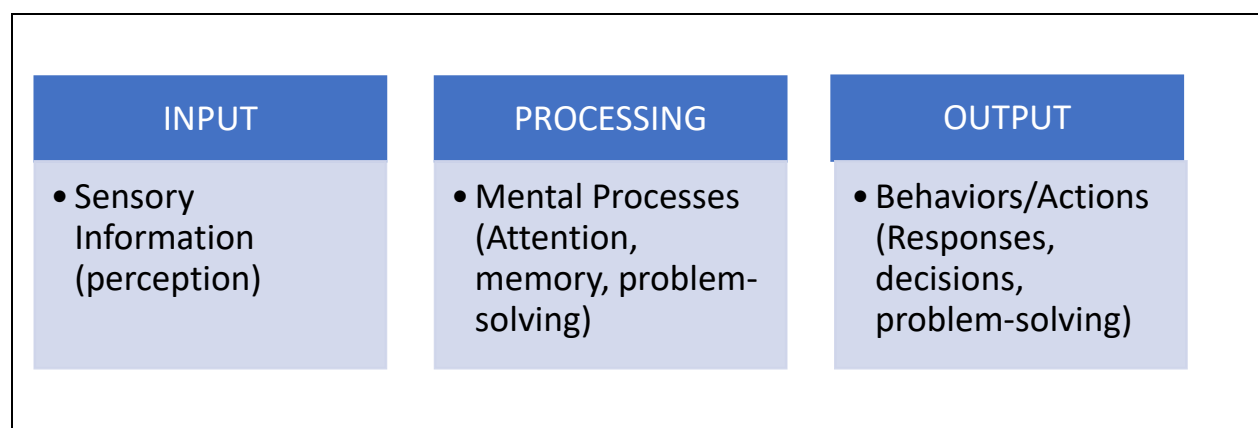


Figure 15: Basic Information-Processing Model of Memory

Source: Atkinson and Shiffrin (1968)

As depicted in Figure 15, the information processing theory provides valuable insights into how individuals handle information at the cognitive level. However, its focus on personal learning and memory limited its applicability to this study, which examined organisational capabilities and competitive advantage. Consequently, while informative, this theory was not directly relevant to big data analytics capabilities. The next section therefore continues by examining frameworks more suited to organisational-level analysis.

To expand the theoretical discussion and address the dual demands of innovation and efficiency in organisational strategy, the following section turns to the ambidexterity theory, which explains how organisations balance exploration and exploitation to achieve sustained competitive advantage.

3.3.9 Ambidexterity Theory

According to this theory, the need arises for organisations to find a balance using established capabilities and new ones to gain and maintain competitive advantage (Saeed et al., 2023). The three avenues available to organisations in pursuing competitive advantage are organisational ambidexterity, exploration, and exploitation. This concept can be achieved through several mechanisms, including structural

disconnection, contextual flexibility, and cyclical focus (Ferraris et al., 2020). Contextual factors, such as organisational characteristics and management style, affect the usage and efficacy of such strategies.

Moreover, collaborations and alliances with other companies can strongly enable the exploration-exploitation trade-off. In the setting of big data analytics, this concept is concerned with the simultaneous employment of current analytics capabilities for profitability and operational effectiveness and exploring new data analytics tools, approaches, and applications to discover new insights and potentialities (Addagada, 2025).

This framework underscores the importance of leveraging existing data analytics capabilities to reduce existing business processes while creating new frontiers for supporting innovation, market adaptation, and differentiation of competition (Addagada, 2025). While the ambidexterity theory balances exploitation and exploration, it is not likely to address the specific challenges and trade-offs of creating and managing big data analytics capabilities (Birkinshaw and Gibson, 2017).

Figure 16 below illustrates the ambidexterity theory, which places emphasis on simultaneity of two complementary activities: the exploitation of existing capabilities and the exploration of new ones (Birkinshaw and Gibson, 2017). Exploration means venturing into new opportunities, technologies, markets, or ideas through activities aimed at uncovering new knowledge, trial and error with new approaches, and identifying innovation (Raisch, Birkinshaw, Probst and Tushman, 2009). Exploitation is focused on maximising and building up existing skills, assets, and procedures to improve advantage, productivity, and efficiency, whereas organisational learning is a bridge between exploration and exploitation that aims at obtaining, assimilating, and utilising new learning from exploration as well as exploitation (Raisch et al., 2009).

To visualise this perspective, Figure 16 illustrates the general causal relationships proposed by ambidexterity theory, which emphasises the organisational balance between exploration and exploitation.

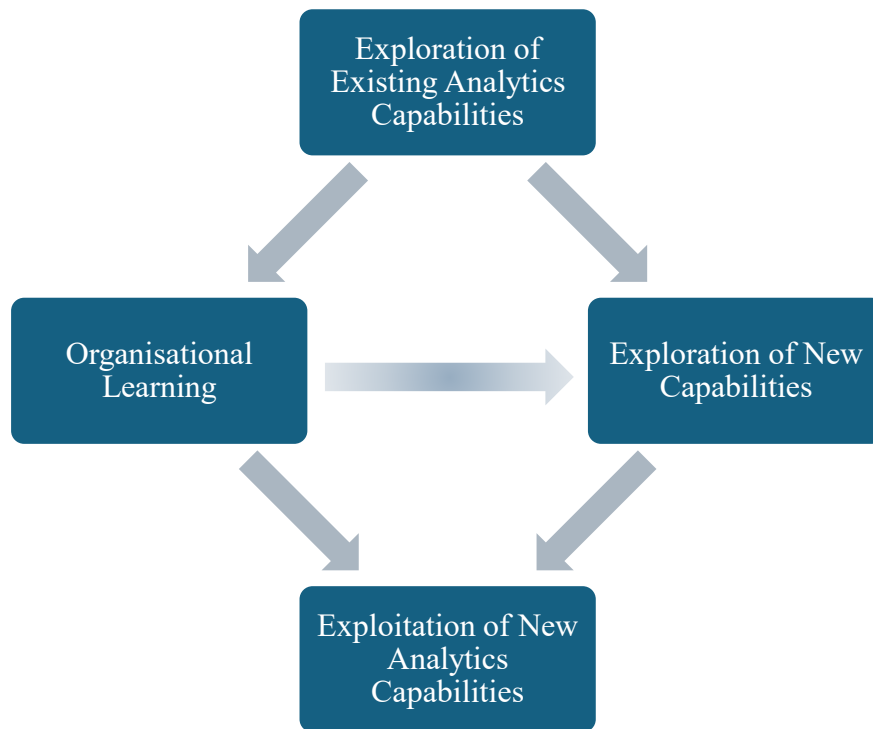


Figure 16: General causal relationships from ambidexterity theory

Source: Author

As shown in Figure 16, ambidexterity theory provides useful insights into balancing competing organisational priorities, but it does not explicitly address how big data analytics capabilities translate into competitive advantage. Given these limitations, the study now turns to the resource-based theory, which offers a more robust foundation by focusing on the internal resources and strategic assets that firms can leverage to build sustainable advantage.

3.4 THEORETICAL INTEGRATION AND COMPARATIVE ANALYSIS

Collectively, these theories provide a multi-faceted explanation of how big data analytics capabilities can be created, embedded, and leveraged for competitive advantage, especially in the turbulent and complex South African business landscape.

Table 9 below presents the integrated theoretical framework guiding this research and shows the relationships between the theoretical foundations, core constructs, and research questions addressed in the study.

Table 9: Link between theoretical perspectives, core constructs and research questions

Source: Author

Theory	Core constructs supported	Research questions addressed
Resource-based theory	Core theory for big data analytics capabilities (tangible, human, intangible resources) as sources of competitive advantage. Sets foundational logic for RQ1–RQ4.	RQ1, RQ2, RQ3, RQ4
Dynamic capabilities theory	Frames sensing, seizing, and transforming as mediators between big data analytics capabilities and competitive advantage. Critical for dynamic business environments.	RQ2, RQ4
Capability maturity model	Organisational readiness and maturity of big data analytics capabilities adoption. Supports staged development of tangible, human, and intangible resources.	RQ1, RQ4
Value chain model	Identifies where competitive advantage can emerge along the value chain. Helps assess how big data analytics capabilities enhance firm activities through operational capabilities.	RQ1, RQ3
Knowledge-based theory	Justifies human skills and intangible resources (e.g., organisational learning) as sources of sustained advantage. Links knowledge management to big data analytics capabilities effectiveness.	RQ1, RQ2, RQ4
Social network theory	Explains how data-driven culture and collaborative environments enhance big data analytics capabilities. Underpins intangible resources and networked learning.	RQ1, RQ2, RQ4
Resource dependency theory	Highlights how external partnerships and access to tangible resources influence big data analytics capabilities. Addresses resource constraints in the SA context.	RQ1, RQ4

Information processing theory	Explains the role of big data analytics capabilities in managing complex information flows. Underpins data integration, real-time analytics, and decision-making.	RQ1, RQ2, RQ3
Ambidexterity theory	Frames the dynamic capabilities of exploration (sensing) and exploitation (seizing/responding) of big data analytics capabilities. Links directly to transformation agility.	RQ2, RQ4

While each of these theories brings certain strengths, it also has some limitations if used in isolation. For instance, the resource-based theory serves as a powerful lens for the identification of valuable, rare, inimitable, and non-substitutable resources; yet it underplays the adaptive and temporal dimensions of capability renewal. On the other hand, the dynamic capabilities theory focuses on agility and transformation; sensing, seizing, and reconfiguring resources; but relies on the resource-based view foundation to define what constitutes a valuable resource base.

By integrating both, this study benefits from the resource-based theory's static resource perspective and the dynamic capabilities theory's dynamic, process-oriented view. It provides a comprehensive framework that captures both the possession and deployment of big data analytics capabilities as sources of competitive advantage.

Therefore, the integration of these theories provides a holistic theoretical foundation. The resource-based theory anchors the study in the strategic value of data-related resources (tangible, human, and intangible), while the dynamic capabilities theory explains how these resources are continuously reconfigured to achieve sustained competitive advantage in South Africa's volatile and resource-constrained environment.

The following table (Table 10) provides a comparative summary of these models and theories, highlighting their potential contributions as well as their limitations in explaining the relationship between big data analytics capabilities and competitive advantage.

Table 10: Analysis of models and theories

Source: Author

Model	Advantages	Disadvantages	Suitability
Resource-based theory	Starts with internal resources, abilities, and capabilities as sources of competitive advantage. Emphasise sizes the significance of unique and difficult-to-imitate resources in sustaining competitive advantage. Provides a method to diagnose and leverage internal resources for value creation and strategic success. Enables the identification of core competencies and prospective resource expansion and investment possibilities.	It is sometimes difficult to identify and quantify key resources and capabilities that indeed confer a competitive advantage. The theory can in no way account for the impact of external environments and market forces on organisational outcomes. The theory can in no way explain dynamic processes of resources and constant adaptation and renewal requirements. Implementation of the theory can be varied across different industries and organisational settings.	Resource-based theory focuses on internal capabilities, skills, and resources as competitive advantage sources. Difficulty may arise in identifying and measuring the main resources and capabilities that truly bring a competitive edge. While resource-based theory does recognise the importance of capabilities and resources, it does not prioritise the linkage between big data analytics capabilities and competitive advantage. It focuses on general resource-based advantages rather than on the specific capabilities related to big data analytics
Dynamic capabilities theory	Dynamic capabilities theory targets a business's ability to sense and respond to outside changes and opportunities. Embodies respect for innovation, learning, and reconfiguring abilities and assets. Provides a framework for creating and sustaining competitive advantage in dynamic and uncertain environments.	The theory may be challenging to implement due to the need for ongoing learning, adaptation, and organisational adaptability. Challenges may arise in balancing stability with flexibility in the firm. The theory has been criticized as not having clear operational guidance and measurement standards.	Dynamic capabilities theory can be used for this study because it especially talks about an organisation's ability to sense and respond to external changes and opportunities, which is aligned to understand how big data analytics capabilities lead to competitive advantage.

	Helps with strategic choice-making regarding resource allocation, strategic alliances, and organisational design.	The theory may be more suitable to apply to larger organisations with greater capabilities and means.	
Capability Maturity Model	Provides an organisational process and capabilities improvement and assessment framework. Allows organisations to identify areas for improvement and set objectives for process maturity. Allows benchmarking and enables the organisation to benchmark its level of maturity against best practice within the industry. Can enhance organisational efficiency, consistency, and quality.	Can be resource- and time-intensive to implement. Can require significant cultural and organisational transformation. Some critics contend that it can also be too prescriptive and may stifle innovation. It may be challenging to measure and quantify progress exactly.	It is not directly applicable to the research on big data analytics capabilities and competitive power. It focuses on process maturity and can miss the specific dynamics of big data
Value chain analysis model	Helps organisations identify primary and support activities, which create value in their business. Provides a systematic approach to analysis and understanding of how activities and processes drive competitive advantage. Enables organisations to identify areas with potential cost savings, differentiation, and value creation. Helps organisations align their activities around customers'	Requires access to good quality and timely data to provide meaningful analysis. Focuses primarily on internal processes and may overlook external factors and market dynamics. Implementation problems may be brought about by change resistance or lack of familiarity with the idea. Does not specifically address the relationship between	Does not specifically address the relationship between big data analytics capabilities and competitive advantage. Is primarily concerned with value creation and may overlook the unique characteristics of big data analytics.

	needs and wants. Simplifies complex business processes and dynamic s.	big data analytics capabilities and competitive advantage. Is primarily concerned with value creation and may overlook the unique characteristics of big data analytics.	
Knowledge-based theory	Perceives the strategic value of intellectual capital and knowledge in organisations. Provides information on how organisations can utilise knowledge to create a competitive advantage. Emphasise sizes learning and building knowledge and sharing knowledge at the organisational level. Supports organisational flexibility and creativity in dynamic environments.	May be challenging to quantify and measure knowledge. Requires continuous efforts and investment in knowledge management. It can be challenging to capture tacit knowledge and transfer it seamlessly across the organisation. Can be challenging to integrate knowledge-based approaches into existing organisational structures and processes.	While knowledge is a positive, the focus of this study is on big data analytics capabilities and their influence on competitive advantage. The knowledge-based theory does not explicitly discuss this
Social network theory	Provides a theory of understanding the social structure and interpersonal relations in organisations. Helps to identify key individuals, groups, and information flows within the organisation. Facilitates innovative collaboration, knowledge sharing, and exchange of information through	Social network complexity can make analysis and interpretation difficult. Quantification and measurement of social network traits and dynamic s might be challenging. Social network dynamic s tend to be very dynamic, which makes it hard to	Social network analysis may be helpful, but it does not address the relationship between big data analytics capabilities and competitive advantage directly. It is a people and personal relationship theory and not about technological capabilities.

	better communication and relationships. Facilitates identification of potential bottlenecks, knowledge gaps, and opportunities for improvement.	keep track of accurate and up-to-date analysis of the network. The theory's validity is varied across organisational contexts and across industries. Social network theory Provides a way of analysing social organisation and interpersonal relations in organisations. Social networks are complex and difficult to analyse and interpret.	
Resource dependency theory	Highlights the importance of external relations and resources in organisations. Helps organisations manage dependencies as well as negotiate favourable resources exchanges with external actors. Provides insights into power and influence within inter-organisational networks. Enhances strategic decision-making on resources allocation, acquisition, and alliances.	Organisations risk becoming overly reliant on outside resources, which can pose threats or dependency. There might be difficulties in identifying and coping with complex interdependencies from various sources outside. The applicability of the theory can differ between industries and organisational settings. The critics argue that the theory will not entirely address internal capabilities and variables within organisations. Resource dependency theory highlights how external resources	Resource dependency theory highlights the importance of external resources and relationships in organisations. Organisations may become overly reliant on external resources, leading to potential vulnerabilities or dependence. While resource dependency theory recognises the importance of resources, it does not specifically address the relationship between big data analytics capabilities and competitive advantage. It focuses more on resource management and interdependencies.

		and relationships are crucial in organisations. Organisations tend to over-rely on external resources, and thus, they will have potential vulnerabilities or dependence. Resource dependency theory highlights the importance of resources but does not specifically state the relationship between big data analytics capabilities and competitive advantage. It instead focuses on resource management and interdependencies.	
Information processing theory	The theory is concerned with mental processes and how information is seen, processed, and stored, providing accounts of how individuals learn, remember, and reason. Information processing theory has practical applications in fields such as education, cognitive psychology, and human-computer interaction, helping to design effective learning environments and information systems. It offers a framework for describing decision-making behaviour, information acquisition, information integration, and information	The theory oversimplifies complex cognitive processes by breaking them down into discrete stages, which does not necessarily reflect the complexity and variety of human information processing. The theory focuses mainly on internal mental processes and may not be able to explain social and contextual factors influencing information processing. The theory will most likely overlook the impact of affect factors and emotions	The theory emphasises cognitive processes and how information is received, processed, and stored, providing insights into how individuals learn, remember, and problem-solve. The theory oversimplifies complex cognitive processes by breaking them down into discrete stages, which may not fully capture the intricacies and variability of human information processing. While information processing theory is relevant to understanding individual cognition, it does not directly address the relationship between big

	evaluation, which allows the individual and organisations to make more effective decisions. Predictive Power: The theory forms a basis for the prediction of human action in information activities like problem-solving, information searching, and decision-making.	in information processing, which have a significant influence on cognitive processes and decision-making. Lack of Focus on motivation: The theory does not even mention motivational factors influencing information processing, such as individual goals, interests, and incentives. The theory gives tremendous importance to thinking processes and how the information is perceived, processed, and retained, with consequences for the way people learn, remember, and solve problems. The theory oversimplifies complex cognitive processes by breaking them down into discrete stages, but then again, it may not totally capture the complexity and variability of human information processing. While information processing theory can be applied to the explanation of individual cognition, it does not address the relationship between big data	data analytics capabilities and competitive advantage. It focuses on individual-level processes rather than organisational capabilities.

		analytics capabilities and competitive advantage directly. It is about individual-level processes, not organisational	
Ambidexterity theory	The theory highlights the necessity of balancing exploration (innovation, experimentation) and exploitation (efficiency, optimisation) to succeed in the long run. It promotes organisational resiliency and flexibility through the encouragement of capabilities' development that enables organisations to respond to changing environments. Development of ambidexterity, as posited by the theory, could lead to increased innovation through the marriage of the exploration of new opportunity with the exploitation of existing capabilities. Organisations that can execute ambidexterity well could have a strategic advantage in being able to function in uncertain and dynamic environments.	Practice ambidexterity could be challenging due to conflicting aims, resource restrictions, and organisational cultural issues. Balancing exploration and exploitation entails trade-offs and tensions between conflicting organisational goals, and such tensions could lead to internal conflicts and complexities. Pursuing both exploration and exploitation simultaneously is likely to require significant resources and skills and may not be possible for resource-constrained organisations. Ambidexterity can prove to be effective in varying ways across various organisational environments and sectors, and hence to lesser degrees in all situations. The theory highlights the need to reconcile exploration (experimentation, innovation) and exploitation	Theory on ambidexterity recognises exploration and exploitation as important but does not consider synergies between big data analytics capabilities and competitive advantage. It focuses on balancing different organisational priorities rather than on the specific capacity required for big data analytics.

		(efficiency, optimisation) in achieving long-term organisational success. Acquiring ambidexterity in practice is challenging due to conflicting priorities, resource use dilemmas, and organisational cultural issues.	

As shown in Table 10, while several models and theories provide valuable perspectives on organisational processes, resources, and relationships, most do not directly capture the unique dynamics of big data analytics capabilities and their influence on competitive advantage. This comparison strengthened the choice of the resource-based theory and the dynamic capabilities theory as the most appropriate foundations for this research, as they together explain both the strategic value of resources and the adaptive processes required to sustain advantage in volatile environments.

3.5 ORGANISATIONAL LEARNING AND DATA INTERPRETATION CAPABILITIES

Beyond technical and infrastructural resources, the effectiveness of big data analytics capabilities is strongly influenced by an organisation's ability to interpret and act on data insights. Organisational learning theory (Rhodes et al., 1996 and Senge) emphasises the role of continuous learning, knowledge creation, and adaptive thinking in enabling firms to respond to complex and changing environments. In the context of big data analytics, this extends to the ability of individuals and teams to translate analytical outputs into meaningful insights, often referred to as data interpretation or data storytelling. These capabilities are critical in ensuring that data-driven insights are understood, communicated, and embedded into decision-making processes. As such, organisational learning and data interpretation represent key intangible and human capability dimensions that support the transformation of data resources into sustained competitive advantage.

As such, organisational learning and data interpretation represent key tangible and human capability dimensions that support the transformation of data resources into sustained competitive advantage.

3.6 JUSTIFICATION FOR THEORETICAL INTEGRATION AND MODEL STRUCTURE

This study is grounded in the resource-based theory and the dynamic capabilities theory, as these perspectives provide a complementary foundation for explaining how big data analytics capabilities contribute to competitive advantage. While resource-based theory emphasises the role of valuable, rare, inimitable, and non-substitutable resources in achieving competitive advantage, it does not fully account for how organisations adapt and reconfigure these resources in dynamic and uncertain environments. This limitation is particularly relevant in the South African context, where organisations operate under conditions of infrastructural constraints, skills shortages, and regulatory complexity.

To address this limitation, dynamic capabilities theory is incorporated to explain how organisations transform and reconfigure resources in response to environmental change. The emphasis on sensing, seizing, and transforming capabilities provides a dynamic lens through which to understand how firms leverage big data analytics capabilities to achieve sustained competitive advantage. The integration of resource-based theory and dynamic capabilities theory therefore allows for a more comprehensive explanation of both resource possession and resource utilisation.

The inclusion of these dual mediators reflects prior empirical findings that dynamic capabilities exert a stronger and more direct influence on competitive outcomes in volatile environments, while operational capabilities contribute more incrementally.

This integrated framework is particularly suited to the South African context, where organisations must not only invest in analytics resources but also continuously adapt and reconfigure them to respond to changing market conditions. The framework therefore provides a structured basis for examining how big data analytics capabilities are transformed into competitive advantage through both adaptive and operational pathways. This theoretical integration directly informs the conceptual model and hypotheses developed in the following sections.

3.7 CONCEPTUAL MODEL DEVELOPMENT

This study adopts and extends the conceptual model proposed by Framnes and Danielsen (2017), which conceptualises big data analytics capabilities as a higher-order construct comprising three key dimensions: tangible resources, human skills, and intangible resources. These dimensions collectively represent an organisation's ability to acquire, process, and utilise data for strategic decision-making.

However, the relationship between big data analytics capabilities and competitive advantage is not direct. Instead, this relationship operates through mediating mechanisms that explain how resources are transformed into performance outcomes. In this study, two categories of mediators are incorporated: dynamic capabilities and operational capabilities.

Dynamic capabilities reflect the organisation's ability to sense opportunities, seize them, and reconfigure resources in response to changing environmental conditions. These capabilities are particularly important in dynamic and resource-constrained environments, where adaptability and responsiveness are critical for sustained competitiveness. In contrast, operational capabilities relate to the effective execution of business processes, including marketing activities and technological implementation, which support the delivery of value.

The resulting conceptual model therefore reflects a structured pathway in which big data analytics capabilities influence competitive advantage through both dynamic and operational mechanisms. This model is particularly relevant in the South African context, where organisations must balance resource constraints with the need for strategic agility and responsiveness.

3.8 HYPOTHESES DEVELOPMENT

Based on the theoretical integration of Resource-Based Theory and Dynamic Capabilities Theory, this study develops a set of hypotheses to examine the relationships between big data analytics capabilities, dynamic capabilities, operational capabilities, and competitive advantage.

Big Data Analytics Capabilities and Dynamic Capabilities

Drawing on Dynamic Capabilities Theory, organisations with strong big data analytics capabilities are better positioned to sense emerging opportunities, interpret complex data, and respond effectively to environmental changes. These capabilities enhance organisational agility and strategic responsiveness by enabling firms to continuously adapt their resource base.

H1: Big data analytics capabilities have a positive effect on dynamic capabilities.

Dynamic Capabilities and Competitive Advantage

Dynamic capabilities enable organisations to reconfigure resources and processes in response to changing conditions, thereby supporting sustained competitive advantage. This relationship is particularly significant in volatile and resource-constrained environments, where adaptability and responsiveness are critical for maintaining competitiveness.

H2: Dynamic capabilities have a positive effect on competitive advantage.

Big Data Analytics Capabilities and Operational Capabilities

Big data analytics capabilities also contribute to improvements in operational processes, including marketing effectiveness and technological execution. These capabilities support the efficient implementation of strategies and enhance organisational performance at the operational level.

H3: Big data analytics capabilities have a positive effect on operational capabilities.

Operational Capabilities and Competitive Advantage

Operational capabilities contribute to competitive advantage by improving efficiency, consistency, and execution. However, their influence is typically more incremental compared to dynamic capabilities, particularly in dynamic environments.

H4: Operational capabilities have a positive effect on competitive advantage.

Mediating Effects

Based on the integration of resource-based theory and dynamic capabilities theory, it is expected that the relationship between big data analytics capabilities and competitive advantage is mediated by both dynamic and operational capabilities.

Although mediation is not formally tested as separate hypotheses in this study, the conceptual model is structured to reflect the indirect influence of big data analytics capabilities on competitive advantage through dynamic and operational capabilities. In line with the dynamic capabilities theory, it is expected that dynamic capabilities will play a more significant mediating role in translating analytics capabilities into competitive outcomes.

3.9 SUMMARY OF CHAPTER 3

Chapter 3 has reviewed various theories relevant to the research to establish a conceptual basis for understanding the topic of the research. The chapter reviewed the resource-based theory, dynamic capabilities theory, capability maturity model, value chain analysis model, knowledge-based theory, social network theory, information processing theory, resource dependency theory, and the ambidexterity theory. A close comparison of these theories, as shown in Table 10, reveals their respective strengths and weaknesses in relation to organisational effectiveness, competitive advantage, and resource allocation.

While the dynamic capabilities theory emphasises organisational adaptability and requires ongoing learning and a balance between stability and flexibility, it is applicable to this study because it specifically focuses on an organisation's ability to sense and respond to external changes and opportunities, which aligns with understanding how big data analytics capabilities lead to competitive advantage. Understanding each of these theories' strengths and limitations helped to establish a strong theoretical framework for this research study.

Having established the theoretical foundation, developed the conceptual model, and formulated the research hypotheses, the following chapter describes the research design and methodology employed to empirically test these propositions.

CHAPTER 4: RESEARCH METHODOLOGY

4.1 CHAPTER OVERVIEW AND INTRODUCTION

This chapter outlines the research methodology employed to investigate the relationship between big data analytics capabilities and competitive advantage within South African businesses. Building on the foundations established in Chapter 3, it presents the empirical approach taken to operationalise the research objectives and link theory with practice.

The chapter begins by introducing the research philosophy underpinning the study, namely pragmatism. This stance was selected for its flexibility and emphasis on practical outcomes, as it accommodates both qualitative and quantitative strategies. Pragmatism recognises that positivist and interpretivist approaches are not mutually exclusive but can be combined to generate knowledge that is both rigorous and useful in addressing complex, dynamic business realities (Morgan, 2014; Saunders et al., 2023).

Aligned with this philosophy, the study employed an exploratory sequential mixed methods design (Creswell and Plano Clark, 2018; Feters and Molina-Azorin, 2021). This enabled the researcher to first gather in-depth insights through semi-structured interviews with key business leaders and then validate and test those findings through a structured questionnaire survey (Subramoney and Dagada, 2024). Results were analysed using PLS-SEM. The phased approach combined the richness of qualitative inquiry with the generalisability of quantitative analysis, making it especially appropriate for investigating an emergent and multi-layered phenomenon such as big data analytics capabilities in South Africa.

The chapter describes the study's design, target population, and sampling procedures applied in each phase of the research. It further details the data collection instruments, procedures, and analysis strategies employed, showing how findings were derived and interpreted. Issues of trustworthiness, validity, reliability, and ethics are discussed to demonstrate methodological rigour and adherence to professional standards. Methodological limitations, such as sampling and generalisability, are also

acknowledged, alongside the strategies adopted to mitigate them. Overall, this chapter provides the comprehensive plan for how the study was designed and carried out. It shows how the research questions were operationalised, how theoretical constructs were tested in practice, and how methodological integrity was maintained. It also serves as the foundation for Chapter 5, which presents the findings of the qualitative research phase. Figure 17 depicted below represents the chapter overview.

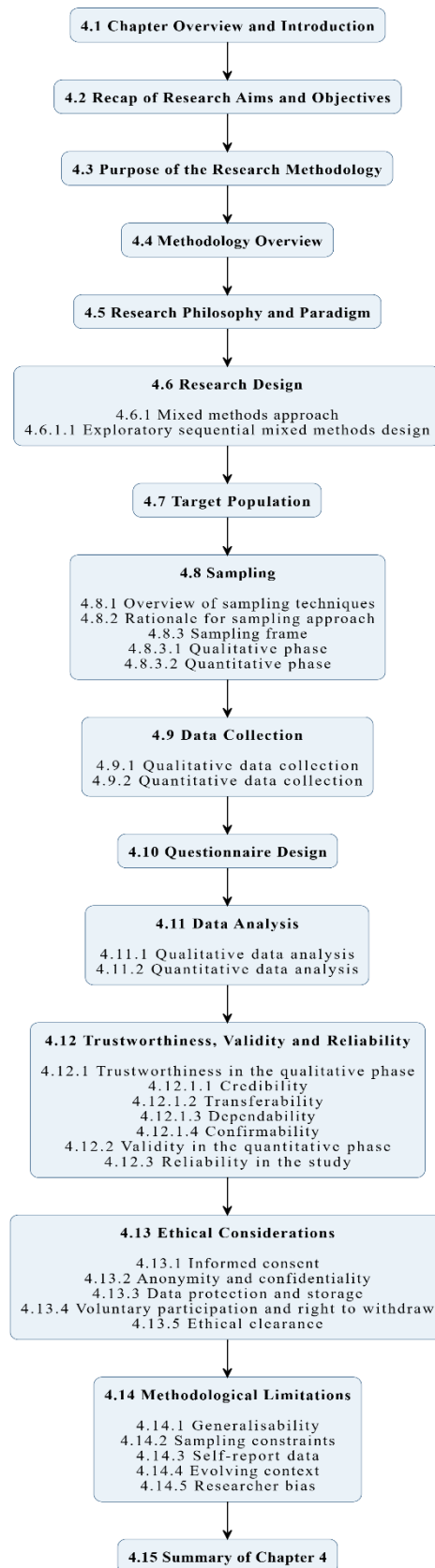


Figure 17: Overview of Chapter 4 – Research Methodology

Source: Author

The Figure 17 above provides a visual summary of how this chapter is structured, outlining the key methodological components, from philosophical orientation through to data collection, analysis, and validation. It highlights the sequential flow of the research design, showing how the qualitative phase informed the quantitative phase within an overarching mixed-methods framework. Following this overview, the discussion now transitions to a recap of the study's aims and objectives to ensure conceptual continuity. Reiterating these elements helps to establish a clear connection between the overall purpose of the study and the methodological choices made, demonstrating how each stage of the research design was logically derived from the theoretical framework and research questions. To ensure methodological coherence, it was ensured that the research design aligned closely with the broader purpose of the study. As such, the following section restates the overall aim and objectives of the research, linking them back to the theoretical foundations discussed in Chapter 3 and establishing their role in shaping both the qualitative and quantitative phases.

4.2 RECAP OF RESEARCH AIMS AND OBJECTIVES

This study examined how South African companies develop and implement big data analytics capabilities to achieve and sustain competitive advantage. In accordance with Mikalef et al. (2021), it built on existing literature that identified big data analytics capabilities as a critical enabler of both dynamic and operational capabilities. This was particularly relevant in the environment characterised by the uncertainty, resource constraints, and institutional complexity factors prominent in the South African context.

The study was guided by several key objectives. It sought to examine the core components and dimensions of big data analytics capabilities that contribute to enhanced business performance. It investigated the ways in which these capabilities enabled the development of dynamic capabilities, sensing, seizing, and transforming, within South African businesses. It assessed how big data analytics capabilities influence operational capabilities, including process optimisation, efficiency, and responsiveness. The study evaluated the impact of dynamic and operational capabilities, as enabled by big data analytics, on the attainment of competitive advantage. It provided contextually relevant insights into how South African businesses can align the development of big data analytics capabilities with their strategic goals and market realities. These objectives not only guided the structure of

the conceptual model presented in Chapter 3 but also informed the design and execution of both the qualitative and quantitative phases of the research.

4.3 PURPOSE OF THE RESEARCH METHODOLOGY

This chapter now expounds and justifies the systematic approach taken to address the research questions of the study. Its purpose is to provide an express account of the philosophical bases, study design, data collection processes, and analysis strategies employed. Through this exercise, this chapter emphasises the academic merit of the study and ensures the validity, credibility, and relevance of the findings.

The chapter first outlines the philosophical foundations of the study, followed by a discussion of the exploratory sequential mixed methods design. It then explains the sampling strategies, data collection techniques, and analytical procedures used across the qualitative and quantitative phases. Attention is also given to issues of reliability, validity, and ethics, which were carefully addressed to strengthen the academic rigour and integrity of the research (Resnik, 2018). The chapter concludes with a summary of these methodological choices, setting the stage for the presentation of findings in the next chapter.

4.4 METHODOLOGY OVERVIEW

The vertical chevron below provides an overview of how the methodology structure flows

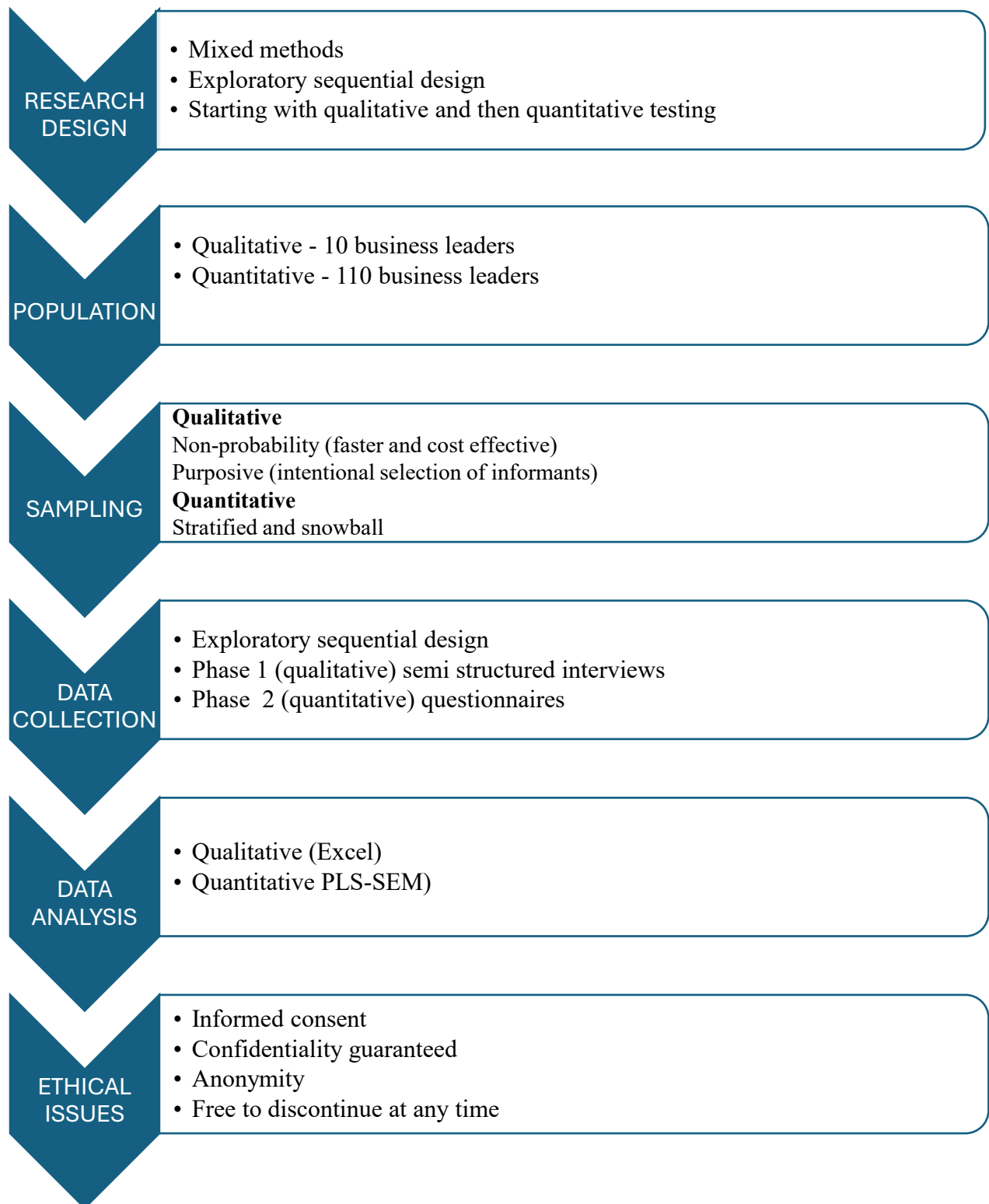


Figure 18: Methodology Overview

Source: Author

As shown in Figure 18, the methodology was carefully structured to balance philosophical grounding, research design, and empirical execution. In big data analytics capabilities and competitive advantage situations, where traditional theory frameworks are being constructed and context problems remain topical methodological rigour is especially relevant (Mikalef et al., 2021; Wamba, Queiroz et al., 2023). Furthermore, because this research constituted the integration of qualitative and quantitative data into an exploratory sequential mixed methods design (Creswell and Plano Clark, 2018), it was essential to explain how these components were designed to supplement each other and provide a harmonious picture of the phenomenon under investigation.

This chapter is thus the methodology foundation of the study, providing a rational walkthrough on how the research was conducted and enabling other researchers to replicate or enhance this study in subsequent studies. As outlined above, these aims and objectives served as the guiding framework for the study's methodological approach. They provided a direct link between the theoretical foundations, the conceptual model, and the practical steps undertaken in data collection and analysis. The next section discusses the research philosophy and methodological stance that underpinned this study, clarifying why an exploratory sequential mixed-methods design was the most suitable approach.

4.5 RESEARCH PHILOSOPHY AND PARADIGM

This section reflects the philosophical stance that underpinned the study and its implications for methodological choices. As Saunders et al. (2023) note, research philosophy is the set of assumptions and beliefs about how knowledge comes into being. It shapes the researcher's worldview and guides methodological decisions (Saunders et al., 2023).

The pragmatist philosophy selected for this research values practical problem-solving and the generation of knowledge that offers actionable insights (Morgan, 2014; Saunders et al., 2023). Pragmatism recognises that no single philosophical stance, whether positivist or interpretivist, can adequately address the complexity of multidimensional phenomena such as big data analytics capabilities and their impact on competitive advantage (Mikalef et al., 2021). It therefore advocates for

methodological pluralism, encouraging the use of whichever approaches are most appropriate to the research problem.

This study was firmly rooted in a pragmatic tradition, reflected in the adoption of an exploratory sequential mixed methods design. Pragmatism emphasises the practical implications of research and accommodates the integration of qualitative and quantitative approaches to provide a more comprehensive account of complex business realities (Creswell and Plano Clark, 2018; Morgan, 2014). Because this study investigated both the nature of big data analytics capabilities and their impact on competitive advantage within South African businesses, pragmatism offered the necessary flexibility.

Pragmatism allowed quantitative analysis to measure external relationships between constructs while also embracing qualitative inquiry to capture the lived experiences of managers and practitioners. This was consistent with the exploratory sequential mixed methods design, where qualitative findings guide and refine subsequent quantitative testing (Creswell and Plano Clark, 2018). The pragmatic paradigm also acknowledges the value of multiple forms of data in generating insights that are both theoretically valid and relevant. In the case of South African businesses, where the adoption of big data analytics capabilities is still emerging, methodological flexibility is crucial. It permits the researcher to first explore participant experiences through qualitative methods and then to validate patterns and relationships using quantitative techniques.

Pragmatism therefore captured the practical focus of this research. The aim was not only to extend theoretical knowledge but also to produce insights and recommendations to guide management practice and help South African businesses use big data analytics capabilities more effectively to sustain competitive advantage. In a resource-constrained and uneven business context such as South Africa, this pragmatic orientation ensured that the study remained grounded, contextually relevant, and of practical value. Moreover, pragmatism promotes methodological flexibility and places the research questions above allegiance to any single philosophical school. By allowing the combination of qualitative and quantitative approaches, it ensures that outcomes are solution-oriented, contextually appropriate, and aligned with the study's overarching objectives.

4.6 RESEARCH DESIGN

Research design is the structured blueprint that guides the entire research process, from the formulation of research questions to data collection, analysis, and interpretation. It serves as the strategic plan that ensures alignment between the research objectives and the methods employed, thereby enabling rigour, coherence, and academic integrity (Saunders et al., 2023). The goal of a good research design is to ensure that the gathered evidence is sound so that the researcher can reach conclusions that are believable and defensible. Singh (2006) specifies that research design is a systematic plan that guides empirical data collection according to the research problem type. It guarantees reliability, validity, and good methodology. For challenging, cross-disciplinary problems such as big data analytics capabilities and competitive advantage in South African businesses, a formal design ought to offer evidence for more than a single question dimension.

It is well accepted that the planning stage of a study significantly affects its eventual quality. Dhawan (2010); Kumar and Rawat (2021), and Leonardi (2011) stress that research must be undertaken with clear goals and a structured sequence of activities that reflect the study's objectives, while remaining flexible enough to respond to emergent insights. Mukherjee (2019) further observes that an excellent design must strike a balance between comprehensiveness and adaptability, especially in the dynamic environments of the fast-paced contemporary business world.

From a theoretical angle, Denzin and Lincoln (2011) and Venkatesh, Brown and Bala, (2013) define research design as a set of interpretive practices linking theory's abstract space with empirical scrutiny. Within this view, design serves as a requisite bridge between conceptual plans and concrete procedures implemented to follow them (Denzin and Lincoln, 2011; Venkatesh et al., 2013). Here, the selected methodological approach must be aligned with both the philosophical stance of the research and the type of research problem at hand.

4.6.1 Mixed Methods Approach

The adoption of a mixed methods approach in this study was guided by both the complexity of the research problem and the need to generate actionable insights. Mixed methods research integrates both qualitative and quantitative techniques within

a single study, enabling the researcher to capitalise on the strengths of each while offsetting their respective limitations (Creswell and Plano Clark, 2018). As Onwuegbuzie and Leech (2005) advise, mixed methods approaches are particularly beneficial when a topic requires both width and depth, especially when researching emergent areas while statistically confirming observations. Given the goal of understanding how big data analytics capabilities construct competitive advantage in South African businesses, such an approach was considered highly suitable. The big data analytics capabilities domain is new, and local knowledge remains underdeveloped; thus, it was essential to first explore practitioner perspectives qualitatively and then test emergent patterns quantitatively.

The justification for adopting mixed methods stemmed from several considerations. First, the complexity of big data analytics capabilities spanned technological, business, and human dimensions, requiring both interpretive and statistical lenses to fully capture their effects (Maroufkhani, Wagner, Wan Ismail, Baroto and Nourani, 2019). Second, the emergent nature of the topic meant that the literature did not fully capture the contribution of big data analytics capabilities to competitive advantage in developing economies. South African businesses vary widely in size and adoption of big data analytics capabilities, making qualitative research important to ensure contextual relevance (Fletcher, 2017). Third, theory development and validation were central to this research, as it drew from the resource-based and dynamic capabilities theories while integrating practical empirical knowledge. By combining qualitative exploration with quantitative confirmation, the study enhanced its contribution to both theory and practice (Tashakkori, 2009). Finally, triangulation and credibility were strengthened through the combination of qualitative and quantitative methods. Using multiple means to collect data enhanced the quality of the research evidence (Fetters and Molina-Azorin, 2021). By following this design, the study generated findings that were both contextually rich and empirically validated, aligning with its goal of offering actionable insights for South African businesses. The mixed methods design was not only methodologically sound but also necessary to address the multi-faceted, character of the research problem.

4.6.1.1 Exploratory sequential mixed methods design

The sequential exploratory mixed methods design was selected for this study. Big data analytics capabilities remain an emergent domain in South Africa, where technology uptake, business culture, and human competencies are unevenly distributed across industries. This reflects both the complexity of the subject and the gaps identified in the existing literature. A design that would facilitate both qualitative in-depth probing and quantitative verification was therefore required.

An exploratory sequential design is particularly suitable in research contexts where limited empirical studies exist, or where contextual differences are expected to influence the phenomenon under study (Sarpong and Pushpanadham, 2025). The study began with a qualitative phase, during which participant perceptions were explored, emergent themes were developed, and a more informed understanding of big data analytics capabilities was gained. Insights from this phase were then used to refine the quantitative questionnaire distributed to a larger sample. By combining qualitative and quantitative methods, the design achieved methodological triangulation and strengthened both internal and external trustworthiness and validity. It also provided flexibility, allowing the researcher to adapt instruments based on fieldwork results, which is a necessity in South Africa's diverse business environment. The design consisted of two phases. The qualitative phase explored how South African business leaders perceive and use big data analytics capabilities to build dynamic and operational capabilities for competitive advantage. This phase generated rich, context-specific data on mechanisms and challenges influencing adoption and utilisation, which were then used to refine the quantitative instrument. The quantitative phase validated the relationships outlined in the conceptual model (Chapter 3) using PLS-SEM to analyse the combined impact of big data analytics capabilities, dynamic capabilities, and operational capabilities on competitive advantage (Ghasemaghaeu, 2021).

This sequential strategy ensured that qualitative findings informed, though did not directly dictate, the quantitative instrument, thereby increasing its construct validity and applicability to the South African context. Such an approach was particularly important given that most big data analytics research is limited locally and often drawn from advanced economy settings (Sarstedt, Ringle and Hair, 2021). Moreover, the

exploratory sequential design was realistic in its philosophical stance, acknowledging that strategic issues like big data analytics capabilities are inherently complex and require thorough qualitative inquiry followed by rigorous quantitative validation (Saunders et al., 2023). It also supported triangulation, which maximised the overall validity and reliability of results (Fetters and Molina-Azorin, 2021). By integrating qualitative discovery and quantitative confirmation, this study has provided a detailed, context-specific account of how big data analytics capabilities enable competitive advantage in South African businesses. In sum, the selection of an exploratory sequential mixed methods design aligned with the relevance and complexity of the research problem, the need to integrate theoretical insight with practical application, the pragmatic orientation of the study, and the dynamic nature of the South African business environment.

4.7 TARGET POPULATION

According to Sekaran and Bougie (2016), a research population refers to the entire group of individuals or entities that possess the characteristics of interest to the study. The target population defines the broad group of individuals or entities from which data will be drawn and to which the study seeks to generalise its findings (Sekaran and Bougie, 2016). For this research, the target population was South African business leaders, specifically those actively engaged in developing or managing big data analytics in their businesses.

As big data analytics capabilities were applied across various industries, purposive sampling was used to choose participants from the population across a range of industries. The participant inclusion criteria required roles of responsibility for data-driven strategy or operations for example, chief data officers, heads of analytics, chief information officers, or senior managers with direct responsibility for big data analytics deployment. A target population should be defined based on participants' relevance to the research questions and their capacity to provide meaningful insights (Creswell, 2014). This study therefore excluded business leaders who had limited or no involvement with big data analytics. The focus was rather placed on businesses where big data analytics was already in use, to explore how it contributes to competitive advantage.

It must be noted here that this research did not include business leaders who had little or no contact with big data analytics. The objective was to study big data analytics where it is already adopted and not on back-end industry awareness or adoption barriers. This aligned with the research objective of exploring how big data analytics capabilities could lead to competitive advantage. This population was chosen to reflect the diversity of South African business practices and to capture variations in big data analytics capabilities development across industries and business types.

4.8 SAMPLING

Sampling plays a critical role in determining the validity and quality of research findings, particularly in contexts where it is not possible to conduct a full census. It involves selecting a subset of the population that adequately represents the features and variability of the overall population, thereby enabling the researcher to draw accurate conclusions (Hair et al., 2019). In applied business research, sampling offers several advantages; for example, it allows for cost-effective data collection when dealing with widespread or dispersed populations and enables intensive questioning of key informants with relevant expertise. It is especially useful in situations where access to the entire population is constrained by time, resources, or confidentiality. In mixed methods research, the sampling process must remain coherent with the broader philosophical assumptions, the overall research design, and the practical constraints of the study (Creswell and Plano Clark, 2018).

4.8.1 Overview of sampling techniques

Broadly, sampling techniques are categorised into probability and non-probability strategies. Probability sampling involves the selection of participants where each member of the population has a known, non-zero chance of being included. This approach allows for statistical generalisation of results to the wider population (Etikan, Musa and Alkassim, 2016). Within probability sampling, several techniques are commonly employed. Simple random sampling ensures that every individual has an equal chance of selection. Systematic sampling involves selecting participants at fixed intervals from a population list, making the process structured while still maintaining randomness. Stratified sampling divides the population into smaller groups, or strata, based on shared characteristics or traits, and then randomly selects participants from each group. This ensures proportional representation across subgroups, thereby

enhancing diversity and balance in the sample (Taherdoost, 2016). In contrast, non-probability sampling involves the deliberate selection of participants based on factors relevant to the research. Although this approach does not yield statistical representativeness, it is widely applied in qualitative and exploratory research, where the emphasis lies on depth of insight rather than generalisability (Palinkas, Horwitz, Green, Wisdom, Duan and Hoagwood, 2015). Techniques of non-probability sampling include purposive sampling, where participants are selected for their expertise or relevance to the study question, while convenience sampling relies on participants who are readily available. Snowball sampling involves current participants recruiting others who meet the inclusion criteria; while quota sampling selects predetermined numbers of participants chosen from subgroups, although selection within these groups is not randomised. Each of these approaches carries trade-offs in terms of generalisability and depth. Probability sampling may maximise external validity but can sometimes overlook the contextual richness of specific cases. Non-probability sampling, particularly purposive techniques, delivers rich and relevant information and is especially valuable in new or under-researched areas such as big data analytics capabilities in South Africa. To clarify the options considered, Table 11 below contrasts the main types of sampling approaches, outlining their techniques, strengths, and limitations. This comparison provided the foundation for selecting the most appropriate strategies for the present study.

Table 11: Overview of the sampling types
Source: Author

Sampling Type	Techniques	Strengths	Limitations
Probability Sampling	Simple Random, Systematic, Stratified	Ensures representativeness; allows for statistical generalisation; reduces selection bias.	May be costly and time-consuming; requires complete population lists; may underplay contextual insights.

Non-Probability Sampling	Purposive, Convenience, Snowball, Quota	Provides rich, in-depth and contextually relevant data; practical for exploratory studies; useful in hard-to-reach populations.	Not statistically generalisable; risk of researcher bias; may lack diversity if poorly managed.

As shown in the table, both probability and non-probability sampling methods have distinct advantages and drawbacks. In this study, the choice of sampling was guided by the need to balance representativeness with contextual richness. The rationale for combining different strategies is outlined in the following section, which explains how the qualitative and quantitative phases were designed to complement one another within the overall mixed-methods approach.

4.8.2 Rationale for sampling approach

Given the exploratory sequential mixed methods design of the study, different sampling strategies were employed for the qualitative and quantitative phases to ensure methodological coherence and maximise both depth and breadth of findings (Ivankova, Creswell and Stick, 2006). The research focused on a specialised population namely South African business leaders and professionals actively involved in big data analytics, which made probability-based sampling impractical due to the absence of a comprehensive sampling frame. Consequently, non-probability sampling methods were adopted, with additional stratification applied during the quantitative phase to ensure diversity across industries and professional roles. This multi-tiered sampling strategy allowed the study to meet its dual aims: rich contextual understanding from the qualitative phase and empirical generalisation through the quantitative phase. The use of stratified sampling further ensured that insights were not disproportionately drawn from a single industry or business size, thereby improving the credibility of findings.

4.8.3 Sampling frame

Purposive sampling was employed during the qualitative phase in the selection of executives, managers and leaders who lead big data analytics initiatives, while the quantitative phase extended participation to data experts and business strategists across different industries. Consequently, to the exploratory sequential mixed methods

design, two samples were utilised, each for a different stage of the study to reduce bias and ensure methodological rigour.

4.8.3.1 Qualitative phase

The sample consisted of ten senior executives including chief data officers, heads of data analytics, IT directors, and senior managers utilising big data in their operations. These participants were from a range of industries like financial services, telecommunication, healthcare, retail, etc. Participants were recruited from professional networks, targeted recruitment, and referrals by existing contacts (small snowball sampling was used to add to the purposive method). Participants were given clear details of the study purpose, terms of participation, and ethical protections, including voluntariness and confidentiality. Selection of ten participants for interviews was informed by the data saturation principle. As Guest, Bunce and Johnson (2006) highlight, small and targeted qualitative samples can still yield strong findings when the research topic is contained, and participants are carefully selected. In this study, saturation was met at 8 interviews, and no new significant themes emerged in the final two interviews.

4.8.3.2 Quantitative phase

The sampling strategy for this phase was a combination of purposive sampling and stratified convenience sampling. Purposive sampling facilitated participation only from the corresponding big data analytics experts. Stratification made industry and firm size coverage. The participants were South African business executives involved in big data analytics. The sample size included 118 surveys, with 110 valid responses used for analysis. This exceeded the minimum recommended sample size for PLS-SEM involving multiple constructs (Hair et al., 2019). Snowball sampling assisted in encouraging further participation. The survey targeted individuals holding data-driven roles in South African businesses, with an assurance that the responses were drawn from proficient and experienced big data analytics practitioners.

Purposive sampling is especially suitable for studies in emerging fields such as big data analytics, where knowledge is not uniformly spread and constructing a general sampling frame is often not feasible (Creswell and Plano Clark, 2018). The approach suited the study's aim of obtaining both rich qualitative insight and a general sense of practice within various business environments.

4.9 DATA COLLECTION

This is a detailed process of collecting and measuring data from relevant sources to answer the research questions (Saunders et al., 2023). This research employed an exploratory sequential mixed method design with qualitative and quantitative phases to collect the data. The approach was used to gain deep contextual understanding of big data analytics capabilities and their influence on competitive advantage in South African businesses (Subramoney and Dagada, 2025; Plano Clark and Ivankova, 2016). The research took place over a period of nine months. The qualitative phase, through semi-structured interviews, was conducted during the first three months. Following the analysis of the interview data, the quantitative survey tool was developed and piloted, and the overall quantitative data collection process was undertaken in the next six months. This phased approach enabled the qualitative phase findings to directly inform the quantitative survey, making the study methodologically coherent and responsive to the research setting.

4.9.1 Qualitative data collection

The first phase involved semi-structured interviews with ten business leaders and executives from South African businesses engaged in big data analytics initiatives. These participants were purposively selected from various industries to provide rich and relevant insights (Maluleka and Dagada, 2024; Saar and Dagada, 2024). Six of the ten interviews were recorded (with consent), and four were conducted without recording, with detailed notes taken instead. All interview participants were provided with an information sheet explaining the purpose and procedures of the study (please see Appendix E). Participant consent was obtained, and the interviews were transcribed to ensure accuracy. The data collected were then used to inform the development of the quantitative survey instrument. Semi-structured interviews have been recognised as a powerful way of researching complex phenomena such as big data analytics because they can offer space and depth in the achievement of participants' experience, ideas, and opinions (Kallio, Pietilä, Johnson and Kangasniemi, 2016).

Development of the interview schedule was based on the theoretical framework and the literature. The questions were designed to provide detailed views of how big data analytics is conceptualised, implemented, and leveraged to achieve competitive

advantage in South African businesses. This approach ensured that key resources, including tangible, human, and intangible resources, as well as dynamic and operational capabilities, were explored in more detail. During interviews, the researcher was guided by the semi-structured interview guide developed for business leaders (please see Appendix F). The interviews were held online (using Microsoft Teams or Zoom), considering the spatial distribution of participants around South Africa and the necessity to fit the schedules of business leaders. The interviews took between 45 and 60 minutes and were audio recorded (with permission from the participants) to maintain precision. The recordings were transcribed verbatim and prepared for analysis using thematic coding methods.

4.9.2 Quantitative data collection

The second phase of data collection involved the administration of a structured survey to a wider group of business leaders, managers, and analytics professionals in South African businesses. The quantitative data were intended to test and validate insights emerging from the qualitative phase and to evaluate hypothesised relationships between big data analytics capabilities and competitive advantage. The aim was to validate insights from the qualitative phase and test hypothesised relationships between big data analytics capabilities, dynamic and operational capabilities, and competitive advantage using PLS-SEM.

The survey instrument was developed using established constructs and validated measurement scales from prior studies (Framnes and Danielsen, 2017; Kuratko, Morris and Schindehutte, 2015), as well as qualitative themes that emerged in Phase 1 of the study. The questionnaire measured both formative and reflective constructs. The data were collected through a web-based Google Survey platform and LinkedIn network sites to facilitate easy distribution and extensive geographic coverage. An initial sample of 250 business leaders was targeted using purposive and stratified sampling techniques. The focus was on identifying respondents with the right experience in big data analytics and strategic decision-making. Survey participants were given a participant information sheet outlining the purpose and scope of the online questionnaire prior to completing the questionnaire (please see Appendix A).

A total of 118 responses were received, of which 110 were complete and used for further analysis. The final sample size of 110 responses is considered appropriate for PLS-SEM, particularly within exploratory research contexts. According to Hair et al., (2019), PLS-SEM is well suited to studies involving complex models and smaller sample sizes, where the primary objective is prediction and theory development rather than strict theory confirmation.

The adequacy of the sample size is further supported by the widely applied 10-times rule, which suggests that the minimum sample size should be at least ten times the maximum number of structural paths directed at any construct in the model. Given the structure and complexity of the model tested in this study, the sample size of 110 exceeds this threshold and is therefore considered statistically acceptable.

While more recent methodological guidance recommends supplementing such rules with considerations of statistical power and model complexity, the present study adopts an exploratory approach aimed at generating contextually grounded insights into Big Data Analytics Capabilities within the South African environment. As such, the sample size is considered appropriate for the study's objectives and methodological approach. However, the findings should be interpreted with caution and not assumed to be broadly generalisable across all South African organisations.

4.10 QUESTIONNAIRE DESIGN

The design of the questionnaire was a critical stage of the process of ensuring that the quantitative component of this study would yield valid, reliable, and contextually appropriate data on big data analytics capabilities and competitive advantage in South African businesses. According to Creswell and Creswell (2017) research requires well-designed survey instruments to successfully measure complex constructs and capture the interactions between them (Creswell and Creswell, 2017). In alignment with the exploratory sequential research design, the questionnaire was theory-driven and based on the study theory and the qualitative interview findings of the initial phase. This helped to guarantee that the survey tool captured the reality of the South African business environment without straying from established theoretical frameworks.

The design of the questionnaire was based on the conceptual model of big data by Framnes and Danielsen (2017). Its constructs included tangible, human, and intangible resources; dynamic capabilities (sense, seize, transform); operational capabilities (technology and marketing) (Harrison and Reilly, 2011); and competitive advantage. Pre-existing measurement scales were adopted where applicable and adapted to the local context. Items were piloted and validated in a pilot stage to enhance clarity and applicability. The survey instrument was designed to capture constructs aligned to the conceptual framework and is presented in Appendix C.

There were four principal sections in the survey:

Section A: Business demographics (e.g., industry sector, company size, geographic location)

Section B: Big data analytics capabilities (formative indicators)

Section C: Dynamic and Operational Capabilities (reflective indicators)

Section D: Competitive Advantage outcomes (reflective indicators)

Responses were rated on a five-point Likert scale ranging from strongly disagree to strongly agree for most attitudinal items, in line with widespread practice in similar research (Hair et al., 2019). Scaling contributed toward ease of interpretation and comparability across constructs. Open-ended questions were not included in the final survey instrument, as the exploratory depth required to uncover new insights was achieved in the qualitative phase. The quantitative phase instead focused on validation and hypothesis testing, which are more suited to closed-ended, structured formats (Bird, 2009; Denscombe, 2017). The questionnaire was pilot tested on a limited sample of business leaders (n=12) to verify face validity, readability, and content relevance. Pre-testing feedback informed minimal revisions prior to the full-scale launch of the survey. In summary, the design of the questionnaire balanced academic integrity with practical applicability, enabling an effective quantitative measurement of the impact that big data analytics capabilities are having on competitive advantage within the South African business context. The final questionnaire used for data collection is provided in Appendix C.

4.11 DATA ANALYSIS

Data analysis is a scientific process of analytical application of statistical and logical methods to frame, summarize, and report data in meaningful ways. Data analysis provides researchers with a platform where conclusions can be drawn, hypotheses tested, and research questions eventually formulated based on evidence-based findings (Babbie, 2020). In mixed methods research, data analysis serves a double role; it unearths rich descriptive patterns in qualitative data as well as empirical generalisation through quantitative modelling. In this study, data analysis followed the principles of the exploratory sequential mixed methods design, where findings from Phase 1 (qualitative) were used to inform the construction of the Phase 2 (quantitative) survey. The overarching goal was to explore and examine the interrelationships between big data analytics capabilities, dynamic capabilities, operational capabilities, and competitive advantage within South African businesses.

4.11.1 Qualitative data analysis

The qualitative data consisted of the transcribed responses from 10 senior business leaders, including chief data officers, IT executives, and analytics managers. The primary aim of this phase was to identify how big data analytics capabilities is developed and implemented in South African businesses, together with the enablers and challengers that influence its strategic adoption. Thematic analysis was used to analyse the interview data. It is most frequently used in identification, exploration, and detailing of themes or patterns within qualitative data (Braun and Clarke, 2008). It provides theoretically versatile methods and enables further depth of understanding.

The analysis was informed by Braun and Clarke's six-stage process. Familiarisation involved intensive re-reading and reading transcripts to attain immersion. Generating initial codes consisted of creating systematic labels for sections of data pertinent to the research. Searching for themes involved coding data together into potential primary themes. Reviewing the themes required refining them and then comparing them across the data set and the theory. Defining and naming the themes meant clearly defining the scope and relevance of each theme. Producing the report involved summarising and presenting the themes with the accompanying data extracts.

Microsoft Excel was used throughout the analysis process to manage the coding structure, organise emerging themes, and track patterns (Subramoney and Dagada, 2025). This included tabulating participant responses, recording frequency counts, and grouping codes to support synthesis. The final themes, including strategic alignment, skills shortages, infrastructure and data quality constraints, business readiness, and regulatory pressures served a dual function. They informed both the refinement of the conceptual model, and the development of the quantitative survey instrument used in Phase 2. Table 12 summarises how each of Braun and Clarke's (2008) six-step approach to thematic analysis was applied to the qualitative data collected in Phase 1.

Table: 12: Braun and Clarke's Six-Step Approach to Thematic Analysis.

Source: Adapted from Braun and Clarke (2008)

Phase	Description of the Step (Braun and Clarke, 2008)	Application in This Study
1. Familiarisation	Immersion in the data through repeated reading of transcripts.	Intensive re-reading and careful review of the 10 interview transcripts to gain immersion.
2. Generating Initial Codes	Systematically labelling relevant features of the data.	Created systematic codes for key segments of data related to enablers and challenges.
3. Searching for Themes	Grouping codes into potential themes.	Organised initial codes into clusters forming potential primary themes.
4. Reviewing Themes	Refining themes to ensure coherence and consistency across the dataset.	Compared emerging themes against the dataset and theoretical foundations for alignment.
5. Defining and Naming Themes	Clearly defining scope and meaning of each theme.	Finalised scope, labels, and relevance of themes such as strategic alignment, skills, and infrastructure.

6. Producing the Report	Presenting final analysis with supporting extracts.	Summarised and presented themes supported by direct participant quotations.

As illustrated in the Table 12 above the thematic analysis process enabled the identification of core themes that not only shaped the refinement of the conceptual model but also guided the design of the survey instrument used in Phase 2. Building on these qualitative insights, the next stage of analysis involved applying quantitative methods to test the conceptual model and hypotheses.

4.11.2 Quantitative data analysis

Quantitative data collected from the survey were subjected to descriptive and inferential statistical analysis. Data were first screened for completeness, missing values, and outliers. Descriptive statistics, such as frequencies, means, and standard deviations, were used to summarise the data and profile the sample. PLS-SEM was employed for the inferential analysis, utilising SmartPLS 4 software. PLS-SEM was used since it is suitable for exploratory studies with complex models and small to medium sample sizes (Hair et al., 2019). The approach was also suitable in this study, where both formative and reflective constructs were present.

The analysis proceeded in two stages. Measurement model assessment involved analysing the reliability and validity of the constructs with indicators such as Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), and discriminant validity using the Fornell-Larcker criterion and HTMT ratios. Structural model assessment entailed examining path coefficients to assess the hypothesised relationships between constructs. Bootstrapping with 5,000 subsamples was used to test the significance of the paths, while R^2 values and effect sizes were used to determine the explanatory power of the model.

Quantitative analysis provided empirical support for the conceptual model by providing evidence of how big data analytics capabilities, dynamic capabilities, and operational capabilities affect competitive advantage in South African businesses. This systematic approach to data analysis ensured that qualitative and quantitative findings were

critically examined, hence enabling the researcher to draw informed conclusions about the contribution of big data analytics capabilities to competitive advantage in South African businesses. Table 13 outlines the two main stages of model assessment, measurement and structural, together with their focus, techniques, and outcomes.

Table: 13: Measurement and Structural Models.

Source: Author

Stage	Focus of Assessment	Indicators/ Techniques Used	Outcome
Measurement model assessment	Reliability and validity of constructs	Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), Fornell-Larcker criterion, HTMT ratios	Established construct reliability, convergent validity (AVE > 0.50), and discriminant validity.
Structural model assessment	Testing hypothesised relationships and explanatory power of the model	Path coefficients, bootstrapping (5,000 subsamples), R ² values, effect sizes (f ²)	Confirmed significance of paths and explanatory power of big data analytics, dynamic, and operational capabilities on competitive advantage.

As shown in Table 13, the combination of measurement and structural model assessments ensured that both the reliability of constructs and the significance of hypothesised relationships were rigorously tested. This comprehensive approach provided robust evidence of how big data analytics capabilities, dynamic capabilities, and operational capabilities influence competitive advantage. Having established

these results, the next section addresses the trustworthiness and validity of the research to confirm the credibility and trustworthiness of the study's conclusions.

4.12 TRUSTWORTHINESS, VALIDITY AND RELIABILITY

Trustworthiness, validity and reliability are important measures of methodological rigour. They show whether the study was conducted in a credible, accurate and dependable manner. In qualitative research, trustworthiness refers to the extent to which the findings reflect the experiences and meanings shared by participants, rather than the assumptions of the researcher (Lincoln and Guba, 1985). In quantitative research, validity refers to whether the research instrument measures what it is intended to measure, while reliability refers to the consistency and stability of the measurement process (Heale and Twycross, 2015).

Given the exploratory sequential mixed methods design adopted in this study, both qualitative and quantitative quality criteria were applied. The qualitative phase was assessed through trustworthiness, using the criteria of credibility, transferability, dependability and confirmability. The quantitative phase was assessed through validity and reliability, including content validity, construct validity, discriminant validity, pilot testing, Cronbach's alpha and composite reliability. These strategies ensured that the findings were both contextually grounded and methodologically sound.

4.12.1 Trustworthiness in the Qualitative Phase

Trustworthiness in the qualitative phase was assessed using the four criteria proposed by Lincoln and Guba (1985), namely credibility, transferability, dependability and confirmability. These criteria were appropriate because the qualitative phase aimed to explore the experiences, perceptions and practices of business leaders involved in big data analytics capabilities in South African organisations.

The study strengthened trustworthiness through several practical steps. Semi-structured interviews were used to allow participants to provide detailed and context-specific responses. Six interviews were audio recorded with permission, while detailed notes were taken for the remaining four interviews where recordings were not made. The recorded interviews were transcribed, and the transcripts and notes were reviewed to ensure accuracy. A systematic thematic analysis process was then

followed, supported by coding, theme development and an audit trail that documented key analytical decisions.

Triangulation was also achieved through the broader mixed methods design. Insights from the qualitative phase informed the development of the quantitative questionnaire, and the subsequent survey provided an opportunity to examine whether the qualitative insights were reflected across a wider group of respondents. This helped to strengthen the credibility and overall coherence of the study.

4.12.1.1 Credibility

Credibility refers to the extent to which the findings accurately reflect participants' views and lived experiences (Noble and Smith, 2015). In this study, credibility was strengthened through the careful selection of participants who had direct knowledge of big data analytics capabilities, data-driven decision-making and business strategy. This ensured that the data were obtained from individuals who were well positioned to speak to the phenomenon under investigation.

Credibility was also enhanced through the use of semi-structured interviews, which allowed the researcher to explore common themes while still giving participants space to explain their experiences in detail. Audio recordings, detailed notes and transcript checking further supported the accuracy of the data. Where possible, participants were allowed to confirm or clarify the accuracy of their responses, which reduced the risk of misinterpretation.

Triangulation further supported credibility. The study drew on participants from multiple sectors, including financial services, telecommunications, healthcare and retail. In addition, the qualitative findings were later connected to the quantitative survey, allowing the study to compare insights across both phases. Peer review and academic scrutiny also strengthened credibility through doctoral colloquia, academic presentations, conference feedback and publication review processes.

The following publications and academic outputs contributed to the peer examination process:

Subramoney, S., and Dagada, R. (2025). The Big Data Analytics Capabilities and Competitive Advantage in South Africa: Perspectives from Qualitative Study. In R. Dagada (Ed.), *Research in Southern African Digital Business* (Vol. V). Mercury Books.

Subramoney, S., and Dagada, R. (2025). The Big Data Analytics Capabilities and Competitive Advantage in South Africa: Perspectives from Quantitative Study. In R. Dagada (Ed.), *Research in Southern African Digital Business* (Vol. V). Mercury Books.

Subramoney, S., and Dagada, R. (2024). Big Data Analytics Capabilities and Competitive Advantage in South Africa: The Case for Further Research. In R. Dagada (Ed.), *Research in Southern African Digital Business* (Vol. 3, pp. 157–187). Mercury Books.

Subramoney, S., and Dagada, R. (2025). Big Data Analytic Capabilities and Competitive Advantage in South Africa. Paper presented at the International Conference of Accounting and Business, University of Cape Town, 19–20 June 2025. Feedback from these processes helped to refine the study's arguments, strengthen the analysis and improve methodological rigour.

4.12.1.2 Transferability

Transferability refers to the extent to which the findings may be applicable to other contexts (Lincoln and Guba, 1985). Unlike statistical generalisation, transferability depends on the provision of sufficient contextual detail so that readers can determine whether the findings may be relevant to similar settings.

In this study, transferability was supported by providing detailed descriptions of the research context, the participant profile and the industries represented. Participants were drawn from different South African business sectors, including financial services, telecommunications, healthcare and retail. This multi-sector focus strengthened the contextual depth of the findings and allowed the study to reflect different organisational realities.

Although the study was not designed to produce broad statistical generalisations across all South African businesses, the inclusion of diverse sectors and roles provides useful insights for organisations operating in similar emerging market

contexts. The findings may therefore be transferable to businesses facing comparable challenges in developing and using big data analytics capabilities.

4.12.1.3 Dependability

Dependability refers to the consistency and transparency of the research process over time. It requires the researcher to show that the study followed a clear and traceable process that could be understood and reviewed by others.

In this study, dependability was supported through the use of a semi-structured interview guide, which ensured that all participants were asked questions aligned with the research objectives while still allowing flexibility for deeper discussion. The researcher also maintained an audit trail that documented key methodological decisions, data collection procedures, coding processes and analytical steps.

Thematic analysis was conducted systematically, following the process described by Braun and Clarke (2008). Microsoft Excel was used to organise interview data, codes, categories and emerging themes. This helped to improve consistency in the analysis and made it easier to trace how final themes were developed from the raw data.

4.12.1.4 Confirmability

Confirmability refers to the extent to which the findings are shaped by the data and participants' views rather than by researcher bias. This is especially important in qualitative research, where interpretation plays a central role in the analysis process. In this study, confirmability was strengthened through the use of an audit trail, reflexive note-taking and careful documentation of analytical decisions. The researcher remained aware of the possibility of personal or professional bias and used systematic coding procedures to ensure that themes were grounded in the data.

Participant quotations were also used in Chapter 5 to support the themes and demonstrate the link between the findings and the original interview responses. All transcripts, notes, coding files and analytical records were securely stored and organised. This supported transparency and helped to ensure that the findings could be traced back to the data collected.

4.12.2 Validity in the Quantitative Phase

Validity in the quantitative phase refers to the extent to which the survey instrument measured the constructs it was intended to measure. In this study, validity was addressed through content validity, construct validity, convergent validity and discriminant validity.

Content validity was strengthened by grounding the questionnaire items in the existing literature on big data analytics capabilities, dynamic capabilities, operational capabilities and competitive advantage. The questionnaire was also informed by the qualitative findings from Phase 1, ensuring that the instrument was not only theoretically grounded but also relevant to the South African business context.

Construct validity was assessed through the measurement model in PLS-SEM. The model tested whether the indicators adequately represented the underlying constructs.

Convergent validity was assessed using average variance extracted values, while discriminant validity was assessed using the Fornell-Larcker criterion and HTMT ratios. These tests helped to confirm that the constructs were both internally coherent and empirically distinct from one another.

The pilot testing of the questionnaire also contributed to validity. The pilot helped to identify unclear wording, possible ambiguity and issues of readability before the questionnaire was distributed more widely. This strengthened the quality of the final survey instrument and improved the accuracy of the data collected.

Table 14: Summary of Validity Strategies in the Study

Source: Author

TYPE OF VALIDITY	HOW IT WAS ASSESSED
Content validity	Questionnaire items were anchored in existing literature and informed by qualitative findings to ensure adequate coverage of the study constructs.
Construct validity	Established through PLS-SEM measurement model testing.
Convergent validity	Assessed using average variance extracted values
Discriminant validity	Assessed using the Fornell-Larcker criterion and HTMT ratios.
Pilot testing	Used to refine wording, readability and clarity before full data collection.
Triangulation	Qualitative and quantitative findings were integrated to strengthen the overall credibility of the study.

4.12.3 Reliability in the Study

Reliability refers to the consistency, stability and reproducibility of the research process and measurement instruments (Heale and Twycross, 2015). In this study, reliability was addressed in both the qualitative and quantitative phases.

In the qualitative phase, reliability was supported through the use of a semi-structured interview guide, verbatim transcription, detailed notes, systematic coding and an audit trail. These procedures helped to ensure that the qualitative analysis followed a

consistent and transparent process. The use of participant quotations in the findings chapter also improved transparency by showing how interpretations were linked to the data.

In the quantitative phase, reliability was assessed through Cronbach's alpha and composite reliability. These measures were used to determine whether the items measuring each construct were internally consistent. Values above the recommended threshold of 0.70 were regarded as acceptable, indicating that the constructs demonstrated adequate reliability (Taber, 2018; Hair et al., 2019).

The questionnaire was also pilot tested before full data collection. The pilot test helped to identify wording issues, improve clarity and reduce possible misunderstanding among respondents. This contributed to the overall reliability of the quantitative instrument.

Table 15: Summary of Trustworthiness and Reliability Strategies
Source: Author

Phase	Approach used	Outcome
Qualitative	Semi-structured interview guide	Ensured consistency across interviews while allowing depth of response
Qualitative	Interviews recorded and transcribed verbatim where consent was provided	Improved accuracy of the qualitative data.
Qualitative	Detailed notes taken where interviews were not recorded	Ensured that all participant contributions were captured.
Qualitative	Audit trail maintained during thematic analysis	Provided transparency and traceability of analytical decisions.

Qualitative	Systematic coding using Microsoft Excel	Enhanced consistency in theme identification
Qualitative	Participant quotations used in reporting	Improved transparency and dependability of findings.
Quantitative	Pilot testing of questionnaire	Refined wording and reduced ambiguity before full data collection.
Quantitative	Cronbach's alpha assessed	Indicated internal consistency of constructs.
Quantitative	Composite reliability assessed	Confirmed measurement model reliability

This section demonstrates that the study applied appropriate procedures to ensure quality across both research phases. The qualitative phase was strengthened through trustworthiness strategies, while the quantitative phase was strengthened through validity and reliability testing. Together, these measures supported the credibility, accuracy and dependability of the study's findings.

4.13 ETHICAL CONSIDERATIONS

Careful attention was given, in the design and execution of this study, to maintaining high standards, both in line with the university code of ethics and widely accepted standards for research on human subjects (British Psychological Society, 2021; Saunders et al., 2023).

4.13.1 Informed consent

All of the participants were fully informed of the aim, scope, and voluntary nature of the study prior to the collection of data. In the qualitative phase, participants received an information sheet and consent form detailing the nature of the study, the right to

withdraw at any point, what would become of their data, and how it would be kept secure. Written consent was obtained before interviews commenced, and informed consent for the online questionnaire was obtained through a form provided to participants (please see Appendix B). Similarly, the web-based survey included an informed consent message that the respondents had to acknowledge prior to proceeding. (please see Appendix D).

4.13.2 Anonymity and confidentiality

The identities of participants and their business affiliations were protected throughout the research. Interview transcripts and survey responses were anonymised, and all identifying information was removed. Data were stored securely in password-protected digital files accessible only to the researcher. In reporting the findings, individual responses were presented in ways that prevented identification of specific participants or businesses, particularly given the sensitive nature of discussions about competitive capabilities and data strategies.

4.13.3 Data protection and storage

Data management adhered to the principles of the Protection of Personal Information Act (POPIA) of South Africa and General Data Protection Regulation (GDPR) principles. Data were to be retained for five years in accordance with university policy and then securely destroyed.

4.13.4 Voluntary participation and right to withdraw

Participation in both the qualitative and quantitative phases was strictly voluntary. Participants were informed of their right to decline participation or withdraw from the study at any time, without penalty or consequence.

4.13.5 Ethical clearance

Full ethical clearance for the study was obtained from the University's Ethics Committee prior to the commencement of data collection. All the research activities were carried out according to the university's ethics guidelines. By adhering to these guidelines, the study ensured that participants' rights and anonymity were fully protected, and the research was conducted with the highest standards of academic

integrity and professional responsibility.

4.14 METHODOLOGICAL LIMITATIONS

While this study employed a rigorous and well-considered methodology, several limitations must be acknowledged, which informed the interpretation of findings and guided future research.

4.14.1 Generalisability

As is typical with exploratory sequential mixed methods designs, the study was not intended to produce statistically generalisable findings across all South African businesses (Creswell and Plano Clark, 2018). The qualitative phase of the study sought depth of understanding as opposed to breadth, and the quantitative phase, while adequately powered for PLS-SEM analysis utilised non-probability sampling (Hair et al., 2019). The results are thus to be understood as illustrative and not necessarily representative of all of South Africa's business leaders.

4.14.2 Sampling constraints

The use of purposive and stratified convenience sampling in the quantitative phase introduced potential for selection bias. While efforts were made to include participants from a range of industries and firm sizes, the sample over-represented businesses already investing in big data analytics capabilities which may have skewed findings towards businesses with greater digital maturity.

4.14.3 Self-report data

Both the qualitative interviews and quantitative survey relied on self-reported data from managers and professionals. Although steps were taken to minimise social desirability bias (e.g., ensuring anonymity and confidentiality), responses may still have reflected some degree of optimism or strategic positioning on the part of participants.

4.14.4 Evolving context

There exists an intense level of technological advancement and shifting regulatory climates in South Africa and globally. This means that findings captured while collecting data may at some point in time need to be revised to reflect new twists in big data analytics capabilities practice and business landscapes. Furthermore, the

ongoing impact of emerging technologies such as artificial intelligence has the potential to reshape the world of big data analytics capabilities and competitive advantage in dimensions not yet systematically captured by this study.

4.14.5 Researcher bias

The researcher's professional background in big data analytics may have introduced interpretive bias during qualitative analysis. This was mitigated through structured interview guides, member checking, an audit trail, and reflexivity, although the potential for subjectivity cannot be entirely excluded (Kallio et al., 2016). Despite these limitations, the integrated design combining qualitative exploration with quantitative validation provided a solid foundation for generating both theoretical and practical insights into big data analytics capabilities and competitive advantage in the South African business landscape (LaValle, Lesser, Shockley, Hopkins and Kruschwitz, 2011).

4.15 SUMMARY OF CHAPTER 4

This chapter has provided a detailed explanation of the research approach employed to examine big data analytics capabilities and competitive advantage in South African businesses. It has outlined the philosophical and methodological underpinnings of the study, explaining the use of an exploratory sequential mixed methods design grounded in pragmatism. The research design, population, sampling procedures, and data collection methods have been described for both the qualitative (semi-structured interviews) and quantitative (structured survey) phases. The application of thematic analysis and PLS-SEM to analyse the data in alignment with the conceptual framework has been detailed. Methodological rigour of the study has been clearly described. This was maintained through clear attention to validity, reliability, and ethical compliance across all phases of the study. Limitations related to generalisability and sampling constraints were acknowledged to ensure proper interpretation of the findings. Overall, the methodological framework outlined in this chapter provides a solid foundation for the empirical analysis presented in the next chapter, which reports the qualitative themes followed by the quantitative results derived from the PLS-SEM analysis.

CHAPTER 5: QUALITATIVE FINDINGS

5.1 CHAPTER OVERVIEW AND INTRODUCTION

This chapter presents the qualitative findings of the study, which was the first phase of the exploratory sequential mixed methods design. From the methodological platform presented in Chapter 4, the qualitative phase sought to produce rich context-specific insights into the way South African organisations are developing, executing, and embedding big data analytics capabilities to achieve competitive advantage.

The chapter starts with an overview of the purpose of the qualitative phase in the context of the overall research design and then presents a demographic profile of participants to establish the diversity and representativeness of the interview sample. It then describes the methods used to manage and analyse the data, for instance, the use of Braun and Clarke's (2008) six-step thematic analysis process facilitated by Microsoft Word and Excel to ensure rigour, transparency, and traceability.

Underpinning the chapter are the six key themes that have been distilled from the data. These are challenges of strategic alignment, talent and skills shortages, constraints of infrastructure and data quality, competitive differentiation and value creation, organisational readiness and cultural transitions, and regulatory and environmental pressures. Each theme is underpinned with direct quotes from participants to ensure authenticity and place the analysis in the lived world of business leaders across a variety of sectors (Dangale and Dagada, 2024).

The qualitative findings served two primary roles. The first was to provide in-depth, context-specific information about the obstacles and consequences of implementing big data analytics capabilities in South African businesses. The second was to facilitate the process of developing the quantitative instrument and solidifying the conceptual model that was piloted through the quantitative phase as described in Chapter 6.

This chapter presents a detailed thematic analysis, drawing from semi-structured interviews conducted with ten business leaders and professionals across a range of

industries. These included Finance, Public Sector, Retail, Telecommunications, Insurance, Technology, Healthcare, Logistics, and Manufacturing, (Saar and Dagada, 2024). In alignment with the study's conceptual foundations in resource-based and dynamic capabilities theories, the analysis sought to move beyond surface-level adoption of big data, focusing instead on the organisational, human, and contextual enablers and constraints that influence big data analytics capabilities and their contribution to competitive advantage.

The thematic analysis followed Braun and Clarke's (2008) six-phase framework, which was applied using Microsoft Excel to ensure systematic and auditable coding. This dual-tool approach supported academic rigour and transparency in identifying meaningful patterns in the data. Themes were generated inductively but were interpreted with reference to the study's guiding theoretical perspectives. Six core themes were derived from the results, and each of these was a core challenge that South African businesses face on their journey toward data-driven competitiveness. These were strategic alignment challenges, talent and skills shortfalls, infrastructure and data quality challenges, competitive differentiation and value creation, organisational preparedness and cultural change, and environmental and regulatory pressures. All the above themes are outlined in the following sections of this chapter, with supporting quotations from interview respondents to ensure authenticity and richness of their understanding.

The chapter also shows to what extent qualitative findings contributed to the quantitative survey instrument design used in Chapter 6. By thematizing constructs and survey questions, the research ensured that the subsequent quantitative phase was solidly anchored in practitioner reality and theoretically aligned with resource-based and dynamic capabilities theories. Finally, the chapter discusses the limitations and advantages of the qualitative phase, clarifies the measures taken to maximise trustworthiness and rigour, and highlights the integrative purpose of qualitative findings in informing the overall research insights. It therefore forms an essential foundation for the quantitative analysis presented in the next chapter. To provide a visual guide to the structure of this chapter, Figure 19 presents an overview of how the qualitative findings were organised and how they contributed to the study's overall research design.

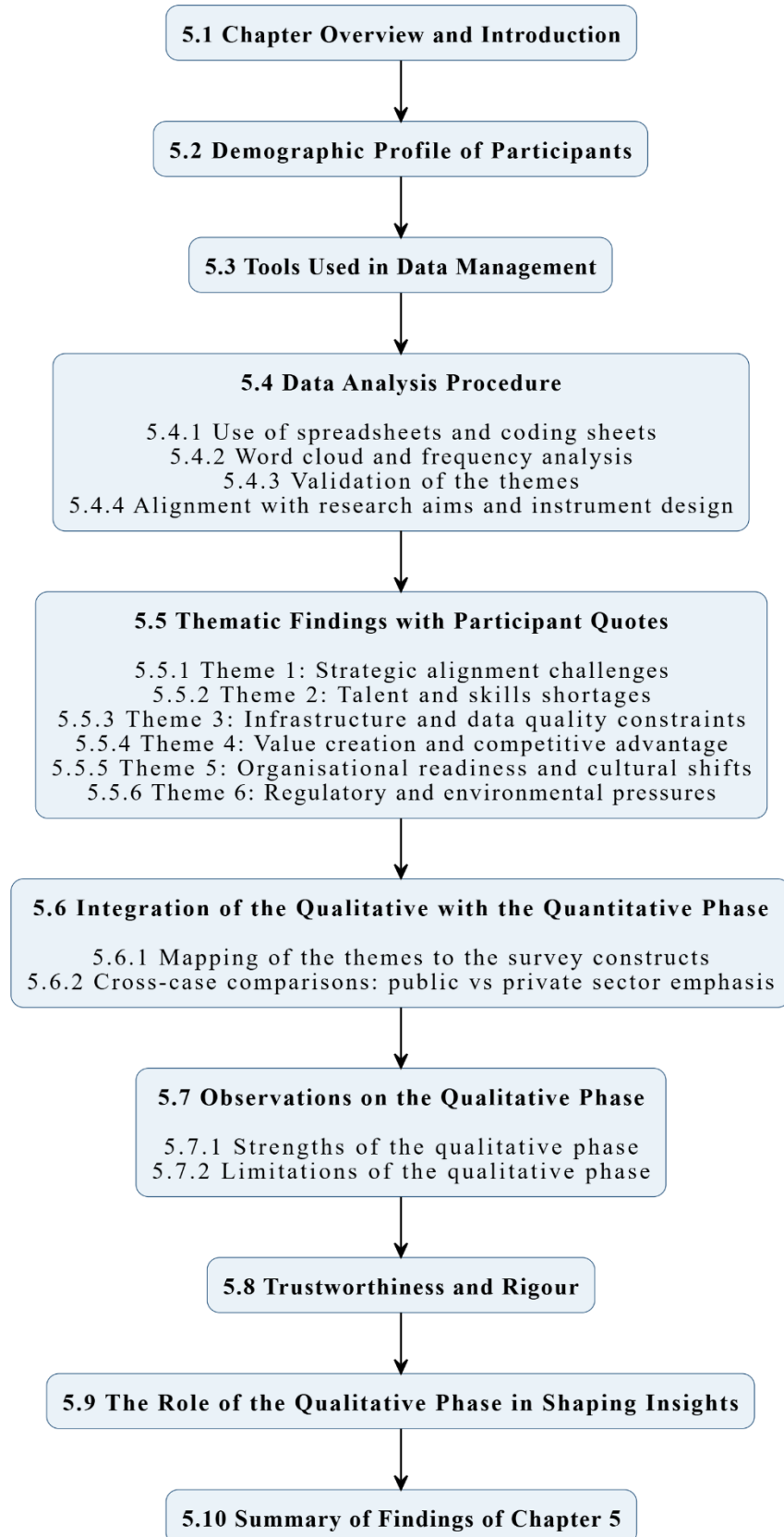


Figure 19: Overview of Chapter 5 – Qualitative Findings

Source: Author

As depicted the qualitative phase played a central role in establishing the foundation for the quantitative analysis that followed in Chapter 6. The first step in presenting these findings was to outline the demographic profile of participants, which provided essential context for interpreting the themes. By understanding the diverse professional roles, qualifications, and sectoral affiliations of the respondents, the analysis gained credibility and depth, ensuring that the insights reflected a broad spectrum of perspectives within South African business.

5.2 DEMOGRAPHIC PROFILE OF PARTICIPANTS

To ensure the credibility and contextual depth of the qualitative phase, the interview participants (presented in Table 16 below) were purposefully selected to reflect variations in gender, age, experience, educational background, and industry representation. This diversity enriched the thematic analysis with a wide range of perspectives. The demographic profiles of the participants reflected their professional roles, qualifications, and sectoral affiliations. This diversity highlights the multidimensional nature of big data analytics capabilities implementation across the South African business landscape (Subramoney and Dagada, 2025).

Table 16: Demographic profile of interview participants across sectors, roles, and experience levels.

Source: Author

Participant	Gender	Age Group	Position	Years at Current Org	Highest Qualification	Sector
P1	M	36 - 40	Manager	3	Masters	Finance
P2	F	51 - 55	Director	12	PhD	Government
P3	F	36 - 40	Manager	2	LLB	Retail
P4	M	41 - 45	Head of Analytics	5	Honors	Telecommunications
P5	F	56 - 60	CIO	15	PhD	Public Sector
P6	M	46 - 50	Data Scientist	6	Masters	Insurance

P7	M	40 - 45	CTO	8	PhD	Technology
P8	F	31 - 35	Analyst	4	Bachelors	Logistics
P9	F	50 - 55	Executive	20	PhD	Healthcare
P10	M	45 - 50	IT Director	10	Masters	Manufacturing

In addition, to visually summarise sectoral diversity, a distribution chart (Figure 20) is also presented, illustrating the representation across industries.

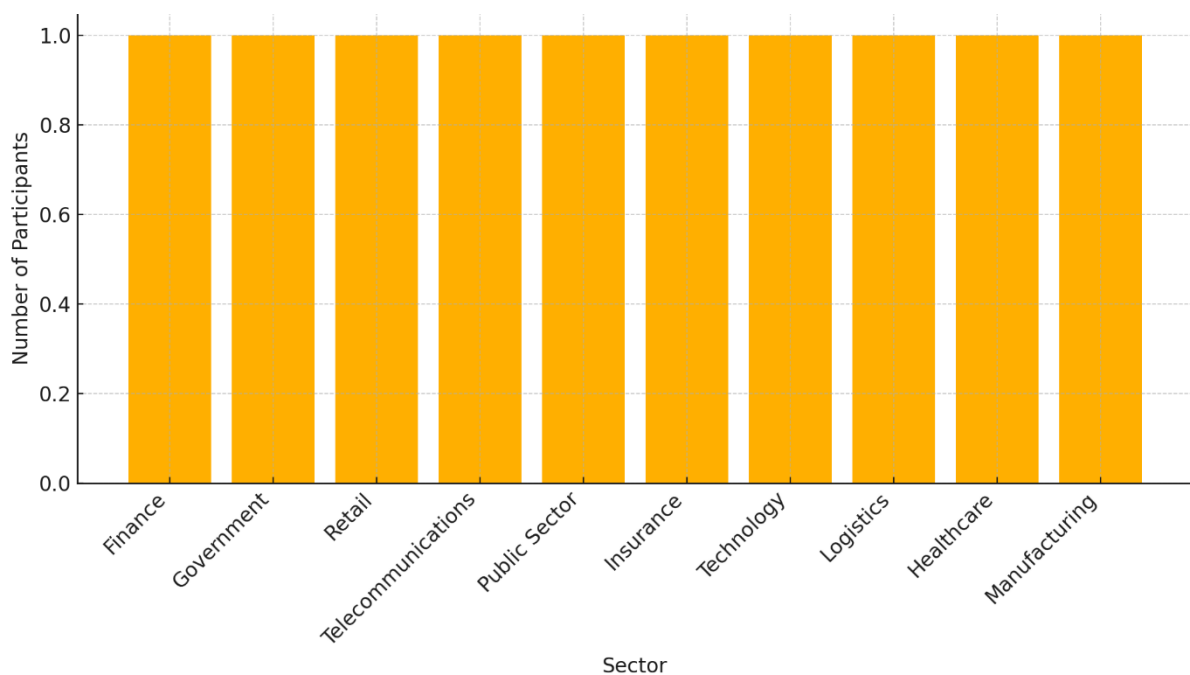


Figure 20: Distribution of interview participants by sector.

Source: Author

To manage and analyse the qualitative data effectively, appropriate tools were required to ensure systematic coding, transparency, and rigour. The following section therefore outlines the data management tools employed, explaining how Microsoft Word and Microsoft Excel were used to capture, code, and structure the interview material.

5.3 TOOLS USED IN DATA MANAGEMENT

Use of Microsoft Word and Microsoft Excel ensured systematic and rigorous data analysis during the qualitative phase. The interview transcripts were read and annotated in Word first, where preliminary codes were manually utilised through margin comments and keyword tagging. Microsoft Excel was subsequently enabled transfer of the coded data into a hierarchical framework. Each row was a coded unit of analysis, while each column displayed valuable information such as the participant Identification number, the sector they belong to, the thematic code, as well as the representative data excerpts. Excel's built-in capabilities allowed for the simple cross-case comparison across the participants and sectors, and colour-coding of the thematic categories enabled more dense visual ordering. This strategy facilitated both depth and traceability, making the thematic analysis process more credible and auditable. In permitting iterative checking and refinement, this ensured that final themes arose from participant data.

Theme No.	Theme	Participant	Sector	Interview Excerpt
1	Strategic Alignment Challenges	Participant 3	Retail	We collect data from everywhere — but there's no formal roadmap for what happens next. The insights don't flow up to inform business units in real time, which defeats the purpose of pre
1	Strategic Alignment Challenges	Participant 7	Technology	There's a major push for dashboards and data lakes, but very little attention to how this fits into our key strategic goals. It becomes tech for tech's sake.
1	Strategic Alignment Challenges	Participant 5	Public Sector	We're still catching up in terms of leadership awareness. Data is seen as an IT function — not a strategic asset.
1	Strategic Alignment Challenges	Participant 3	Retail	We have a head of data now, but he reports to the CTO, not to the CEO. That tells you everything about our priorities.
2	Talent and Skills Shortages	Participant 5	Public Sector	We can find junior data analysts — but finding experienced people who can connect the dots and really drive business value is very tough.
2	Talent and Skills Shortages	Participant 3	Retail	We are losing talent to Europe and the US. Local firms can't compete on salaries for top data scientists.
2	Talent and Skills Shortages	Participant 9	Healthcare	The leadership team doesn't always understand what the analytics people are talking about — there is still a skills gap at the executive level.
2	Talent and Skills Shortages	Participant 2	Government	We're always chasing skills. Either we find data scientists who are too academic or engineers who don't understand the business. The hybrid profiles we need are just not available locally.
2	Talent and Skills Shortages	Participant 6	Insurance	Even when we find great talent, they get poached quickly by international firms or banks. Our HR budgets can't match that.
2	Talent and Skills Shortages	Participant 9	Healthcare	Junior analysts come in knowing Python or Power BI, but they have no idea how to structure a hypothesis or interpret results. We spend more time training than analyzing.
2	Talent and Skills Shortages	Participant 10	Manufacturing	Most of our data people are outsourced consultants. We don't have institutional knowledge being built. That's risky.
2	Talent and Skills Shortages	Participant 4	Telecommunications	We can't grow beyond pilot projects because there's nobody to take ownership. Data governance expertise is scarce.
3	Infrastructure and Data Quality Constraints	Participant 8	Logistics	Our biggest challenge is not analytics — it's the data itself. Legacy systems don't talk to each other, and the data is often unreliable.
3	Infrastructure and Data Quality Constraints	Participant 6	Insurance	We have made investments in cloud platforms — but until we fix the data quality, we can't move forward.
3	Infrastructure and Data Quality Constraints	Participant 1	Finance	Data ownership is fragmented — every business unit runs their own systems, and integration is a major hurdle.
3	Infrastructure and Data Quality Constraints	Participant 1	Finance	We have data sitting across multiple legacy systems that don't talk to each other. It takes weeks just to extract and clean what we need before any analysis even begins.
3	Infrastructure and Data Quality Constraints	Participant 3	Retail	We spend more time fixing data than analyzing it. There are no enterprise-wide data ownership structures, so no one is accountable for data quality.
3	Infrastructure and Data Quality Constraints	Participant 5	Public Sector	Our infrastructure is outdated. We still rely on on-prem servers, and system downtimes are frequent. Cloud migration is talked about but not implemented.
3	Infrastructure and Data Quality Constraints	Participant 7	Technology	We have dashboards showing KPIs from bad data. Then leadership makes decisions based on that. It's dangerous.
3	Infrastructure and Data Quality Constraints	Participant 9	Healthcare	We handle sensitive data, so we must comply with POPIA. But our systems aren't robust enough to track access or encryption across datasets.
3	Infrastructure and Data Quality Constraints	Participant 4	Telecommunications	We can't do real-time analytics. Our systems only process data in overnight batches.
4	Value Creation and Competitive Differentiation	Participant 1	Finance	The value is not just in storing data, it's in how fast and smartly we use it. Our entire loyalty programme is now driven by predictive models, and that has improved client retention.
4	Value Creation and Competitive Differentiation	Participant 6	Insurance	We've moved from static risk models to real-time pricing based on behavioural data from telematics. That's a direct competitive edge.
4	Value Creation and Competitive Differentiation	Participant 8	Logistics	In logistics, routing used to be reactive. Now with big data, we can simulate and optimize in advance, saving costs and reducing delays.
4	Value Creation and Competitive Differentiation	Participant 4	Telecommunications	We no longer just sell products. We sell insights. That's what clients are paying for—our ability to make sense of their own data.
4	Value Creation and Competitive Differentiation	Participant 6	Insurance	Leadership must trust the data. If decisions are still made from the gut, then BDA won't deliver value.
4	Value Creation and Competitive Differentiation	Participant 6	Insurance	We used analytics to reduce fraudulent claims by 25%. That's a major win.
4	Value Creation and Competitive Differentiation	Participant 3	Retail	Improved segmentation through clustering techniques helped us increase our campaign hit rates. That had direct impact on sales.
4	Value Creation and Competitive Differentiation	Participant 3	Retail	Without our analytics capability, we would not have been able to develop our new customer loyalty platform — it's now a key differentiator.
4	Value Creation and Competitive Differentiation	Participant 4	Telecommunications	The biggest value is agility — being able to respond faster to changing customer needs and market shifts.
4	Value Creation and Competitive Differentiation	Participant 1	Finance	We are using data to drive innovation — we've launched three new products in the last year based on analytics insights.
5	Organisational Readiness and Cultural Shifts	Participant 7	Technology	The technology is the easy part — the hard part is getting people to trust the data and use it in their daily decisions.
5	Organisational Readiness and Cultural Shifts	Participant 10	Manufacturing	We still see silos — each unit protects its data, which limits what we can achieve with analytics.
5	Organisational Readiness and Cultural Shifts	Participant 1	Finance	Without leadership driving the message that data is a strategic asset, the culture will not change.
5	Organisational Readiness and Cultural Shifts	Participant 3	Retail	The tools are there, but if your people are not open to using data in their daily decisions, then it all collapses.
5	Organisational Readiness and Cultural Shifts	Participant 5	Public Sector	We had to train even senior managers on how to read dashboards and interpret KPIs. It took months before they trusted the numbers.
5	Organisational Readiness and Cultural Shifts	Participant 10	Manufacturing	Data is owned in pockets—IT owns some, marketing owns some, and no one talks to each other. That's a major obstacle.

Figure 21: Screen shot of the Excel interface used to visualise and manage qualitative data.

Source: Author

With this auditable structure established, the analysis moved systematically through Braun and Clarke's six-stage thematic procedure (Saar and Dagada, 2024). The next section details each step, from familiarisation and initial coding to theme generation, review, definition, and final reporting.

5.4 DATA ANALYSIS PROCEDURE

Braun and Clarke's (2008) systematic yet flexible approach produced rich, meaningful findings from interview material. The procedure was adapted to fit the setting of the research and made use of Microsoft Word and Excel to facilitate traceable, auditable analysis. Each transcript was analysed independently to preserve within-case depth, and cross-case comparisons to identify common patterns among participants and industry sectors afterward. A two-level strategy in such a manner enhanced the reliability of thematic construction.

Step 1 involved familiarisation with the data.

Six of the interviews were audio recorded with the respondents' consent and transcribed verbatim through Google Docs. Comprehensive handwritten notes were taken during the sessions in the remaining four interviews, where participants did not give consent for recording. Transcripts and notes were read many times to facilitate saturation with the data, and initial patterns, key expressions, and conceptual relationships were documented at this point.

Step 2 was generating initial codes.

A line-by-line coding process was applied. This used both descriptive codes such as skills shortage, legacy systems, and regulatory pressure, and in vivo codes derived from participants' own words such as **"data sits in silos"** and **"we don't trust the numbers."** The process combined an inductive approach that was data-driven with a deductive lens drawn from the study's conceptual framework, resource-based and dynamic capabilities theories. This ensured that the analysis was both theoretically anchored and empirically grounded.

Step 3 involved searching for themes.

Coded excerpts were assembled into Microsoft Excel to facilitate pattern recognition and thematic grouping. Each row in the spreadsheet captured the participant ID,

sector, excerpt, and provisional theme category. Colour-coding was applied to cluster similar codes, aiding visual organisation and thematic coherence. From this process the following detailed information was derived: identification of industry- and role-specific patterns, aggregation of related meanings into potential themes and sub-themes, and iterative refinement of codes and categories. At this stage, 184 initial raw codes were generated. These served as the foundation for theme development, which was aligned with the study's objectives and theoretical grounding.

Theme No.	Theme	Participant	Sector	Interview Excerpt
1	Strategic Alignment Challenges	Participant 3	Retail	We collect data from everywhere — but there's no formal roadmap for what happens next. The insights don't flow up to inform business units in real time, which defeats the purpose of predictive analytics.
1	Strategic Alignment Challenges	Participant 7	Technology	There's a major push for dashboards and data lakes, but very little attention to how this fits into our key strategic goals. It becomes tech for tech's sake.
1	Strategic Alignment Challenges	Participant 5	Public Sector	We're still catching up in terms of leadership awareness. Data is seen as an IT function — not a strategic asset.
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3	Infrastructure and Data Quality Constraints	Participant 1	Finance	Data ownership is fragmented — every business unit runs their own systems, and integration is a major hurdle.
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5	Organisational Readiness and Cultural Shifts	Participant 3	Retail	The tools are there, but if your people are not open to using data in their daily decisions, then it all collapses.
5	Organisational Readiness and Cultural Shifts	Participant 5	Public Sector	We had to train even senior managers on how to read dashboards and interpret KPIs. It took months before they trusted the numbers.
5	Organisational Readiness and Cultural Shifts	Participant 10	Manufacturing	Data is owned in pockets — IT owns some, marketing owns some, and no one talks to each other. That's a major obstacle.
5	Organisational Readiness and Cultural Shifts	Participant 5	Public Sector	Where leaders promote experimentation and allow for data-driven innovation, things move. But many still don't understand analytics themselves.
5	Organisational Readiness and Cultural Shifts	Participant 9	Healthcare	Every time we introduce a new analytics tool, there's resistance. Not because the tool is bad, but because change is scary.
5	Organisational Readiness and Cultural Shifts	Participant 4	Telecommunications	People fear data because they think it will expose inefficiencies. So instead of embracing it, they resist.
5	Organisational Readiness and Cultural Shifts	Participant 10	Manufacturing	We're seeing a gradual shift. Training is helping. There's a policy push from the top. It's slow, but it's happening.
6	Regulatory and Environmental Pressures	Participant 6	Insurance	POPIA compliance is necessary — but it slows down a lot of our data projects because legal is nervous about risks.
6	Regulatory and Environmental Pressures	Participant 7	Technology	We can't do as much cross-border data work as we would like — the legal uncertainty is a major blocker.
6	Regulatory and Environmental Pressures	Participant 3	Retail	Load-shedding disrupts our data centres — it's hard to run real-time analytics when the power isn't stable.
6	Regulatory and Environmental Pressures	Participant 3	Retail	Compliance with data protection laws delayed our analytics rollout by six months.

Figure 22: Screenshot of Excel-based coding structure used to manage and synthesise qualitative data.

Source: Author

Step 4 focused on verifying the themes.

The themes were verified iteratively to support the fact that they represented the underlying data and were distinguishable, coherent, and analytically relevant. This involved re-reading all coded pieces and ensuring consistency and representativeness in the dataset. Using an inductive thematic analysis approach, the researcher thoroughly reviewed all 184 raw original codes and condensed them into broader thematic themes. Similar codes such as **"shortage of skilled data staff"** and **"hiring difficulties for analytics"** were merged into the common theme **"talent and skills**

shortages." Internal homogeneity ensured that each unit of data under a theme shared a similar underlying idea or concept. External heterogeneity ensured that each of the topics was theoretically distinct and not overlapping with any of the other topics.

To facilitate greater analytical efficiency, coded quotes were pulled into Microsoft Excel, where they were organised in a cross-case matrix by participant, industry sector, and thematic category. This kind of presentation facilitated visual pattern identification, cross-case consistency checking, and the identification of sector-level differences or outliers. This process helped to guide the production of the thematic organisation and continuity to make sure it accurately reflected participant realities and theoretical significance.

Step 5 involved defining, refining, and naming themes.

Once the thematic categories were finalised, each theme was clearly defined and given a concise, descriptive name that encapsulated its core message. These labels were crafted to reflect both the content of participant narratives and their strategic relevance to the conceptual framework, of the resource-based and dynamic capabilities theories. Each theme was defined by a short, explanatory name such as **"strategic alignment challenges,"** a central organising concept that summarised what the theme captured, and, where appropriate, supporting sub-themes or dimensions to provide deeper granularity. To ensure analytical rigour and alignment with the original participant narratives, the themes were refined through a rigorous validation process.

All themes were re-examined in the context of the full transcripts to verify that they were grounded in the data and reflective of interview content. During this refinement stage, redundant or weakly supported codes were removed, and overlapping codes were merged into clearer conceptual groupings. For example, responses such as **"struggle to find data scientists"** and **"lack of skilled talent"** were consolidated under the broader theme "talent and skills shortages."

This inductive process resulted in six finalised core themes: strategic alignment challenges, talent and skills shortages, infrastructure and data quality constraints, value creation and competitive differentiation, organisational readiness and cultural shifts, and regulatory and environmental pressures. These themes formed the analytical foundation for the findings presented and guided the design of the quantitative instrument used in Chapter 6. Figure 23 below shows the finalised thematic map of big data analytics challenges and opportunities.

Theme Development and Refinement

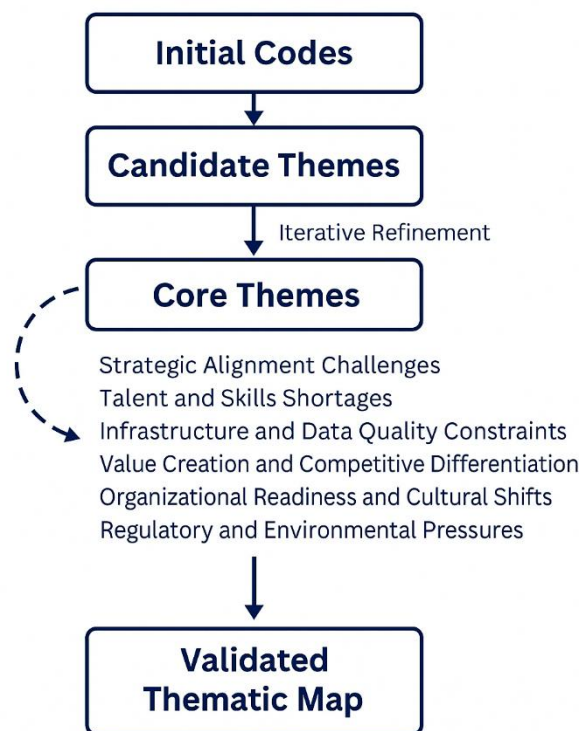


Figure 23: Process of Theme Development and Refinement following Braun and Clarke’s Six-Step Method.

Source: Author

The above figure 23 provides a visual summary of how the raw codes were organised into candidate themes, refined through iterative analysis, and finalised as six core themes aligned to the research objectives and theoretical framework.

Step 6 involved integration with research questions and thematic mapping.

In the final step of the thematic analysis, the six refined themes were systematically mapped to the study's central and sub-research questions to ensure analytical alignment and relevance. This integration confirmed that the themes emerged organically from participant narratives and directly addressed the study's objectives and theoretical foundations. Two key purposes were achieved through this process: analytical alignment, which ensured that each theme meaningfully contributed to answering the research questions, and instrument design, which guided the structure and content of the quantitative survey instrument used in the next phase of the study.

To further enhance coherence and transparency, a thematic map was created. This graphical tool illustrates the entire progression of the analysis, from transcription and coding to theme generation and final alignment with the research questions. The map reinforces the logical and iterative nature of the qualitative analysis and its direct contribution to the overall mixed methods research design.



Figure 24: Thematic Mapping and Alignment with Research Questions

Source: Author

The above figure 24 is a demonstration of the process from preliminary qualitative data to recursive coding and refinement, ultimately producing six end themes that directly corresponded to the study's research questions and conceptual framework. By being rigorous and transparent in methodology, the study ensured qualitative findings were credible, reliable, and methodologically sound. Using Microsoft Word for transcription and Excel for thematic consolidation and visual tracking made it easy to have a rigorous audit trail characteristic of best practice qualitative research (Braun and Clarke, 2008). This process established the basis for the quantitative component of

the study and allowed methodological triangulation, thereby enhancing the generalisability of the mixed-methods strategy (Saar and Dagada, 2024). The study ensured that the qualitative findings were credible, trustworthy, and grounded in the data. The use of both Microsoft Word and Excel supported a transparent and auditable analysis process consistent with best practices in qualitative research (Braun and Clarke, 2008).

5.4.1 Use of spreadsheets and coding sheets

In support of analytical rigour and data traceability, Microsoft Excel was used as a key analytical tool to organise and compare coded data from the Word transcripts. The coding spreadsheet allowed for cross-case analysis by participant and sector and supported pattern detection across themes. This structured layout permitted clustering of keywords, code frequency analysis, and identification of theme saturation points. The spreadsheet also provided for the presentation of visual aids such as word clouds and frequency tables to facilitate theme salience.

5.4.2 Word cloud and frequency analysis

To strengthen the thematic validation process, keyword frequencies were analysed using the formulas within Excel. This allowed for the detection of dominant terms and problems most cited by participants by sectors. The word cloud below is a visual image of the most cited concepts, and another aspect is offered in terms of coded themes.



Figure 25: Word Cloud of Commonly Used Terms

Source: Author

5.4.3 Validation of the themes

To ensure that the analysis was rigorous and credible, the themes were validated through different strategies. For example, triangulation between interviews from diverse sectors and organisational levels was undertaken, and frequency analysis helped to determine repeated ideas and thematic saturation. Peer debriefing with two independent qualitative researchers was used to create coherence, naming accuracy, and conceptual clearness. This process of validation had the effect of ensuring each theme was solidly rooted in the data and connected to both participant experience and theoretical concepts.

5.4.4 Alignment with research aims and instrument design

In the ultimate step of the qualitative analysis, the six core themes were mapped to the study's research questions. Mapping was essential because it confirmed that the qualitative findings answered research purpose and contributed meaningfully to the study's theoretical model. Informed by these validated themes, the quantitative survey instrument (used in Chapter 6) was developed. Each theme was translated into a series of constructs or indicators to be tested through structural equation modelling.

5.5 THEMATIC FINDINGS WITH PARTICIPANT QUOTES

The six core themes in Figure 26 represent the key challenges, enablers, and strategic insights related to the implementation and use of big data analytics capabilities within their businesses. The themes are organised to reflect both theoretical alignment (with resource-based and dynamic capabilities theories) and practical insights gathered from the field. Each theme is substantiated by verbatim participant quotes to preserve authenticity, provide interpretive depth, and highlight the diverse experiences and perspectives of decision-makers engaged in data-driven strategy. Each theme is discussed in the subsections below, with illustrative quotations drawn from across the participant sample to show variation and consistency of experiences across sectors.



Figure 26: Key Themes

Source: Author

5.5.1 Theme 1: Strategic Alignment Challenges

A dominant theme that emerged from the interviews was the persistent misalignment between big data analytics initiatives and the overarching business strategies. While many businesses have made significant investments in big data analytics capabilities, participants consistently emphasised that these efforts are often fragmented and poorly integrated with broader strategic business goals, resulting in limited business impact.

Several key patterns were identified which revealed a disconnect between big data analytics capabilities and business strategy. In many businesses, big data analytics capabilities initiatives were led by the IT section or individual champions rather than being included in the business strategy. The effect of these fragmented efforts is a failure to generate meaningful value. There are challenges with short-term and project-based thinking. Participants highlighted that big data analytics capabilities initiatives were often funded as short-term projects rather than long-term capabilities development. This leads to incorrect resource allocation and budgets, which limits the

ability of the business to build sustainable competitive advantage. There is a lack of executive buy-ins. Many interviewees stated that senior leadership in many businesses still lacked a clear understanding of the strategic value of big data analytics capabilities, viewing it as a technical rather than a strategic asset. These challenges were expressed by participants in various ways:

“We have great data scientists but unless the executives understand how this fits into the business model, the projects tend to run in isolation.” (Participant 4, Telecommunications sector)

This highlights the gap between technical capability and strategic orchestration.

“The board still sees data as an IT thing not as something that drives innovation or competitive edge.” (Participant 7, Technology)

Here, analytics is viewed as a support function rather than a strategic lever.

From the public sector perspective, Participant 5 noted:

“We’re still catching up in terms of leadership awareness. Data is seen as an IT function and not a strategic asset.” (Participant 5, Public Sector)

This highlights the common issue in governments and parastatals where big data analytics is undervalued by management, leading to poor organisational momentum. Broadly speaking, 8 out of 10 participants cited at least one of this misalignment’s components, ranging from ambiguity regarding data ownership to lack of executive sponsorship. A further dimension of this theme relates to the operational inefficiencies caused by the absence of structured strategic integration pathways for analytics outcomes. While data insights are generated, these rarely influence strategic choices at the executive level.

“We collect data from everywhere but there is no formal roadmap for what happens next. The insights do not flow up to inform business units in real time, which defeats the purpose of predictive analytics.” (Participant 3, Retail)

This highlights the need for structured integration pathways from insight to action.

“There’s a major push for dashboards and data lakes, but very little attention to how these fits into our key strategic goals. It becomes tech for tech’s sake.”
(Participant 7, Technology)

With this statement the participant draws attention to the danger of technological investments that reach far beyond the business goals. Despite investments in analytic tools and technologies, such initiatives often fail to deliver competitive advantage due to poor strategic integration. Overall, this theme confirms that strategic alignment is a critical enabler of big data analytics impact, which is consistent with the literature (Mikalef et al., 2021). Businesses that fail to align big data analytics capabilities with their core strategy are unlikely to realise sustained competitive advantage, regardless of their investments in technology tools or talent. To support the interpretation of Theme 1, Table 17 consolidates key participant insights on strategic alignment challenges. These excerpts illustrate how misalignment between data functions and core business strategy weakens the ability of organisations to leverage big data analytics capabilities for sustainable advantage.

Table 17: Summary of evidence for theme 1 – Strategic alignment challenges

Source: Author

Participant	Sector	Key Insight
P1	Finance	Data seen as an IT tool, and not a strategic lever for business competitive advantage
P3	Retail	The insights from data investments are disconnected from the leadership decision-making
P5	Public Sector	The data lead is structurally removed from the strategy
P7	Technology	Tech investments are not linked to the business objectives
P2	Government	There is fragmented ownership of data initiatives
P6	Insurance	While the strategy documents mention data, there is a lack of mechanisms for execution

P8	Logistics	Big data analytics use is ad hoc and is not aligned with the business wide key advantage indicators (KPIs)
P10	Manufacturing	There is a misalignment between content teams and the data science units

As highlighted in Table 17, strategic misalignment was a pervasive challenge across multiple industries, with participants consistently pointing to fragmented ownership, limited executive sponsorship, and disconnection between data teams and decision-makers. These findings underline that without strategic integration, investments in technology and data assets may fail to generate meaningful business value.

5.5.2 Theme 2: Talent and Skills Shortages

Another prominent theme that emerged was the widespread shortage of talent and skills necessary to fully develop and leverage big data analytics capabilities in South African businesses. This challenge was raised consistently across sectors and organisations. While there is significant growth in technological investments, many participants emphasised that human skills remain the most significant blockage to unlocking big data analytics' full potential. These findings echo broader research in South Africa, where regulatory uncertainty and persistent skills shortages have been identified as major obstacles to digital transformation and industrial revitalisation (Dagada and Lekaba, 2024).

Participants highlighted several aspects of this theme. For example, there exists a scarcity of experienced data professionals such as data scientists, data engineers, and analytics translators in the South African market. Many businesses are struggling to recruit or retain skilled professionals and are often forced to compete with other multinational corporations and the global tech industry. There is a high cost associated with talent acquisition. If skilled professionals are available, they command high salaries, thus making it difficult for mid-sized or resource-constrained businesses to build effective big data analytics capabilities. There are also significant skills gaps at leadership level. Many participants noted a lack of data literacy and analytics understanding among senior managers, which further limits the ability to ensure that

big data analytics capabilities are embedded into strategic processes. These challenges were expressed by participants in various ways:

“We can find junior data analysts but finding experienced people who can connect the dots and really drive business value is very tough.” (Participant 5, Public Sector)

“We are losing talent to Europe and the US. Local business can’t compete on salaries for top data scientists.” (Participant 3, Retail)

“The leadership team doesn’t always understand what the analytics people are talking about and there is still a skills gap at the executive level.” (Participant 9, Healthcare)

Participant 2, a director within a government department, highlighted the difficulty in finding professionals with both technical expertise and business acumen and stated as follows:

“We’re always chasing skills. Either we find data scientists who are too academic or engineers who don’t understand the business. The hybrid profiles we need are just not available locally.” (Participant 2, Government)

This quote illustrates that the demand for cross-functional talent, those individuals who can bridge data science and strategic problem-solving, is far outpacing the supply. Participant 6, who works in the insurance sector, added that even when the right talent is identified, retaining that talent becomes a major challenge due to other businesses offering bigger salaries and benefits:

“Even when we find great talent, they get poached quickly by international business or banks. Our HR budgets can’t match that.” (Participant 6, Insurance)

The competition for quality personnel, particularly with multinationals offering teleworking at high-line salaries, has created a high-turnover environment in South Africa, which erodes institutional backbone. From the health perspective, Participant

9 offered another, no less revealing comment:

“Junior analysts come with Power BI or Python knowledge but are absolutely clueless regarding how to structure a hypothesis or interpret results. We spend more of the time training than we do analysing.” (Participant 9, Healthcare)

This indicates that there is a gap between technical expertise and critical thinking, thus indicating that being only technically literate is not sufficient without analytical thinking and domain expertise. Participant 10 mentioned the issue of over-reliance on external consultants:

“Most of our data people are outsourced consultants. We don’t have institutional knowledge being built. That’s risky.” (Participant 10, Manufacturing)

While outsourcing might offer short-term fixes, a lack of internal knowledge transfer or building capacity carries long-term risks, including strategic discontinuity and operational fragility. Participant 4, from the telecommunication sector, noted that these skill gaps are obstacles to upgrading BDA projects:

“We can’t scale up beyond pilot projects because there’s no one to own it. Data governance skills are scarce.” (Participant 4, Telecommunications)

Collectively, these quotations point out that BDA’s talent shortage is not only about quantity but about quality, retention, and strategic fit. Seven out of the ten participants specifically identified this theme as their number one challenge, even bigger than their challenges related to their access to funding or to technology. This aligns with existing literature on big data analytics capabilities creation in emerging markets (Corea, 2019). It emphasises importance of business reacting to talent pipelines, invest in training and development, and develop collaboration with universities to fill the skills gap. Without addressing these talent shortages, the ability of South African business to realise the full value of big data analytics capabilities will remain constrained.

To illustrate the widespread concern around skills gaps, Table 18 summarises participant perspectives on the shortage of big data talent. The excerpts reveal the depth of the challenge across sectors, from government and healthcare to retail and telecommunications, confirming that talent-related constraints are systemic rather than sector-specific.

Table 18: Summary of evidence for theme 2 – Talent and skills shortages

Source: Author

Participant	Sector	Key Insight
P2	Government	Struggle to find hybrid data-business professionals
P6	Insurance	High attrition due to international recruitment
P9	Healthcare	Lack of critical thinking in junior staff
P10	Manufacturing	Heavy reliance on consultants; limited internal capabilities
P3	Retail	Skills mismatch even within existing teams
P4	Telecommunications	Inability to scale big data analytics due to lack of skills in data governance
P8	Logistics	Need for continuous upskilling and domain-specific data fluency

As shown in Table 18, the issue of talent and skills shortages emerged as the most pressing challenge for most participants, outweighing even concerns about funding and technology. This reinforces the literature that emphasises the centrality of human capital in unlocking the value of big data analytics capabilities. Beyond skills, however, participants also pointed to the enabling infrastructure and quality of data as equally critical barriers. The next theme therefore examines how legacy systems, fragmented architectures, and unreliable datasets undermine the development and integration of big data analytics capabilities in South African businesses.

5.5.3 Theme 3: Infrastructure and Data Quality Constraints

The principal challenge highlighted by the participants was that there are infrastructure and data quality constraints that will limit the ability of businesses to build big data analytics capabilities. Even where there was a strategic intent to do big data analytics

capabilities investments, organisations were confronted with fundamental problems relating to legacy systems, fragmented data sources, poor data quality, and gaps in infrastructure.

Most South African business, particularly those in mature sectors (e.g., finance, manufacturing), maintained legacy information systems not designed for high-volume data integration or advanced analytics. The data that is maintained across departments, platforms and legacy systems is fragmented (Dangale and Dagada, 2024). This creates data silos that disrupt integration in the business and erode analytic value. Incomplete, inconsistent, or incorrect data were most frequently cited as barriers to effective analytics. Respondents stressed that poor quality data (often referred to as “dirty data”) undermines the legitimacy of the analytics results and erodes the trust of decision makers in big data analytics capabilities. Smaller businesses and government departments frequently had limited computing capacity or access to sophisticated analytics environments thus excluding the possibility of advancing beyond basic reporting. Representative participants are quoted as follows:

“Analytics is not the largest challenge. The data is. Legacy systems don’t talk to one another, and the data isn’t trustworthy.” (Participant 8, Logistics)

“We have made investments in cloud platforms but until we’ve solved the data quality problem, we’re not able to make progress.” (Participant 6, Insurance)

“Data ownership is fragmented where every business unit has their own systems, and integrating the data across the business is a major challenge.” (Participant 1, Finance)

This challenge is aligned with the previous work of Dremel et al. (2020) and Mikalef et al. (2021), which emphasises that sound data infrastructure and governance are important preconditions for effective big data analytics capabilities. Unless the limitations are addressed, businesses will not be able to unlock their analytics investments to the fullest for the advantage of competitive strategy. A third general theme that emerged from the interviews was the limitation of existing infrastructure and the endemic issue of bad quality data. Interviewees repeatedly emphasised that

without up-front investments in upgraded IT environments and good quality data governance, big data analytics programs are severely handicapped. Participant 1, who represented the finance sector, conveyed the problem of fragmentation in systems:

“We hold data in a range of old systems that don’t talk to each other. Weeks are spent just pulling and scrubbing what we require before we even begin analysing.” (Participant 1, Finance)

This is a too-familiar complaint, siloed systems equalling latency-to-insight and additional operational inefficiencies. Participant 3, in retail, discussed the governance void:

“We spend more time repairing data than analysing it. There are no enterprise-wide data ownership frameworks, so nobody is responsible for data quality.” (Participant 3, Retail)

Lacking defined roles and responsibilities for data stewardship, issues with quality abound, diminishing trust in the analytics output and its dependability in making decisions. Participant 5, in the public sector, introduced a technical infrastructure perspective:

“Infrastructure is outdated. We still have on-prem servers, and system downtime occurs too frequently. Cloud migration is talked about but not implemented.” (Participant 5, Public Sector)

The challenge of out-of-date infrastructure and the glacial uptake of cloud was the constant strain, especially in public sector and semi-public organisations where procurement and change cycles are protracted. Participant 7 warned against the high cost of poor data integrity:

“We have KPIs from poor data in dashboards. And then leadership will make decisions from that. It’s risky.” (Participant 7, Technology)

This highlights the strategic danger, when leadership makes decisions based on flawed information, and poor data harms operations but also has an impact on trust and accountability at the top. Participant 9 provided a regulatory view from the healthcare sector:

“We handle personal information, so we must be POPIA compliant. But our systems are not capable enough to track access or encryption over groups of data.” (Participant 9, Healthcare)

Data quality and infrastructure challenges in regulated environments become compliance risks, exposing businesses to penalties, breaches, and reputational damage. Participant 4 described how infrastructure gaps directly limited their analytics:

“We are unable to do real-time analytics. Our systems can only do overnight batch processing of data.” (Participant 4, Telecommunications)

This restraint limits flexibility and responsiveness, competencies which are fundamental to competitiveness in fast-moving markets where quick insight can be an advantage. During the interviews, eight out of ten mentioned infrastructure and data quality as major hurdles. These are not short term, but long-term issues and of a structural nature, that require strategic investment and executive focus. To capture the extent of these infrastructure and data quality issues, Table 19 summarises the perspectives of participants across industries. Their experiences illustrate how weak systems, fragmented architectures, and compliance risks combine to limit the full potential of big data analytics capabilities.

Table 19: Summary of evidence for theme 3 – Infrastructure and data quality constraints

Source: Author

Participant	Sector	Key Insight
P1	Finance	Fragmented legacy systems; time-consuming data extraction
P3	Retail	Lack of data governance and ownership
P5	Public Sector	Outdated infrastructure and delayed cloud migration
P7	Technology	Risk of misinformed decisions based on inaccurate dashboards
P9	Healthcare	Inability to meet POPIA due to weak data tracking and encryption
P4	Telecommunications	Batch processing systems hinder real-time analytics
P6	Insurance	Missing metadata and incomplete data lineage
P10	Manufacturing	Data loss risks due to inconsistent backup protocols

5.5.4 Theme 4: Value creation and competitive advantage

As reflected in Table 19, infrastructure and data quality constraints were consistently raised as long-term, structural barriers to effective big data analytics adoption. These challenges not only slow down innovation but also expose organisations to strategic and compliance risks. Despite these constraints, however, participants also described significant opportunities for value creation where big data analytics capabilities were effectively embedded into business processes.

The next theme therefore explores how organisations are leveraging analytics for customer insights, operational efficiency, fraud detection, and competitive repositioning, highlighting the tangible business benefits that big data can deliver when properly harnessed. In addition to challenges such as infrastructure limitations and

skill shortages, participants provided a compelling narrative regarding the value creation potential of big data analytics capabilities.

Interviewees from various sectors shared practical experiences of how big data analytics capabilities enabled operational efficiencies, product improvements, fraud detection, and strategic repositioning. Sub-dimensions of value creation that were identified are discussed as follows:

Enhanced customer insights were noted, where businesses with mature big data analytics capabilities leveraged data to gain deep insights into customer behaviour, enabling targeted marketing, personalised services, and improved retention.

“The value does not lie in holding onto information, but in how fast and how smartly we utilise it. Our entire loyalty programme is now forecast model driven, and that has increased client retention.” (Participant 1, Finance)

Process optimisation was also emphasised, with big data analytics capabilities playing a critical role in enhancing planning, reducing operational waste, and improving service delivery.

“In logistics, routing used to be reactive. Now with big data, we’re able to simulate and optimise in advance, saving costs and preventing delays.” (Participant 8, Logistics)

Innovation and new revenue streams emerged, where some businesses used big data analytics capabilities to develop new business models and products particularly in the services sectors.

“We no longer just sell products. We sell insights. That’s what clients are paying for, our ability to make sense of their own data.” (Participant 4, Telecommunications)

“We are using data to drive innovation; we’ve launched three new products in the last year based on analytics insights.” (Participant 1, Financial Services)

Competitive pricing and risk management were cited, including sector-specific innovations such as usage-based pricing enabled by real-time data analytics.

“We’ve moved from static risk models to usage-based pricing, based on behavioural data from telematics. That’s a direct competitive edge.” (Participant 6, Insurance)

Market responsiveness increased as big data analytics capabilities enhanced agility, allowing businesses to respond rapidly to changing customer needs and competitive threats.

“Improved segmentation through clustering techniques helped us increase our campaign hit rates. That had a direct impact on our sales.” (Participant 3, Retail)

“Without our analytics capabilities, we would not have been able to develop our new customer loyalty platform, it’s now a key differentiator.” (Participant 3, Retail)

Fraud detection and operational risk mitigation were also evidenced.

“We used analytics to reduce fraudulent claims by 25%, that is a major win.” (Participant 6, Insurance)

While the benefits of big data analytics capabilities were clear, several participants emphasised that such value creation depends on leadership buy-in and a culture that supports data-driven decision-making:

“Leadership must trust the data. If decisions are still made from the gut, then big data analytics won’t deliver value.” (Participant 6, Insurance)

Overall, nine out of ten participants confirmed that big data analytics capabilities had already delivered or were expected to deliver tangible business benefits. The findings emphasise that businesses derive competitive advantage from big data analytics capabilities through technical investment and by embedding data analytics into their

strategic core, innovation processes, and daily decision-making (Fosso Wamba et al., 2020; Mikalef et al., 2021).

To further illustrate how businesses are already realising tangible outcomes, Table 20 summarises participant insights into the diverse ways value is being created through big data analytics capabilities. These examples cut across government, telecommunications, retail, logistics, manufacturing, and healthcare, showing that the benefits of analytics extend beyond efficiency to innovation, differentiation, and strategic repositioning.

Table 20: Summary of evidence for theme 4 – Value creation and competitive differentiation

Source: Author

Participant	Sector	Insight Summary
P2	Government	Strategic buy-in required for value realisation
P4	Telecommunications	Value created by offering insights as a product
P6	Insurance	Dynamic pricing via telematics data
P8	Logistics	Route optimisation and cost reduction through simulation
P10	Manufacturing	Supply chain improved through predictive analytics
P3	Retail	Improved campaign targeting through customer segmentation
P5	Public Sector	Data-driven asset management and outage forecasting
P7	Technology	Data monetisation via proprietary benchmarking tools
P9	Healthcare	Faster diagnosis and intervention planning using big data tools

As seen in Table 20, Value creation from big data analytics capabilities is multidimensional, including operational, strategic, and financial domains. This theme illustrates that businesses derive the most competitive advantage when data analytics

is not just a technical tool, but a core strategic asset embedded across the entire business operations.

5.5.5 Theme 5: Organisational Readiness and Cultural Shifts

A recurring insight across the interviews was that successful implementation of big data analytics capabilities depends not only on tools and talent but also on organisational readiness and cultural transformation. Participants highlighted that several cultural and structural barriers continue to limit the realisation of big data analytics capabilities' potential.

Several issues were consistently reported. Resistance to change persists, as many employees and managers remain sceptical of data-driven methods, preferring intuition or traditional decision-making. Moreover, siloed structures prevent effective collaboration and data-sharing across business units. Low data literacy was found across many businesses, especially among senior managers, reducing confidence in data analytics outcomes. Leadership commitment emerged as critical, with businesses that showed strong leadership commitment to data transformation reporting greater progress and cultural buy-in. Participant 7, from the technology sector, remarked:

“The technology is the easy part; the hard part is getting people to trust the data and use it in their daily decisions.” (Participant 7, Technology)

Participant 3, from retail, echoed the gap between tools and mindset:

“The tools are there, but if your people are not open to using data in their daily decisions, then it all collapses.” (Participant 3, Retail)

Participant 5, from the public sector, described how organisational readiness required targeted investment in literacy:

“We had to train even senior managers on how to read dashboards and interpret KPIs. It took months before they trusted the numbers.” (Participant 5, Public Sector)

Participant 10 also highlighted structural barriers:

“Data is owned in pockets, IT owns some, marketing owns some, and no one talks to each other. That’s a major obstacle.” (Participant 10, Manufacturing)

The value of strong leadership arose as a key factor. Participant 5 stated:

“Where leaders promote experimentation and allow for data-driven innovation, things move. But many still don’t understand analytics themselves.” (Participant 5, Public Sector)

Participant 9, from healthcare, explained:

“Every time we introduce a new analytics tool, there’s resistance. Not because the tool is bad, but because change is scary.” (Participant 9, Healthcare)

Participant 4 offered another reason for such resistance:

“Most people fear data because they think it will expose their inefficiencies in using it. So instead of embracing it, they resist it.” (Participant 4, Telecommunications)

Despite these challenges, signs of progress were noted:

“We’re seeing a gradual shift. Training is helping. There’s a policy push from the top. It’s slow, but it’s happening.” (Participant 10, Manufacturing)

This theme strongly supports the literature which emphasises that organisational culture is a pivotal enabler or inhibitor of big data analytics capabilities success (Mikalef et al., 2021). Without deliberate cultural transformation and executive-level modelling of data-driven behaviour, analytics initiatives may remain underutilised.

Table 21: Summary of evidence for theme 5 – Organisational readiness and cultural shifts

Source: Author

Participant	Sector	Key Insight
P1	Finance	Lack of daily data use slows analytics impact
P3	Retail	Cultural inertia and underutilisation of available tools
P4	Telecommunications	Resistance tied to fear of exposure and accountability
P5	Public Sector	Literacy campaigns necessary to build dashboard trust
P6	Insurance	Leadership knowledge affects analytics integration
P7	Technology	Culture is more difficult to change than technology itself
P9	Healthcare	Change fatigue and lack of communication inhibit adoption
P10	Manufacturing	Data ownership silos and slow cultural transition

5.5.6 Theme 6: Regulatory and Environmental Pressures

This theme examines the way in which external regulatory arrangements, changing policy requirements, and the wider environment shape the formation and use of big data analytics capabilities in South African business. Regulation is normally conceptualised as a constraint, but the interviews spoke of a more complex relationship, one in which legal and policy pressures were both sources of constraint and stimuli to data capabilities building.

Regulatory Compliance as a Double-Edged Sword

Several participants from highly regulated industries described compliance as a ubiquitous motivator of their analytics strategy. South Africa's Protection of Personal Information Act (POPIA) was also cited as a lead motivator of data governance and infrastructure investments in the last few years. Participant 3, for a retail chain, expressed the initial frustration:

“Compliance with data protection regulations held back our analytics deployment by six Months.” (Participant 3, Retail)

This indicates how legal requirements may delay project timelines, especially where legacy systems and dispersed data stores need to be re-engineered to comply with the legal requirements. Participant 6, from the insurance industry, agreed:

“Regulation forces a lot of our data governance policies. It is not a choice.” (Participant 6, Insurance)

In highly regulated industries, such as insurance and finance, compliance is obligatory, often diverting resources that would otherwise be put towards innovation and growth of analytics.

Misalignment Between Regulation and Capacity

Participant 2, from the government sector, emphasised the huge disconnect between infrastructure challenges and the capacity to deliver:

“We’re expected to be digitally transformed, but basic infrastructure like broadband access in some departments is still a challenge. The laws haven’t caught up with how fast the tech is moving.” (Participant 2, Government)

This encases the challenge of dealing with transformation imperatives in scenarios of limited infrastructural readiness or systemic adjustments.

Compliance as a Driver of Analytics Maturity

However not all was negative, with several participants describing compliance obligations as a forcing mechanism for more disciplined, structured, and mature analytics ecosystems.

“POPIA forced us to finally build a proper data inventory and classification structure. That’s now become the backbone of our analytics platform.”
(Participant 9, Healthcare)

“The more we engaged with compliance, the more we discovered gaps in our architecture. Now we have a roadmap to modernise. It’s been painful but useful.” (Participant 8, Logistics)

In these cases, regulation triggered long-overdue internal reforms and facilitated more strategic approaches to big data analytics capabilities development. Businesses with greater organisational maturities were more likely to leverage regulation as an opportunity rather than a constraint.

Environmental Constraints: Energy and Economic Volatility

Besides formal regulation, participants also cited the wider environmental challenges that they face. These challenges include unstable energy, such as load-shedding, economic volatility, and inequality of broadband width, all of which significantly hamper business ability to maintain real-time data capabilities and continuous analytics operations.

“Load-shedding disrupts our data centres, it’s hard to run real-time analytics when the power isn’t stable.” (Participant 3, Retail)

This indicates that such infrastructural pressures disproportionately affect smaller businesses and public sector organisations, further widening the digital divide in analytics capabilities across the South African economy.

Strategic Opportunity for Policy Alignment

Finally, several participants called for national harmonisation of data governance standards and the development of open data policies to support analytics innovation. Multinational businesses highlighted the need to navigate not only POPIA, but also international regimes such as the General Data Protection Regulation (GDPR), further adding to compliance complexity.

“We can’t do as much cross-border data work as we would like the legal uncertainty is a major blocker.” (Participant 7, Technology)

This indicates that, without any coherent policy direction, businesses run the risk of being trapped between evolving regulatory demands and the pressures of global competitiveness.

Table 22: Summary of Evidence for Theme 6 – Regulatory and Environmental Pressures

Source: Author

PARTICIPANT	SECTOR	KEY INSIGHTS
P2	Government	Misalignment between infrastructure capacity and digital transformation mandates
P6	Insurance	Regulation is the primary driver of data governance
P8	Logistics	Compliance process revealed architecture gaps, promote modernisation roadmap
P9	Healthcare	POPIA catalysed structured data governance improvements

P1	Finance	Complex audit requirements delay access to real-time data insights
P3	Retail	Compliance slowed analytics rollout
P10	Manufacturing	Call for standardised national data policies to support open innovation

While regulatory and environmental pressures often constrain speed, flexibility, and innovation, they also have the potential to serve as inflection points for digital and analytics maturity. The critical insight from this theme is that compliance and innovation are not mutually exclusive, when regulation is treated as a strategic enabler, it can lay the foundation for secure, ethical, and sustainable data ecosystems in South African business.

5.6 INTEGRATION OF THE QUALITATIVE WITH THE QUANTITATIVE PHASE

The qualitative phase of this study served as the foundation for the development of the quantitative survey instrument, which is consistent with the exploratory sequential mixed methods design. The insights derived from the thematic analysis of the interviews helped to shape the constructs, the items, and the dimensions explored in the quantitative phase.

5.6.1 Mapping of the themes to the survey constructs

Each of the six core themes that were identified from the qualitative analysis was systematically translated into a corresponding survey construct and item as follows:

Table 23: Mapping of the themes to the survey constructs**Source: Author**

Qualitative theme	Mapped survey construct	Sample survey items
Strategic alignment challenges	Big data strategy alignment	Q5, Q6
Talent and skills shortages	Human resource capabilities	Q12, Q13
Infrastructure and data quality constraints	Technology infrastructure	Q15, Q16
Value creation and competitive differentiation	Competitive advantage; big data analytics outcomes	Q20–Q24
Organisational readiness and cultural shifts	Change readiness; Data-driven culture	Q8, Q9
Regulatory and environmental Pressures	Data governance and compliance	Q18

This mapping ensured that the survey instrument was grounded in lived organisational experiences, enhancing its contextual relevance and construct validity. The strategic alignment challenges informed the inclusion of the questions under the big data strategy alignment construct (Q5, Q6), measuring the extent to which analytics efforts are being aligned with business goals. Talent and skills shortages directly shaped items under the human resource capabilities construct (Q12, Q13), reflecting the availability and sufficiency of big data analytics-related expertise. Infrastructure and data quality constraints contributed to the technology infrastructure construct (Q15, Q16), highlighting significant barriers such as legacy systems and data inconsistencies. Value creation and competitive differentiation was incorporated into items assessing big data analytics-driven outcomes and competitive advantage (Q20–Q24). Organisational readiness and cultural shifts supported the design of items under organisational culture and change readiness (Q8, Q9). Regulatory and environmental pressures were reflected in data governance and compliance constructs (Q18), especially concerning the influence of regulations like the Protection of Personal Information Act (POPIA).

This integration process ensured coherence and continuity across the research phases and strengthened the internal trustworthiness and validity of the study by allowing qualitative insights to shape the empirical testing that followed. This integrative process not only reflected methodological rigour but also ensured that the quantitative testing phase remained directly informed by practitioner realities, thereby increasing the overall trustworthiness and utility of the research outcomes.

5.6.2 Cross-case comparisons: Public vs Private sector emphasis

To better comprehend the context, cross-case comparison was employed to comprehend sectoral differences in how themes arose in public and private organisations. Cross-case comparison revealed extensive variation in thematic focus between public and private sector respondents. Government and healthcare respondents highlighted infrastructure issues and regulatory concerns most, including POPIA, disparate systems, and absence of dedicated analytics resources. Private sector participants (e.g., finance, retail, insurance) emphasised strategic alignment, value generation, and skills shortages, pointing to a stronger drive for market differentiation and agility. This comparative insight supported the importance of stratifying the survey analysis across sectors, which was reflected in the demographic and subgroup breakdowns presented in the quantitative phase. These sectoral differences highlight the importance of tailoring big data analytic strategies to institutional mandates and organisational contexts (Mikalef et al. 2021).

5.7 OBSERVATIONS IN THE QUALITATIVE PHASE

This section provides an understanding of the qualitative phase of this study by recognising its methodological merits, limitations, and how it contributed to informing the overall research findings in the exploratory sequential mixed methods design.

5.7.1 Strengths of the qualitative phase

The ten semi-structured interviews, provided a rich and contextualised understanding of how business leaders in various industries perceive big data analytics capabilities implementation and value in South Africa. They demonstrated several key strengths. Firstly, there was considerable depth of insight, as the semi-structured interviews allowed participants to elaborate on their organisational experiences, providing detailed accounts of challenges related to infrastructure, talent, and cultural change.

Secondly, the sectoral representation in the sample encompassed both public and private organisations, enabling meaningful cross-case comparisons and offering broader insights into organisational and systemic enablers and constraints. Lastly, the qualitative findings directly informed the development of the quantitative survey instrument, ensuring that the constructs and questions were grounded in lived organisational realities and accurately reflected the context of big data analytics implementation in South Africa.

5.7.2 Limitations of the qualitative phase

Despite the strengths of this phase, several limitations were recorded. The study used a small sample size of ten participants for the qualitative phase. While ten interviews were deemed sufficient to reach thematic saturation, the small sample size limited the generalisability of the findings, particularly for underrepresented industries or smaller companies. Another limitation related to the dangers of self-reporting bias, as participants may have overreported their successes and underreported internal challenges during interviews. Furthermore, because the interviews were conducted remotely via Zoom and Google Meet, the establishment of rapport may have been constrained, and the researcher's ability to observe non-verbal cues was consequently reduced.

5.8 TRUSTWORTHINESS AND RIGOUR

To ensure trustworthiness, the study adhered to the four widely accepted criteria of qualitative research (Lincoln and Guba, 1985). Credibility was maintained through member checking, which was conducted where possible to validate the interpretation of interview content. Transferability was ensured by providing thick descriptions of participants' roles, sectors, and business contexts to enable meaningful contextual comparisons. Dependability was achieved by maintaining a transparent audit trail using Word and Excel to record coding and theme extraction processes. Confirmability was established using verbatim transcripts and a structured coding spreadsheet, which enhanced the objectivity of the study and allowed independent verification of interpretations. These processes ensured that the qualitative phase findings were credible, dependable, and analytically sound, forming a solid foundation for the quantitative phase of the study.

5.9 THE ROLE OF THE QUALITATIVE PHASE IN SHAPING INSIGHTS

The qualitative phase guided the development of the quantitative survey instrument and provided a critical interpretive lens through which the quantitative findings were understood. By revealing the real-world organisational dynamics, the interviews offered a valuable context for understanding how big data analytics capabilities evolve within South African businesses.

Themes such as strategic alignment, talent and skills shortages, and regulatory pressures emerged as key foundations, framing both the capacity for big data analytics implementation and its potential to influence organisational advantage. These themes contextualised the quantitative results, allowing for a deeper understanding of sectoral readiness, capabilities gaps, and enabling conditions.

In summary, the qualitative phase provided depth to the quantitative phase by ensuring its validity, focus, and explanatory power. This dual phased, mixed-methods approach enabled the study to go beyond simply measuring the presence of big data analytics capabilities; it provided rich insights into the organisational conditions, barriers, and drivers under which big data analytics capabilities could be developed and translated into tangible value. Such an approach strengthened the study's contribution to both theory and practice in the South African context.

5.10 SUMMARY OF THE FINDINGS OF CHAPTER 5

This chapter presented and analysed the qualitative results derived from ten semi-structured interviews conducted across a diverse set of South African organisations, including those in the insurance, telecommunications, financial services, manufacturing, healthcare, and public sectors (Saar and Dagada, 2024).

All interviews were conducted via Zoom and Google Meet, transcribed manually, and analysed using a dual-tool approach involving Microsoft Word and Excel. The purpose of the qualitative phase was to explore how South African organisations perceive, develop, and apply big data analytics capabilities to achieve competitive advantage. This exploration was guided by the overarching research question: ***“How do organisations in South Africa develop and utilise big data analytics capabilities to gain competitive advantage?”***

To provide structured insight, the analysis was aligned with the research questions that probed the enablers, barriers, strategic integration, and sectoral context. Thematic analysis yielded six core themes, which were supported by participant quotes, coding matrices, summary Tables, and visual artefacts. Strategic alignment challenges revealed that many businesses face difficulty integrating big data analytics capabilities into broader organisational strategy. Participants described a disconnect between analytics teams and executive leadership, with big data analytics often relegated to a support function rather than a strategic partner.

Shortages of skills and talent demonstrated a critical deficit of data-skilled professionals, particularly those with expertise in both data science and business. The shortage was further compounded by low data literacy at top management levels and excessive dependence on outside consultants, which compromises the sustainability of big data analytics capabilities. Infrastructure and data quality constraints showed that legacy systems, absence of data governance, and scattered sources of data hinder real-time analytics as well as insight generation. These are technical problems that are specific to constrained environments.

Value creation and competitive differentiation illustrated that despite the constraints businesses face, those that had rolled out big data analytics capabilities strategically reported quantifiable value creation, such as operational efficiencies, enhanced customer segmentation, fraud reduction, and product development. Organisational readiness and cultural shifts highlighted that the success of big data analytics capabilities hinge on leadership commitment and a data-driven organisational culture. Cultural resistance, siloed data ownership, and limited data literacy emerged as major barriers to adoption. These tensions echo wider debates on whether employees and technology can sustainably coexist in organisational settings (Dagada, 2024).

Regulatory and environmental pressures demonstrated that external compliance obligations such as the Protection of Personal Information Act (POPIA), and infrastructure limitations, shape businesses' ability to implement big data analytics capabilities. For some participants, regulation acted as a barrier whilst for others, it propelled improvements in data governance.

A sectoral contrast emerged where public sector participants focused more on accountability, compliance, and regulatory readiness, while private sector respondents emphasised competitive agility, customer value, and profitability. This divergence highlighted the need for context-sensitive big data analytics capabilities strategies across sectors. These findings reinforce the literature which points out that technology alone is insufficient to drive competitive advantage. Instead, businesses must address a range of interdependent factors such as strategic alignment, leadership support, skills development, robust infrastructure, organisational culture, and regulatory compliance.

Qualitative Theme	Mapped Survey Construct
Strategic Alignment Challenges	Big Data Strategy Alignment
Talent and Skills Shortages	Human Resource Capability
Infrastructure and Data Quality Constraints	Technology Infrastructure
Value Creation and Competitive Differentiation	Competitive Performance, BDA Outcomes
Organisational Readiness and Cultural Shifts	Change Readiness, Data-Driven Culture
Regulatory and Environmental Pressures	Data Governance and Compliance

Figure 27: Thematic Framework Linking Qualitative Findings to Survey Design

Source: Author

The findings from this qualitative analysis provided critical input in shaping the quantitative instrument used in the second phase of the study. The themes identified were used to refine the constructs and ensure that the survey items captured the real-world dynamics of big data analytics capabilities application in South African business. The next chapter presents the results of the quantitative phase.

CHAPTER 6: QUANTITATIVE RESEARCH FINDINGS

6.1 CHAPTER OVERVIEW AND INTRODUCTION

This chapter presents the findings of the quantitative phase of the study, which formed the second stage of the exploratory sequential mixed methods design. Building on the six core themes identified in the qualitative phase (Chapter 5), the structured survey instrument was designed and administered to test the research hypotheses, validate the conceptual model, and examine the relationships between big data analytics capabilities, dynamic capabilities, operational capabilities, and competitive advantage within South African organisations. The qualitative phase identified six core themes as strategic alignment challenges, talent and skills shortages, infrastructure and data quality constraints, value creation and competitive differentiation, organisational readiness and cultural shifts, and regulatory and environmental pressures. These themes directly informed the development of the structured questionnaire used in the quantitative phase, ensuring conceptual alignment, content validity, and relevance to the South African business context.

The objectives of the quantitative phase were to validate the proposed conceptual model and to test the research hypotheses formulated in Chapter 3. Specifically, the aim was to examine the role of big data analytics capabilities enabling dynamic and operational capabilities (including technological and marketing capabilities), and to assess their impact on competitive advantage. Data were collected through a structured survey distributed across South African businesses in various sectors. Constructs were operationalised using both formative and reflective indicators and analysed using PLS-SEM using the SmartPLS v4, an appropriate method for complex and exploratory models (Hair et al., 2019).

The analytical approach incorporated both descriptive and inferential statistics. Descriptive statistics summarised respondent characteristics, organisational profiles, and response patterns. Inferential statistics were applied to test the hypotheses and assess generalisability of findings to the broader population (McMillan and Schumacher, 2010; Tabachnick, Fidell and Ullman, 2007). The analysis proceeded through sequential steps: firstly, data screening and cleaning (including checks for

missing values, outliers, and normality). This was followed by preliminary descriptive analysis of raw data conducted to confirm data quality and response distribution. Next was measurement model evaluation (Cronbach's alpha, composite reliability, average variance extracted, Fornell-Larcker criterion, and HTMT ratio). The analysis concluded with structural model testing (path strengths, statistical significance, explained variance [R^2], effect sizes [f^2], and predictive relevance [Q^2]).

This quantitative phase complemented the qualitative phase by providing generalisable and statistically validated results. It not only assessed the current state of big data analytics capabilities maturity in South Africa but also clarified the conditions under which these capabilities translate into measurable business outcomes. The findings confirmed that, while big data analytics capabilities significantly predicted both dynamic and operational capabilities, only dynamic capabilities demonstrated a strong and consistent contribution to competitive advantage. These results highlighted the central role of dynamic capabilities in converting big data analytics investments into tangible strategic outcomes and set the stage for the integrative discussion presented in Chapter 7.

The chapter overview is presented in the Figure 28 below.

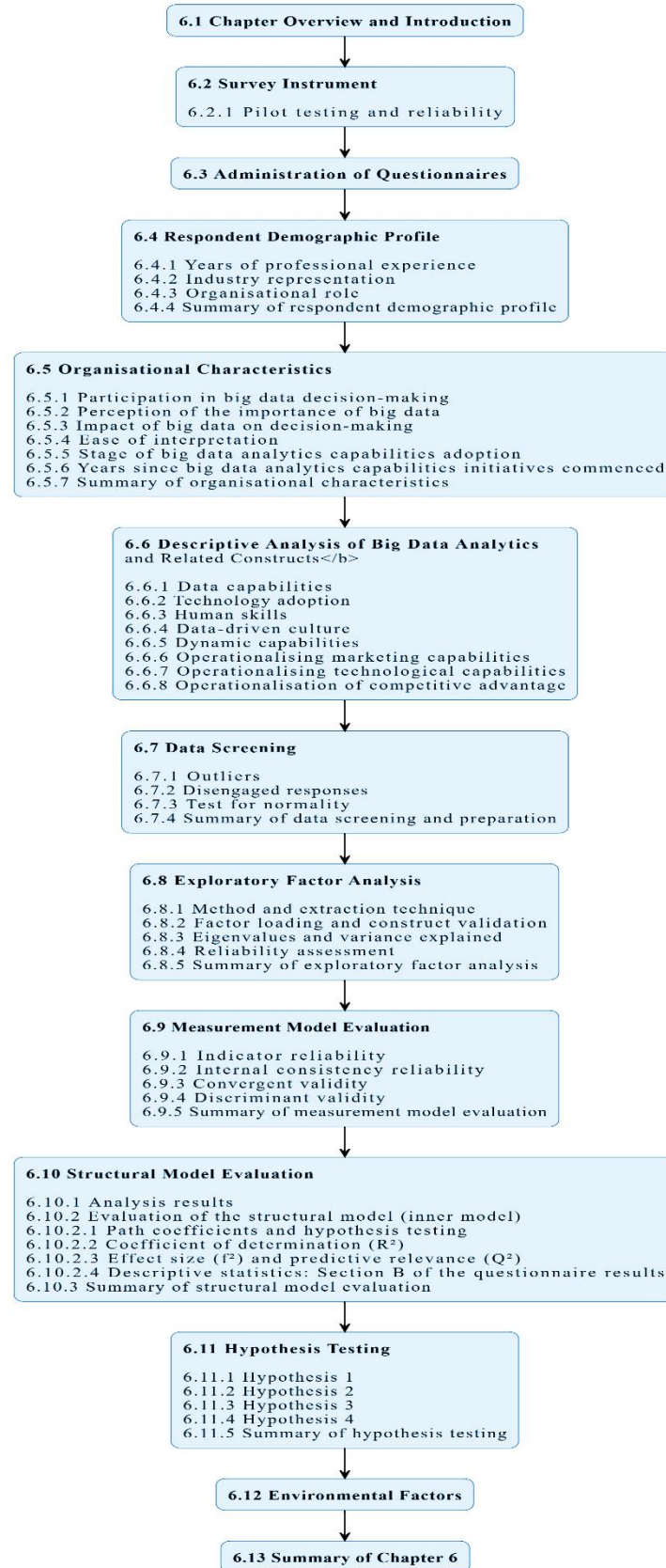


Figure: 28: Overview of Chapter 6 – Quantitative findings

Source: Author

Having outlined the purpose, scope, and analytical procedures of the quantitative phase, it is important to describe the instrument used to collect the data. The structured questionnaire was directly informed by the six core themes identified in the qualitative phase, ensuring that the measures were grounded in the South African business context and theoretically consistent with the study's conceptual framework. The next section therefore details the survey instrument, including how items were developed, structured, and validated to capture both formative and reflective constructs aligned with the proposed model.

6.2 SURVEY INSTRUMENT

The quantitative data in this study were collected using a structured self-administered questionnaire, developed in alignment with the six core themes identified in the qualitative phase (Chapter 5). These themes, strategic alignment, skills and talent, infrastructure constraints, value creation, organisational readiness, and regulatory environment served as the conceptual foundation for constructing measurement items (Dagada, 2023; Subramoney and Dagada, 2025) This ensured theoretical consistency and continuity across the mixed-methods design.

The questionnaire was designed to capture perceptions from senior business leaders across South African businesses regarding the development and deployment of big data analytics capabilities in their organisations. The instrument drew on established constructs from prior literature (Gupta and George, 2016; Mikalef et al., 2021). This included elements from Kuratko et al. (2015) for innovation and organisational capabilities and was structured in alignment with the conceptual model outlined in Chapter 3. The instrument was further refined to suit the South African business context. The final questionnaire was divided into two main sections:

Section A: Participant Information

This section gathered background data, including industry affiliation, years of leadership experience, and involvement in big data initiatives.

Section B: Data Capabilities

This section operationalised the latent constructs using both formative and reflective indicators, grouped as follows:

- Data
- Technology
- Human Skills
- Data Driven Culture

Section C:

Operationalising Sense, Seize and Transform

Section D:

Operationalising Marketing Capabilities

Section E:

Operationalising Technological Capabilities

Section F:

Operationalising Competitive Advantage

Responses were measured using Likert-type scales (3-point or 7-point), depending on the nature of the construct, allowing for nuanced and scale-appropriate measurement across dimensions. The questionnaire was distributed electronically via Google Forms, and participation was voluntary, with informed consent provided through an introductory section. The last version of the questionnaire is included in Appendix 2.

6.2.1 Pilot testing and reliability

Prior to dissemination, the survey instrument was subjected to review by two experienced analytics industry professionals to ensure construct validity and alignment with the study's conceptual framework. A formal pilot test (n=12) was then conducted to evaluate item clarity and relevance in the South African business environment. Feedback from the pilot test was used to refine ambiguous wording and improve overall questionnaire flow.

6.3 ADMINISTRATION OF QUESTIONNAIRES

The questionnaire was self-administered by the researcher using a combination of online and limited paper-based formats to reach a broad and diverse sample of senior

business leaders, analytics professionals, and IT executives across various South African industries. This approach aligned with the study's objective of exploring the role of big data analytics capabilities in enhancing competitive advantage in the local business context. To maximise reach and accessibility, the questionnaire was distributed electronically via email to targeted individuals, through professional networks and industry associations, and via an online survey platform (Google Forms). The use of Google Forms allowed participants to complete the questionnaire at their convenience and ensured broad coverage across different geographic locations and industry sectors (Saunders et al., 2023). The digital distribution strategy was particularly effective in accessing senior-level respondents across diverse sectors, including financial services, logistics, healthcare, consulting, telecommunications, and the public sector. The use of an online platform also ensured that data collection was conducted in line with ethical standards for privacy and data protection under the Protection of Personal Information Act (POPIA), as responses were anonymised and securely stored.

A combination of purposive sampling and stratified convenience sampling was used to ensure that participants had relevant expertise in big data analytics adoption and were drawn from a cross-section of industries. When initial response rates were lower than anticipated, snowball sampling was applied to supplement participation. Respondents were encouraged to share the questionnaire with eligible colleagues in their professional networks (Creswell and Plano Clark, 2018). This approach was appropriate given the exploratory nature of the study and the aim to capture senior-level perspectives on big data analytics capabilities maturity and value creation (Saunders et al., 2023).

Data collection took place over approximately six months, resulting in 118 completed responses. Of these, 110 responses were retained for analysis, representing participants who confirmed their direct involvement in big data analytics initiatives within their organisations. Respondents were assured of confidentiality and anonymity, and participation was entirely voluntary, in line with the approved ethics protocol. No personal identifiers were collected, and informed consent was obtained prior to participation. By employing a multi-channel, flexible administration process grounded in rigorous ethical standards, the study was able to obtain a sufficiently

diverse and expert sample to support empirical testing of the conceptual model and to generate insights relevant to big data analytics capabilities adoption in South African business (Leonardi and Treem, 2020).

6.4 RESPONDENT DEMOGRAPHIC PROFILE

This section presents the demographic profile of the 110 participants who confirmed their involvement in big data analytics initiatives within their respective organisations. The respondents represent a diverse cross-section of industries, professional experience, and organisational roles, offering a comprehensive and reliable foundation for analysing how South African business are developing and leveraging big data analytics capabilities. A diverse participant profile is essential for exploring big data analytics capabilities given that such capabilities are context-dependent shaped by industry characteristics, organisational maturity, and managerial experience (Gupta and George, 2016; Mikalef et al., 2021). The following subsections detail the years of experience, industry representation, and organisational roles of the sample.

Of the 250 business leaders contacted, 129 surveys were distributed to chief information officers (CIOs), chief executive officers (CEOs), managers, and heads of big data departments (one survey per business leader). A total of 118 participants completed the survey, of which 110 confirmed active use of big data solutions in their organisations. Only these 110 valid responses were retained for analysis. The participant group represents a wide range of industries, organisational sizes, and levels of big data analytics experience. The sample reflects a predominance in sectors such as healthcare, finance, manufacturing, and technology, and is composed of well-established organisations with substantial operational histories. The initial survey question asked whether the organisation used big data solutions (respondents answering no were excluded). A follow-up question examined the length of experience with such solutions, revealing a notable proportion of organisations with more than 10 years of big data usage.

The diverse participant profile is important when exploring big data analytics capabilities, as such capabilities are context-dependent and shaped by industry dynamics, organisational maturity, and leadership experience (Gupta and George, 2016; Mikalef et al., 2021). The subsections below present further detail regarding

years of professional experience, industry representation, and organisational roles. For an overview of the 110 participants and the associated demographic data, see Table 24.

Table 24: Demographic data

Source: Author

Dimension	Population (n)	Frequency (%)
Industry		
Technology	19	17.30%
Finance	19	17.30%
Healthcare	29	20%
Manufacturing	19	17.30%
Retail	10	9.1%
Other	21	19.1%
Years of professional experience		
< 5 years	26	23.6%
5-10 years	30	27.3%
10-15 years	39	35.5%
15-20 years	11	10.0%
> 20 years	4	3.6%

6.4.1 Years of professional experience

To contextualise the survey findings, it was important to examine the professional experience of respondents, as varying levels of expertise could shape perceptions and practices in developing and applying big data analytics capabilities.

How many years of experience do you have in a leadership or decision-making role related to big data analytics?

110 responses

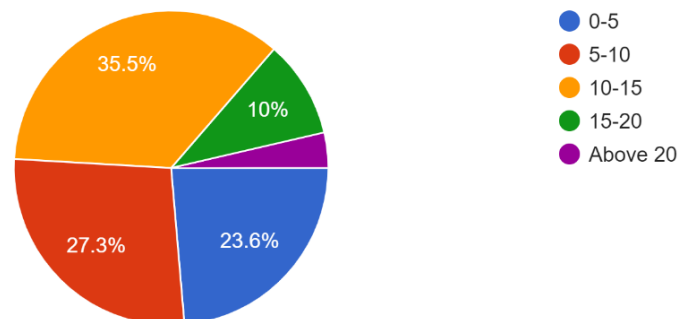


Figure 29: Years of Professional Experience

Source: Author

Most survey respondents had between 0 and 15 years of experience in leadership or decision-making roles related to big data, while a smaller proportion had 15 years or more experience. This suggests that big data analytics capabilities is an area of increasing attention among mid-career professionals. The respondents exhibited varying levels of professional experience, with a balanced representation of mid-career and senior professionals. The distribution provided insights across multiple stages of big data analytics capabilities maturity, from adoption through institutionalisation. Specifically, 26 respondents (23.6%) had 0–5 years of experience, 30 respondents (27.3%) had 6–10 years, 39 respondents (35.5%) had 11–15 years, 11 respondents (10%) had 15–20 years, and 4 respondents (3.6%) had more than 20 years. This range of experience ensured that both emerging and seasoned perspectives on big data analytics capabilities were included. The validity of the findings was thereby enhanced, as experience level may influence how big data analytics capabilities is conceptualised and implemented (Wamba, Gunasekaran et al., 2017).

6.4.2 Industry representation

Understanding the industry backgrounds of respondents was essential, as sectoral context influenced how big data analytics capabilities were adopted, regulated, and leveraged for competitive advantage.

How would you describe your industry experience in relation to big data analytics?

110 responses

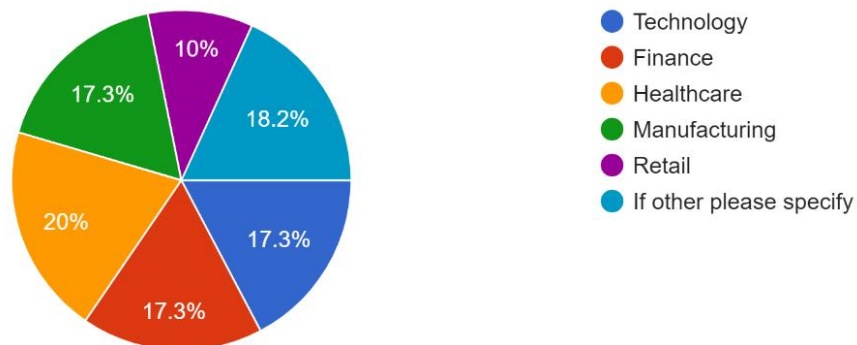


Figure 30: Industry representation

Source: Author

Respondents were drawn from a wide range of sectors, providing a broad cross-section of South Africa's economy. Specifically, nineteen respondents came from financial services (banking, insurance, and fintech), nineteen from technology, twenty-two from healthcare and health technology, nineteen from manufacturing and Industrial services, and eleven from retail and consumer services. A further twenty respondents represented other sectors, including media, education, agriculture, government, and the public sector.

This diverse industry spread allowed for a broad interpretation of big data analytics capabilities across different regulatory environments and levels of digital maturity (Mikalef et al., 2021). Notably, several high-compliance industries (e.g. financial services, healthcare, public sector) were well represented which was important in understanding how governance, ethics, and regulatory constraints shaped big data analytics capabilities initiatives (Fosso Wamba, 2017).

6.4.3 Organisational roles

Respondents occupied a wide range of strategic, technical, and operational positions, underscoring the cross-functional relevance of big data analytics capabilities. In total, 34 respondents were senior managers or executives, 29 were data analysts or data

scientists, 22 were IT or systems professionals, 15 were business unit leads or operational managers, and 10 were consultants or advisors.

This distribution highlights that big data analytics capabilities adoption is no longer confined to technical teams but increasingly influences strategic and operational decision-making (Mikalef et al., 2021). The presence of both C-level executives and technical experts ensured that the survey captured holistic views on big data analytics capabilities, including strategic intent, implementation challenges, and organisational impact.

The combination of organisational size, adoption stage, and participant experience illustrates the dynamic and evolving landscape of big data adoption in South Africa. While some organisations are still in the early stages of adoption, others show full integration of big data analytics capabilities at both strategic and operational levels.

6.4.4 Summary of the respondent's demographic profiles.

The respondent profile presented in this section reflected a diverse and well-qualified participant base, with strong representation across industries, professional roles, and big data analytics capabilities maturity levels. This diversity enhanced the external validity of the study and supported a nuanced understanding of how South African business are adopting and leveraging big data analytics capabilities for competitive advantage. Section A of the survey clearly indicated that individuals working in organisations with active big data use consider big data to be important and influential across multiple business functions.

6.5 ORGANISATIONAL CHARACTERISTICS

This section presents key organisational characteristics of the business represented in the survey, providing context for understanding big data analytics capabilities maturity across participating organisations.

6.5.1 Participation in Big data Decision-Making

To assess the relevance of the sample, it was important to first determine the extent to which respondents were directly engaged in big data decision-making within their organisations.

SECTION A: PARTICIPANT INFORMATION: ARE YOU CURRENTLY INVOLVED
IN DECISION MAKING PROCESSES REGARDING BIG DATA ANALYTICS?

118 Responses



Figure 31: Participation in Big data Decision-Making

Source: Author

A total of 118 respondents completed the survey, of which 110 confirmed active involvement in big data decision-making within their organisations, and only eight reported no involvement. These results confirm that the sample primarily reflected individuals with relevant experience and responsibility in big data initiatives.

6.5.2 Perceptions of the importance of big data

Understanding how organisations perceive the importance of big data provided insight into its strategic positioning and the extent to which businesses view analytics as a driver of competitive advantage.

Business experience: In your experience, how important do you perceive big data analytics to be in gaining a competitive advantage in your industry?

110 responses

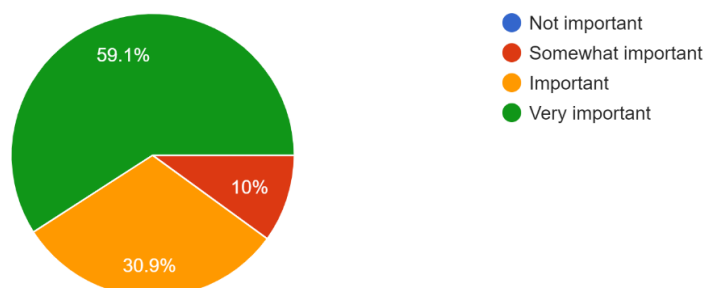


Figure 32: Perceptions of the importance of big data

Source: Author

Approximately 90% of respondents indicated that big data is important to their organisation's competitive advantage. No respondents indicated that big data was unimportant. This finding reinforces the perceived strategic relevance of big data analytics capabilities among South African business.

6.5.3 Impact of Big data on Decision Making

Examining the influence of big data on organisational decision-making highlights the extent to which analytics is being embedded into core business processes and strategic choices.

How do you think big data analytics has influenced decision-making processes within organisations?

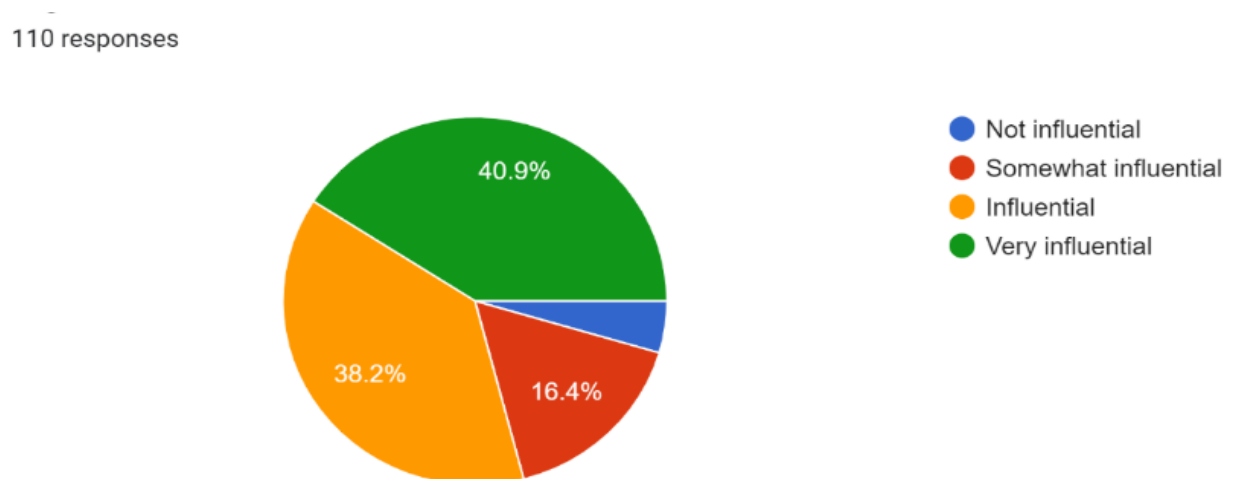


Figure 33: Impact of big data on decision making.

Source: Author

Ninety-five percent (95%) of respondents reported that big data analytics has had a significant impact on decision-making processes within their organisations. Only five respondents indicated that big data had not influenced decision-making. This result suggests increasing maturity in the strategic application of big data within South African business contexts.

6.5.4 Size of organisation

The survey also captured data on organisational size. Eighteen respondents (16.4%) classified their organisations as small, with fewer than 100 employees. Twenty-two respondents (20.0%) indicated medium-sized organisations, employing between 100 and 499 people. Most respondents, seventy in total (63.6%), reported that they were part of large organisations with over 500 employees.

6.5.5 Stage of big data analytics capabilities adoption

Respondents also reported the stage of BDA capabilities adoption in their organisations. Sixteen respondents (14.5%) stated that they were still in the initial stage of adoption. Thirty-eight respondents (34.5%) reported that BDA was partially implemented, while fifty-six respondents (51.0%) confirmed that their organisations had fully implemented big data analytics capabilities.

6.5.6 Years since big data analytics capabilities initiatives commenced.

The duration of big data analytics capabilities implementation varied across organisations. Twelve respondents (10.9%) indicated that their organisations had been implementing initiatives for less than one year. Forty-four respondents (40.0%) reported a duration of between one and three years, while fifty-four respondents (49.1%) indicated that their organisations had been engaged in big data analytics initiatives for more than three years.

Table 25: Summary of organisational profile

Source: Author

Dimension	Categories	Respondents (n)	%
Size of organisation	Small (< 100 employees)	18	16.4%
	Medium (100–499 employees)	22	20.0%
	Large (500+ employees)	70	63.6%
Stage of big data analytics capabilities adoption	Initial	16	14.5%
	Partially implemented	38	34.5%

	Fully implemented	56	51.0%
Years since big data analytics capabilities initiatives commenced	Less than 1 year	12	10.9%
	1–3 years	44	40.0%
	More than 3 years	54	49.1%

6.5.7 Summary of organisational characteristics

This section clearly demonstrates that big data analytics is seen as an important and influential driver of business value in South African businesses. The findings suggest a growing maturity in both the understanding and strategic use of big data analytics capabilities, with increasing integration into decision-making processes across various organisational sizes and industry sectors.

6.6 DESCRIPTIVE ANALYSIS OF BIG DATA ANALYTICS AND RELATED CONSTRUCTS

This section provides a descriptive analysis of the key constructs related to big data analytics capabilities as reported by the participating organisations. The analysis offers insight into current capabilities and areas for improvement across South African business. These descriptive results reflect positive perceptions of big data analytics capabilities maturity and advantage outcomes across the surveyed business, while also highlighting areas for improvement in certain dimensions particularly in talent and skills development, and infrastructure capabilities.

6.6.1 Data capabilities

Assessing data capabilities was critical, as the accessibility and quality of datasets directly determined how effectively organisations could develop and apply big data analytics.

Section B: Data Capabilities

From your experience, how accessible are extensive datasets for analysis within organisations?

110 responses

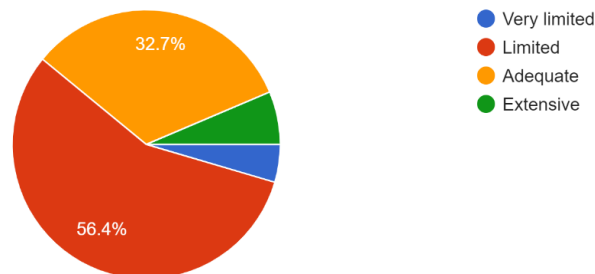


Figure 34: Data capabilities

Source: Author

A significant portion (56.4%) reported that accessibility to extensive datasets is limited. This could indicate barriers such as data silos, insufficient data infrastructure, or privacy concerns that limit the effective use of large datasets. While 32.7% felt that the accessibility is adequate, only 9.1% believed it is extensive. This reinforces the view that data accessibility remains a challenge for organisations. There seems to be a noticeable gap in data accessibility within organisations, which could hinder the ability of companies to leverage big data to its fullest potential.

In your opinion, how effectively do organisations integrate various data sources for analysis purposes.

110 responses

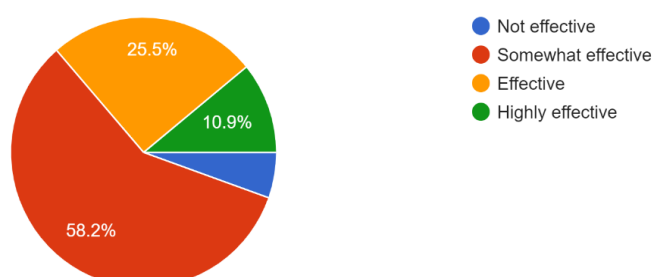


Figure 35: Effectiveness of integrating data sources for analysis.

Source: Author

The majority (58.2%) believed that organisations are somewhat effective in integrating various data sources. This suggests that while there is some level of integration happening, it may not be optimal or seamless. Only 10.9% of respondents felt that organisations are highly effective in data integration, while a combined 63.6% (effective and not effective) indicated that there is room for improvement in this area. Organisations in South Africa may still face challenges in fully integrating multiple data sources for effective analysis, which could be a key area of focus for improvement. Challenges in data integration remain an obstacle to optimising big data use, and improving seamless data access and integration should be a key focus for South African business.

6.6.2 Technology adoption

Evaluating the extent of technology adoption provided insight into how organisations are integrating advanced tools such as parallel computing and data visualisation into their big data strategies, and the barriers that may limit their widespread use.

Technology: From your experience, how common is the adoption of parallel computing approaches like Hadoop for big data processing?
110 responses

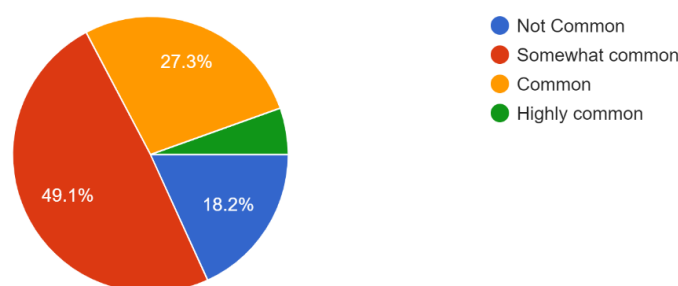


Figure 36: Technology adoption

Source: Author

The largest segment of respondents (49.1%) believed that parallel computing approaches, such as Hadoop, are somewhat common. This suggests that while these technologies are being used, their adoption may not be as widespread or deeply ingrained across industries. Only 5.4% of respondents felt that the adoption of these approaches is highly common, indicating that there may be organisational, technical,

or financial barriers to more widespread implementation. With 27.3% of respondents finding the use of these technologies common, parallel computing solutions are growing in adoption but are not yet ubiquitous. The 18.2% who believed these technologies are not common may reflect industries or sectors where big data processing infrastructure is less developed or where legacy systems are still predominant. There is thus a clear opportunity for organisations to invest more in parallel computing technologies like Hadoop, which can improve the speed and efficiency of big data processing. The fact that only 5.4% of respondents said these approaches are highly common suggests that there may be challenges related to cost, expertise, or scalability that organisations need to overcome to fully leverage these technologies.

In your opinion what level of importance do organisations place on utilising data visualisation tools for analysing big data?

110 responses

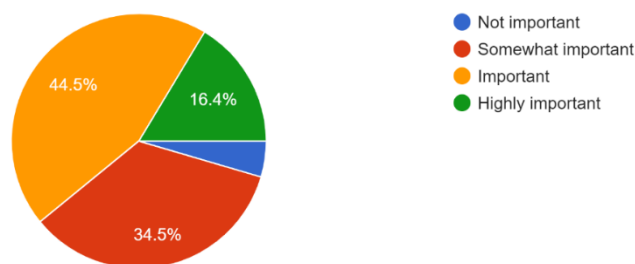


Figure 37: Data visualisation tools

Source: Author

Most organisations place a high degree of importance on the use of data visualisation but only 16.4% of respondents said that data visualisation is incredibly important, suggesting that although most organisations see the value of data visualisation, not all believe that the visualisation of data is critical.

6.6.3 Human skills

Human skills represent a critical pillar of big data analytics capabilities, as the effectiveness of technological tools depends on the expertise, training, and adaptability of the professionals who apply them.

HUMAN SKILLS, Technology Skills: Based on your observations, how equipped are big data analytics staff with the necessary skills for their roles?

110 responses

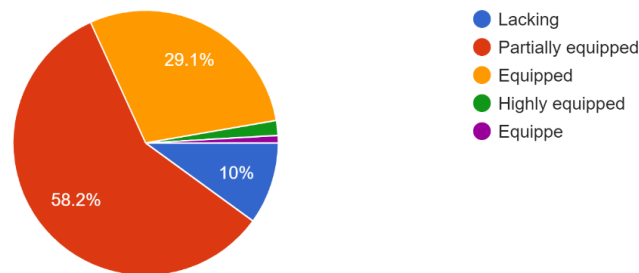


Figure 38: Human Skills

Source: Author

A significant majority (58.2%) of respondents believed that big data analytics staff are partially equipped with the necessary skills. This suggests that while many professionals in this field possess some of the required knowledge and skills, they may lack expertise in specific areas, due to the rapidly evolving nature of data analytics technology and methodologies. Organisations might be facing a talent gap, with many respondents' reporting difficulty in retaining big data analytics staff. Staff also have a foundational understanding of big data analytics but lack advanced or specialised skills (e.g., in machine learning, advanced statistical modelling, or cloud-based analytics tools). Only 1.8% of respondents felt that staff are highly equipped, signalling a clear shortage of top-tier expertise. This could hinder organisations from fully using the potential of big data analytics and prevent them from keeping pace with innovative innovations in the field. Organisations may need to focus on more robust training programs, certifications, or hiring experts to bridge this skills gap.

With 10% of respondents indicating that staff are lacking the necessary skills, there may be immediate concern about talent shortages in the industry. These gaps could negatively impact organisational advantage, slowing down projects or leading to inefficient use of big data technologies. Businesses may therefore need to focus more on recruitment, partnerships with educational institutions, or external consultation services to overcome these shortfalls. While 29.1% of respondents believed that staff are equipped for their roles, there's still room for improvement. Given the dynamic and

fast-paced nature of big data, maintaining the status quo might not be sufficient. Investing in continuous education, certifications, and skill upgrades should be a priority for businesses that want to remain competitive. Organisations need to actively invest in upskilling and reskilling programs to ensure that their teams remain current with the latest data science and analytics tools and methods.

The results indicate that while some staff are equipped for their roles, the majority are either partially equipped or lacking key skills. This signals a need for targeted interventions, including training, mentorship, and hiring initiatives, to build a workforce that can leverage the full potential of big data analytics. Companies may need to prioritise both internal and external talent development strategies, focusing on upskilling existing employees and attracting high-level talent with advanced skills.

How effective do you believe the training programs provided to big data analytics staff are?
110 responses

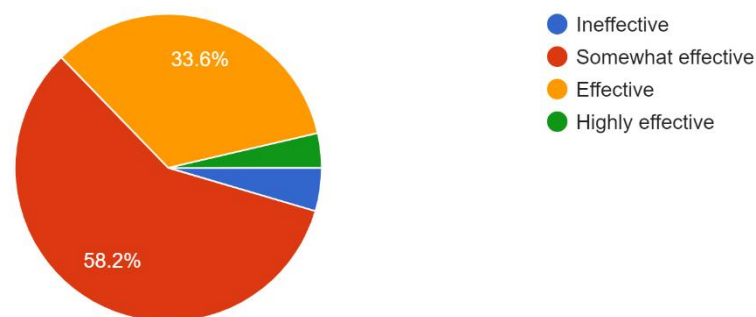


Figure 39: Training programs

Source: Author

The majority (58.2%) of respondents believed that training programs are somewhat effective. This suggests that while the programs offer value, they may not be fully addressing the needs of big data analytics staff. The training covers only foundational or basic topics, leaving more advanced areas underdeveloped. Organisations need to review and optimise their training content to ensure it aligns with the most critical and current demands in the big data field, such as firsthand experience with advanced tools (e.g., Hadoop, Spark) or emerging techniques (e.g., AI-driven analytics).

A combined 37.2% (33.6% effective + 3.6% highly effective) of respondents rated the training programs as either effective or highly effective. This indicates that a portion of the workforce benefits from these programs and feels that they adequately prepare them. While some organisations are doing well in providing training, there is still a gap in ensuring that these programs reach an elevated level of excellence across the board. The small percentage of respondents who viewed the programs as highly effective (3.6%) signals that few organisations are excelling in training. It indicates that most programs are not as effective as they could be. Businesses should aim to elevate their training offerings to better equip employees with advanced and up-to-date skills, by incorporating industry certifications, real-world project simulations, or partnerships with external learning platforms. Only 4.6% of respondents rated the training programs as ineffective, which is a small percentage but still noteworthy. This may reflect isolated cases where training is either outdated, too generic, or fails to align with specific job roles. Companies experiencing this issue should assess whether their training content is relevant and whether it is delivered in a way that engages and empowers staff to apply what they have learned.

6.6.4 Data driven culture.

Exploring the role of organisational culture is essential, as the extent to which businesses prioritise, and trust data-driven decision-making determines how effectively big data analytics can influence strategy and performance.

From your perspective to what extent do organisations prioritise data-driven decision-making over intuition or gut feelings?

110 responses

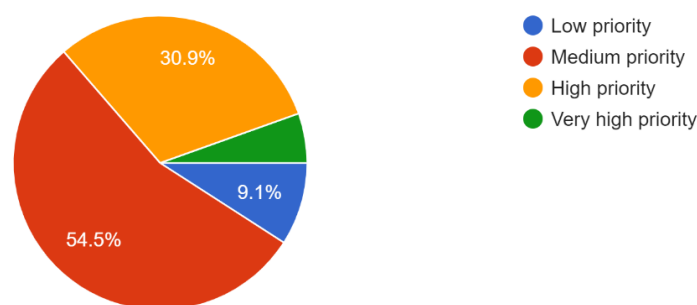


Figure 40: Data-driven culture.

Source: Author

The largest portion of respondents (54.5%) indicated that organisations place a medium priority on data-driven decision-making over intuition. This suggests that while data is considered important, there is still a balance between data and gut instinct, and organisations may not fully rely on data alone to drive key decisions. There might be organisational or cultural barriers that prevent companies from making data the primary basis for decision-making, such as a lack of trust in data, incomplete data, or reliance on traditional decision-making processes.

A significant 30.9% of respondents felt that organisations treat data-driven decision-making as a high priority, indicating that a fair number of companies are moving towards embedding data into their decision processes. Organisations that prioritise data-driven decisions are seeing the benefits of using data for competitive advantages, improving efficiency, or driving innovation. However, there remains a gap in fully making data the foundation for all key decisions.

A total of 9.1% of respondents reported that organisations give data-driven decision-making a low priority, suggesting that some companies may still be slow to adopt data-centric approaches. This could stem from a lack of data literacy, underdeveloped data infrastructures, or resistance from leadership who prefer intuition-based decisions. These organisations risk falling behind competitors who are leveraging data more effectively. To address this, businesses may need to foster a culture of data literacy and trust in data insights across all levels. Only 5.5% of respondents believed that organisations place a very high priority on data-driven decision-making. This small percentage indicates that few organisations have reached the maturity level where data consistently and systematically guides most business decisions. There is still considerable opportunity for companies to increase the role of data in decision-making. For those already emphasising a high priority on data, the next step might be to integrate data even more deeply into everyday decision processes, automate data insights, and democratize data access across teams. The results show that many organisations still balance data with intuition, with a medium priority on data-driven decision-making dominating. This signals that, while data plays a key role, it is not yet fully central to decision-making in many companies.

How receptive do you find organisations to changing decisions based on data-driven insights, even if they contradict existing viewpoints?

110 responses

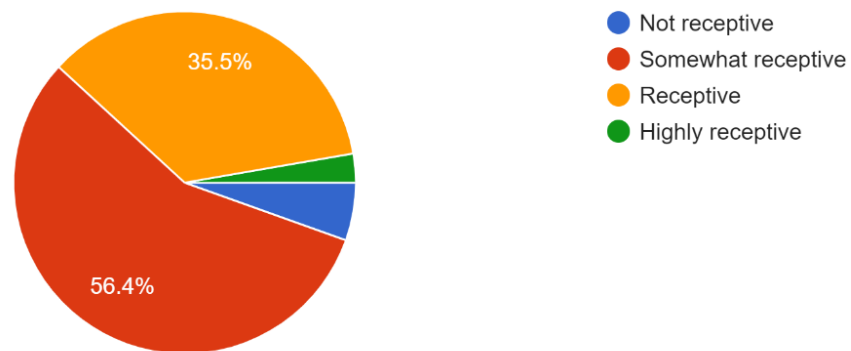


Figure 41: Data-driven insights.

Source: Author

A significant 56.4% of respondents found organisations to be somewhat receptive to changing decisions based on data-driven insights. This indicates a willingness to consider data but also suggests that there may be hesitation or resistance to fully embracing data that contradicts established viewpoints. Organisations may need to create a more supportive environment where data-driven insights can challenge existing beliefs and foster a culture of open-mindedness, reducing fear of reevaluating long-held practices or assumptions.

A total of 35.5% of respondents felt that organisations are receptive to changing their decisions based on data insights. This suggests that a notable portion of companies values data and is willing to pivot based on evidence, which is a positive trend towards a more data-centric culture. Companies that are receptive to data-driven insights may experience greater agility and adaptability in decision-making, allowing them to respond more effectively to market changes or emerging opportunities.

Only 2.7% of respondents believed that organisations are highly receptive to changing decisions based on data-driven insights. This small percentage indicates that very few

organisations have fully ingrained data-driven decision-making into their culture, where data insights can readily overturn existing beliefs or practices. Organisations aiming for high receptivity should focus on fostering trust in data, ensuring that decision-makers understand the validity and relevance of the insights presented to them.

The fact that only 5.4% of respondents found organisations not receptive to data-driven insights is a slight concerning indication of potential cultural resistance to adopting a data-driven approach. This could hinder organisations from leveraging valuable insights and improving overall advantage. Overcoming this resistance will require leadership to advocate data usage, create transparent communication channels regarding data insights, and establish processes to incorporate these insights into decision-making.

The responses indicate that while many organisations are receptive to changing decisions based on data, there is still significant room for improvement. The limited percentage of highly receptive organisations highlights the need for cultural change. To enhance receptivity, organisations should focus on building a culture that values data, encourages experimentation, and supports data literacy among all employees. This cultural shift can facilitate more data-driven decision-making, even when it challenges existing perspectives.

These results show that while many South African organisations are increasingly open to data-driven decision-making, there is still considerable scope for building stronger data cultures. Enhanced leadership support, training, and trust in data will be required to embed data insights more deeply into strategic processes.

6.6.5 Dynamic capabilities

Evaluating dynamic capabilities is important, as it reflects how organisations use data not only to identify new business opportunities but also to plan and execute solutions in ways that enhance adaptability and long-term competitiveness.

Section C: Operationalising Sense, Seize and Transform

In your experience, how proactive are organisations in identifying new business opportunities through data analysis?

110 responses

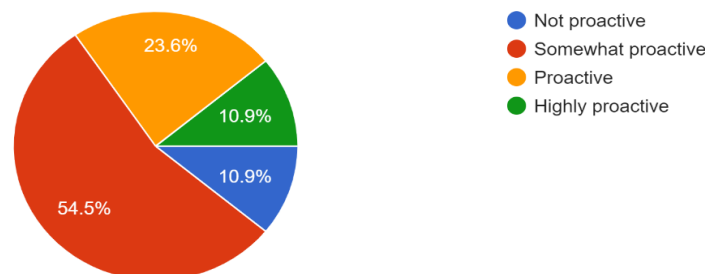


Figure 42: New business opportunities

Source: Author

Most respondents (54.5%) categorised organisations as somewhat proactive in identifying new business opportunities through data analysis.

This indicates a recognition of the importance of data analysis, yet it suggests that many organisations may not be fully leveraging their data capabilities to uncover new opportunities. Companies may be using data analysis to some extent but could benefit from more structured processes or frameworks to actively seek out and evaluate potential business opportunities. A total of 23.6% of respondents consider organisations to be proactive in their data-driven efforts to identify new business opportunities. This shows that a good portion of companies are actively looking for ways to utilise data analysis to gain a competitive edge. Organisations in this category may have established practices that prioritise data analysis in their strategic planning, enabling them to capitalise on trends and market shifts more effectively.

Only 10.9% of respondents felt that organisations are highly proactive in leveraging data analysis for identifying new business opportunities. This low percentage highlights a gap where very few organisations are truly excelling in this area, potentially missing valuable insights, and growth prospects. To elevate to a highly proactive stance, organisations may need to enhance their data capabilities, invest in advanced analytical tools, and cultivate a culture that encourages data-driven

exploration and innovation. The same percentage (10.9%) of respondents indicates that organisations are not proactive in this regard. This raises concerns that some companies may not be utilising their data analysis capabilities at all, which can lead to missed opportunities in an increasingly data-driven business landscape. Organisations that are not proactive need to identify barriers to data usage, such as lack of skills, inadequate tools, or cultural resistance, and work to address these challenges to remain competitive.

The results reveal that while many organisations recognise the importance of data analysis for identifying new business opportunities, the majority are only somewhat proactive, with limited instances of high proactivity. There is a clear opportunity for organisations to enhance their approach to data analysis, moving towards a more proactive stance that prioritises data-driven insights in strategic decision-making. There is limited strategic alignment between big data analytics initiatives and business goals. Businesses should therefore focus on establishing a data-centric culture, investing in training and tools, and developing processes to regularly review data for identifying emerging opportunities.

How frequently do organisations plan and execute potential solutions based on data analysis?

110 responses

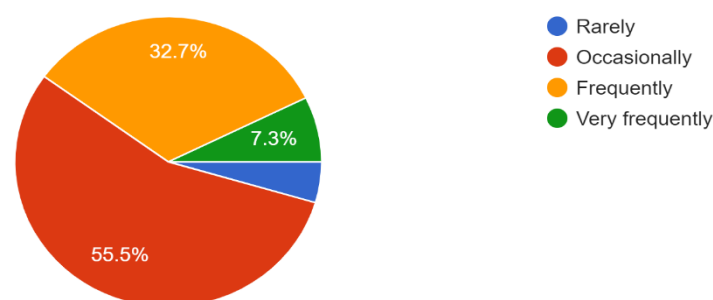


Figure 43: Planning and execution

Source: Author

The largest segment of respondents (55.5%) indicates that organisations plan and execute potential solutions based on data analysis occasionally. This suggests that while data is considered in decision-making, it may not be a consistent or systematic

approach across organisations. Organisations may therefore need to develop more regular processes for integrating data analysis into their solution planning and execution, ensuring that data-driven insights are utilised consistently.

Of respondents, 32.7% report that organisations plan and execute solutions frequently based on data analysis. This indicates a proficient level of engagement with data in the decision-making process, allowing organisations to leverage insights to drive actions. Companies that frequently utilise data analysis in planning are likely to see better outcomes and increased innovation, as they can respond to findings and adapt strategies effectively.

Only 7.3% of respondents describe organisations as planning and executing solutions very frequently based on data analysis. This small percentage points to a gap where few organisations have fully integrated data analysis into their regular operational processes. To achieve a higher frequency of planning based on data insights, organisations may need to automate data processes or create dedicated teams focused on interpreting data to inform strategic decisions (Subramoney and Dagada, 2025).

A small percentage (4.5%) of respondents said that organisations rarely plan and execute potential solutions based on data analysis. While this is a minority, it highlights that some organisations may be ignoring data-driven insights altogether. Organisations falling into this category may face significant risks, as they are missing critical insights that could enhance their strategies and competitive edge. They should examine the barriers preventing them from leveraging data effectively.

6.6.6 Section D: Operationalising marketing capabilities

Analysing how organisations operationalise marketing capabilities sheds light on the extent to which data-driven insights are being translated into effective market strategies and distribution practices.

How well do organisations utilise market knowledge derived from data analytics to inform their marketing strategies?

110 responses

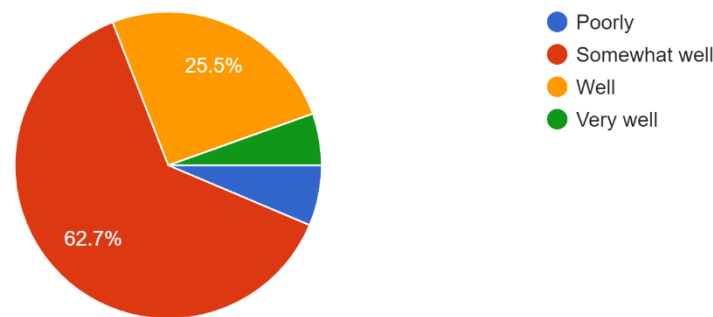


Figure 44: Operationalising marketing capabilities

Source: Author

A significant 62.7% of respondents felt that organisations utilise market knowledge from data analysis somewhat well. This indicates that while organisations are incorporating market insights into their marketing strategies, they may not be doing so effectively or consistently. Companies may have the data available but could be struggling with how to apply it effectively, potentially missing deeper insights or more refined strategies. Of the respondents, 25.5% reported that organisations use market knowledge well. This suggests that a portion of companies has developed effective practices for integrating data-driven insights into their marketing strategies.

Organisations that utilise market knowledge well are likely to be more responsive to consumer needs, market trends, and competitive pressures, which can enhance their overall marketing effectiveness. Only 5.5% of respondents believed that organisations utilise market knowledge from data analysis very well. This low percentage indicates that few organisations have fully optimised their data-driven marketing capabilities. Consequently, organisations aiming for a very well status may need to invest in advanced analytics, enhance their data interpretation skills, and build a culture that prioritises data-driven decision-making in marketing.

A small percentage (6.3%) of respondents indicate that organisations utilise market knowledge poorly. While this is a minority, it highlights that some organisations may not be leveraging available data to inform their marketing strategies at all. Companies in this category may need to assess barriers such as lack of data literacy, inadequate

data systems, or poor alignment between marketing teams and data analytics teams to improve their advantage.

How effectively do organisations leverage their control and access to distribution channels based on insights derived from data analytics?

110 responses

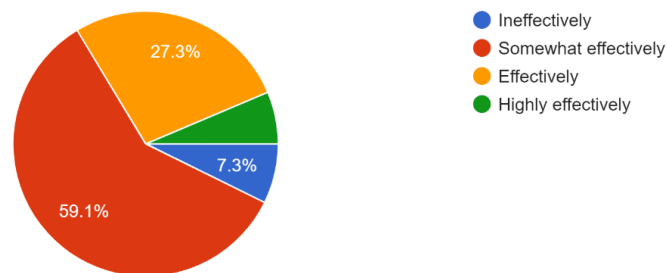


Figure 45: Distribution channels

Source: Author

Most respondents (59.1%) believed that organisations leverage their distribution channels somewhat effectively. This indicates a moderate level of engagement with data insights when managing distribution, suggesting that while organisations are aware of their distribution strategies, they may not fully capitalise on data analysis to optimise them.

Companies may have had access to valuable data but could benefit from more focused efforts to analyse and apply this information to enhance their distribution effectiveness. Of the survey respondents, 27.3% felt that organisations leverage their distribution channels effectively. This suggests that a massive portion of organisations are making meaningful use of data insights to optimise their distribution strategies.

Organisations that effectively leverage data analysis in their distribution channels enjoy better alignment with market demands, improved customer satisfaction, and potentially increased sales through optimised distribution pathways. Only 6.3% of respondents reported that organisations leverage their distribution channels highly

effectively. This low percentage indicates that few organisations have achieved an elevated level of proficiency in using data analysis for distribution channel management. To achieve highly effective status, organisations may need to enhance their data analytics capabilities, develop sophisticated models to predict distribution needs, and create real-time data usage processes to adapt to changing market conditions.

A small percentage (7.3%) indicated that organisations leverage their distribution channels ineffectively. This reflects a concern that some organisations may be missing opportunities to optimise their distribution strategies based on available data insights. Organisations falling into this category should investigate the root causes, which could include insufficient data collection methods, a lack of integration between data analysis and distribution planning, or inadequate training for staff on data-driven decision-making.

6.6.7 Section E: Operationalising technological capabilities

Examining the operationalisation of technological capabilities provided insight into how effectively organisations are applying tools, systems, and databases to process and manage big data, and highlights both areas of strength and opportunities for improvement.

On a scale of 1 to 7, how effectively do organisations leverage technological capabilities to enhance big data processing and analysis?

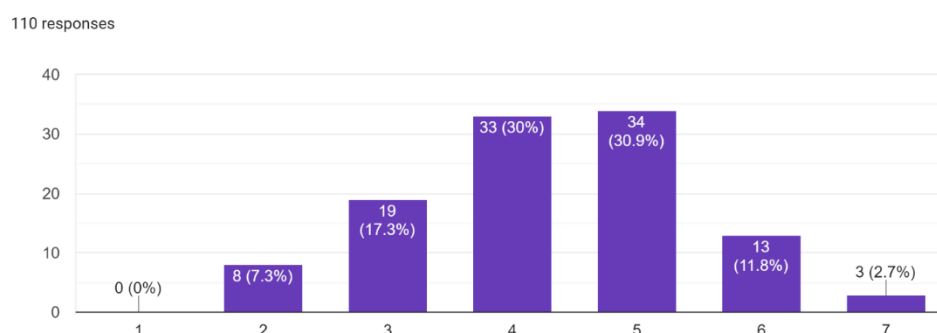


Figure 46: Operationalising technological capabilities

Source: Author

The responses appear normally distributed, with 30.9% rating their effectiveness as 5 and 30.0% rating it as 4. This indicates a tendency toward moderate effectiveness in leveraging technological capabilities for big data processing and analysis. While a significant number of organisations recognised some level of effectiveness, this also points to a lack of confidence in their technological capabilities, suggesting room for improvement. Very few respondents rated their effectiveness as 1 (0%) or 7 (2.7%), which indicates a notable absence of organisations that felt they are at the extremes of effectiveness, either very ineffective or highly effective. This suggests that organisations may feel they are in a transition phase, working toward improving their capabilities but not yet reaching a high level of effectiveness.

The average rating can be estimated to be around 4 to 5, suggesting that while organisations are using technological capabilities, there is significant room for enhancement. Companies may need to invest in advanced technologies, improve existing systems, or enhance staff training and skills to leverage big data more effectively. The 11.8% who rated their effectiveness as 6, and the 2.7% who rated it as 7 represent organisations that have made significant investments in technology and processes for big data. These businesses could serve as case studies for best practices, highlighting strategies and tools that lead to effective big data processing and analysis.

On a scale of 1 to 7, how proficiently do organisations implement and optimise various databases, such as NoSQL, to store and manage large datasets?

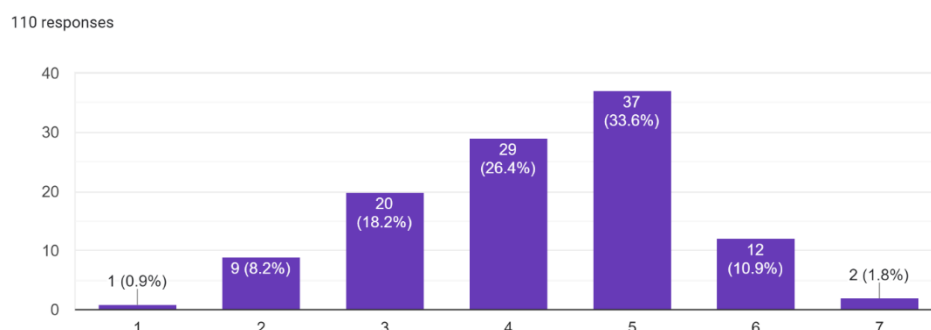


Figure 47: Databases

Source: Author

A significant portion of respondents rated their proficiency as 5 (33.6%) and 4 (26.4%), indicating that many organisations felt they have a moderate level of proficiency in implementing and optimising databases for managing large datasets. This suggests that organisations demonstrate moderate competency in using databases, there is still room for improvement. Only 0.9% rated their proficiency as 1, and 1.8% as 7.

The extreme ratings highlight a lack of organisations that are either completely ineffective or highly proficient in this area. Organisations may be in a transitional phase, not having fully established best practices for database implementation and optimisation, thus indicating the potential for significant enhancement. A third of organisations reported lower ratings, with 27.3% rating their proficiency as 3 or lower. This indicates that many organisations may struggle with implementing and optimising database technologies effectively, and they should consider evaluating their database strategies, staff expertise, and infrastructure to identify gaps.

On the other hand, 10.9% rated their proficiency as 6, suggesting that some organisations have achieved a higher level of optimisation. However, with only 1.8% feeling highly proficient (7), there may be few case studies of exemplary practices in this area. Those organisations that rate themselves high may provide valuable insights or methodologies that others can adopt to improve their database management practices.

6.6.8 Section F: Operationalisation of competitive advantage

Assessing the competitive advantage is essential, as it reveals how effectively organisations are translating big data analytics into tangible business outcomes such as profitability, return on investment, sales growth, and cost reduction.

On a scale of 1 to 7, how successfully do organisations achieve higher profitability compared to their competitors?

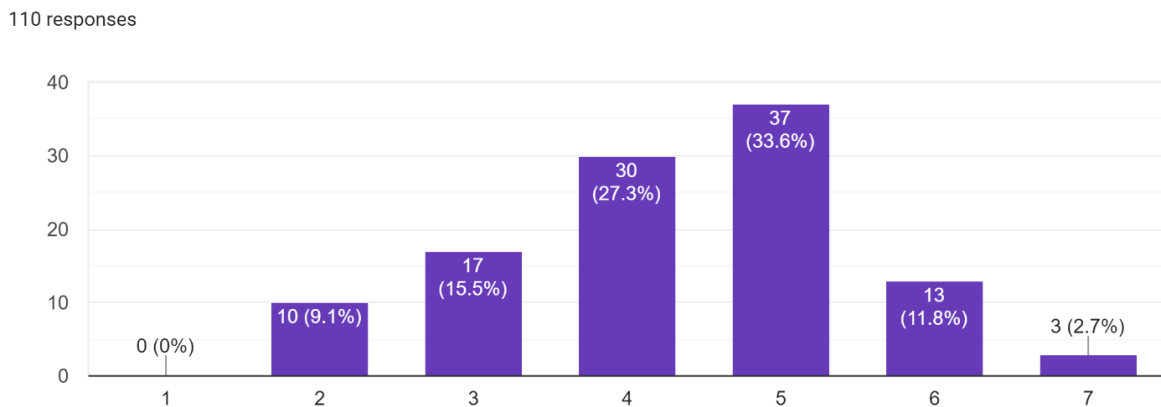


Figure 48: Competitive advantage

Source: Author

A significant proportion of respondents rated their success at achieving higher profitability as 5 (33.6%) or 4 (27.3%), indicating a tendency towards moderate success in relation to competitors. While organisations felt they are successful in achieving higher profitability, there is still room for growth, and they may not be fully capitalising on competitive advantages. Very few respondents rated their success as 1 (0%) or 7 (2.7%), which suggests that they did not perceive themselves as either completely ineffective or highly successful in this area. This points to a gap where many may be experiencing challenges in differentiating themselves effectively within their competitive landscape.

Almost a quarter of respondents (24.6%) rated their success as 2 or 3, reflecting a notable portion of businesses that may be struggling to achieve higher profitability compared to competitors. Organisations in this category may need to reassess their competitive strategies, identify barriers to profitability, and explore new approaches to enhance their market position. At the higher end, 11.8% rated their success as 6, indicating that some organisations are closer to achieving better profitability, but with only 2.7% feeling highly successful (7), very few have fully optimised their profitability

in comparison to competitors. These organisations could provide insights or strategies that others may adopt, highlighting best practices in competitive positioning.

On a scale of 1 to 7, how effectively do organisations measure and enhance their return on investment (ROI) compared to their competitors?

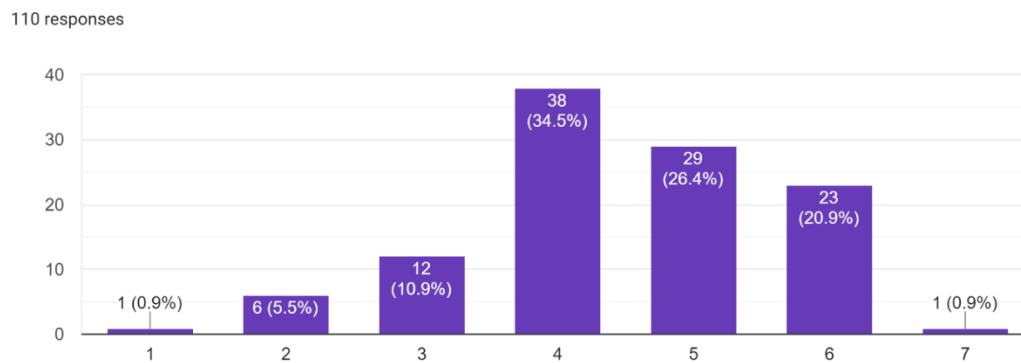


Figure 49: Return on investment.

Source: Author

A significant portion of respondents rated their effectiveness at measuring and enhancing ROI as 4 (34.5%) and 5 (26.4%), indicating a tendency toward moderate effectiveness in this area. This suggests that organisations demonstrate moderate capability in measuring and enhancing ROI, there remains considerable room for improvement. Only 0.9% rated their effectiveness as either 1 or 7, indicating that very few organisations perceive themselves at the extremes of being completely ineffective or highly successful. This middle-ground distribution suggests that most organisations are still working to develop stronger ROI measurement and enhancement practices.

A total of 16.4% of respondents rated their effectiveness as 2 or 3, highlighting a group of organisations that may struggle to effectively measure and enhance ROI compared to competitors. These organisations may need to investigate their measurement techniques, data analysis practices, and overall strategies for ROI improvement. By contrast, 20.9% rated their effectiveness as 6, suggesting that some are approaching effective ROI management. However, with only 0.9% rating it as 7, very few have fully

optimised this capability. Organisations achieving higher ratings could serve as benchmarks for best practices in ROI measurement and enhancement strategies.

On a scale of 1 to 7, how well do organisations achieve significant sales growth compared to their competitors within your industry?

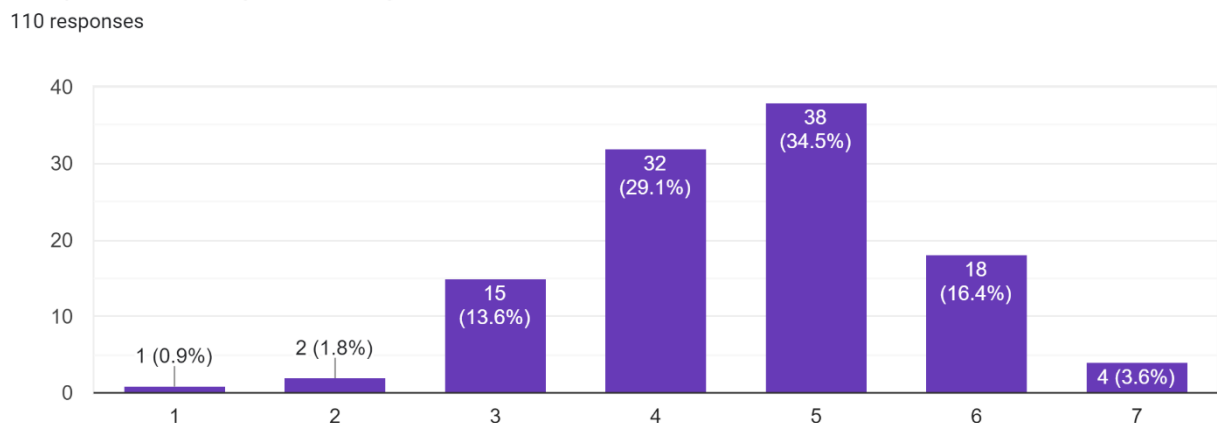


Figure 50: Sales growth

Source: Author

Respondents reported moderate success in achieving sales growth, with 34.5% rating themselves at 5 and 29.1% at 4. While many organisations perceive themselves as achieving reasonable growth, there is still substantial room for improvement to strengthen competitiveness. Very few respondents rated their success as 1 (0.9%) or 2 (1.8%), suggesting that few organisations felt completely ineffective. Conversely, only 3.6% rated themselves as highly successful (7), reflecting only a small proportion who viewed their organisations as achieving significant sales growth. In total, 16.3% rated their success as 3 or lower, showing that some organisations may struggle to achieve significant growth compared to their competitors. These organisations may need to analyse their sales strategies, market positioning, and competitive tactics to identify barriers to growth. On the other hand, 16.4% of respondents rated their success as 6, indicating that some are nearing effective sales growth, though very few (3.6%) have mastered this area. Those that have achieved higher ratings may provide insights into effective strategies that can be adopted by others to strengthen sales performance.

On a scale of 1 to 7, how efficiently do organisations reduce operating costs compared to their competitors?

110 responses

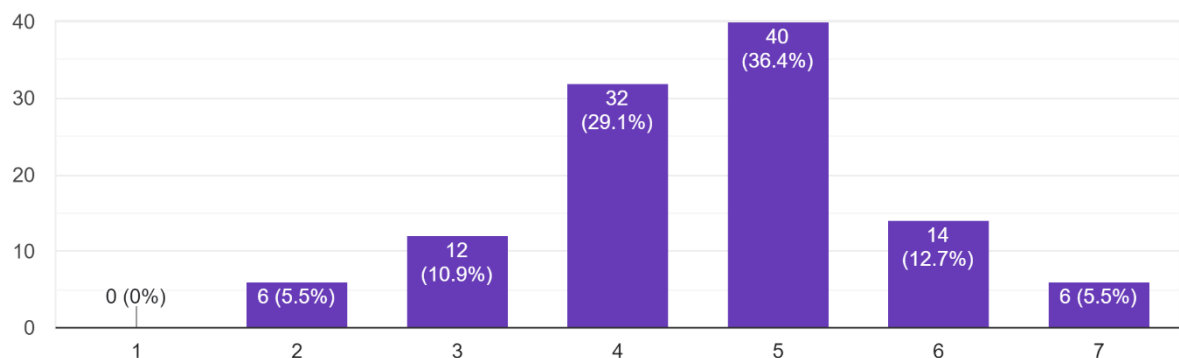


Figure 51: Reducing operating costs.

Source: Author

A considerable portion of respondents rated their efficiency in reducing operating costs as 5 (36.4%) and 4 (29.1%), indicating that many perceive moderate success in this area. While organisations felt effective in managing and reducing costs, there remains significant potential for further optimisation. None of the respondents rated their efficiency as 1, suggesting that no organisations felt completely ineffective. However, 5.5% rated their efficiency as 7, meaning only a small number consider themselves highly efficient. This distribution suggests that most organisations are operating within the middle range of cost efficiency.

A total of 16.4% rated their efficiency as 2 or 3, showing that a notable segment of organisations may struggle to reduce operating costs efficiently compared to competitors. These may benefit from reviewing their operational processes, cost management strategies, and resource allocation to identify inefficiencies.

Meanwhile, 12.7% rated their efficiency as 6, suggesting some organisations are approaching higher levels of efficiency. However, the low percentage rating as 7 indicates that very few have fully optimised this capability. Organisations that have achieved higher ratings could provide valuable insights into effective practices and strategies that others may adopt to enhance cost reduction.

6.7 DATA SCREENING

Data screening is a critical preparatory step in quantitative research, aimed at identifying any data issues that could compromise the validity of the results (Hair et al., 2019; Kock and Hadaya, 2016). Prior to conducting the main analysis, a rigorous data screening process was therefore undertaken to ensure the integrity, reliability, and suitability of the dataset for PLS-SEM. The screening process followed established best practices for PLS-SEM (Hair et al., 2019; Sarstedt et al., 2021). It involved several stages, including checks for completeness, outliers, response quality, and distributional properties. The survey instrument consisted of thirty-five items, measured on a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), with three representing a neutral response. A total of 118 questionnaires were received. Of these, 110 cases were retained for analysis after filtering to include only respondents who confirmed direct involvement in big data analytics initiatives within their companies. Participation in the survey was voluntary, responses were anonymised, and ethical approval was granted by the University's Research Ethics Committee (see Chapter 4).

Table 26: Data screening and preparation summary

Source: Author

Screening item	Procedure applied	Result	Decision
Total questionnaires received	Initial completed survey responses reviewed	118	Included for initial screening
Eligibility screening	Respondents checked for direct involvement in big data analytics initiatives	110 eligible responses	Retained for analysis
Excluded responses	Respondents not directly involved in big data analytics initiatives	8 responses	Removed from analysis
Missing data	Dataset checked for incomplete responses	No missing data identified	No imputation required
Outliers	Mahalanobis Distance assessed for multivariate outliers	No serious distortion identified	Dataset retained

Screening item	Procedure applied	Result	Decision
Disengaged responses	Standard deviation and response pattern checks conducted	No zero-variance response patterns identified	Responses retained
Normality	Skewness and kurtosis examined for survey items	Most values within acceptable ranges	Suitable for PLS-SEM
Final usable sample	Cleaned dataset used for PLS-SEM	110 responses	Accepted

6.7.1 Outliers

Potential multivariate outliers were assessed using Mahalanobis Distance (D^2). This was done to determine whether any cases deviated substantially from the overall data pattern and could therefore distort the model estimates. Cases with unusually high Mahalanobis D^2 values were reviewed. The assessment did not identify any serious outlier-related distortion that required further removal of cases. The dataset was therefore retained for subsequent analysis.

6.7.2 Disengagement in responses

To ensure response quality, further screening was conducted to identify cases reflecting inattentive or disengaged participation, which could otherwise bias results (Berinsky, Margolis, Sances and Warshaw, 2021). This included checking whether respondents gave the same answer across all Likert-scale items and reviewing response patterns for signs of repetitive or careless answering. Standard deviation checks did not identify any zero-variance responses across the full set of Likert-scale items. The retained dataset was therefore considered sufficiently consistent and suitable for further analysis.

6.7.3 Test for normality

Although PLS-SEM does not assume strict multivariate normality due to its non-parametric nature, it remains useful to assess distributional properties of the data (Hair et al., 2019). The skewness and kurtosis were examined for each survey item. Most items fell within acceptable ranges for skewness (between -1 and +1) and kurtosis (between -2 and +2), consistent with commonly accepted thresholds (Kline, 2023). A

small number of variables exhibited mild non-normality; however, this did not compromise the validity of the PLS-SEM analysis, given the method's robustness to such deviations (Hair et al., 2019).

6.7.4 Summary of data screening and preparation

The data screening process confirmed that the final set of 110 cases was complete, consistent, and of suitable quality for further analysis. No missing data were identified, no serious outlier-related distortion was found, and there was no evidence of disengaged response patterns that would compromise the results. The dataset therefore met the necessary quality requirements for the exploratory factor analysis and measurement model evaluation that followed.

6.8 EXPLORATORY FACTOR ANALYSIS

Exploratory Factor Analysis (EFA) was conducted to examine the underlying structure of the measurement instrument and to determine whether the survey items grouped in a manner consistent with the conceptual framework developed in Chapter 3. This step was important because the quantitative instrument was informed by the qualitative phase and needed to demonstrate that the observed variables reflected the intended constructs before proceeding to the PLS-SEM measurement model evaluation.

The EFA was conducted using the 110 valid responses retained after data screening. The analysis assessed whether the items clustered around the expected dimensions of big data analytics capabilities, dynamic capabilities, operational capabilities, competitive advantage and environmental factors. The purpose was not to replace the theoretically developed model, but to provide preliminary evidence that the measurement items were suitable for further reliability and validity testing.

6.8.1 Method and extraction technique

Only data from the 110 valid responses, in which participants confirmed their involvement in big data analytics initiatives, were included in the exploratory factor analysis. The factorability of the dataset was first assessed using two standard tests, the Kaiser-Meyer Olkin (KMO) and the Bartlett's test of Sphericity. The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy revealed an overall value exceeding

0.60, confirming that the sample was adequate for factor analysis (Kaiser, 1974). The Bartlett's Test of Sphericity was similarly significant, ($p < 0.001$), indicating that the correlation matrix was sufficiently different from an identity matrix, confirming suitability for factor extraction (Bartlett, 1954).

6.8.2 Factor loadings and construct validation

The factor analysis revealed a clear and interpretable factor structure aligned with the six conceptual constructs identified during the qualitative phase. These were strategic alignment, talent and skills shortages, infrastructure and data quality constraints, value creation and competitive differentiation, organisational readiness, and regulatory and environmental pressures.

Each factor demonstrated strong item loadings, with most exceeding 0.70, and all above the commonly accepted threshold of 0.60 (Hair et al., 2019). Minimal cross-loadings were observed (cross-loadings above 0.40 were rare), confirming satisfactory discriminant validity between constructs. Items that failed to meet the loading threshold or exhibited cross-loadings (above 0.40 on multiple factors) were reviewed. However, most items showed strong alignment with their intended factors, supporting the validity and reliability of the measurement instrument.

Table 27: Summary of exploratory factor analysis results

Source: Author

Assessment area	Result	Interpretation
Factor structure	Clear and interpretable	Items grouped according to the expected theoretical dimensions
Factor loadings	Most loadings exceeded 0.70	Strong item-to-factor alignment
Minimum retained loading	Above 0.60	Acceptable for exploratory analysis
Cross-loadings	Minimal problematic cross-loadings observed	Supported construct separation

Assessment area	Result	Interpretation
Construct validation	Theoretical alignment confirmed	Suitable for measurement model evaluation

The results indicate that the survey items were generally aligned with their intended constructs. This provided initial evidence that the measurement instrument captured the main dimensions required for the study.

6.8.3 Eigenvalues and variance explained

A multi-factor solution was retained based on eigenvalues greater than 1. The cumulative variance explained exceeded 70%, which indicates that a substantial proportion of the variance in the survey responses was captured by the extracted factors. This result is considered strong for social science research and supports the multidimensional nature of the constructs used in the study.

Table 28: Eigenvalues and variance explained
Source: Author

Criterion	Result	Decision
Eigenvalue rule	Factors retained where eigenvalues were greater than 1	Accepted
Cumulative variance explained	Exceeded 70%	Strong explanatory result
Factor solution	Multi-factor structure retained	Supported

6.8.4 Reliability assessment

Internal consistency was assessed using Cronbach's alpha and composite reliability. The results indicated that the extracted factors demonstrated acceptable reliability, with values exceeding the recommended threshold of 0.70. This confirmed that the items within each factor were internally consistent and suitable for further testing in the PLS-SEM model.

Table 29: Reliability assessment from exploratory factor analysis
Source: Author

Reliability Measure	Recommended Threshold	Result	Decision
Cronbach's alpha	> 0.70	All retained factors exceeded the threshold	Accepted
Composite reliability	> 0.70	All retained factors exceeded the threshold	Accepted
Internal consistency	Acceptable reliability required	Confirmed	Suitable for further analysis

The reliability results provided further support for the quality of the measurement instrument. The constructs demonstrated adequate internal consistency and were therefore appropriate for the next stage of analysis.

6.8.5 Summary of exploratory factor analysis

The exploratory factor analysis provided preliminary empirical support for the structure of the measurement instrument. The KMO and Bartlett's Test results confirmed that the data were suitable for factor analysis, while the factor loadings, eigenvalues, variance explained and reliability results supported the validity and reliability of the retained items. The results therefore provided a sound basis for proceeding to the measurement model evaluation using PLS-SEM.

6.9 MEASUREMENT MODEL EVALUATION

Before assessing the structural model, the measurement model was evaluated to determine whether the constructs demonstrated adequate reliability, convergent validity and discriminant validity (Hair et al., 2019). This was necessary because the study's conceptual model included both formative and reflective constructs. The measurement model evaluation therefore followed established PLS-SEM procedures for assessing the quality of the indicators and the validity of the latent constructs (Hair et al., 2019).

The evaluation considered indicator reliability, internal consistency reliability, convergent validity and discriminant validity. For formative measures, indicator weights, t-values, p-values and variance inflation factors (VIF) were examined. For reflective measures, outer loadings, Cronbach's alpha, composite reliability and average variance extracted (AVE) were assessed. This process confirmed whether the constructs used in the model were appropriately operationalised and whether the indicators provided valid representations of the theoretical concepts derived from the literature and the qualitative phase of the study (Gupta and George, 2016; Mikalef et al., 2022).

6.9.1 Indicator reliability

Indicator reliability was evaluated by examining the outer loadings of reflective indicators. Loadings above 0.70 were considered satisfactory because they indicate that the construct explains more than 50% of the variance in the indicator (Hair et al., 2019). Indicators with loadings between 0.60 and 0.70 were reviewed and retained where theoretical justification supported their inclusion, particularly because the study was exploratory.

Formative indicators were assessed using weights, t-values, p-values and VIF values. The purpose of this assessment was to determine whether each formative indicator made a meaningful contribution to its construct and whether multicollinearity was present.

Table 30: Formative indicators of big data analytics capabilities components

Source: Author

Latent Variable	Indicator	Weight	T-Value	P	VIF	Decision
Data	D1	0.610	12.902	$p < 0.05$	1.35	Retained
	D2	0.564	11.403	$p < 0.05$	1.35	Retained
Technology	T1	0.752	14.827	$p < 0.05$	1.20	Retained
	T2	0.435	5.976	$p < 0.05$	1.20	Retained

The results in Table 30 show that all formative indicators were statistically significant and had acceptable VIF values. This confirmed that the indicators contributed meaningfully to their respective constructs and that multicollinearity was not a concern.

Table 31: Formative measurement second and third order construct

Source: Author

Construct	Measures	Weight	T-Value	P	VIF	R ²
Tangibles	Data	0.634	23.835	p<0.05	1.473	0.998
	Technology	0.493	20.521	p<0.05	1.473	
Human Skills	Technology Skills	0.550	17.942	p<0.05	1.129	1.000
	Managerial Skills	0.669	18.885	p<0.05	1.129	
Intangibles	Organisational Learning	0.581	18.314	p<0.05	1.145	1.000
	Data-Driven Culture	0.632	19.789	p<0.05	1.145	
Big data analytics capabilities (Second Order)	Tangibles	0.333	17.823	p<0.05	1.586	1.000
	Human Skills	0.393	31.643	p<0.05	5.009	
	Intangibles	0.391	29.203	p<0.05	4.851	
Dynamic capabilities	Sense	0.431	23.448	p<0.05	2.001	1.000
	Seize	0.425	15.075	p<0.05	2.370	
	Transform	0.354	16.130	p<0.05	1.971	
Operational capabilities.	Marketing capabilities	0.524	20.588	p<0.05	1.941	1.000
	Technological capabilities	0.606	23.551	p<0.05	1.483	

The results in Table 31 confirm that all second- and third-order formative measures were statistically significant. The VIF values were also within acceptable limits, indicating that multicollinearity did not undermine the formative measurement model. The findings therefore supported the retention of the formative indicators and higher-order constructs.

6.9.2 Internal consistency reliability

Internal consistency reliability was assessed using Cronbach's alpha and composite reliability. Cronbach's alpha provides a conservative estimate of reliability, while composite reliability is commonly preferred in PLS-SEM because it accounts for differences in indicator loadings (Hair et al., 2019). Values above 0.70 were considered acceptable.

The results for the reflective indicators are presented in Table 32. Indicators with loadings below the accepted threshold were reviewed. EC3, ED3, EH4 and CP4 were removed because their loadings were below the recommended loading threshold. The retained indicators were then used for the final reliability and validity assessment.

Table 32: Composite reliability, Cronbach's alpha and indicator reliability

Source: Author

Latent Variable	Indicator	Loadings	Cronbach's alpha	Composite reliability
Technology skills	TS1	0.866	0.739	0.777
	TS2	0.724		
Managerial skills	MS1	0.831	0.771	0.823
	MS2	0.842		
Organisational learning	OL1	0.837	0.839	0.78
	OL2	0.761		
Data driven culture	DD1	0.82	0.702	0.801
	DD2	0.814		
Sense	S1	0.846	0.710	0.802
	S2	0.79		
Seize	SZ1	0.856	0.871	0.823
	SZ2	0.817		
Transform	TR1	0.802	0.774	0.761
	TR2	0.766		
Marketing capabilities	MC1	0.82	0.762	0.788
	MC2	0.792		
Technology capabilities	TC1	0.859	0.816	0.839

	TC2	0.841		
Environmental complexity	EC1	0.775	0.841	0.802
	EC2	0.84		
	EC3	0.654		
Environmental dynamism	ED1	0.828	0.731	0.757
	ED2	0.703		
	ED3	0.602		
Environmental hostility	EH1	0.711	0.71	0.822
	EH2	0.791		
	EH3	0.728		
	EH4	0.695		
Competitive advantage	CP1	0.711	0.71	0.822
	CP2	0.791		
	CP3	0.728		
	CP4	0.695		

The results show that the retained constructs achieved acceptable internal consistency reliability. Cronbach's alpha and composite reliability values were above the recommended threshold of 0.70. The retained indicators also showed acceptable loadings, supporting indicator reliability. Four indicators, namely EC3, ED3, EH4 and CP4, were removed because they fell below the required loading threshold.

6.9.3 Convergent validity

Convergent validity refers to the extent to which indicators of the same construct share a high proportion of variance in common (Fornell and Larcker, 1981). In this study, convergent validity was assessed using the Average Variance Extracted (AVE). An AVE value of 0.50 or higher indicates that the construct explains at least 50% of the variance in its indicators and is therefore considered acceptable (Hair et al., 2019).

Table 33: Convergent validity**Source: Author**

Construct	Retained indicators	Retained loadings	AVE	Decision
Technology Skills	TS1, TS2	0.866; 0.724	0.637	Accepted
Managerial Skills	MS1, MS2	0.831; 0.842	0.700	Accepted
Organisational Learning	OL1, OL2	0.837; 0.761	0.640	Accepted
Data-Driven Culture	DD1, DD2	0.820; 0.814	0.667	Accepted
Sense	S1, S2	0.846; 0.790	0.670	Accepted
Seize	SZ1, SZ2	0.856; 0.817	0.700	Accepted
Transform	TR1, TR2	0.802; 0.766	0.615	Accepted
Marketing Capabilities	MC1, MC2	0.820; 0.792	0.650	Accepted
Technology Capabilities	TC1, TC2	0.859; 0.841	0.723	Accepted
Environmental Complexity	EC1, EC2	0.775; 0.840	0.653	Accepted
Environmental Dynamism	ED1, ED2	0.828; 0.703	0.590	Accepted
Environmental Hostility	EH1, EH2, EH3	0.711; 0.791; 0.728	0.554	Accepted
Competitive Advantage	CP1, CP2, CP3	0.711; 0.791; 0.728	0.554	Accepted

As shown in Table 33, all AVE values exceeded the recommended threshold of 0.50. This confirms that each construct explained more than half of the variance in its retained indicators, thereby supporting convergent validity.

6.9.4 Discriminant validity

Discriminant validity was assessed to determine whether each construct measured a concept that was distinct from the other constructs in the model. This was evaluated using the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio (HTMT). The

Fornell-Larcker criterion requires the square root of the AVE for each construct to be greater than its correlations with other constructs (Fornell and Larcker, 1981). The HTMT ratio was also examined because it is widely used in PLS-SEM to assess discriminant validity more rigorously (Henseler, Ringle and Sarstedt, 2015).

Table 34: Fornell-Larcker criterion
Source: Author

Table Number	Assessment	Criterion/Threshold	Result	Decision
31	Fornell-Larcker criterion	Square root of AVE should exceed inter-construct correlations	All constructs satisfy the criterion	Accepted
31	Construct distinctiveness	Constructs should measure empirically separate concepts	Constructs were empirically distinct	Accepted
32	HTMT conservative threshold	< 0.85	Values were within acceptable range	Accepted
32	HTMT liberal threshold	< 0.90	All values were below 0.90	Accepted
32	Discriminant validity	Constructs should be empirically distinct	Confirmed	Accepted

The HTMT results confirmed that all values met acceptable thresholds. Some authors recommend a threshold of 0.85 (Clark and Watson, 1995; Kline, 2023), while others allow a slightly higher threshold of 0.90 (Gold and Malhotra, 2001; Teo, 2008). In this study, all HTMT values were below 0.90, confirming acceptable discriminant validity. Together, the Fornell-Larcker and HTMT results provide evidence that the constructs were empirically distinct. This confirmed that each construct measured a separate dimension of big data analytics capabilities, dynamic capabilities, operational capabilities, environmental conditions and competitive advantage.

6.9.5 Summary of the measurement model evaluation

The measurement model evaluation confirmed that the constructs demonstrated acceptable reliability and validity. The formative indicators were statistically significant and did not present problematic multicollinearity. The reflective indicators demonstrated acceptable internal consistency reliability, while the AVE values supported convergent validity. Discriminant validity was confirmed through the Fornell-Larcker criterion and HTMT ratio. The measurement model was therefore considered suitable for structural model evaluation using PLS-SEM.

6.10 STRUCTURAL MODEL EVALUATION

Following the validation of the measurement model in Section 6.9, the structural model was evaluated to test the hypothesised relationships between the constructs and to assess the explanatory power of the model. The structural model evaluation included the assessment of path coefficients, t-values, p-values, coefficient of determination (R^2), predictive relevance (Q^2), and variance inflation factors (VIF), in accordance with PLS-SEM guidelines (Hair et al., 2019).

The purpose of the structural model evaluation was to determine whether big data analytics capabilities significantly influenced dynamic capabilities and operational capabilities, and whether these capabilities contributed to competitive advantage. The results also provided insight into the extent to which big data analytics capabilities are translated into organisational outcomes within South African businesses.

6.10.1 Analytic results

PLS-SEM was used to test the structural model. The results confirmed that big data analytics capabilities significantly predicted both dynamic capabilities and operational capabilities. This suggests that organisations with stronger big data analytics capabilities are more likely to develop the ability to sense opportunities, seize them, transform resources, and strengthen operational processes.

Dynamic capabilities demonstrated a significant positive effect on competitive advantage. This finding highlights the importance of organisational adaptability, responsiveness and the ability to translate data-driven insights into strategic action. In

contrast, the relationship between operational capabilities and competitive advantage was weak and statistically insignificant. This suggests that operational capabilities alone may not be sufficient to convert big data analytics investments into sustained competitive advantage without the presence of higher-order dynamic capabilities.

The overall model explained a meaningful proportion of the variance in competitive advantage. This indicates that the hypothesised relationships captured an important part of the factors influencing competitive advantage in South African businesses. The findings also point to the importance of human and intangible capabilities, particularly organisational learning and data interpretation, in enabling organisations to derive value from big data analytics.

6.10.2 Evaluation of the structural model (inner model)

To assess the structural model, the study examined path coefficients, t-values, p-values, R^2 values, Q^2 values and VIF values. VIF values were used to determine whether multicollinearity was present among the predictor constructs. The results confirmed that the VIF values were within acceptable limits, indicating that multicollinearity was not a concern.

Table 35: : Structural model evaluation
Source: Author

Path	Weight	T Value	P Value	Coefficient of determination (R^2)	Predictive relevance (Q^2)	Variance inflation factors (VIF)	Decision
Big data analytics capabilities→ Dynamic capabilities	0.682	8.415	$p < 0.05$	0.345	0.256	1.000	Significant
Big data analytics capabilities→	0.582	4.695	$p < 0.05$	0.284	0.148	1.000	Significant

operational capabilities							
Dynamic capabilities → Competitive advantage	0.510	7.365	p < 0.05	0.465	0.247	2.454	Significant
Operational capabilities → Competitive advantage	0.098	0.689	n. s.			1.846	Not significant

The results in Table 35 show that big data analytics capabilities had a strong positive effect on dynamic capabilities and operational capabilities. Dynamic capabilities also had a significant positive effect on competitive advantage. However, operational capabilities did not have a statistically significant effect on competitive advantage. This finding suggests that operational improvements may support internal efficiency, but they do not automatically translate into competitive advantage unless they are linked to broader dynamic capabilities.

6.10.2.1 Path coefficients and hypothesis testing

The path coefficients were assessed using bootstrapping procedures with 5,000 resamples, as recommended for PLS-SEM analysis (Hair et al., 2019). Bootstrapping was used because it does not require the assumption of normal data distribution and is therefore suitable for testing the significance of path relationships in PLS-SEM.

The results indicated that three of the four structural paths were statistically significant. Big data analytics capabilities significantly influenced dynamic capabilities and operational capabilities. Dynamic capabilities significantly influenced competitive advantage. However, operational capabilities did not significantly influence competitive advantage. This result indicates that dynamic capabilities played a

stronger role than operational capabilities in converting big data analytics capabilities into competitive advantage.

To test mediation, the study also employed the bootstrapping method using 5,000 resamples in SmartPLS v4, based on the original sample of 110 respondents. This approach follows the logic of non-parametric bootstrapping as outlined by Preacher and Hayes (2008) and was used to estimate indirect effects and assess the significance of mediation relationships.

6.10.2.2 Coefficient of determination (R^2)

The coefficient of determination (R^2) was examined to assess the explanatory power of the model. The R^2 value indicates the proportion of variance in an endogenous construct that is explained by its predictor constructs.

The results showed that big data analytics capabilities explained variance in both dynamic capabilities and operational capabilities. The model also explained a substantial proportion of variance in competitive advantage. This indicates that the structural model had acceptable explanatory power and was suitable for interpreting the relationships between the constructs.

Table 36: Coefficient of determination

Source: Author

Endogenous construct	R^2 value	Interpretation
Dynamic Capabilities	0.345	Moderate explanatory power
Operational Capabilities	0.284	Moderate explanatory power
Competitive Advantage	0.465	Moderate to substantial explanatory power

The R^2 values show that the model explained 34.5% of the variance in dynamic capabilities, 28.4% of the variance in operational capabilities, and 46.5% of the variance in competitive advantage. These results suggest that the model has meaningful explanatory strength within the context of this study.

6.10.2.3 Predictive relevance (Q²)

Predictive relevance was assessed using the Q² statistic obtained through blindfolding procedures. A Q² value greater than zero indicates that the model has predictive relevance for a particular endogenous construct (Hair et al., 2019).

Table 37: Predictive relevance
Source: Author

Endogenous construct	Q ² value	Decision
Dynamic Capabilities	0.256	Predictive relevance confirmed
Operational Capabilities	0.148	Predictive relevance confirmed
Competitive Advantage	0.247	Predictive relevance confirmed

The Q² values for dynamic capabilities, operational capabilities and competitive advantage were all above zero. This confirms that the model had predictive relevance and was able to predict the endogenous constructs to an acceptable degree.

6.10.2.4 Descriptive statistics: Section B–F of the quantitative survey results

Descriptive statistics were also reviewed to provide additional insight into the current state of big data analytics capabilities, related organisational capabilities and competitive advantage among the participating South African businesses. The mean scores and standard deviations are presented in Tables 38 to 43.

Table 38: Big data analytics capabilities — Data and technology resources
Source: Author

Item	Mean (M)	SD
Data Accessibility (D1-D3)	3.78	0.92
Technology Readiness (T1-T3)	3.85	0.88

Table 39: Big data analytics capabilities- Human skills
Source: Author

Item	Mean (M)	SD
Technology Skills (TS1-TS2)	3.66	0.95

Managerial Skills (MS1-MS3)	3.72	0.91

Table 40: Data-driven culture

Source: Author

Item	Mean (M)	SD
Data-Driven Culture (DD1-DD3)	3.82	0.87

Table 41: Dynamic capabilities

Source: Author

Item	Mean (M)	SD
Sensing (S1-S3)	3.79	0.89
Seizing (SZ1-SZ3)	3.75	0.91
Transforming (TR1-TR3)	3.70	0.92

Table 42: Operational capabilities

Source: Author

Item	Mean (M)	SD
Operational Capabilities	3.68	0.88
Marketing Capabilities (MC1-MC4)	3.74	0.85
Technological Capabilities (TC1-TC4)	3.80	0.86

Table 43: Competitive advantage

Source: Author

Item	Mean (M)	SD
Competitive Advantage (CP1-CP4)	3.81	0.84

The descriptive statistics show generally positive perceptions of big data analytics capabilities maturity across the participating organisations. Technology readiness recorded the highest mean score (M = 3.85), followed by data-driven culture (M = 3.82)

and competitive advantage ($M = 3.81$). Human skills and operational capabilities recorded slightly lower mean values, suggesting that skills development and operational implementation remain areas requiring further improvement. These results are consistent with the qualitative findings in Chapter 5, which highlighted talent shortages, data integration challenges and the need to strengthen data-driven organisational culture.

6.10.3 Summary of structural model evaluation

The structural model evaluation demonstrated that big data analytics capabilities had a significant positive effect on both dynamic capabilities and operational capabilities. Dynamic capabilities, in turn, significantly predicted competitive advantage. However, operational capabilities did not have a statistically significant direct effect on competitive advantage.

These findings suggest that big data analytics capabilities contribute to competitive advantage mainly through dynamic capabilities. In other words, the value of big data analytics does not come only from data, technology or operational processes, but from the organisation's ability to sense opportunities, seize them and transform resources in response to changing conditions. The results therefore support the argument that dynamic capabilities are central to converting big data analytics investments into competitive advantage within South African businesses.

6.11. HYPOTHESIS TESTING

After establishing the reliability and validity of the measurement model, the study hypotheses were tested using the structural model results. The hypotheses were developed to examine the relationships between big data analytics capabilities, dynamic capabilities, operational capabilities and competitive advantage. The analysis considered path coefficients, t-values and p-values to determine the strength and statistical significance of each relationship.

According to Hair et al. (2019), path coefficients below 0.10 generally indicate a weak effect, values around 0.30 indicate a moderate effect, and values of 0.50 or above indicate a strong effect. The hypotheses were assessed using bootstrapping in SmartPLS, and the results are presented in Table 44.

6.11.1 Hypothesis 1

Hypothesis 1 stated that big data analytics capabilities have a positive relationship with dynamic capabilities. The results showed a path coefficient of 0.682, a t-value of 8.452 and a p-value of less than 0.001. This indicates a strong and statistically significant relationship. Hypothesis 1 is therefore supported.

This finding suggests that organisations with stronger big data analytics capabilities are better able to develop dynamic capabilities. In practical terms, this means that data, technology, human skills and data-driven culture help organisations sense changes, seize opportunities and transform resources in response to changing business conditions.

6.11.2 Hypothesis 2

Hypothesis 2 proposed that dynamic capabilities have a positive relationship with competitive advantage. The results showed a path coefficient of 0.434, a t-value of 7.369 and a p-value of less than 0.001. This indicates a statistically significant relationship. Hypothesis 2 is therefore supported.

This finding confirms that dynamic capabilities play an important role in converting big data analytics capabilities into competitive advantage. Organisations that can sense market changes, seize opportunities and transform their resources are more likely to achieve stronger competitive outcomes.

6.11.3 Hypothesis 3

Hypothesis 3 stated that big data analytics capabilities have a positive relationship with operational capabilities. The results showed a path coefficient of 0.569, a t-value of 6.964 and a p-value of less than 0.001. This indicates a strong and statistically significant relationship. Hypothesis 3 is therefore supported.

This finding suggests that big data analytics capabilities contribute to the development of operational capabilities. In other words, organisations that have stronger analytics resources are better positioned to strengthen technological and marketing capabilities. This supports the argument that big data analytics capabilities can improve internal business processes and operational decision-making.

6.11.4 Hypothesis 4

Hypothesis 4 proposed that operational capabilities have a positive relationship with competitive advantage. The results showed a path coefficient of 0.064, a t-value of 0.647 and a p-value greater than 0.05. This indicates a weak and statistically insignificant relationship. Hypothesis 4 is therefore not supported.

This finding suggests that operational capabilities did not have a significant direct influence on competitive advantage in this study. While operational capabilities may support efficiency, execution and internal processes, the results indicate that they may not be sufficient on their own to generate competitive advantage. This reinforces the importance of dynamic capabilities as the stronger pathway through which big data analytics capabilities are translated into competitive outcomes.

Table 44: Hypotheses and conclusions

Source: Author

Hypothesis	Independent Variable	Dependent Variable	Weight	T- Value	P	Conclusion
H1	Big data analytics capabilities	Dynamic Capabilities	0.682	8.452	p < 0.001	Supported
H2	Dynamic capabilities	Competitive advantage	0.434	7.369	p < 0.001	Supported
H3	Big data analytics capabilities	Operational capabilities	0.569	6.964	p < 0.001	Supported
H4	Operational capabilities	Competitive Advantage	0.064	0.647	n. s.	Not Supported

6.11.5 Summary of hypothesis testing

The hypothesis testing confirmed three of the four proposed relationships. Big data analytics capabilities had a significant positive relationship with both dynamic capabilities and operational capabilities. Dynamic capabilities also had a significant

positive relationship with competitive advantage. However, operational capabilities did not have a statistically significant direct relationship with competitive advantage.

These findings show that big data analytics capabilities contribute to organisational capability development, but their effect on competitive advantage is mainly realised through dynamic capabilities. The non-significant operational capability path is an important finding because it suggests that operational efficiency alone may not be enough to create sustained competitive advantage. In the South African business context, this may be due to sector differences, resource constraints, skills shortages or uneven levels of digital maturity.

The finding also suggests that the operational capability construct may need further refinement in future research. Alternative dimensions such as process automation, digital integration, real-time decision execution and operational agility may provide a more detailed understanding of how operational capabilities influence competitive outcomes. Overall, the results reinforce the central role of dynamic capabilities in translating big data analytics capabilities into competitive advantage.

6.12 ENVIRONMENTAL FACTORS

Although the study's conceptual model did not specify direct hypotheses for environmental factors, these variables were assessed on an exploratory basis to determine whether they influenced the relationships between organisational capabilities and competitive advantage. The environmental factors considered were environmental hostility, environmental complexity and environmental dynamism.

These factors were examined as possible moderators of the relationship between dynamic capabilities and competitive advantage, as well as the relationship between operational capabilities and competitive advantage. This additional analysis was useful because South African businesses often operate in uncertain, resource-constrained and rapidly changing environments. It was therefore important to consider whether external environmental conditions shaped the extent to which capabilities translated into competitive advantage.

Table 45: Moderating effects of dynamic capabilities on competitive advantage and operational capabilities on competitive advantage

Source: Author

Moderator	Path	Weight	T-Value	P	VIF
Environmental hostility	DC → CP	-0.160	1.654	p < 0.3	2.667
	OC → CP	0.182	0.895	p < 0.4	2.895
Environmental complexity	DC → CP	-0.022	0.154	-	2.145
	OC → CP	0.086	0.689	-	1.856
Environmental dynamism	DC → CP	-0.011	0.035	-	2.996
	OC → CP	-0.265	1.587	p < 0.3	2.365

The results in Table 45 indicate that none of the moderating effects were statistically significant at the conventional 0.05 level.

Environmental hostility showed a weak negative moderating effect on the relationship between dynamic capabilities and competitive advantage, while it showed a weak positive moderating effect on the relationship between operational capabilities and competitive advantage. However, both effects were statistically insignificant and should therefore be interpreted with caution.

Environmental complexity also did not significantly moderate either of the tested relationships. The weak coefficients suggest that complexity did not materially alter the effect of dynamic capabilities or operational capabilities on competitive advantage in this sample.

Environmental dynamism showed a weak negative moderating effect on both tested paths, particularly on the relationship between operational capabilities and competitive advantage. However, this effect was also not statistically significant. This suggests that changing external conditions may place pressure on operational capabilities, but the evidence from this sample is not strong enough to confirm a significant moderating effect.

The exploratory moderation results suggest that environmental factors may have some contextual relevance, but they did not significantly change the main relationships tested in the model. The findings therefore support the conclusion that dynamic capabilities remain the stronger and more direct pathway through which big data analytics capabilities contribute to competitive advantage. At the same time, the weak moderation results indicate that future research could examine environmental factors more closely, particularly across different sectors, organisational sizes and levels of digital maturity.

6.13 SUMMARY OF CHAPTER 6

This chapter presented the quantitative findings of the study. The purpose of the quantitative phase was to test the proposed conceptual model and examine the relationships between big data analytics capabilities, dynamic capabilities, operational capabilities and competitive advantage among South African businesses.

The chapter began by presenting the data screening process. A total of 118 questionnaires were received, of which 110 valid responses were retained for analysis after excluding respondents who were not directly involved in big data analytics initiatives. The data screening process confirmed that the dataset was complete, consistent and suitable for further statistical analysis. No missing data were identified, no serious outlier-related distortion was found, and there was no evidence of disengaged response patterns that would compromise the results.

The chapter then presented the exploratory factor analysis and measurement model evaluation. The results confirmed that the measurement instrument demonstrated acceptable reliability and validity. The formative indicators were statistically significant and did not present serious multicollinearity concerns. The reflective constructs demonstrated acceptable internal consistency reliability, while the AVE values exceeded the recommended threshold of 0.50, thereby supporting convergent validity. Discriminant validity was also confirmed through the Fornell-Larcker criterion and the HTMT ratio. The structural model results showed that big data analytics capabilities had a significant positive relationship with both dynamic capabilities and operational capabilities. This indicates that organisations with stronger data, technology, human and intangible resources are better positioned to develop higher-order capabilities and

strengthen operational processes. However, the findings also showed that dynamic capabilities, rather than operational capabilities, were the stronger pathway to competitive advantage.

The hypothesis testing confirmed three of the four proposed hypotheses. Hypothesis 1 was supported, confirming a significant positive relationship between big data analytics capabilities and dynamic capabilities. Hypothesis 2 was supported, confirming a significant positive relationship between dynamic capabilities and competitive advantage. Hypothesis 3 was supported, confirming a significant positive relationship between big data analytics capabilities and operational capabilities. Hypothesis 4 was not supported, as the relationship between operational capabilities and competitive advantage was weak and statistically insignificant.

The non-significant operational capability path is an important finding. It suggests that operational capabilities may support efficiency and execution, but they may not be sufficient on their own to produce competitive advantage. In the South African business context, this may be due to sectoral differences, skills shortages, infrastructure limitations, uneven digital maturity and the way operational capabilities were measured in the study. This finding points to the need for future research to examine operational capabilities in more detail, particularly through dimensions such as process automation, digital integration, operational agility and real-time decision execution.

The exploratory analysis of environmental factors showed that environmental hostility, environmental complexity and environmental dynamism did not significantly moderate the relationships between capabilities and competitive advantage. Although some weak effects were observed, these were not statistically significant and should be interpreted cautiously. The findings therefore reinforce the central role of dynamic capabilities in converting big data analytics capabilities into competitive advantage.

Chapter 6 provides empirical support for the argument that big data analytics capabilities contribute to competitive advantage mainly through dynamic capabilities. The results show that the value of big data analytics does not lie only in data, technology or operational systems, but in the organisation's ability to interpret data,

learn from insights, sense opportunities, seize them and transform resources in response to changing business conditions. These findings provide the statistical foundation for the discussion, conclusions and recommendations presented in Chapter 7.

CHAPTER 7: INTEGRATION OF THE FINDINGS AND PROPOSED CONCEPTUAL FRAMEWORK FOR THE IMPLEMENTATION OF BIG DATA ANALYTICS IN SOUTH AFRICA

7.1 CHAPTER OVERVIEW AND INTRODUCTION

This study set out to investigate how big data analytics capabilities influence competitive advantage in South African businesses, particularly under contextual constraints such as limited infrastructure, skills shortages, and regulatory complexity. Grounded in the resource-based and dynamic capabilities theories, the study adapted and tested a model originally developed by Framnes and Danielsen (2017), contextualising it for the South African business landscape.

The research followed an exploratory sequential mixed-methods design. In the first phase, qualitative interviews with ten senior business leaders across a range of sectors revealed six recurring themes: strategic alignment challenges, skills shortages, infrastructure and data quality constraints, value creation processes, organisational readiness, and regulatory oversight. These findings informed the design of the structured survey used in the second, quantitative phase.

The quantitative phase tested the conceptual model empirically using PLS-SEM on responses from 110 business leaders. Results confirmed that dynamic capabilities, sensing, seizing, and transforming, powerfully mediate the relationship between big data analytics capabilities and competitive advantage. By contrast, operational capabilities such as marketing and technological capabilities, although hypothesised to exercise a role, did not show a significant direct effect on competitive advantage.

These findings led to the refinement of the conceptual model and the development of a strategic framework tailored to the South African context. The study recommends that companies prioritise building dynamic capabilities alongside investments in data infrastructure, human skills, and intangible resources to strengthen big data analytics maturity. Policymakers and business leaders must also address barriers such as digital inequality and skills gaps to ensure that analytics initiatives are effectively contextualised and strategically aligned with business transformation goals. This

research contributes a tested and contextually adapted framework for understanding how big data analytics capabilities lead to competitive advantage. It provides actionable recommendations for business leaders, policymakers, and scholars in developing economy contexts.

The structure of this chapter is illustrated in Figure 52, which provides a roadmap for how the findings are integrated and how the conceptual framework is refined. This structure ensures that the reader can follow the transition from contextualisation, through the refined conceptual framework, to practice-oriented guidelines, application, and final synthesis.

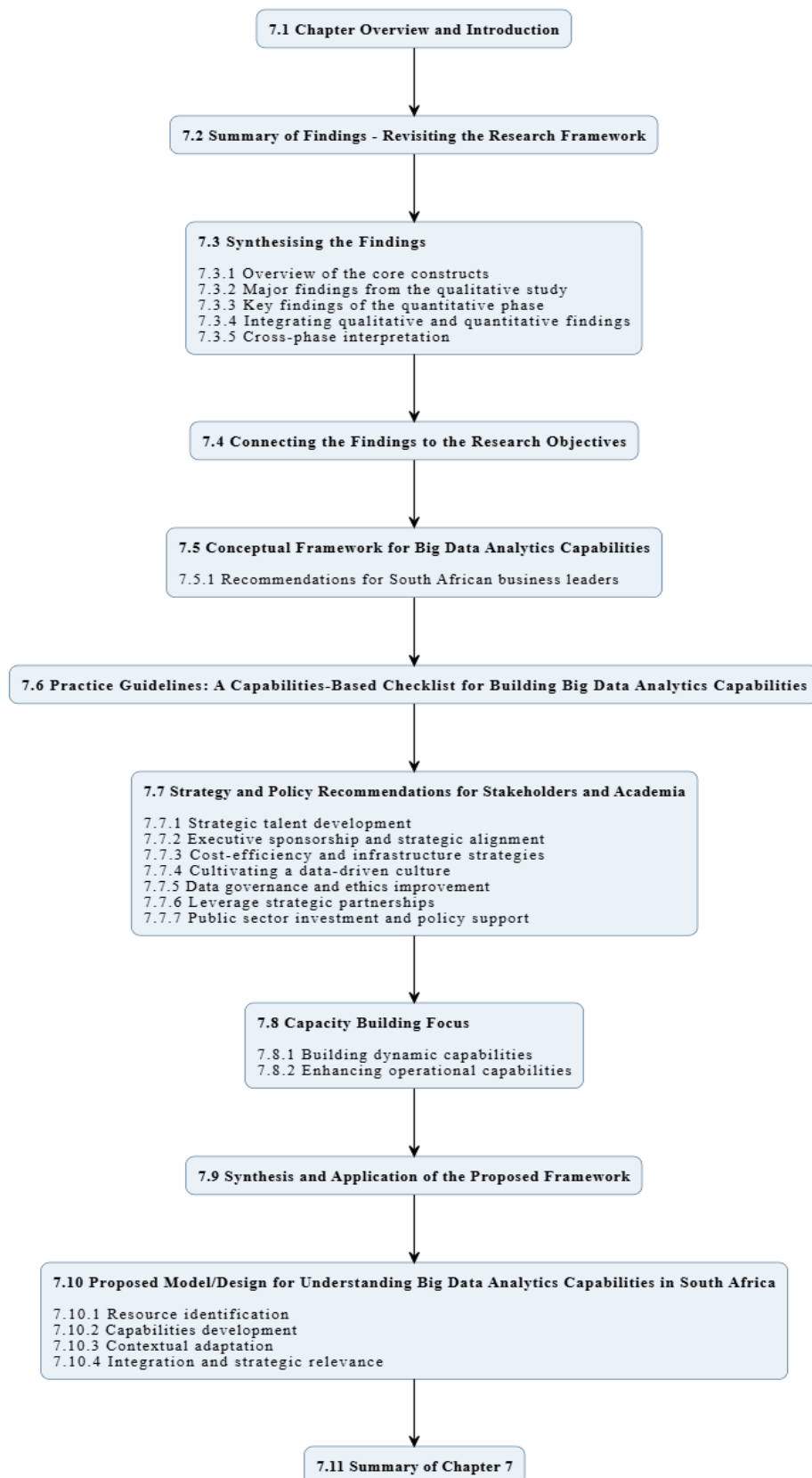


Figure 52: Overview of Chapter 7- Integration of findings and conceptual framework

Source: Author

7.2 SUMMARY OF FINDINGS - REVISITING THE RESEARCH FRAMEWORK

This research was anchored in the resource-based and dynamic capabilities theories, which informed both the data collection and interpretation. The findings from the qualitative phase were used to refine the questionnaire used in the structured quantitative survey that was distributed to 110 business leaders for completion. The collected data were analysed using PLS-SEM, and the results revealed the following hypotheses:

H1: Big data analytics capabilities positively influence dynamic capabilities (sense, seize, transform).

H2: Dynamic capabilities have a positive effect on competitive advantage.

H3: Big data analytics capabilities have a positive impact on operational capabilities, such as marketing and technology capabilities.

H4: Operational capabilities positively influence competitive advantage.

The analysis confirmed support for H1, H2, and H3, but H4 was not supported by the data.

Although big data analytics capabilities enhance operational capabilities, these operational capabilities did not have a significant direct effect on competitive advantage in this context. The descriptive analysis indicated though that many businesses are still in the infant stages of big data analytics capabilities adoption. These businesses often struggle to align technology investments with strategic goals and to foster a data-driven culture.

The quantitative findings emphasised that, while big data analytics capabilities are foundational, they must be embedded within agile and responsive business structures to produce competitive advantage. Businesses that were most able to anticipate changes in the market, react to new opportunities, and adapt internal operations developed better capabilities and acquired better opportunities to transform data into competitive advantage.

In summary, the research achieved its objective of exploring the resource and capabilities paths through which big data analytics capabilities achieve competitive advantage. The derived empirical model offers tangible guidance for business leaders who are seeking to build data-driven strategies in resource-constrained and

dynamically changing environments like South Africa. These findings lay the foundation for the strategic recommendations presented in the next section, offering actionable insights for business leaders and policymakers. These results address the original research objectives by validating the role of dynamic capabilities as mediators while also clarifying the limited direct influence of operational capabilities.

7.3 SYNTHESISING THE FINDINGS

This section synthesises the results of the qualitative and quantitative stages of the research. The discussion revolves around the key constructs of the conceptual framework, i.e., how big data analytics abilities generate competitiveness via the mediating function of dynamic and operational capabilities. The findings are also related to the original research questions and objectives outlined in Chapter one of the study.

This triangulated interpretation adds credibility to the findings and strengthens them in the practical and theoretical context of South African businesses. This section further reflects on how the qualitative insights shaped the hypotheses, how the quantitative results validated or refined the conceptual model, and how these contribute to understanding the role of big data analytics capabilities in driving competitive advantage in the South African context.

7.3.1 Overview of the core constructs

The research drew upon the resource-based and the dynamic capabilities theories to explore how businesses in South Africa develop and apply big data analytics capabilities to achieve competitive advantage. Big data analytics capabilities were explored using tangible resources, such as data, and technology; human skills, including both technical and managerial skills; and intangible resources, like organisational learning and a data-driven culture (Mikalef et al., 2023).

These resources were hypothesised to support both dynamic capabilities (the business's ability to sense, seize, and transform) and operational capabilities (notably in marketing and technology), with the goal of influencing competitive advantage. These concepts were operationalised through first- and second-order constructs in the survey instrument and formed the structural basis of the model tested in Chapter 6.

7.3.2 Major findings from the qualitative study

The interviews with senior business leaders yielded six major themes, as discussed in Chapter 5. Strategic alignment issues revealed a gap between analytics projects and overall business strategy, which mostly occurred due to a lack of awareness at the executive level. Talent and skills shortages further emerged as a major challenge, with many businesses lacking experienced data professionals. Infrastructure and data quality issues were also prominent, as inadequate data quality and disparate systems hindered the effective utilisation of analytics. In terms of value and innovation, businesses recognised the promise of competitive advantage through analytics but struggled to convert that promise into tangible results. Organisational and cultural readiness remained a core challenge, with many businesses finding it difficult to mainstream analytics into routine decision-making. Finally, compliance and market pressure added both urgency and complexity to analytics adoption, as changing regulatory requirements and fluctuating market conditions forced businesses to adapt.

These themes served as guiding principles for the operationalisation of variables in the quantitative instrument and ensured that the structural model tested in Chapter 6 remained grounded in the practical challenges faced by South African businesses. Specifically, strategic alignment and business readiness directly informed the conceptualisation of dynamic capabilities, while themes related to skills shortages and infrastructure influenced the tangible and human skills indicators of big data analytics capabilities.

7.3.3 Key findings of the quantitative phase

Chapter 6 presented the quantitative findings derived from 110 survey responses. Using PLS-SEM, the study confirmed the following hypotheses:

H1, that big data analytics capabilities positively influence dynamic capabilities.

H2, that dynamic capabilities positively affect competitive advantage.

and H3, that big data analytics capabilities positively influence operational capabilities.

However, H4, which proposed that operational capabilities positively impact competitive advantage, was not supported.

These results confirmed that dynamic capabilities play a key mediating role, highlighting their pivotal importance in transforming data potential into realised

advantage outcomes. This finding aligns with the theoretical expectations outlined in Chapter 2 and the qualitative themes identified in Chapter 5. Businesses that demonstrated the ability to speedily reconfigure resources were more likely to achieve favourable competitive advantage outcomes from their analytics investments. Although big data analytics capabilities positively influenced operational capabilities, the latter did not directly contribute to competitive advantage. This suggests that within South African businesses, operational capabilities alone may not be sufficient to achieve competitive advantage without the agility and adaptability provided by dynamic capabilities. These results further contributed to the refinement of the conceptual model, leading to an adjusted framework presented in Chapter 6, which more accurately reflects the relationships between big data analytics capabilities, dynamic capabilities, and competitive advantage.

7.3.4 Integrating Qualitative and Quantitative Findings

The findings highlight that, while many South African businesses have begun exploiting big data analytics capabilities, these investments often lack strategic clarity and are underpinned by weak business cultures and persistent knowledge gaps. As a result, big data analytics capabilities on its own may not deliver meaningful outcomes unless embedded within adaptive, learning-driven, and responsive business paradigms.

The key insight from this integration is that big data analytics capabilities must be tightly linked to dynamic capabilities to generate competitive outcomes. Businesses that can rapidly sense opportunities and threats, recombine internal resources, and adapt to changing environments are more likely to convert data into sustained strategic advantage. This finding bridges the theoretical foundations of the resource-based theory and the dynamic capabilities theory, demonstrating that big data analytics capabilities require more than infrastructure and technical skills. They must be aligned with strategic decision-making processes to produce value in dynamic, resource-constrained environments such as South Africa.

One of the most important insights to emerge from this integration is that big data analytics capabilities can be closely coupled with dynamic capabilities to sustain competitive advantage. Businesses that demonstrate the ability to sense

opportunities, seize them through strategic decision-making, and transform internal processes to align with changing market conditions are better positioned to convert data into value. This finding corroborates the studies of Mikalef and Pateli (2017) and Gupta and George (2016), who identified analytics technologies, together with organisational agility and managerial capabilities, as crucial enablers of competitive advantage benefits.

By contrast, organisations that treat big data analytics capabilities primarily as a technical or operational resource often fail to achieve the expected outcomes. The results therefore strengthen the argument advanced by Teece (2007) that sustainable advantage arises not merely from possessing valuable resources, but from the business's capacity to renew, integrate, and reconfigure them in response to environmental turbulence. This also aligns with the South African findings of Calitz, Poisat, and Cullen (2017) and Maharaj and Pillay (2023), that the strategic integration of analytics into decision-making remains a critical gap in local enterprises. In comparing these results with existing literature, it becomes evident that while global studies frequently emphasise the transformative power of analytics when coupled with managerial foresight, the South African context introduces additional barriers, most notably structural inefficiencies, limited leadership awareness, and cultural resistance to data-driven decision-making. These contextual constraints may explain why BDAC investments often fail to translate into measurable competitive performance.

A reasonable speculation for this outcome is that many South African businesses remain in the early or transitional stages of analytics maturity. Big data analytics capabilities initiatives tend to emerge from isolated IT-led projects rather than integrated enterprise strategies, leading to fragmented data practices and limited organisational learning. Furthermore, ongoing skill shortages and uneven digital infrastructure intensify the difficulty of embedding analytics into everyday business processes. Consequently, while businesses may invest in technology and data infrastructure, they often lack the managerial and cultural alignment required to derive sustained value.

Therefore, big data analytics capabilities must be strategically aligned with business agility, leadership commitment, and innovation-driven cultures to produce tangible

results. This integration is particularly valuable in the South African context, where realistic evidence on BDAC remains scarce and where external constraints such as regulatory complexity and resource limitations further reinforce the need for adaptive, capability-driven business models.

7.3.5 Cross-Phase Interpretation

The combination of insights from both the qualitative and quantitative phases leads to three core conclusions that clarify how big data analytics capabilities add to competitive advantage in South African businesses.

7.3.5.1 Strategic Agility Is Key

Under conditions of uncertainty and rapid change, dynamic capabilities, such as the ability to shift strategy and reconfigure internal resources are more critical than static operational routines. This finding aligns with Teece (2007) and Eisenhardt and Martin (2017), who argue that competitive advantage in volatile contexts depends on organisational agility rather than the mere possession of static assets. Businesses in the study that displayed strategic responsiveness and cross-functional management translated big data analytics capabilities into more sustainable advantage outcomes.

7.3.5.2 Responsive Businesses Perform Better

Businesses that demonstrated a strong ability to anticipate change, act decisively, and adapt internal resources were significantly more likely to achieve positive competitive advantage outcomes from their big data analytics capabilities investments. This result resonates with empirical evidence from Mikalef et al. (2020), who found that responsiveness and integration across business units strengthens big data analytics capabilities and competitive advantage link. In the South African context, responsiveness may also compensate for environmental uncertainty and regulatory complexity by enabling faster, evidence-based decision-making.

7.3.5.3 Operational Capabilities Alone Are Insufficient

While operational capabilities (e.g., marketing and technology functions) are positively influenced by big data analytics capabilities, they did not show a direct effect on competitive advantage. This finding corroborates Teece's (2007) view that ordinary capabilities (those that maintain day-to-day operations) are necessary but not

sufficient for achieving superior advantage. In developed economies, operational excellence can often generate advantage due to established infrastructures and mature markets. However, in South Africa's resource-constrained environment, operational improvements alone cannot offset systemic challenges such as unreliable infrastructure, fragmented data systems, and limited analytical talent (Maharaj and Pillay, 2023; Van Zyl, 2022). Here, advantage depends on the business's ability to continuously adapt, reconfigure, and learn core attributes of dynamic capabilities.

Thus, while big data analytics capabilities strengthen operational processes, it is only through their integration with strategic agility, innovation, and leadership-driven transformation that they yield meaningful competitive outcomes. This interpretation advances prior literature by empirically illustrating the mediating role of dynamic capabilities between analytics resources and firm performance in an emerging-market context, a contribution seldom demonstrated in previous studies (see Akter et al., 2022). This suggests that in South African businesses, operational capabilities on their own are not enough; businesses must also strengthen their strategic agility and flexibility.

Taken together, these cross-phase insights validate the exploratory model introduced in Chapter 3 and support the revised conceptual framework presented in Chapter 6. They reinforce the argument that dynamic capabilities are a crucial mediator for translating BDAC into competitive advantage. This integration strengthens both the theoretical grounding of the study and its contextual relevance, providing a detailed understanding of how South African businesses can harness analytics for sustainable competitive advantage.

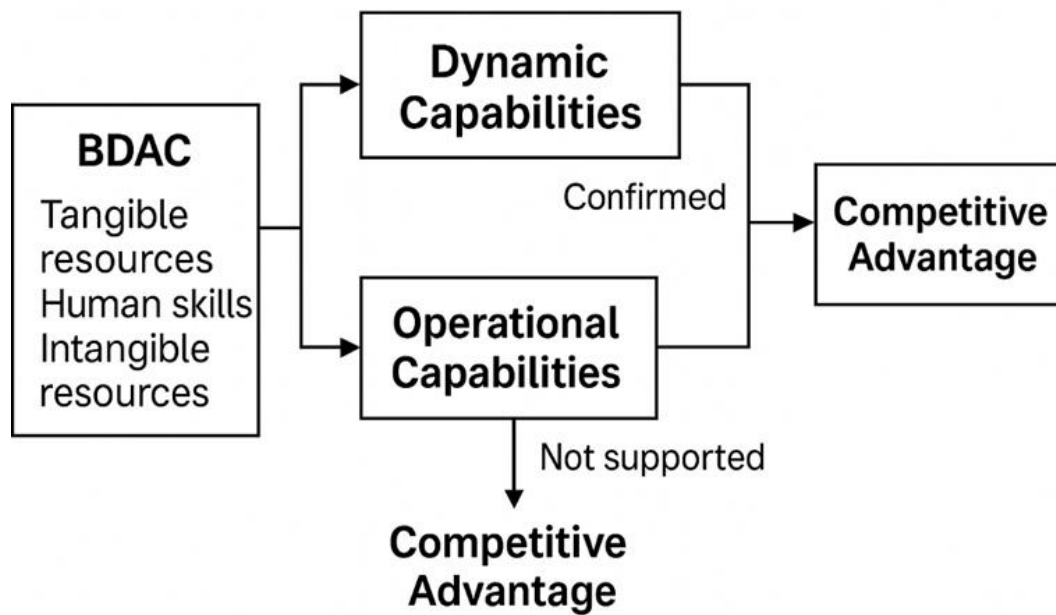


Figure 53: Cross-phase insights linking big data analytics capabilities, dynamic capabilities, and competitive advantage.

Source: Author

Having integrated the qualitative and quantitative findings, the next step is to consider the contributions this study makes to theory, methodology, practice, and context, thereby positioning its value within both scholarly and business domains.

The findings indicate that most South African businesses have embarked on the journey of investing in big data analytics capabilities, but lack strategic clarity, are underpinned by weak business cultures, and persistent knowledge gaps. In such a scenario, big data analytics capabilities itself may not be able to deliver meaningful results unless embedded within adaptive, learning-driven, and responsive business paradigms.

7.4 CONNECTING THE FINDINGS TO THE RESEARCH OBJECTIVES

This section revisits the research objectives set out in Chapter 1 and demonstrates how each was addressed through the integration of qualitative and quantitative findings presented in Chapters 5 and 6. The purpose is to provide a clear link between the study's aims, the analytical process, and the outcomes, ensuring that the research

questions and hypotheses have been comprehensively answered. The Table 46 below summarises the alignment between each objective and the corresponding findings.

Table 46: Alignment of Research Objectives with Findings

Source: Author

Objective No.	Research objectives	Summary of Findings
1	To identify and validate the key dimensions of big data analytics capabilities, tangible resources, human skills, and intangible resources in the South African business context.	Qualitative interviews and exploratory factor analysis (EFA) confirmed three big data analytics capabilities dimensions: tangible resources (infrastructure, technology tools), human skills (technical and managerial), and intangible resources (data-driven culture, organisational learning).
2	To assess the relationship between big data analytics capabilities and dynamic capabilities.	Significant positive relationship confirmed through PLS-SEM; qualitative evidence supports big data analytics capabilities as a driver of agility, adaptability, and innovation readiness.
3	To assess the relationship between big data analytics capabilities and operational capabilities (marketing and technological capabilities).	Big data analytics capabilities significantly influence operational capabilities, but improvements tend to be project-specific rather than strategic.
4	To evaluate the influence of dynamic capabilities on competitive advantage.	Dynamic capabilities have a significant positive effect on competitive advantage, confirming their role as a key mechanism through which big data analytics capabilities translate into strategic outcomes.

5	To evaluate the influence of operational capabilities on competitive advantage.	Operational capabilities did not have a statistically significant effect on competitive advantage, suggesting that in the South African context, they are insufficient to generate sustained advantage without dynamic capabilities.
6	To develop a contextually relevant framework that integrates big data analytics capabilities with broader organisational strategy for sustainable competitive advantage.	The framework integrates quantitative results with contextual factors such as skills shortages, siloed infrastructure, and leadership misalignment.

The results confirm that all six objectives were fully addressed. As noted, the relationships tested in the hypotheses were supported for dynamic capabilities (H1 and H2) but not for operational capabilities (H4), highlighting their differing roles in achieving competitive advantage. The findings highlight that, while big data analytics capabilities are essential, their impact on competitive advantage is realised primarily through dynamic capabilities. The developed framework reflects these insights and offers a practical model for South African business leaders seeking to align big data initiatives with strategic agility. By systematically addressing all six objectives, the study not only validates the proposed framework but also provides the foundation for the theoretical, methodological, practical, and contextual contributions that follow.

7.5 CONCEPTUAL FRAMEWORK FOR BIG DATA ANALYTICS CAPABILITIES

The initial conceptual framework reflected in Chapter 1 proposed that big data analytics capabilities influence competitive advantage through operational and dynamic capabilities. Empirical testing refined this framework, confirming the strong mediating role of dynamic capabilities in shaping competitive outcomes, thus supporting H1 and H2. The results highlight that sensing, seizing, and transforming are necessary dynamic processes for converting big data analytics capabilities into valuable strategic advantage.

While operational capabilities (technology and marketing) were hypothesised to mediate the relationship between big data analytics capabilities and competitive advantage, the data revealed a statistically non-significant effect. This indicates that operational processes, while necessary for functional efficiency, do not independently create competitive outcomes. This finding aligns with hypothesis three but does not support hypothesis four. In addition, there is no evidence that supported a direct pathway between big data analytics capabilities and competitive advantage, reinforcing the central role of dynamic capabilities as the indirect mechanism.

The possible moderating role of environmental and contextual variables should also be considered. Qualitative data identified leadership commitment, talent deficit, regulatory demands, and infrastructure issues, and future models should include such variables to capture how external factors condition the success of big data analytics implementation.

7.5.1 Recommendations for South African business leaders

Building on the conceptual framework these results are consistent with international evidence that data capabilities must be strategically embedded within organisations to yield competitive advantage. Studies conducted in other emerging economies, such as India and China confirm that agility, strategic alignment, integration, and effective access to data are the true value drivers of competitive performance (Gupta and George, 2016; Xie, Wu, Xiao and Hu, 2016). The findings from this South African study reinforce this view.

Despite challenges such as economic volatility and infrastructure shortages, businesses that can respond in real-time to market signals, adapt creatively, and integrate analytics into decision-making processes achieve stronger and more sustainable outcomes. The solution lies in effective leadership. Managers must actively promote a culture of evidence-based decision-making, connect analytics initiatives to strategic planning, and facilitate coordination across departments to ensure cohesive implementation. Leadership must also prioritise the development of a data-driven culture across all functional and hierarchical levels, promote cross-functional teamwork to prevent silo practices, and invest in scalable infrastructure such

as cloud-based technologies to reduce costs and enhance accessibility. For resource-constrained organisations, particularly small and medium-sized enterprises, establishing shared analytic services or forming strategic alliances can be a practical means of expanding access to data-driven capabilities.

Furthermore, organisations must maintain flexibility by responding swiftly to market signals and fostering adaptive approaches to change. While big data analytics capabilities possess immense potential, competitive advantage is only achieved when these abilities are infused into responsive, flexible, and strategically aligned organisational processes. The conceptual model depicted in Figure 53 illustrates that dynamic capabilities serve as the critical link between investment in analytics and the realisation of competitive advantage, particularly within resource-constrained environments such as South Africa.

Having outlined the strategic recommendations for South African business leaders, it is necessary to translate these insights into a structured and actionable framework. The empirical findings, supported by the conceptual model in Figure 53, emphasise that competitive advantage is realised when tangible, human, and intangible resources are supported by dynamic capabilities. To guide organisations in operationalising these insights, the following section presents a capabilities-based checklist that transforms the study's theoretical and empirical contributions into practical tools for implementation. This checklist serves as a roadmap for business leaders seeking to assess, prioritise, and strengthen their big data analytics capabilities in alignment with their strategic objectives.

7.6 PRACTICE GUIDELINES: A CAPABILITIES-BASED CHECKLIST FOR BUILDING BIG DATA ANALYTICS CAPABILITIES

Drawing both on the thematic findings (Chapter 5) and the empirically tested model (Chapter 6), this section provides a detailed list of actionable advice for South African businesses that are willing to develop and utilise big data analytics capabilities to achieve competitive advantage. While Sections 7.5 and 7.6 provide detailed strategic and empirical recommendations, this checklist translates the study's findings into practical steps tailored for real-world application by practitioners.

The guidelines presented here are particularly relevant for businesses at various levels of big data analytics capabilities maturity, thus offering a structured approach to strengthening the foundational pillars of tangible resources, human skills, and intangible resources, as well as the dynamic capabilities needed to respond to a rapidly changing business environment. The framework guides decision-makers, analytics leaders, and digital transformation teams in bench marking progress and aligning big data analytics capabilities development efforts with the broader business strategy. In doing so, it provides both a diagnostic tool and an implementation roadmap.

Drawing also on my professional experience in analytics and advisory roles, this checklist translates academic findings into pragmatic steps that decision-makers in South African organisations can implement immediately. Because it is derived directly from the qualitative themes in Chapter 5 and the empirically validated model in Chapter 6, the checklist is both evidence-based and contextually relevant.

Table 47: Checklist for developing big data analytics capabilities for competitive advantage in South African businesses.

Source: Author

Capability pillar	Recommended guideline
Tangible resource investments	Invest in cost-saving and scalable infrastructures with respect to business maturity
	Integrate data in legacy systems initially before investing in high-end technology
	Obtain internal funding champions to execute big data analytics capabilities roadmap
	Adapt infrastructure decisions to local challenges such as limited bandwidth and high data costs in South Africa.
Human resource development	Build middle-level managers' capabilities in bridging technical and strategic spaces

	Offer cross-functional training in data literacy and analytics use
	Embed analytics thinking into core business activities, not IT processes
	Encourage partnerships with local universities to strengthen analytics talent pipelines
Intangible resource maturity	Establish a culture of experimentation, data-sharing, and ongoing learning
	Empower leadership to be data-driven decision-making role models
	Map big data analytics capabilities strategy to change management processes to reduce cultural resistance
	Recognise and reward employees who champion data driven innovation
Dynamic capabilities focus	Train teams to sense trends ("sensing") and respond ("seizing") rapidly
	Develop feedback loops for learning and change based on data outcomes
	Formulate agile architectures to facilitate inter-departmental response to insights
	Pilot small scale analytics projects before scaling to the enterprise level.
Governance and strategic fit	Institutionalise big data analytics capabilities approach with business goals
	Monitor analytics value contribution through operational and strategic key advantage indicators (KPIs), such as revenue uplift, customer retention, or process efficiency.
	Obtain executive sponsorships of analytics capabilities development
	Ensure compliance with South African data protection regulations (e.g. POPIA) while leveraging analytics for growth

The above big data analytics capabilities checklist supports the strategic ambition to achieve competitive advantage in South African businesses by ensuring alignment across all capabilities and business functions.

7.7 STRATEGY AND POLICY RECOMMENDATIONS FOR STAKEHOLDERS AND ACADEMIA

Following the key gaps and findings in this research, the following recommendations are proposed as useful guidelines for South African businesses, policymakers, and other stakeholders seeking to maximise value from big data analytics capabilities. These suggestions respond to the specific socioeconomic, infrastructural, and cultural issues in the South African context and are informed empirically by findings from the study's mixed methods. They align with recent scholarly work highlighting the importance of strategically embedding big data analytics capabilities in South African firms (Subramoney and Dagada, 2025).

7.7.1 Strategic talent development

As 43% of the survey respondents mentioned lack of skills as a key deterrent to the success of big data analytics capabilities implementation, businesses need to invest in ongoing education, training, and analytics cross-functional skill set development. They are urged to develop in-house training programs, sponsor analytics certifications, and collaborate with analytics bootcamps and academic institutions to develop a data-literate workforce.

7.7.2 Executive sponsorship and strategic alignment

Survey research showed that businesses fail to connect big data implementation with strategic business goals, and many big data projects fail (Li, Shang and Slaughter, 2010). Consequently, executive and business strategies must actively drive alignment of analytics initiatives with core operations. Integrating big data analytics capabilities into the underlying aspects of the business such as supply chain forecasting and customer segmentation will propel measurable business outcomes (Hallikas, Immonen, and Brax, 2021). Qualitative results supported leadership engagement as a deciding factor in connecting big data analytics capabilities projects with core strategy (Jebble, Dubey, Childe, Papadopoulos, Roubaud and Prakash, 2018).

7.7.3 Cost-efficiency and infrastructure strategies

Out of the participants, 42% indicated that to satisfy cost requirements, businesses must embrace scalable technologies such as cloud-based platforms (e.g., AWS, Azure, Google Cloud). These platforms provide small and medium enterprises, with the opportunity to host analytics capabilities without significant upfront capital expenditure. Public–private partnerships may also be leveraged to overcome infrastructure limitations.

7.7.4 Cultivating a data-driven culture

Cultivating a data-driven culture requires more than the use of analytic tools, but only 39% of businesses reported offering internal analytics training. Data literacy must therefore be embedded at all levels of the business and incorporated into daily operations. This cultural shift is essential for sustaining long-term big data analytics capabilities effectiveness.

7.7.5 Data governance and ethics improvement

Effective data governance must be able to support data quality, privacy, and compliance, particularly in terms of the Protection of Personal Information Act (POPIA). Ethical operations, such as non-discrimination in algorithms and data openness, should be enhanced to ensure stakeholder trust and secure long-term competitive advantage.

7.7.6 Leverage strategic partnerships

Partnerships with peer businesses, technology suppliers, and universities is critical to fill gaps in resources and skills. Strategic partnerships facilitate access to emerging technologies, foster innovation, and accelerate big data analytics capabilities integration across operational and strategic domains.

7.7.7 Public sector investment and policy support

Public sector investment and policy support are essential for creating an enabling environment in which big data analytics capabilities can thrive. Several areas of intervention are particularly critical, including infrastructure development and targeted financial support.

7.7.7.1 Invest in digital infrastructure

Government must invest in foundational digital infrastructure such as high-speed internet, electricity stability, and local data centres. Improved infrastructure will support equitable access to big data analytics capabilities, particularly for underserved regions.

7.7.7.2 Offer funding and incentives

Specialised tax credits, grants, and innovation funds need to be established to enable adoption of big data analytics capabilities tools by businesses. This would directly benefit small and medium enterprises that do not possess the capital for significant analytics software investment (Omotayo and Omoloso-Dada, 2025).

7.7.7.3 Implement national training programs

Government, academia, and industry must collaborate to develop and execute national data science, analytics, and related field training programs. These programs must address near-term workforce upskilling as well as pipeline creation for future talent.

7.7.7.4 Foster public–private partnerships

Joint models between the private sector and public sector can facilitate shared infrastructure, open innovation platforms, and data platforms. These efforts will lead to quicker uptake and greater economic and societal value.

7.7.7.5 Develop regulatory frameworks for data use

Regulators need to develop effective frameworks that complement and support the use of big data analytics. These frameworks must provide clear guidelines on data privacy, security, and responsible usage to allow businesses to innovate within defined boundaries. By promoting compliance with such guidelines, the frameworks can minimise risks associated with data misuse, maintain stakeholder trust, and create conditions for sustainable innovation and growth.

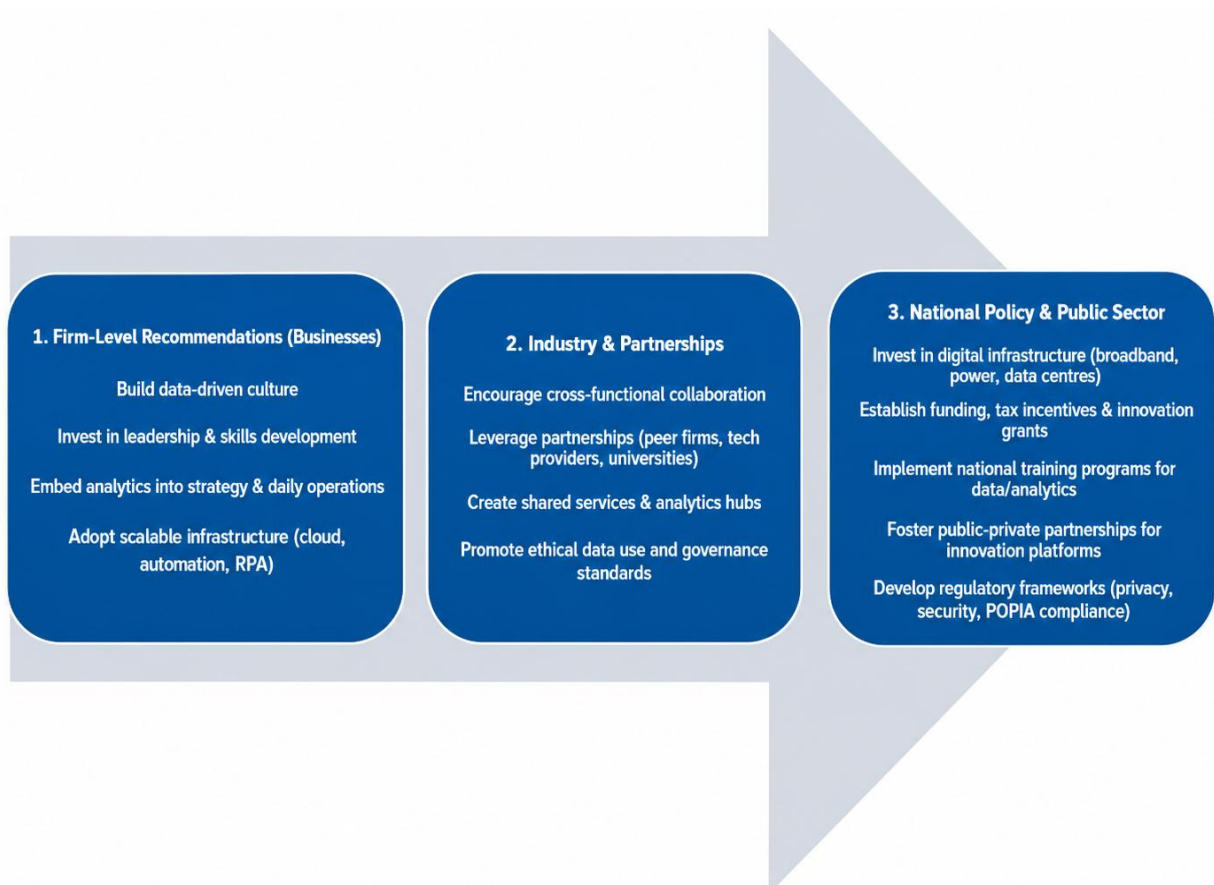


Figure 54: Strategy and policy recommendations

Source: Author

These policy and strategic recommendations provide a multi-stakeholder roadmap for embedding big data analytics into South Africa's socio-economic and business development agenda. This aligns with Dagada's (2025) proposed framework for reindustrialisation, which emphasises prudent policy design, immigration reform for skills attraction, and investments in education to build sustainable digital capabilities.

While the recommendations in Section 7.8 address the systemic and policy-level enablers required to support the growth of big data analytics capabilities in South Africa, it is equally important to recognise that the successful realisation of value depends on how individual organisations strengthen their internal capacities. Thus, the following section (7.8) focuses on capacity building at the organisational level, emphasising the development of both dynamic and operational capabilities. This dual emphasis ensures that businesses can not only access the necessary infrastructure

and policy support but also embed analytics into their own leadership, processes, and culture to achieve sustainable competitive advantage.

7.8 CAPACITY BUILDING FOCUS

The full realisation of value from big data analytics capabilities requires deliberate and sustained investment in capacity building. This applies both to dynamic capabilities, which enable organisations to sense and adapt to change, and to operational capabilities, which drive the execution of strategy at scale. For South African businesses, building such capabilities is especially important, given the skills shortages, infrastructural challenges, and dynamic regulatory environment described earlier in this study.

7.8.1 Building dynamic capabilities

Dynamic capabilities namely sensing, seizing, and transforming are at the heart of competitive advantage in environments characterised by volatility, complexity, and ambiguity (VUCA). To develop these capabilities, South African businesses must prioritise leadership, experimentation, and forward-looking strategic tools.

7.8.1.1 Adaptive leadership development

Organisations must invest in leadership development programmes that cultivate adaptive leaders capable of making agile decisions under uncertainty. Training should emphasise sensing opportunities and risks through data, seizing emerging possibilities through decisive action, and transforming existing business models to remain competitive. Leaders must also be equipped with the ability to redeploy resources quickly to exploit insights derived from analytics.

7.8.1.2 Innovation labs

Establishing innovation labs or “test-and-learn” hubs provides a safe environment for teams to experiment with data-driven solutions, emerging technologies, and novel business models. These labs act as centres of agility, enabling businesses to rapidly prototype, test, and scale analytics-driven initiatives. By embedding innovation practices within organisational culture, firms can continually refine their ability to respond to market shifts.

7.8.1.3 Scenario planning and forecasting training

Scenario planning and predictive analytics are crucial for future-proofing strategy. Organisations should provide structured training that enables decision-makers to anticipate alternative market futures, model potential disruptions, and simulate outcomes of strategic choices. This builds long-term agility and prepares firms to act pre-emptively rather than reactively in fast-changing environments.

7.8.2 Enhancing operational capabilities.

While dynamic capabilities ensure adaptability, operational capabilities provide the foundation for efficient execution. Building these capabilities requires embedding analytics into daily operations and fostering an organisational culture that values data-driven decision-making.

7.8.2.1 Process optimisation training

Employees across functions should be trained to apply analytics in optimising business processes such as inventory management, production scheduling, and customer engagement. This ensures that analytics insights translate directly into cost savings, efficiency gains, and improved customer satisfaction.

7.8.2.2 Automation integration

The integration of artificial intelligence (AI) and robotic process automation (RPA) into business processes is a vital step in operational capacity building. These technologies reduce manual workload, lower costs, and improve productivity. Importantly, automation frees up human resources to focus on strategic initiatives that add greater long-term value to the business.

7.8.2.3 Building data literacy

A core enabler of analytics maturity is data literacy at all levels of the organisation. Firms should implement formal training programmes, workshops, and certification courses that build competencies in reading, interpreting, and acting on data insights. By raising baseline data literacy, businesses can ensure that analytics output informs decision-making not only at the executive level but also among frontline employees.

7.8.2.4 Fostering cross-functional collaboration

Big data analytics capabilities achieve maximum effect when insights permeate the entire organisation. Firms must establish mechanisms for interdepartmental collaboration that connect strategic planning with operational deployment. Cross-functional teams should work together to recognise inefficiencies, align objectives, and ensure that analytics-derived recommendations are translated into cohesive organisational action.

7.9 SYNTHESIS AND APPLICATION OF THE PROPOSED FRAMEWORK

The revised conceptual framework proposed in Chapter 7 integrates the empirical insights from this study, linking big data analytics resources, tangible, human, and intangible, with dynamic and operational capabilities leading to competitive advantage. Businesses are encouraged to use the model as a diagnostic tool to identify gaps in their analytics ecosystem and to apply the pathway logic of resources leading to capabilities, which in turn drive competitive advantage, when structuring big data analytics-related initiatives.

The application ensures that capabilities-building efforts are not isolated but strategically coordinated to promote sustainable advantage. The framework serves as both a strategic blueprint and a practical tool for guiding South African businesses through the maturity curve of big data analytics capabilities. By aligning resource investment with dynamic responsiveness and operational excellence, businesses can unlock measurable value in an increasingly data-driven economy.

Figure 55 illustrates how the proposed framework can be applied in practice, highlighting its dual role as both a strategic guide and an operational tool. It demonstrates how resource investments can generate sustainable competitive advantage in a data-driven environment when aligned with organisational agility and operational excellence.

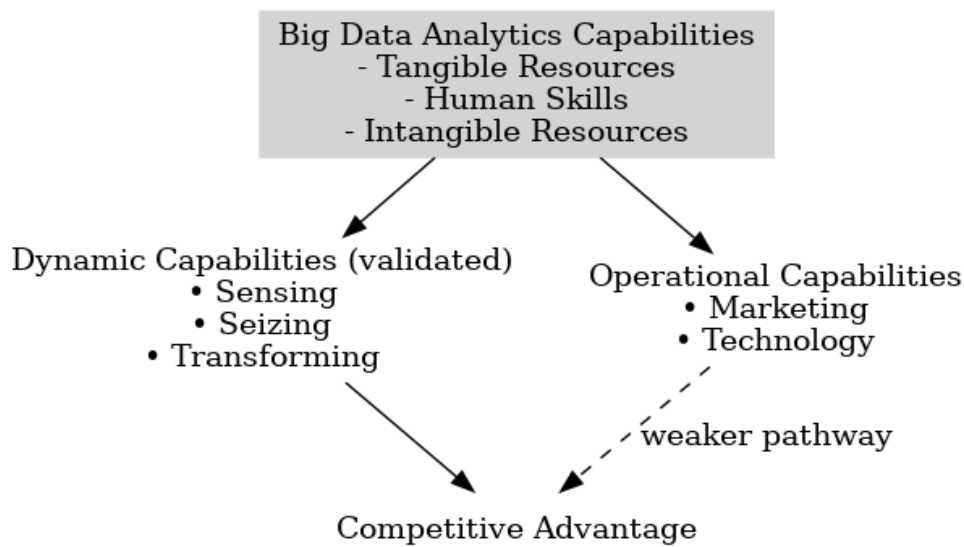


Figure 55: Synthesis and application of the proposed framework

Source: Author

Building on this synthesis, the next section introduces the proposed model for understanding big data analytics capabilities in South Africa. By integrating insights from the resource-based and dynamic capabilities theories, the model provides a conceptual lens through which to analyse how businesses can transform data into a source of long-term competitive advantage, particularly within the country's unique socioeconomic and institutional context.

7.10 PROPOSED MODEL/DESIGN FOR UNDERSTANDING BIG DATA ANALYTICS CAPABILITIES IN SOUTH AFRICA

This study presents an integrative framework that blends the resource-based and the dynamic capabilities theories to demonstrate how big data analytics capabilities can be leveraged to achieve competitive advantage in the South African business context. While the resource-based theory highlights the value of strategic resources, dynamic capabilities theory highlights the importance of organisational agility in volatile environments. This design is particularly relevant to the unique socioeconomic, infrastructural, and cultural challenges that characterise South Africa's business landscape.

7.10.1 Resource identification

At the core of this framework is the identification and leveraging of tangible, intangible, and human resources, consistent with the VRIN (valuable, rare, inimitable, non-substitutable) framework of resource-based theory (Barney, 1991).

a) Tangible resources

These include high-capacity data infrastructure, reliable internet connectivity, and advanced analytics software. They form the backbone for storing and analysing large volumes of data. However, many South African businesses face significant challenges in acquiring such resources due to economic and infrastructural constraints. Cloud-based platforms and public–private partnerships can help narrow this gap by offering scalable and affordable access to advanced tools.

b) Intangible resources

Equally critical are intangible resources such as internal analytics expertise, proprietary algorithms, and robust data governance policies. Businesses must develop in-house competencies in areas such as data science, machine learning, and artificial intelligence, while ensuring compliance with regulatory frameworks such as the Protection of Personal Information Act (POPIA). Partnerships with local universities and international technology vendors can further strengthen these capabilities.

c) Human skills

Analytical and insight-driven decision-making skills are essential to maximising the potential of big data analytics. Companies should invest in training, certification programmes, and capacity development initiatives to build a workforce that can leverage analytics tools for strategic advantage.

7.10.2 Capabilities development

Resources alone do not guarantee advantage; they must be mobilised to sense, seize, and transform opportunities, in line with dynamic capabilities theory.

a) Sensing

Businesses must invest in technologies and data practices that enable the early recognition of shifts in market trends, consumer behaviour, and emerging

technologies. For example, predictive analytics can assist retailers in anticipating demand changes, while real-time analytics can enhance fraud detection in financial services.

b) Seizing

This involves the strategic allocation of resources to act on identified opportunities. Quick, informed decision-making is vital to channel efforts into initiatives aligned with business objectives. For instance, manufacturers can deploy big data analytics to optimise production planning, minimise waste, and improve operational efficiency.

c) Transforming

South African businesses must continuously reconfigure processes, technologies, and skills to adapt to economic volatility, infrastructural challenges, and cultural diversity. Transformation involves both structural and behavioural adjustments that embed the value of data-driven practices across the organisation.

7.10.3 Contextual adaptation

Given South Africa's distinctive environment, businesses must tailor their big data analytics strategies to local realities.

a) Economic volatility

Adopt flexible approaches, leveraging scalable infrastructure and open-source tools to manage fluctuating budgets.

b) Infrastructure constraints

Prioritise cloud-based solutions that can function in low-bandwidth environments and reduce reliance on on-premises infrastructure.

c) Cultural diversity

Leverage analytics to personalise offerings for South Africa's multicultural consumer base, ensuring that services are relevant to diverse cultural and regional needs (Akter et al., 2022).

d) Regulatory environment

Strengthen governance and compliance mechanisms to align with POPIA and related legislation. Transparent, ethical data practices not only ensure compliance but also build trust with consumers and stakeholders.

7.10.4 Integration and strategic relevance

This framework integrates findings from both the qualitative (Chapter 5) and quantitative (Chapter 6) phases of the study. It bridges theoretical perspectives with practical strategies, illustrating how big data analytics capabilities, when aligned with resources, dynamic capabilities, and contextual realities, can deliver sustainable competitive advantage. While grounded in the South African context, the framework is adaptable to other emerging markets facing similar socio-economic and infrastructural challenges (Subramoney and Dagada, 2025).

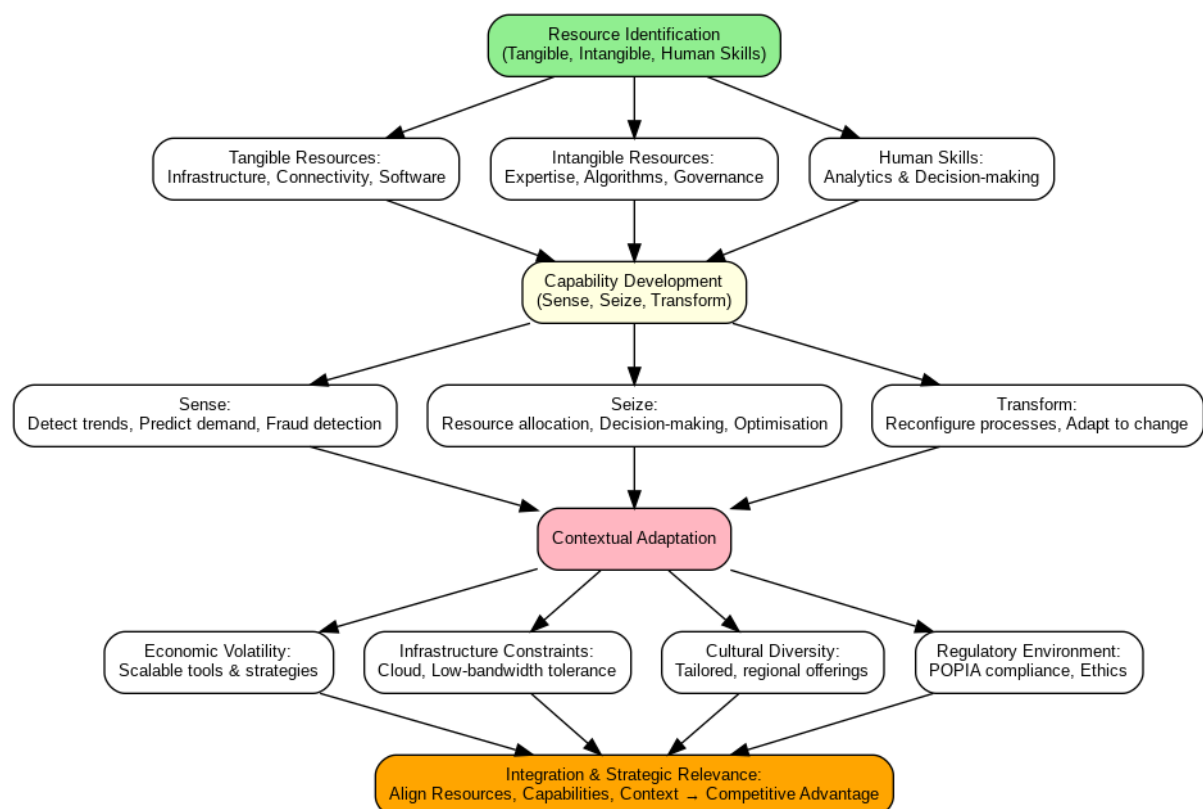


Figure 56: Integrative framework for developing big data analytics capabilities for competitive advantage in South Africa.

Source: Author

This model demonstrates how South African businesses can leverage tangible, intangible, and human resources to build dynamic capabilities (sensing, seizing, transforming) while adapting to contextual realities such as infrastructure gaps, economic volatility, and regulatory requirements to achieve sustained competitive advantage.

7.11 SUMMARY OF CHAPTER 7

This chapter has integrated the qualitative and quantitative findings of the study to provide a deeper understanding of how big data analytics capabilities can be applied to achieve competitive advantage in South African businesses. The findings have confirmed that, while big data analytics capabilities provide the necessary foundation, competitive advantage is realised when these resources are embedded within dynamic capabilities that allow businesses to sense, seize, and transform opportunities. Operational capabilities have been shown to be important for execution but are insufficient on their own to deliver strategic impact.

The conceptual framework developed in this chapter demonstrates that tangible, human, and intangible resources form the base from which big data analytics capabilities are built, and that dynamic capabilities are the decisive mediators in shaping competitive outcomes. This framework has been further translated into practical tools, including a capabilities-based checklist, strategic and policy guidelines for stakeholders, and capacity-building recommendations for organisations.

The revised framework and integrative model presented here deliver a practical roadmap for South African businesses to align data, technology, and human skills with organisational agility and transformation. By embedding big data analytics within adaptive, learning-driven structures, businesses can overcome contextual challenges such as infrastructure gaps, regulatory demands, and skills shortages, and position themselves for sustained competitive advantage in a rapidly evolving digital economy. This synthesis provides the bridge into Chapter 8, which consolidates the study's overall contributions, limitations, and recommendations, while also identifying opportunities for future research and the continued development of big data analytics capabilities in South Africa and other emerging markets.

CHAPTER 8 – OVERVIEW, CONCLUSIONS, LIMITATIONS AND RECOMMENDATIONS

8.1 OVERVIEW OF THE STUDY

This study explored the viability of establishing and applying big data analytics capabilities in a quest to achieve sustained competitive advantage for South African businesses. Built on the resource-based and the dynamic capabilities theories, the research filled a gap in the literature by considering the South African and broader Global South business context, where infrastructure challenges, skill gaps, and regulatory challenges affect the adoption of analytics.

The study utilized an exploratory sequential mixed method. The qualitative phase employed in-depth interviews with senior business executives from various industries. This generated six thematic results on strategic alignment, talent gaps, infrastructural and data quality concerns, cultural readiness, value creation, and regulatory pressures. These themes were then applied to inform the quantitative study, where a survey of 110 industry practitioners was analysed through PLS-SEM.

Findings justified the hypothesis that, while big data analytics capabilities had a positive influence on both dynamic and operational capabilities, dynamic capabilities (sensing, seizing, and transforming) produced a statistically significant effect on competitive advantage. Operational capabilities however were insufficient to affect competitive results which justified an important theoretical distinction and highlighted the importance of agility and adaptability in the setting of resource scarcity.

The research developed and empirically confirmed a multi-level conceptual model that converts tangible, human, and intangible resources into big data analytics capabilities, which subsequently power dynamic and operational capabilities, driving competitive advantage. Building empirical support from theoretical foundations, the research provides both strategic blueprint for firms and policy guidelines for national digital transformation initiatives.

This overview sets the stage for the following sections, which detail the study's theoretical, methodological, empirical, practical, and contextual contributions and limitations, as well as making suggestions for further research (Subramoney and Dagada, 2025).

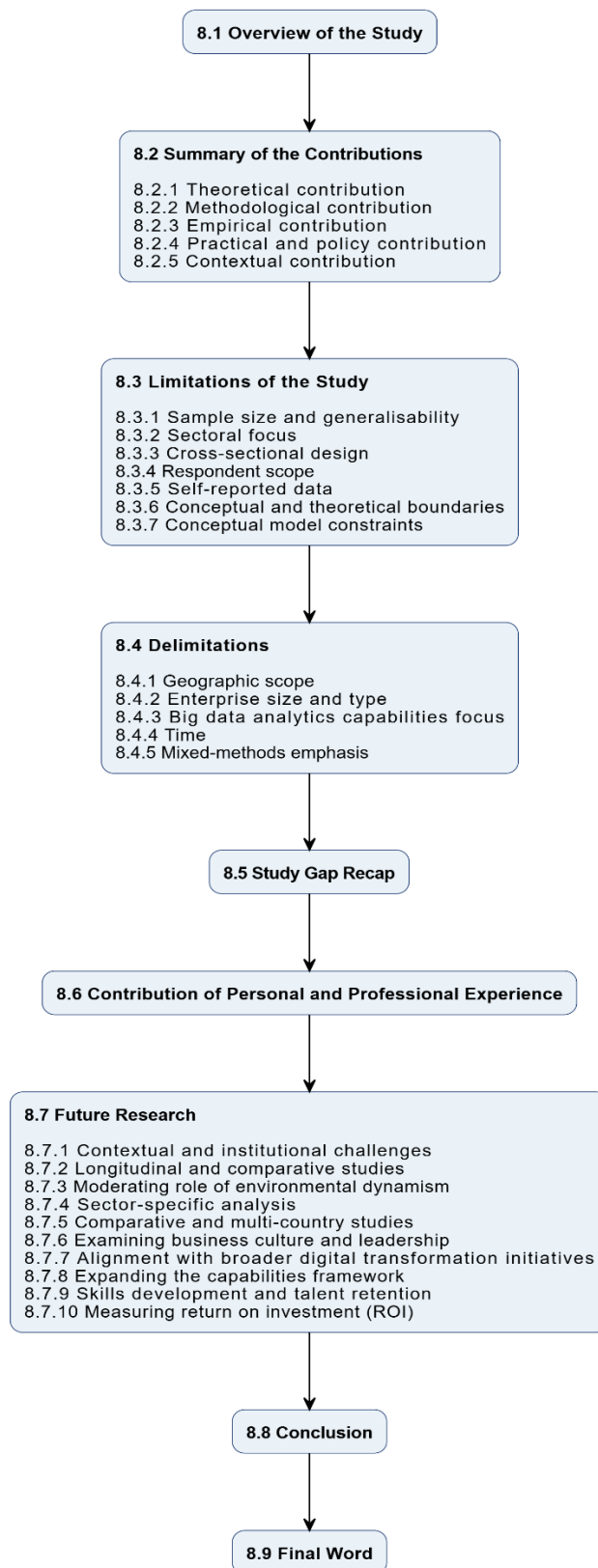


Figure 57: Structure of chapter 8 – Overview, conclusions, limitations, and recommendations

Source: Author

8.2 SUMMARY OF THE CONTRIBUTIONS

The study contributes on several levels, namely theoretical, methodological, empirical, practical, and contextual. These contributions are outlined in the subsections below.

8.2.1 Theoretical contribution

Firstly, this study extends dynamic capabilities theory by demonstrating that big data analytics capabilities are insufficient on their own to deliver competitive advantage unless they are mediated by the dynamic processes of sensing, seizing, and transforming. The study thus confirms that agility, adaptability, and responsiveness are the true levers of value creation in volatile environments such as South Africa (Subramoney and Dagada, 2024).

Second, it advances a systematic multi-level capabilities theory, locating big data analytics capabilities as an upper-level construct cascading from physical, human, and intangible assets down to operational and dynamic capabilities. This multi-layered approach, which has hitherto been absent from much previous literature, provides a richer theoretical explanation of how analytics resources are transformed into strategic products.

Third, the study imposes contextual richness on dynamic capabilities theory and resource-based theory by adding empirical insights from South Africa to theories that previously applied in developed economies. Situating big data analytics capabilities in an emerging market context expands the relevant scope and foundation of these origin theories.

8.2.2 Methodological contribution.

Methodologically, the research contributes by applying an exploratory sequential mixed methods design that combines qualitative interviews with top business leaders and a quantitative survey. Data were analysed using PLS-SEM. The method shows how methodological pluralism can yield richer, context-suited findings in big data analytics capabilities studies.

Most importantly, the study also provided a contextually validated measurement model and ensures that big data analytics capabilities construct, tangible resources, human competencies, and intangible resources reflect the South African business realities. The study also employed a two-step higher-order construct modelling approach in operationalising first-, second-, and third-order constructs, enhancing capabilities-based modelling in empirical investigations. Finally, by testing and validating the entire multi-level conceptual framework (resources → capabilities → competitive advantage) in an under-researched environment, this study provides a methodological precedent that can be replicated in other developing economies.

8.2.3 Empirical contribution

Empirically, this research makes an important empirical contribution through providing evidence from the Global South, a less-represented area of big data analytics capabilities literature. It confirms differences in capability maturity amongst South African businesses and how differences in tangible, human, and intangible assets produce different big data analytics capabilities pathways (Dangale and Dagada, 2024).

Notably, the research empirically defines dynamic and operational capabilities and demonstrates that dynamic capabilities, and not operational capabilities, mediate the relationship between big data analytics capabilities and competitive advantage. It provides valuable contributions to prior arguments that tended to confuse these constructs.

Additionally, by surveying 110 business leaders across multiple industries, the study establishes robust data-driven conclusions regarding South Africa's unique context, adding rare empirical richness to the global big data analytics capabilities domain (Saar and Dagada, 2024).

8.2.4 Practical and policy contribution

Practically, the study provides actionable guidelines for companies and policymakers. For business leaders, it offers strategic channels for building big data analytics capabilities, including investing in building leadership skills, establishing data culture, developing technical and managerial skills, and embedding analytics into corporate

strategy (Maluleka and Dagada, 2024). At the policy level, it advocates for investment in national digital infrastructure, scaling up training interventions to skills development, and designing regulatory frameworks (e.g., POPIA compliance) that promotes innovation while ensuring trust. For businesses at the industry level, the research provides focused suggestions for industries such as financial services, logistics, and manufacturing, enabling more targeted big-data analytics programs. At the national level, the research evidence is consistent with South Africa's Digital Economy Master Plan (DEMP), which features a roadmap for building digital infrastructure, improving digital skills, and imparting data-driven innovation across industries. By drawing attention to the potential of big-data analytics in building competitiveness, the study offers actionable research that is complementary to the Digital Economy Master Plan vision of economic competitiveness and shared growth (Department of Communications and Digital Technologies, 2025). Notably, the results also offer value to other economies of the Global South, across which the same institutional and resource limitations are in effect.

8.2.5 Contextual contribution

Finally, the research also contributes contextually. By conducting this study in South Africa where there exists various socio economic, infrastructural, regulatory and skills challenges the research grounds global theory into local practice. Furthermore, it demonstrates how these factors limit big data analytics capabilities uptake and impact. In doing so, it gives a more reflective picture of international big data analytics capabilities studies, hitherto dominated by the perception of developed countries. This contextualisation not only enhances the generalisability of the study for South African businesses but also facilitates comparative learning for other emerging economies and thus contributes towards Global South scholarship development.

8.3 LIMITATIONS OF THE STUDY

While this study makes a valuable contribution to understanding how big data analytics capabilities influence competitive advantage in South African businesses, several limitations must be acknowledged. Recognising these constraints helps place the findings in context and highlights areas for future research.

8.3.1 Sample size and generalisability

The quantitative phase included 110 usable responses from South African business leaders. Although the sample size of 110 responses is appropriate for PLS-SEM and aligns with the exploratory nature of this study, it remains relatively modest for research proposing a comprehensive framework. While PLS-SEM is recognised for its suitability in smaller samples and complex models, the size of the sample does impose limitations on the extent to which the findings can be generalised.

The results should therefore be interpreted as context-specific and indicative rather than universally generalisable. Caution should be exercised when extending these findings to the broader population of South African organisations, particularly given the diversity of industries, organisational sizes, and varying levels of data maturity.

Furthermore, the use of a cross-sectional design limits the ability to capture the dynamic evolution of Big Data Analytics Capabilities over time. Longitudinal research would provide deeper insight into how these capabilities develop and influence competitive advantage in changing environments.

8.3.2 Sectoral focus

Although the participants represented a variety of industries such as finance, insurance, retail, telecommunications, logistics and consultancy, a comparative analysis per industry was not made in this study. The conclusions therefore provide generalised insight into big data analytics capabilities development and competitive advantage, and not suggestions per sector.

8.3.3 Cross-sectional design

The study adopted a cross-sectional research design, capturing organisational practices and capabilities at a single point in time. As a result, the dynamic evolution of capabilities and their long-term impact on competitive advantage cannot be fully assessed. Longitudinal research would be better suited to understanding how these relationships develop over time.

8.3.4 Respondent type

The study also focused primarily on medium to large organisations and senior decision-makers. While this ensured informed and strategic insights, it may limit the applicability of findings to smaller enterprises or operational-level perspectives.

8.3.5 Self-reported data

Both quantitative and qualitative data were self-reported by the participants. While efforts were made to reduce error and social desirability bias (e.g., anonymity), the self-reporting also carried a threat for response bias, particularly on competitive advantage items.

8.3.6 Conceptual and theoretical boundaries

This study adopted the resource-based and dynamic capabilities theories as its guiding framework. Nevertheless, appropriate, alternative perspectives such as institutional theory, contingency theory, or business learning theory, could offer complementary insights into big data analytics capabilities adoption, especially in highly regulated or resource-constrained contexts.

8.3.7 Conceptual model constraints

The theoretical model, as theory-based and empirically tested, was nevertheless a simplification of reality. All interactions, feedback, and environmental influences from external sources were impossible to include. Environmental dynamism, for example, was identified, but it was not modelled as an explicit moderating variable in the PLS-SEM analysis.

Notwithstanding these limitations, the study provides analytically generalisable insights that contribute to both theory and practice, particularly within resource-constrained and dynamic environments such as South Africa.

8.4 DELIMITATIONS

Delimitations allow the researcher to make choices as to what to include or exclude from the study. They help the researcher to set boundaries so that the scope of the study is not too broad and to ensure that the study remains focused on answering the research problem. The delimitations are within the researchers control and differ from limitations which are not within the researchers' control. Delimitations assist in ensuring that the study is manageable regarding time, budget, and resources (Simon, 2011; Creswell and Creswell 2017). This research was delimited by certain factors as

indicated below that were purposefully defined to guide the scope and enable depth in analysis:

8.4.1 Geographic scope

The research has limited its scope to South African businesses. While implications can be generalised to other emerging economies, they are described specifically in the context of the South African business environment.

8.4.2 Enterprise size and type

The study primarily has included medium to large businesses across various industry sectors. Micro and small enterprises have not been explicitly involved due to differences in their bases and rates of adoption for analytics.

8.4.3 Big data analytics capabilities focus

The study has addressed three big data analytics capabilities dimensions. These are tangibles, human skills, and intangibles and how they are aligned with dynamic and operational capabilities. It has not given full detail about each type of software or tool used in big data analytics.

8.4.4 Time

Because this research was conducted over a certain period it might not be able to track any changes or show any relationships outside of this time.

8.4.5 Mixed-methods emphasis

While there was an emphasis on both qualitative and quantitative methods, the qualitative findings were used to refine the quantitative instrument. The qualitative input was used to support and inform the survey phase.

These boundaries were defined to keep the study focused and manageable while still offering useful insights. They also provide a basis for future research to build upon, without losing the relevance of the current findings.

8.5 STUDY GAP RECAP

This study sought to bridge meaningful gaps existing in the current knowledge base in relation to big data analytics capabilities and competitive advantage in the context of the South African and broader emerging markets.

There has been a clear lack of empirical studies in emerging economies. Existing research has been concentrated on developed markets, where businesses engage in competition with advanced infrastructure and abundant resources. Such imbalance has left the unique challenges and opportunities of resource-constrained environments unexplored. By providing empirical evidence specific to South Africa, this study helps to right that imbalance and extend the scope of big data analytics capabilities research to environments in which institutional vulnerability, infrastructural shortage, and socio-economic strain represent a different reality.

There has also been little convergence of dynamic capabilities theory and resource-based theory. While both theories have been individually applied to explain competitive advantage at the business level, few researches have attempted to integrate them into a unifying framework that can capture the multi-layered and dynamic nature of big data analytics capabilities. This research bridged that gap by proposing and empirically testing a multi-level framework that positions big data analytics capabilities as both a resource base and a driver of dynamic capabilities.

In addition, the literature does not reflect methodological depth in big data analytics capabilities research. Most of the existing studies have adopted either qualitative or quantitative approaches on their own thus limiting the research to the technical aspects and limiting an understanding of the complexity of the phenomenon. Very few studies have adopted a thorough exploratory sequential mixed-methods design, especially in emerging markets. This study contributes by employing a design that integrates qualitative insights into a quantitative framework, enabling a more nuanced and holistic investigation.

Furthermore, there has been persistent ambiguity in distinguishing operational from dynamic capabilities. Many prior studies have either conflated the two or failed to rigorously test their distinct contributions to competitive advantage. The findings of this

study clarified this ambiguity, demonstrating that while operational capabilities are important for efficiency and process optimisation, it is dynamic capabilities, those of sensing, seizing, and transforming, that are more critical in shaping competitive advantage.

And finally, there remain contextual blind spots in the Global South. Much of the extant research has overlooked the institutional, infrastructural, and cultural realities that shape how big data analytics capabilities developed and applied in Africa. This study situates big data analytics capabilities squarely within South Africa's socio-economic and regulatory environment, offering insights that not only speak to local business conditions but also resonate with broader Global South contexts where businesses grapple with similar systemic challenges.

8.6 CONTRIBUTION OF PERSONAL AND PROFESSIONAL EXPERIENCE

In addition to bridging these gaps, this research is strengthened by the lived experience of the researcher. Having worked long hours in fields of data analytics, as well as corruption prevention, the researcher has developed a keen appreciation for what is problematic to South African businesses in acquiring big data analytics capabilities.

This perspective contributes in two ways:

It grounds the study in the realities faced by South African businesses, ensuring that the questions, framework, and recommendations are rooted in practice rather than abstraction. The experience acquired through professional practice ensured the research questions, model building, and suggestions were world-driven. This excluded the tendency to develop abstract or purely theoretical findings not aligned with organisational truths.

It highlights the importance of capacity development, through adaptive leadership, innovation labs, and data literacy, reflecting insights drawn directly from both corporate and public sector experience.

Knowledge of corporate and public sector programs guided the focus on capacity building and skills acquisition. The link between adaptive leadership, innovation labs, and data literacy is more than theoretical recommendations but an outcome of

practical experience with the practice shortfall that the researcher has encountered.

By merging the expertise of the researcher with the participants' experiences, this study represents a unique connection between theory and practice. This insider-practitioner perspective lends strength to the findings and renders them more applicable and acceptable to South African businesses.

8.7 FUTURE RESEARCH

This section consolidates all the suggested future research trajectories into one integrated framework.

8.7.1 Contextual and institutional challenges

Subsequent research needs to examine the institutional and regulatory environments that determine big data analytics capabilities uptake in South Africa. These include government policy, infrastructure constraints, and systemic issues of corruption, inequality, and scarcity of digital infrastructure (Dagada, 2025b; Subramoney and Dagada, 2025). Research of this type can give more insight into how reality present facilitates or incapacitates firms in leveraging big data analytics capabilities for competitive advantage.

8.7.2 Longitudinal and comparative studies

Future research should adopt longitudinal designs to observe how big data analytics capabilities maturity evolves over time and how dynamic capabilities (sense, seize, transform) are developed and institutionalised. This would enable better insight into the causal pathways between analytics investments and competitive advantage outcomes.

This study adopted a cross-sectional approach. Future research could conduct longitudinal studies to research how big data analytics capabilities evolve over time and their sustained impact on competitive advantage. Comparative studies across industries and across different emerging markets could also reveal variations in adoption pathways, resource requirements, and strategic outcomes.

8.7.3 Moderating role of environmental dynamism

Environmental dynamism characterised by rapid technological changes, regulatory uncertainty, and volatile customer preferences was discussed thematically but not explicitly modelled. Future studies should examine how environmental conditions moderate the relationship between big data analytics capabilities, dynamic capabilities, and competitive advantage, building on the dynamic capabilities' theory.

8.7.4 Sector-specific analysis

The study was conducted across different industries to analyse the relationship between big data analytics capabilities and competitive advantage. The future study is recommended to target a specific industry such as healthcare, banking, logistics, or telecommunication.

The non-significant operational capability path identified in this study presents an important opportunity for future research rather than a limitation. Further studies could explore sector-specific differences in how operational capabilities influence competitive advantage, as their role may vary across industries. In addition, future research may consider the development of alternative operational capability constructs that more accurately capture the operationalisation of big data analytics capabilities within organisations (Dzreke and Dzreke, 2025). This would contribute to a more refined understanding of how analytics capabilities translate into performance across different organisational and industry contexts.

8.7.5 Comparative and multi-country studies

As data-driven initiatives continue to increase globally, comparisons between South Africa and other African or developing countries could establish if big data initiatives, digital transformations and readiness, and policy recommendations lead to big data analytics capabilities implementation and competitive advantage. It would also verify and extend the proposed conceptual framework to different geographical contexts.

8.7.6 Examining business culture and leadership.

Despite this study having embraced business readiness and leadership alignment as qualitative themes, they were not included in the quantitative model. The influence of business culture, leadership commitment, and data governance processes on big data

analytics capabilities use can also be explored further.

8.7.7 Alignment with broader digital transformation initiatives

It would also be important to examine how big data analytics capabilities can be linked with other digital projects such as artificial intelligence (AI) internet of things (IoT), and cloud-based applications and systems. Appreciation of these interconnections can help companies formulate synthesised digital strategies from beyond siloed programs of analytics.

8.7.8 Expanding the capabilities framework

Subsequent studies could add to the conceptual framework through the application of institutional theory, absorptive capacity, or learning mechanisms. This will deliver a more integrated understanding of how firms develop and utilise big data analytics capabilities for competitiveness.

8.7.9 Skills development and talent retention

These findings highlighted the lack of technical and managerial data skills in South Africa. Future studies should explore the effectiveness of training interventions, industry and academic partnerships, and talent retention strategies in building big data analytics capabilities related skills. This is particularly relevant to sustaining competitive advantage in resource-constrained contexts.

8.7.10 Measuring return on investment (ROI)

Even with great investments in big data analytics technologies, most organisations lack the capabilities to measure the return on investments. Future studies might expand on the existing frameworks to include measuring both the tangible and intangible benefits of big data analytics initiatives so that businesses can justify and align their analytics investments with their strategic objectives more effectively.

To guide this agenda, Table 48 outlines suggested areas for future research, reflecting both the gaps identified in this study and opportunities highlighted in the wider literature.

Table 48: Suggested areas for future research**Source: Author**

Research area	Focus
Contextual and institutional Challenges	Influence of infrastructure, policy, inequality, and corruption
Longitudinal and comparative studies	Evolution of big data analytics capabilities over time, cross-sector, and cross-country comparisons
Moderating role of environmental dynamism	Role of volatility, regulation, and uncertainty in big data analytics capabilities effectiveness
Sector-specific analysis	Healthcare, banking, logistics, telecom-specific pathways
Comparative and multi-country studies	Adoption differences across South Africa and other emerging economies
Examining business culture and leadership	Role of culture, leadership alignment, and governance
Alignment with broader digital initiatives	Integration with AI, IoT, cloud, and digital transformation
Expanding the capabilities framework	Adding institutional theory, absorptive capacity, learning mechanisms
Skills development and talent retention	Strategies for upskilling and retention of analytics professionals
Measuring return on investment	Linking big data analytics capabilities initiatives to tangible and intangible business outcomes

Taken together, the suggested areas for future research (Table 48) underline that while significant progress has been made in understanding big data analytics capabilities, important gaps remain. These include deeper exploration of contextual factors, leadership and cultural alignment, sector-specific adoption pathways, and methods for quantifying both tangible and intangible returns on analytics investments. Addressing these gaps will not only enrich academic theory but also offer actionable guidance for businesses and policymakers seeking to maximise the value of big data in emerging market contexts.

8.8 CONCLUSION

The research aim was to investigate the contribution of big data analytics capabilities to the competitive advantage of South African businesses, from the perspectives of the resource-based and dynamic capabilities theories. An exploratory sequential mixed-methods research design was followed in which qualitative interviewing was combined with quantitative PLS-SEM analysis to gain a richer understanding of big data analytics capabilities adoption, integration, and effects. The results show that big data analytics capabilities do not automatically translate into enhanced competitive advantage.

Competitive advantage only emerges, however, when big data analytics capabilities are combined with sensing, seizing, and transforming dynamic capabilities. Operational capabilities were found to play a lesser part in this respect. This highlights the critical mediating function of dynamic capabilities in turning data resources into strategic outcomes, especially in emerging markets where resource scarcity and contextual constraints shape adoption pathways.

The study contributes theoretically by extending resource-based theory and dynamic capabilities theory into the South African context, and practically by offering managers a guide to align data, technology, and capabilities investments with organisational agility and competitiveness. For policymakers, the findings emphasise the need to strengthen enabling ecosystems such as digital skills, infrastructure, and regulation to maximise the benefits of big data analytics capabilities.

By situating the analysis in South Africa while drawing implications for other emerging economies, this research provides a transferable model for studying big data analytics capabilities in environments marked by both opportunities and constraints. It advances the conversation on how organisations can harness big data not merely as a technological asset, but as a strategic capability shaping long-term competitive positioning.

8.9 FINAL WORD

This study is more than an intellectual exercise. It is a contribution to the ongoing discussion on how businesses in South Africa and across the Global South can

maximise strategic advantage through the effective use of data. The research confirmed that while technology provides the foundational building blocks, it is ultimately people, organisational culture, and adaptive leadership that unlock the full potential of big data analytics capabilities.

South Africa's challenges, skill shortages, constrained infrastructure, and regulatory restrictions are not obstacles but challenges that need innovative solutions. By embracing big data analytics and dynamic capabilities, South African businesses can overcome these context-dependent limitations and emerge as leaders in digital competitiveness among emerging economies. As Dagada (2025) argues, there needs to be policy and institutional reform if South Africa is not to get left behind further with the 4IR.

The greatest strength of this study is that it closes the gap between theory and practice. It adds to scholarly research in that it positions the resource-based theory and the dynamic capabilities theory in an African setting and, simultaneously, provides managers and policymakers with practical frameworks and tools for further action.

Further research is required to extend these findings. The questions raised, the models proposed, and the guidelines established are intended to stimulate deeper dialogue and discussion. Big data analytics is a dynamic and evolving field, and its successful application in South Africa will require constant cooperation among government, industry, and academia.

In conclusion, this thesis is an intervention and challenge. An intervention to add to the body of work on big data analytics capabilities, and a challenge to researchers, practitioners, and policymakers to step up to the task of creating data-driven, adaptive, and competitive businesses for South Africa and the wider Global South.

REFERENCES

- Addagada, T. C. (2025). Navigating governance dynamics: the interplay between data governance, corporate governance, and organizational performance.
- Africa Data Revolution Report. (2016). Africa Data Revolution Report 2016: Highlighting developments in Africa's data ecosystems. United Nations Economic Commission for Africa. <https://www.uneca.org/data-and-statistics>
- Aftab, U and G. F. Siddiqui, G. F., Big Data Augmentation with Data Warehouse: A Survey, in 2018 IEEE International Conference on Big Data (Big Data), Seattle, WA, USA, 2018, pp. 2775-2784, <https://doi.ieeecomputersociety.org/10.1109/BigData.2018.8622182>
- Agnihotri, R., Dingus, R., Hu, M. Y., and Krush, M. T. (2023). Social media, big data, and dynamic capabilities: A resource-based view perspective. *Journal of Business Research*, 157, 113592. <https://doi.org/10.1016/j.indmarman.2015.09.003>
- Ahmed, A., Pereira, L., & Jane, K. J. (2024). *Mixed methods research: Combining both qualitative and quantitative approaches* [Manuscript]. ResearchGate.
- Akter, S. (2016). Understanding the influence of data analytics capabilities on firm advantage. *Journal of Management Information Systems*, 33(2), 381–406.
- Akter, S., Haque, M. R., and Jahan, I. (2022). Understanding big data analytics capabilities and their role in competitive advantage: A review and future research directions. *Journal of Business Research*, 145, 636–648.
- Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., and Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment? *International Journal of Production Economics*, 182, 113–131. <https://doi.org/10.1016/j.ijpe.2016.08.018>
- Alaskar, T. H., Mezghani, K., & Alsadi, A. K. (2021). Examining the adoption of Big data analytics in supply chain management under competitive pressure: evidence from Saudi Arabia. *Journal of decision systems*, 30(2-3), 300-320.
- Alharthi, A., Krotov, V., & Bowman, M. (2017). Addressing barriers to big data. *Business Horizons*, 60(3), 285-292 <https://doi.org/10.1016/j.bushor.2017.01.002>
- Antonetti, P., and Rosengren, S. (2022a). Ethics in marketing: A review and research agenda. *Journal of Business Ethics*, 180(3), 561–577.

- Antunes, P., Pino, J.A., Tate, M. Eliciting Process Knowledge Through Process Stories. *Inf Syst Front* **22**, 1179–1201 (2020). <https://doi.org/10.1007/s10796-019-09922-0>
- Arthur, L. (2013). *Big Data Marketing: Engage Your Customers More Effectively And Drive Value*. Wiley.
- Atkinson, R. C., and Shiffrin, R. M. (1968). Human memory: A proposed system and its control processes. In K. W. Spence and J. T. Spence (Eds.), *The Psychology Of Learning And Motivation: Advances In Research And Theory* (Vol. 2, pp. 47–89). Academic Press. [https://doi.org/10.1016/S0079-7421\(08\)60422-3](https://doi.org/10.1016/S0079-7421(08)60422-3)
- Aversa, P., Haeffliger, S., & Reza, D. G. (2017). Building a winning business model portfolio. *MIT SLOAN MANAGEMENT REVIEW*, 58(4), 49-54.
- Ayankoya, K., Calitz, A. P., & Greyling, J. H. (2016). Real-time grain commodities price predictions in South Africa: A big data and neural networks approach. *Agrekon*, 55(4), 483-508.
- Babbie, E. R. (2020). *The practice of social research* (15th ed.). Cengage Learning
- Baotlong, M. H., Baharuddin, C., Sasmita, H., and Salam, K. N. (2025). Leveraging big data for competitive advantage: A review in business analytics. *Advances in Management and Financial Reporting*, 3(3), 714–728.
- Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99–120. <https://doi.org/10.1177/014920639101700108>
- Bartlett, M. S. (1954). A note on the multiplying factors for various chi square approximations. *Journal of the Royal Statistical Society: Series B (Methodological)*, 16(2), 296–298.
- Berinsky, A. J., Margolis, M. F., Sances, M. W., and Warshaw, C. (2021). Using screeners to measure respondent attention on self-administered surveys: Which items and how many? *Political Science Research and Methods*, 9(2), 430–437.
- Bird, D. K. (2009). The use of questionnaires for acquiring information on public perception of natural hazards and risk mitigation: A review of current knowledge and practice. *Natural Hazards and Earth System Sciences*, 9(4), 1307–1325. <https://doi.org/10.5194/nhess-9-1307-2009>

- Birkinshaw, J., and Gibson, C. B. (2017). The antecedents, consequences, and mediating role of organisational ambidexterity. *Academy of Management Journal*, 47(2), 209–226. <https://doi.org/10.5465/20159573>
- Birt, J., Safari, M., and de Castro, V. B. (2023). Critical analysis of integration of ICT and data analytics into the accounting curriculum: A multidimensional perspective. *Accounting and Finance*, 63(4), 4037–4063.
- Borgatti, S. P., and Halgin, D. S. (2011). On network theory. *Organisation Science*, 22(5), 1168–1181. <https://doi.org/10.1287/orsc.1100.0641>
- Braganza, A., Brooks, L., Nepelski, D., Ali, M., and Moro, R. (2017). Resource management in big data initiatives: Processes and dynamic capabilities. *Journal of Business Research*, 70, 328–337. <https://doi.org/10.1016/j.jbusres.2016.08.006>
- Brass, D. J., Butterfield, K. D., and Skaggs, B. C. (1998). Relationships and unethical behavior: A social network perspective. *Academy of Management Review*, 23(1), 14–31.
- Braun, V., and Clarke, V. (2008). Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), 77–101. <https://doi.org/10.1191/1478088706qp063oa>
- British Psychological Society. (2021). *Code Of Human Research Ethics* (4th ed.). <https://www.bps.org.uk/sites/www.bps.org.uk/files/Policy/Policy%20-%20Files/BPS%20Code%20of%20Human%20Research%20Ethics%20%282021%2C%204th%20edn%29.pdf>
- Bryman, A. (2016). *Social research methods* (5th ed.). Oxford University Press.
- Brynjolfsson, E., & McElheran, K. (2016). *Data in action: Data-driven decision making in US manufacturing*. University of Toronto-Rotman School of Management.
- Burt, R. S. (2005). *Brokerage and closure: An introduction to social capital*. Oxford University Press, USA.
- Calitz, A.P., Poisat, P., & Cullen, M. (2017). The future African workplace: The use of collaborative robots in manufacturing. *SA Journal of Human Resource Management/SA Tydskrif vir Menslikehulpbronbestuur*, 15(0), a901.
- Cervone, H. (2017). Evaluating social media presence: A practical application of big data and analytics in information organizations. *Digital Library Perspectives*. 33 (1). 2-7. [10.1108/DLP-10-2016-0040](https://doi.org/10.1108/DLP-10-2016-0040)

- Chang, S. C., and Gurbaxani, V. (2012). An Empirical Analysis of Technical Efficiency: The Role of IT Intensity and Competition.
<https://doi.org/10.1287/isre.1120.0438>
- Chatterjee, S., Rana, N. P., & Dwivedi, Y. K. (2024). How does business analytics contribute to organisational performance and business value? A resource-based view. *Information Technology & People*, 37(2), 874-894.
- Chen, D. Q., Preston, D. S., and Swink, M. (2016). How the use of big data analytics affects value creation in supply chain management. *Journal of Management Information Systems*, 32(4), 4–39.
<https://doi.org/10.1080/07421222.2015.1138364>
- Chen, H., Chiang, R. H. L., and Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS Quarterly*, 36(4), 1165–1188.
<https://doi.org/10.2307/41703503>
- Christodoulou, A., and Cullinane, K. (2019). Identifying the Main Opportunities and Challenges from the Implementation of a Port Energy Management System: A SWOT/PESTLE Analysis *Sustainability*, 11(21), 6046.
<https://doi.org/10.3390/su11216046>
- Chen, Y., Wang, Y., Nevo, S., Jin, J., Wang, L., and Chow, W. S. (2017). IT capabilities and organisational advantage: The roles of business process agility and environmental factors. *European Journal of Information Systems*, 23(3), 326–342. <https://doi.org/10.1057/ejis.2013.4>
- Ciacchi, A., & Penco, L. (2024). Business model innovation: harnessing big data analytics and digital transformation in hostile environments. *Journal of Small Business and Enterprise Development*, 31(8), 22-46.
- Clark, L. A., and Watson, D. (1995). Constructing validity: Basic issues in objective scale development. *Psychological Assessment*, 7(3), 309–319.
<https://doi.org/10.1037/1040-3590.7.3.309>
- Corea, F. (2019). *The artificial intelligence renaissance: Towards a new world of meaning*. Springer.
- Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches*. Sage publications.
- Creswell, J. W., and Plano Clark, V. L. (2018). *Designing And Conducting Mixed Methods Research* (3rd ed.). SAGE Publications.

- Custers, B., & Uršič, H. (2016). Big data and data reuse: a taxonomy of data reuse for balancing big data benefits and personal data protection. *International data privacy law*, 6(1), 4-15.
- Dagada, R. (2023). The impact of regulatory overreach on digital transformation: Lessons from South Africa. In G. J. Lee and R. Dagada (Eds.), *Research in Southern African Digital Business Volume II*. Silk Route Press.
- Dagada, R. (2024). The advancement of 4IR technologies and increasing cyberattacks in South Africa. *Southern African Journal of Security*. <https://doi.org/10.25159/3005-4222/15157>
- Dagada, R. (2025a). Compliance with ICT governance in corporate South Africa. In Proceedings of the 24th European Conference on Cyber Warfare and Security (Vol. 24, pp. 84–93). <https://doi.org/10.34190/eccws.24.1.3767>
- Dagada, R. (2025b). Migration of applications and information systems to cloud data infrastructure: Lessons from a South African retail bank. *Mousaion: South African Journal of Information Studies*. <https://doi.org/10.25159/2663-659X/16035>
- Dagada, R., and Lekaba, F. (2024). Has South Africa's macroeconomic policy framework been successful in reindustrialising the economy? *Journal of Public Administration*, 59(2), 188–209. <https://doi.org/10.53973/jopa.2024.59.2.a3>
- Dangale, V., and Dagada, R. (2024). Conceptual framework on the use of big data to manage risks in the South African insurance sector. In 4th IEEE International Multidisciplinary Information Technology and Engineering (Vaal University of Technology, 27–29 November 2024, pp. 124–132).
- Danielsen, F., Olsen, D., & Framnes, V. A. (2021). Toward an understanding of big data analytics and competitive performance. *Scandinavian Journal of Information Systems*, 33(1), 6.
- Davenport, T. H., and Bean, R. (2018). Big companies are embracing analytics, but most still do not have a data-driven culture. *Harvard Business Review*.
- Davenport, T. H., & Dyché, J. (2013). *Big data in big companies*. International Institute for Analytics. <https://www.iqpc.com/media/7863/11710.pdf>
- Davenport, T. H., and Patil, D. J. (2012). Data scientist: The sexiest job of the 21st century. *Harvard Business Review*, 90(10), 70–76. <https://hbr.org/2012/10/data-scientist-the-sexiest-job-of-the-21st-century>

- Delen, D., and Demirkan, H. (2013). Data, information, and analytics as services. *Decision Support Systems*, 55(1), 359–363.
- Delke, V. (2015). The role of knowledge management in innovation. *Journal of Economics and Business Research*, 21(1), 7–15.
- Delton, A. W., & Robertson, T. E. (2016). How the mind makes welfare tradeoffs: Evolution, computation, and emotion. *Current Opinion in Psychology*, 7, 12–16.
- Delton, M. (2020). Predictive analytics and profitability. *Journal of Strategic Data Science*, 4(1), 45–52.
- De Mauro, A., Greco, M., and Grimaldi, M. (2016). A formal definition of big data based on its essential features. *Library Review*, 65(3), 122–135.
- Denscombe, M. (2017). *EBOOK: The good research guide: For small-scale social research projects*. McGraw-Hill Education (UK).
- Denzin, N. K., & Lincoln, Y. S. (Eds.). (2011). *The Sage handbook of qualitative research*. sage.
- Department of Communications and Digital Technologies. (2025, June 26). Harnessing digital innovation: South Africa's vision for collaboration in the intelligent age. Government of South Africa. <https://www.dcdt.gov.za/minister-s-speeches/554-harnessing-digital-innovation-south-africa-s-vision-for-collaboration-in-the-intelligent-age-minister-solly-malatsi-s-pre-wef-speech.html>
- Destefanis, A., Neirotti, P., Paolucci, E., & Raguseo, E. (2021). Estimating the impact of sharing economy accommodation platforms on rural tourism ecosystems: an empirical investigation in Italian “Borghi”. In *16th International Forum on Knowledge Asset Dynamics BOOK OF ABSTRACTS* (pp. 96-96). Arts for Business Institute.
- Dhawan, S. (2010). *Research methodology for business and management studies*. Swastik Publications.
- Doshi-Velez, F., and Kim, B. (2017). *Towards A Rigorous Science Of Interpretable Machine Learning*. <https://doi.org/10.48550/arXiv.1702.08608>
- Dremel, C., Herterich, M. M., Wulf, J., & Vom Brocke, J. (2020). Actualizing big data analytics affordances: A revelatory case study. *Information & Management*, 57(1), 103121.

- Dritsas, E and Trigka, M. (2025). Big data and Internet of Things applications in smart cities: Recent advances, challenges, and critical issues, *Internet of Things*, Volume 34, 101770, ISSN 2542-6605, <https://doi.org/10.1016/j.iot.2025.101770> (<https://www.sciencedirect.com/science/article/pii/S2542660525002847>)
- Drnevich, P. L., and Kriauciunas, A. P. (2011). Clarifying the conditions and limits of the contributions of ordinary and dynamic capabilities to relative firm advantage. *Strategic Management Journal*, 32(3), 254–279. <https://doi.org/10.1002/smj.882>
- Duan, Y., Cao, G., and Edwards, J. S. (2020). Understanding the impact of business analytics on innovation. *European Journal of Operational Research*, 281(3), 673–686. <https://doi.org/10.1016/j.ejor.2018.06.021>
- Dubey, R., Gunasekaran, A., Bryde, D. J., Dwivedi, Y. K., and Papadopoulos, T. (2020). Blockchain technology for enhancing swift trust, collaboration, and resilience within a humanitarian supply chain setting. *International Journal of Production Research*, 58(11), 3381–3398. <https://doi.org/10.1080/00207543.2020.1722860>
- Dzreke, S. S., & Dzreke, S. E. (2025). The causal mechanisms linking Big Data Analytics Capability (BDAC) to AI-Driven dynamic capabilities: A mixed-methods investigation. *Computer Science & IT Research Journal*, 6(9), 616-631.
- Eisenhardt, K. M., & Martin, J. A. (2017). Dynamic capabilities: what are they?. *The SMS Blackwell handbook of organizational capabilities*, 341-363.
- Erevelles, S., Fukawa, N., and Swayne, L. (2016). Big data consumer analytics and the transformation of marketing. *Journal of Business Research*, 69(2), 897–904. <https://doi.org/10.1016/j.jbusres.2015.07.001>
- Ertl, J., Setzke, D. S., Böhm, M., & Krcmar, H. (2020). The Role of Dynamic Capabilities in Overcoming Socio-Cognitive Inertia During Digital Transformation-A Configurational Perspective. In *Wirtschaftsinformatik (Zentrale Tracks)* (pp. 1381-1395).
- Etikan, I., Musa, S. A., and Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. *American Journal of Theoretical and Applied Statistics*, 5(1), 1–4. <https://doi.org/10.11648/j.ajtas.20160501.11>

- European Union. (2016). Regulation (EU) 2016/679 (General Data Protection Regulation). *Official Journal of the European Union*, L119, 1–88. <https://eur-lex.europa.eu/eli/reg/2016/679/oj>
- Fabijan, A., Holmström Olsson, H., Pantić, M., and Bosch, J. (2017). The effect of developer-involved data analytics on the development speed and software quality. *Empirical Software Engineering*, 22(6), 2763–2801.
- Ferraris, A., Santoro, G., & Scuotto, V. (2020). Dual relational embeddedness and knowledge transfer in European multinational corporations and subsidiaries. *Journal of Knowledge management*, 24(3), 519-533.
- Ferrier, W. J., Smith, K. G., & Grimm, C. M. (1999). The role of competitive action in market share erosion and industry dethronement: A study of industry leaders and challengers. *Academy of management journal*, 42(4), 372-388.
- Fetters, M. D., & Molina-Azorin, J. F. (2021). Guidance on using mixed methods from diverse international organizations in the behavioral, social, fundamental, and health sciences. *Journal of Mixed Methods Research*, 15(4), 470-484.
- Fleck, C. (2016). *Knowledge for Whom?: Public Sociology in the Making*. Routledge
- Fletcher, A. J. (2017). Applying critical realism in qualitative research: Methodology meets method. *International Journal of Social Research Methodology*, 20(2), 181–194. <https://doi.org/10.1080/13645579.2016.1144401>
- Floridi, L., & Cowls, J. (2019). A unified framework of five principles for AI in society. *Harvard Data Science Review*, 1(1), 1–15. <https://doi.org/10.1162/99608f92.8cd550d1>
- Fornell, C., and Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. <https://doi.org/10.1177/002224378101800104>
- Fosso Wamba P.S. (2017), "Big data analytics and business process innovation". *Business Process Management Journal*, Vol. 23 No. 3 pp. 470–476, <https://doi.org/10.1108/BPMJ-02-2017-0046>
- Fosso Wamba, S., Gunasekaran, A., Akter, S., Ren, S. J. F., Dubey, R., and Childe, S. J. (2020). Big data analytics and firm advantage: Effects of dynamic capabilities. *Journal of Business Research*, 124, 1–13.
- Fowowe, O. O., & Adedapo, A. (2025). Leveraging predictive analytics to optimize business performance and drive operational excellence. *International journal of Computer Applications Technology and Research*, 14(02), 66-81.

- Framnes, V. A., & Danielsen, F. (2017). Towards an understanding of Big Data Analytics as a weapon for competitive advantage. *European Journal of Business and Management*, 9(9), 55–67.
- Frey, C. B., and Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114, 254–280. <https://doi.org/10.1016/j.techfore.2016.08.019>
- Friedman, M. (1994). The methodology of positive economics. *The philosophy of economics: An anthology*, 2(1), 180-213.
- Galbraith, J. R. (2014). *Designing organizations: Strategy, structure, and process at the business unit and enterprise levels*. John Wiley & Sons.
- Gandomi, A., and Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management*, 35(2), 137–144. <https://doi.org/10.1016/j.ijinfomgt.2014.10.007>
- GDPR. (2016). General Data Protection Regulation (EU) 2016/679. *Official Journal of the European Union*, L119, 1–88. <https://eur-lex.europa.eu/eli/reg/2016/679/oj>
- George, G., Haas, M. R., & Pentland, A. (2014). Big data and management. *Academy of Management Journal*, 57(2), 321–326. <https://doi.org/10.5465/amj.2014.4002>
- Ghasemaghaei, M. (2021). Understanding the impact of big data on firm performance: The necessity of conceptually differentiating among big data characteristics. *International Journal of Information Management*, 57, 102055
- Gold, A. H., Malhotra, A., & Segars, A. H. (2001). Knowledge management: An organisational capabilities perspective. *Journal of Management Information Systems*, 18(1), 185–214. <https://doi.org/10.1080/07421222.2001.11045669>
- Grant, R. M. (1996a). Prospering in dynamically competitive environments: Organisational capabilities as knowledge integration. *Organisation Science*, 7(4), 375–387. <https://doi.org/10.1287/orsc.7.4.375>
- Grant, R. M. (1996b). Toward a knowledge-based theory of the firm. *Strategic Management Journal*, 17(S2), 109–122. <https://doi.org/10.1002/smj.4250171110>
- Green, A. (2025). AI-driven financial intelligence systems: A new era of risk detection and strategic analysis (OSF Preprint No. ynph2_v1). OSF. https://doi.org/10.31219/osf.io/ynph2_v1

- Gressel, S. (2019). *Management decision making in the age of big data: an exploration of the roles of analytics and human judgment: a thesis presented in partial fulfilment of the requirements for the degree of Doctor of Philosophy in Management at Massey University, Auckland, New Zealand* (Doctoral dissertation, Massey University).
- Guest, G., Bunce, A., and Johnson, L. (2006). How many interviews are enough? *Field Methods*, 18(1), 59–82. <https://doi.org/10.1177/1525822X05279903>
- Gulati, R., Nohria, N., & Zaheer, A. (2000). Strategic networks. *Strategic management journal*, 21(3), 203-215.
- Gupta, M., and George, J. F. (2016). Toward the development of a big data analytics capability. *Information and Management*, 53(8), 1049–1064. <https://doi.org/10.1016/j.im.2016.07.004>
- Kane, G. C., Alavi, M., Labianca, G., and Borgatti, S.P. (2014). What's Different about Social Media Networks? A Framework and Research Agenda. Information technology capabilities and firm advantage: Contradictory findings and their possible causes. *MIS Quarterly* (2014) 38 (1): 275–303. <https://doi.org/10.25300/MISQ/2014/38.1.13>
- Kanniah, M. P., & Pelsner, T. (2024). The influence of big data analytics capabilities on the performance of manufacturing firms.
- Hair, J. F., Risher, J. J., Sarstedt, M., and Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24. <https://doi.org/10.1108/EBR-11-2018-0203>
- Hallikas, J., Immonen, M., & Brax, S. (2021). Digitalizing procurement: the impact of data analytics on supply chain performance. *Supply Chain Management: An International Journal*, 26(5), 629-646.
- Hämäläinen, E., & Inkinen, T. (2019). Industrial applications of big data in disruptive innovations supporting environmental reporting. *Journal of Industrial Information Integration*, 16, 100105.
- Hansen, M. T., Podolny, J. M., & Pfeffer, J. (2001). So many ties, so little time: A task contingency perspective on corporate social capital in organizations.
- Harrison, R. L., & Reilly, T. M. (2011). Mixed methods designs in marketing research. *Qualitative market research: an international journal*, 14(1), 7-26.
- Hashem, I. A. T., Yaqoob, I., Anuar, N. B., Mokhtar, S., Gani, A., and Khan, S. U. (2015). The rise of “big data” on cloud computing: Review and open research

- issues. *Information Systems*, 47, 98–115.
<https://doi.org/10.1016/j.is.2014.07.006>
- Hayes, B. (2014, July 30). What and where of big data: A data definition framework. Northwest Center for Performance Excellence.
<https://businessoverbroadway.com/2014/07/30/the-what-and-where-of-big-data-a-data-definition-framework/>
- Heale, R., and Twycross, A. (2015). Validity and reliability in quantitative studies. *Evidence-Based Nursing*, 18(3), 66–67. <https://doi.org/10.1136/eb-2015-102129>
- Helfat, C. E., and Peteraf, M. A. (2003). The dynamic resource-based view: Capabilities lifecycles. *Strategic Management Journal*, 24(10), 997–1010.
<https://doi.org/10.1002/smj.332>
- Henseler, J., Ringle, C. M., and Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modelling. *Journal of the Academy of Marketing Science*, 43(1), 115–135.
<https://doi.org/10.1007/s11747-014-0403-8>
- Hillman, A. J., & Hitt, M. A. (1999). Corporate political strategy formulation: A model of approach, participation, and strategy decisions. *Academy of management review*, 24(4), 825-842
- Hoffman, D. L., and Novak, T. P. (2018). Consumer and object experience on the Internet of things: An assemblage theory approach. *Journal of Consumer Research*, 44(6), 1178–1204. <https://doi.org/10.1093/jcr/ucx105>
<https://www.6sigma.us>: accessed on 2023-09-01
https://saylordotorg.github.io/text_principles-of-management-v1.1/s13-02-an-introduction-to-the-lexicon.html: **Accessed on 2023-03-05**
- Hussinki, H., Ritala, P., Vanhala, M., Kianto, A., & Mero, J. (2025). Effects of big data analytics on firm innovativeness: The role of a data-driven culture. *Knowledge and Process Management*, 32, 161–173. <https://doi.org/10.1002/kpm.70000>
- Intezari, A., & Gressel, S. (2017). Information and reformation in KM systems: big data and strategic decision-making. *Journal of knowledge management*, 21(1), 71-91.
- Ivankova, N. V., Creswell, J. W., and Stick, S. L. (2006). Using mixed-methods sequential explanatory design: From theory to practice. *Field Methods*, 18(1), 3–20. <https://doi.org/10.1177/1525822X05282260>

- Janssen, M., van der Voort, H., and Wahyudi, A. (2017). Factors influencing big data decision-making quality. *Journal of Business Research*, 70, 338–345.
<https://doi.org/10.1016/j.jbusres.2016.08.007>
- Jeble, S., Dubey, R., Childe, S. J., Papadopoulos, T., Roubaud, D., & Prakash, A. (2018). Impact of big data and predictive analytics capability on supply chain sustainability. *The International Journal of Logistics Management*, 29(2), 513–538.
- Kache, F., and Seuring, S. (2017). Challenges and opportunities of digital information at the intersection of big data analytics and supply chain management. *International Journal of Operations and Production Management*, 37(1), 10–36. <https://doi.org/10.1108/IJOPM-02-2015-0078>
- Kaiser, H. F. (1974). An index of factorial simplicity. *Psychometrika*, 39(1), 31–36.
<https://doi.org/10.1007/BF02291575>
- Kallio, H., Pietilä, A. M., Johnson, M., and Kangasniemi, M. (2016). Systematic methodological review: Developing a framework for a qualitative semi-structured interview guide. *Journal of Advanced Nursing*, 72(12), 2954–2965.
<https://doi.org/10.1111/jan.13031>
- Kiron, D., Prentice, P. K., & Ferguson, R. B. (2014). The analytics mandate. *MIT Sloan management review*, 55(4), 1.
- Kitchin, R. (2014b). The real-time city? Big data and smart urbanism. *GeoJournal*, 79(1), 1–14. <https://doi.org/10.1007/s10708-013-9516-8>
- Kline, R. B. (2023). *Principles and practice of structural equation modeling*. Guilford publications.
- Kock, N., and Hadaya, P. (2016). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. *Information Systems Journal*, 28(1), 227–261. <https://doi.org/10.1111/isj.12131>
- Koka, B. R., Madhavan, R., & Prescott, J. E. (2006). The evolution of interfirm networks: Environmental effects on patterns of network change. *Academy of Management Review*, 31(3), 721–737
- Kraaijenbrink, J., Spender, J. C., and Groen, A. J. (2010). The resource-based view: A review and assessment of its critiques. *Journal of Management*, 36(1), 349–372. <https://doi.org/10.1177/0149206309350775>
- Krackhardt, D., Nohria, N., & Eccles, B. (2003). The strength of strong ties. *Networks in the knowledge economy*, 82.

- Kshetri, N. (2022). Blockchain as a tool to facilitate property rights protection in the Global South: lessons from India's Andhra Pradesh state. *Third World Quarterly*, 43(2), 371-392.
- Kuhn, T. S. (1997). *The structure of scientific revolutions* (Vol. 962). Chicago: University of Chicago press.
- Kuiper, C., & Smit, J. (2022). Scaffolding genre-based writing in the subjects: Lecturers' learning processes in a design-based research project. *Journal of University Teaching and Learning Practice*, 19(5), 1-15.
- Kumar, A., & Rawat, N. K. (2021). SOCIAL SCIENCE CONTRIBUTORS. *Development of Social Sciences: A Librarians Companion*, 87.
- Kuratko, D. F., Morris, M. H., & Schindehutte, M. (2015). Understanding the dynamics of entrepreneurship through framework approaches. *Small Business Economics*, 45(1), 1-13.
- Kwon, O., Lee, N., and Shin, B. (2014). Data quality management, data usage experience and acquisition intention of big data analytics. *International Journal of Information Management*, 34(3), 387–394.
<https://doi.org/10.1016/j.ijinfomgt.2014.02.002>
- Laney, D. (2001). 3D data management: Controlling data volume, velocity, and variety. META Group Research Note. <https://blogs.gartner.com/doug-laney/files/2012/01/ad949-3D-Data-Management-Controlling-Data-Volume-Velocity-and-Variety.pdf>
- LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., and Kruschwitz, N. (2011). Big data, analytics, and the path from insights to value. *MIT Sloan Management Review*, 52(2), 21–32. <https://sloanreview.mit.edu/article/big-data-analytics-and-the-path-from-insights-to-value>
- Lee, I. (2017). Big data: Dimensions, evolution, impacts, and challenges. *Business Horizons*, 60(3), 293–303. <https://doi.org/10.1016/j.bushor.2017.01.004>
- Leonardi, P. M. (2011). When flexible routines meet flexible technologies: Affordance, constraint, and the imbrication of human and material agencies. *MIS Quarterly*, 35(1), 147–167. <https://doi.org/10.2307/23043493>
- Leonardi, P. M., and Treem, J. W. (2020). Behavioural visibility: A new paradigm for organisation studies in the age of digitization, digitalization, and datafication.

- Organisation Studies*, 41(12), 1601–1625.
<https://doi.org/10.1177/0170840620970728>
- Leung, L. (2015). Validity, reliability, and generalizability in qualitative research. *Journal of family medicine and primary care*, 4(3), 324-327.
- Li, S., Shang, J., & Slaughter, S. A. (2010). Why do software firms fail? Capabilities, competitive actions, and firm survival in the software industry from 1995 to 2007. *Information Systems Research*, 21(3), 631-654.
- Li, Y., Ye, F., & Sheu, C. (2014). Social capital, information sharing and performance: evidence from China. *International Journal of Operations & Production Management*, 34(11), 1440-1462.
- Liberatore, M. J., Pollack-Johnson, B., & Clain, S. H. (2017). Analytics Capabilities and the Decision to Invest in Analytics. *Journal of Computer Information Systems*, 57(4), 364–373. <https://doi.org/10.1080/08874417.2016.1232995>
- Lin, J., Wu, S., & Luo, X. (2025). How does big data analytics capability affect firm performance? Unveiling the role of organisational resilience and environmental dynamism. *European Journal of Information Systems*, 34(3), 502-528.
- Lincoln, Y. S., & Guba, E. G. (1985). *Naturalistic inquiry*. Sage Publications.
- Lioutas, E. D., and Charatsari, C. (2020). Big data in agriculture: Does the new oil lead to sustainability? *Geoforum*, 109, 1–3.
<https://doi.org/10.1016/j.geoforum.2019.12.019>
- Lu, Y., & Ramamurthy, K. (2011). Understanding the link between information technology capability and organizational agility: An empirical examination. *MIS Quarterly*, 35(4), 931–954. <https://doi.org/10.2307/41409967>
- Maharaj, S., & Pillay, N. (2023). An evaluation of digital and artificial intelligent tools in an electronic and computer engineering curriculum at a university of technology in South Africa. *In Association with*, 206.
- Maluleka, M. L., and Dagada, R. (2024). Developing an artificial intelligence adoption model for the South African insurance industry: A case for further research. In R. Dagada (Ed.), *Research In Southern African Digital Business* (Vol. 4, pp. 3–19). Mercury Books.
- Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., & Byers, A. H. (2011). *Big data: The next frontier for innovation, competition, and productivity*. McKinsey Global.

- Maroufkhani, P., Wagner, R., Wan Ismail, W. K., Baroto, M. B., and Nourani, M. (2019). Big data analytics and firm performance: A systematic review. *Information*, 10(7), 226. <https://doi.org/10.3390/info10070226>
- McAfee, A., Brynjolfsson, E., Davenport, T. H., and Patil, D. J. (2012). Big data: The management revolution. *Harvard Business Review*, 90(10), 60–68. <https://hbr.org/2012/10/big-data-the-management-revolution>
- McCombes, S. (2025). *How To Write A Literature Review*. Scribbr. <https://www.scribbr.com/methodology/literature-review/>
- McKinsey & Company. (2016). *The age of analytics: Competing in a data-driven world*. McKinsey Global Institute. <https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/the-age-of-analytics-competing-in-a-data-driven>
- McMillan, J. H., & Schumacher, S. (2010). Research in education: Evidence-based inquiry. (No Title).
- Mecca, A. (2025). The influence of artificial intelligence implementation on firm scaling: An exploratory approach.
- Mikalef, P., Boura, M., Lekakos, G., and Krogstie, J. (2019). Big data analytics capabilities and innovation: The mediating role of dynamic capabilities and moderating effect of the environment. *British Journal of Management*, 30(2), 272–298. <https://doi.org/10.1111/1467-8551.12343>
- Mikalef, P., Krogstie, J., Pappas, I. O., and Pavlou, P. A. (2021). Investigating the effects of big data analytics capabilities on firm advantage: The mediating role of dynamic capabilities. *Information and Management*, 58(7), 103393.
- Mikalef, P., Pappas, I. O., Krogstie, J., and Giannakos, M. (2018). Big data analytics capabilities: A systematic literature review and research agenda. *Information Systems and e-Business Management*, 16(3), 547–578. <https://doi.org/10.1007/s10257-017-0362-y>
- Mikalef, P., Gupta, M., Pappas, I. O., and Krogstie, J. (2023). The impact of big data analytics capabilities on firm performance: A dynamic capabilities perspective. *Information and Management*, 60(1), 103702.
- Mikalef, P., & Pateli, A. (2017). Information technology-enabled dynamic capabilities and their indirect effect on competitive performance: Findings from PLS-SEM and fsQCA. *Journal of business research*, 70, 1-16.
- Miles, M. B., Huberman, A. M., & Saldana, J. (2014). *Qualitative data analysis*. sage.

- Morgan, D. L. (2014). Pragmatism as a paradigm for social research. *Qualitative Inquiry*, 20(8), 1045–1053. <https://doi.org/10.1177/1077800413513733>
- Nunu, K. (2019). *A big data framework to improve government service delivery in South Africa* (Doctoral dissertation, Cape Peninsula University of Technology).
- Mukherjee, S. P. (2019). *A guide to research methodology: An overview of research problems, tasks and methods*. Crc Press.
- Muthukrishna, M., and Henrich, J. (2019). A problem in theory. *Nature Human Behaviour*, 3, 221–229. <https://doi.org/10.1038/s41562-018-0522-1>
- Nambisan, S., Wright, M., & Feldman, M. (2019). The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. *Research policy*, 48(8), 103773.
- Naudé, W., & Nagler, P. (2021). *The rise and fall of German innovation* (No. 14154). IZA Discussion Papers.
- Newman, A., Obschonka, M., Moeller, J. and Chandan, G.G. (2021), Entrepreneurial Passion: A Review, Synthesis, and Agenda for Future Research. *Applied Psychology*, 70: 816-860. <https://doi.org/10.1111/apps.12236>
- New Vantage Partners NVP 2020. Big Data and AI. Executive Survey 2020: Executive Summary of Findings. Research Report. Boston et al.
- Nguyen, T., Li, Z. H. O. U., Spiegler, V., Ieromonachou, P., & Lin, Y. (2018). Big data analytics in supply chain management: A state-of-the-art literature review. *Computers & operations research*, 98, 254-264
- Nguyen, T. H., Ngo, L. V., & Ruël, H. (2021). The role of corporate social responsibility and innovation capability in sustainable performance. *Corporate Social Responsibility and Environmental Management*, 28(1), 173-184.
- Noble, H., & Smith, J. (2015). Issues of validity and reliability in qualitative research. *Evidence-based nursing*, 18(2), 34-35.
- Nowell, L. S., Norris, J. M., White, D. E., & Moules, N. J. (2017). Thematic analysis: Striving to meet the trustworthiness criteria. *International journal of qualitative methods*, 16(1), 1609406917733847.
- OECD. (2021). *OECD Digital Economy Outlook 2021*. OECD Publishing. <https://www.oecd-ilibrary.org>
- Oladuji, T. J., Akintobi, A. O., Nwangele, C. R., and Ajuwon, A. (2023). A model for leveraging AI and big data to predict and mitigate financial risk in African

- markets. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(6), 1843–1859. <https://doi.org/10.62225/2583049X.2023.3.6.4404>
- Omotayo, M. J., & Omoloso-Dada, B. (2025). Bridging experience and execution: an analytical perspective on customer experience management and retail sales and distribution in the nigeria's telecommunications sector.
- Onwuegbuzie, A. J., and Leech, N. L. (2005). On becoming a pragmatic researcher: The importance of combining quantitative and qualitative research methodologies. *International Journal of Social Research Methodology*, 8(5), 375–387. <https://doi.org/10.1080/13645570500402447>
- Orero-Blat, M., Rodríguez, A. L. L., & Palacios-Marqués, D. (2025). The strategic advantage of innovative organizational culture: An exploratory analysis in digital transformation and big data analytics capabilities. *Journal of Management & Organization*, 31(2), 443-462.
- Palinkas, L.A., Horwitz, S.M., Green, C.A., Wisdom, J. P., Duan, N., Hoagwood. K. Purposeful Sampling for Qualitative Data Collection and Analysis in Mixed Method Implementation Research. *Adm Policy Ment Health* **42**, 533–544 (2015). <https://doi.org/10.1007/s10488-013-0528-y>
- Pathak, B., Mohapatra, S., & Rath, A. (2018). A framework for processing big data in cloud. *Journal of Big Data*, 5(1), 28.
- Paulk, M. C., Curtis, W., Chrissis, M. B., and Weber, C. V. (1993, February). *Capability Maturity Model for Software (Version 1.1)* (Technical Report CMU/SEI-93-TR-024). Software Engineering Institute, Carnegie Mellon University. <https://www.sei.cmu.edu/library/capability-maturity-model-for-software-version-11/>
- Pavlou, P. A., and El Sawy, O. A. (2011). Understanding the elusive black box of dynamic capabilities. *Decision Sciences*, 42(1), 239–273. <https://doi.org/10.1111/j.1540-5915.2010.00287.x>
- Penrose, E. T. (2009). *The Theory of the Growth of the Firm*. Oxford university press.
- Peteraf, M. A. (1993). The cornerstones of competitive advantage: A resource-based view. *Strategic Management Journal*, 14(3), 179–191. <https://doi.org/10.1002/smj.4250140303>
- Pfeffer, J. (2003). Introduction to the classic edition. *Pfeffer, J. and Salancik, GR, The External Control of organizations: A Resource Dependence Perspective (classic edition)*, Stanford University Press, Stanford, CA.

- Pitelis, C., and Wang, C. L. (2023). Dynamic capabilities: What are they and what are they for? *British Journal of Management*, 34(2), 324–329.
<https://doi.org/10.1111/1467-8551.12346>
- Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., and Podsakoff, N. P. (2003). Common method biases in behavioral research. *Journal of Applied Psychology*, 88(5), 879–903. <https://doi.org/10.1037/0021-9010.88.5.879>
- Popper, K. (2014). *Conjectures and refutations: The growth of scientific knowledge*. routledge.
- Porter, M. E. (2008). *Competitive advantage: Creating and sustaining superior performance*. Simon and Schuster.
- Pöyhönen, A. (2004). Modeling and measuring organizational renewal capability.
- Preacher, K. J., and Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects. *Behavior Research Methods*, 40(3), 879–891. <https://doi.org/10.3758/BRM.40.3.879>
- Provost, F., and Fawcett, T. (2013). Data science and its relationship to big data and data-driven decision making. *Big Data*, 1(1), 51–59.
<https://doi.org/10.1089/big.2013.1508>
- Rai, A., & Tang, X. (2010). Leveraging IT capabilities and competitive process capabilities for the management of interorganizational relationship portfolios. *Information Systems Research*, 21(3), 516–542.
<https://doi.org/10.1287/isre.1100.0299>
- Raisch, S., Birkinshaw, J., Probst, G., and Tushman, M. L. (2009). Organisational ambidexterity: Balancing exploitation and exploration for sustained advantage. *Organisation Science*, 20(4), 685–695. <https://doi.org/10.1287/orsc.1090.0428>
- Raisch, S., and Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review*, 46(1), 192–210. <https://doi.org/10.5465/amr.2018.0072>
- Resnik, D. B. (2018). *The ethics of research with human subjects: Protecting people, advancing science, promoting trust*. Springer.
- Rhodes, C., Argyris C., and Schön, D. (1996): Organizational learning II: Theory, method and practice Reading, MA: Addison-Wesley, ISBN 0-201-62983-6. Asia Pacific Journal of Human Resources, 36: 107-109.
- Rumelt, R. P. (1984). Towards a strategic theory of the firm. *Competitive strategic management*, 26(3), 556-570.

- Saar, G., & Dagada, R. (2024). Securing Zambia's Business Future. *Journal of Information Warfare*, 23(3), 1-16.
- Sachdeva, J. K. (2009). *Business research methodology*. Himalaya Publishing House.
- Saeed, M., Adiguzel, Z., Shafique, I., Kalyar, M. N., & Abrudan, D. B. (2023). Big data analytics-enabled dynamic capabilities and firm performance: examining the roles of marketing ambidexterity and environmental dynamism. *Business Process Management Journal*, 29(4), 1204-1226
- Saide, S., & Sheng, M. L. (2020). Toward business process innovation in the big data era: a mediating role of big data knowledge management. *Big data*, 8(6), 464-477.
- Sarpong, R. A., & Pushpanadham, K. (2025, January). Data Analytics in Education: Global Practices. In *International Forum of Teaching and Studies* (Vol. 21, No. 1, pp. 15-75). American Scholars Press, Inc.
- Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial least squares structural equation modeling. In *Handbook of market research* (pp. 587-632). Cham: Springer International Publishing.
- Saunders, M. N. K., Lewis, P., and Thornhill, A. (2023). *Research Methods For Business Students (9th Ed.)*. Pearson.
- Schilke, O. (2014). On the contingent value of dynamic capabilities for competitive advantage: The nonlinear moderating effect of environmental dynamism. *Strategic management journal*, 35(2), 179-203.
- Schubert, K & Barrett, D (2024). Data Governance, Privacy, and Ethics.
- Schwab, K. (2016). The fourth industrial revolution. In *World Economic Forum* (Vol. 12).
- Sekaran, U., & Bougie, R. (2016). *Research methods for business: A skill building approach*. John Wiley & Sons.
- Senge, P. M. (2006). *The fifth discipline: The art and practice of the learning organization*. Broadway Business.
- Shah, S. I. H., Peristeras, V., & Magnisalis, I. (2021). Government big data ecosystem: definitions, types of data, actors, and roles and the impact in public administrations. *ACM Journal of Data and Information Quality*, 13(2), 1-25.

- Shamim, S., Cang, S., Yu, H., & Li, Y. (2016). Management Approaches for Industry 4.0. Evolutionary Computation (CEC), 2016 IEEE Congress, 5309-5316.
- Shi, W., & Dustdar, S. (2016). The promise of edge computing. *Computer*, 49(5), 78-81.
- Simon, M. K. (2011). *Dissertation and scholarly research: Recipes for success*. Dissertation Success, LLC.
- Singh, Y. K. (2006). *Fundamental of research methodology and statistics*. New Age International.
- Srinivasan, R., and Swink, M. (2018). An investigation of visibility and flexibility as complements to supply chain analytics: An organisational information processing theory perspective. *Production and Operations Management*, 27(10), 1849–1867. <https://doi.org/10.1111/poms.12746>
- Statista. (2021, May 17). *Global data creation is expected to reach 181 zettabytes by 2025 Statista*. <https://www.statista.com/chart/17727/global-data-creation-forecasts/>
- Stengel, R. (2021, October 20). Data drives the world. You need to understand it. *Time*. <https://time.com/6108001/data-protection-richard-stengel/>
- Subramoney, S., and Dagada, R. (2024). Big data analytics capabilities and competitive advantage in South Africa: The case for further research. In R. Dagada (Ed.), *Research In Southern African Digital Business* (Vol. 3, pp. 157–187). Mercury Books.
- Subramoney, S., and Dagada, R. (2025). Big data analytic capabilities and competitive advantage in South Africa. International Conference of Accounting and Business, University of Cape Town, 19–20 June 2025, Cape Town.
- Sultana, S., Akter, S., & Kyriazis, E. (2024). Theorising data-driven innovation capabilities to survive and thrive in the digital economy. *Journal of Strategic Marketing*, 32(7), 864-890.
- Tabachnick, B. G., Fidell, L. S., & Ullman, J. B. (2007). *Using multivariate statistics* (Vol. 5, pp. 481-498). Boston, MA: pearson.
- Taber, K. S. (2018). The use of Cronbach's alpha when developing and reporting research instruments in science education. *Research in Science Education*, 48, 1273–1296. <https://doi.org/10.1007/s11165-016-9602-2>

- Taherdoost, H. (2016). Sampling methods in research methodology. *International Journal of Academic Research in Management (IJARM)*, 5(2), 18–27.
<https://ssrn.com/abstract=3205035>
- Tashakkori, A. (2009). Foundation of Mixed Methods Research
- Teece, D. J. (2007). Explicating dynamic capabilities: The nature and micro-foundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28(13), 1319–1350. <https://doi.org/10.1002/smj.640>
- Teece, D. J. (2017). Business models and dynamic capabilities. *Long Range Planning*, 51(1), 40–50. <https://doi.org/10.1016/j.lrp.2017.06.007>
- Teece, D. J. (2018). Dynamic capabilities as (workable) management systems theory. *Journal of Management and Organisation*, 24(3), 359–368.
<https://doi.org/10.1017/jmo.2017.75>
- Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic management journal*, 18(7), 509-533.
- Teo, T. (2008). Understanding preservice teachers' attitudes towards computer use: An application and extension of the Technology Acceptance Model (TAM). *Australasian Journal of Educational Technology*, 24(4), 413–429.
<https://doi.org/10.14742/ajet.1201>
- Thacker, L. R. (2020). What is the big deal about populations in research?. *Progress in Transplantation*, 30(1), 3-3.
- Ubara, M. O. (2025). *Entrepreneurial orientation and business model innovation in small businesses: the moderating role of big data analytic capability* (Doctoral dissertation, The University of North Carolina at Charlotte).
- UNCTAD. (2021). *Digital Economy Report 2021: Cross-Border Data Flows And Development*. United Nations. https://unctad.org/system/files/official-document/der2021_en.pdf
- van de Wetering, R., Mikalef, P., & Dennehy, D. (2022, September). Artificial intelligence ambidexterity, adaptive transformation capability, and their impact on performance under tumultuous times. In *Conference on e-Business, e-Services and e-Society* (pp. 25-37). Cham: Springer International Publishing.
- van Zyl, S. (2022). *Big data in the public interest: applications, limitations, and relevance in the Western Cape Provincial Department of Agriculture* (Doctoral dissertation, Stellenbosch: Stellenbosch University).

- Venkatesh, V., Brown, S. A., and Bala, H. (2013). Bridging the qualitative–quantitative divide: Guidelines for conducting mixed methods research in information systems. *MIS Quarterly*, 37(1), 21–54.
<https://doi.org/10.25300/MISQ/2013/37.1.02>
- Vidgen, R., Shaw, S., and Grant, D. B. (2017). Management challenges in creating value from business analytics. *European Journal of Operational Research*, 261(2), 626–639. <https://doi.org/10.1016/j.ejor.2017.02.023>
- Walker, R. (2015). *From big data to big profits: Success with data and analytics*. Oxford University Press.
- Wamba, S. F., Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2015). How “big data” can make big impact: Findings from a systematic review and a longitudinal case study. *International Journal of Production Economics*, 165, 234–246. <https://doi.org/10.1016/j.ijpe.2014.12.031>
- Wamba, S. F., Akter, S., Trinchera, L., & De-Bourmont, M. (2021). Turning information quality into business value: a theoretical model and empirical analysis. *Inf Manag*, 57(3), 1-30
- Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J. F., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, 70, 356–365.
<https://doi.org/10.1016/j.jbusres.2016.08.009>
- Wamba, S. F., Ngai, E. W., Riggins, F., & Akter, S. (2017). Transforming operations and production management using big data and business analytics: future research directions. *International Journal of Operations & Production Management*, 37(1), 2-9.
- Wang, Y., and Hajli, N. (2017). Exploring the path to big data analytics success in healthcare. *Journal of Business Research*, 70, 287–299.
<https://doi.org/10.1016/j.jbusres.2016.08.002>
- Warner, K. S. R., and Wäger, M. (2019). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Planning*, 52(3), 326–349. <https://doi.org/10.1016/j.lrp.2018.12.001>
- Warren, J., & Marz, N. (2015). *Big Data: Principles and best practices of scalable realtime data systems*. Simon and Schuster.

- Welbotha, D. and van den Berg, C. 2024. Big data analytics capabilities and the organisational performance of South African retailers. *South African Computer Journal*. 36, 2 (Dec. 2024). <https://doi.org/10.18489/sacj.v36i2/17937>.
- Wilden, R., Gudergan, S. P., Nielsen, B. B., & Lings, I. (2013). Dynamic capabilities and performance: strategy, structure and environment. *Long range planning*, 46(1-2), 72-96.
- Wilson, B., & Cong, C. (2021). Beyond the supply side: Use and impact of municipal open data in the US. *Telematics and Informatics*, 58, 101526.
- Winter, S. G. (2003). Understanding dynamic capabilities. *Strategic Management Journal*, 24(10), 991–995. <https://doi.org/10.1002/smj.318>
- World Bank. (2020). *World development report 2021: Data for better lives*. World Bank Group. <https://www.worldbank.org/en/publication/wdr2021>
- World Economic Forum. (2024). Global risks report 2024. <https://www.weforum.org/reports/global-risks-report-2024/>
- Xie, K., Wu, Y., Xiao, J., and Hu, Q. (2016). Value co-creation between business and customers: The role of big data-based cooperative innovation. *Information and Management*, 53(8), 1034–1048. <https://doi.org/10.1016/j.im.2016.06.003>
- Ye, Y., Yu, Q. and Zheng, Y. (2022). Investigating the effect of social media application on firm capabilities and performance: The perspective of dynamic capability view, *Journal of Business Research*, 139, 510-519. ISSN 0148-2963. <https://doi.org/10.1016/j.jbusres.2021.10.008>
- Zack, M. H. (1999). Developing a knowledge strategy. *California Management Review*, 41(3), 125–145. <https://doi.org/10.2307/41166000>
- Zicari, R. V. (2014). Big data: Challenges and opportunities. *Big data computing*, 564, 103.

APPENDICES

APPENDIX A: PARTICIPANT SHEET FOR ONLINE QUESTIONNAIRE/ SURVEY

Dear Respondent

I am currently pursuing a PhD in the Graduate School of Business and Leadership at the University of South Africa, under the supervision of Prof. Rabelani Dagada. My research focuses on developing "A comprehensive framework for Big Data Analytics Capabilities and Competitive Advantage in South Africa."

I am writing to invite you to participate in an Online Questionnaire/Survey as part of this study. Your involvement would require approximately 10-15 minutes of your time. For academic rigour, responses will be securely stored on a password-protected computer and may be used for future secondary analysis by authorised researchers only.

The Questionnaire/Survey, will inquire about your professional background, including your job title, academic qualifications, and relevant experience. Please rest assured that all information shared will be treated confidentially and anonymously. Any data used in reporting the study results will be anonymised, ensuring your privacy is protected.

Your participation in this study is entirely voluntary, and you are free to withdraw at any time without consequence. There are no direct benefits for participating, nor will there be any costs incurred, including travel expenses. The risks associated with this study are minimal, akin to those encountered in everyday life.

Upon completion, the findings from this research will form the basis of my PhD thesis, which will be accessible through the university library website. If you would like, I would be happy to provide you with a summary of the thesis upon its completion.

Should you have any questions or require further clarification about the research study, please do not hesitate to contact me or my supervisor using the details provided

below. For ethics-related inquiries within Unisa's Graduate School of Business Leadership (SBL), you may also contact the Unisa Ethics Hotline at 0800 075 278 or via email at unisa@thehotline.co.za

Thank you for considering this invitation. I look forward to your favourable response.
Yours sincerely,

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**APPENDIX B: CONSENT FORM FOR PARTICIPATION IN ONLINE
QUESTIONNAIRE/ SURVEY**

Title of project: **A Comprehensive Framework for Big Data Analytics Capabilities
and Competitive Advantage in South Africa**

Name of researcher: Sivakumarie Subramoney (Mrs)

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

I agree to the following:

(Please circle the relevant options below)

The research study was explained to me. I understand what this study is about.	Yes	No

I understand that I can volunteer to take part in the study	Yes	No

I agree that the focus group interview may be audio recorded	Yes	No

I agree that direct quotations from the focus group interview may be used by the researcher in their PhD Thesis	Yes	No

I agree that my participation will remain anonymous (my name or other identifying data will not be used by the researcher in their PhD thesis)	Yes	No

I agree that other researchers may use the information I provide in the focus group interview (depending on their own ethics clearance being obtained) but my name and any personal information will not be used or passed on	Yes	No

Signature

Name of Participant

Date

Signature

Name of researcher/person seeking
consent

Date

APPENDIX C: ONLINE QUESTIONNAIRE/SURVEY

Title of Project: A Comprehensive Framework for Big Data Analytics Capabilities and Competitive Advantage in South Africa

I am a DBL student researching “**A Comprehensive Framework for Big Data Analytics Capabilities and Competitive Advantage in South Africa**”, under the supervision of Professor Rabelani Dagada, toward the partial fulfilment of a doctoral thesis. Please participate in my research by clicking on the link below. You will be directed to the questionnaire, where you are required to respond to questions by simply inserting a tick in the relevant box.

Your participation is voluntary, and all responses are confidential and anonymised. This survey will take approximately **10–12 minutes** to complete.

Should you have any questions, please contact the researcher:

Sivakumarie Subramoney – 38027429@unisa.ac.za

By continuing, you confirm that you are 18 years or older and that you consent to participate in this research.

You may also post comments if you wish to provide any suggestions.

Please feel free to pass this on or post it as your status. I will sincerely appreciate your support.

A. PARTICIPANT INFORMATION

1. Are you currently involved in decision-making processes regarding big data analytics?

YES	NO

2. How many years of experience do you have in a leadership or decision-making role related to big data analytics?

0 to 5	
5 to 10	
10 to 15	

15 to 20	
20 and above	

3. How would you describe your industry experience in relation to big data analytics?

TECHNOLOGY	
FINANCE	
HEALTHCARE	
MANUFACTURING	
RETAIL	
OTHER (SPECIFY)	

A. Business Experience

1. In your experience, how important do you perceive big data analytics to be in gaining a competitive advantage in your industry?

NOT IMPORTANT	
SOMEWHAT IMPORTANT	
IMPORTANT	

2. How do you believed big data analytics has influenced decision-making processes within organisations?

NOT INFLUENTIAL	
SOMEWHAT INFLUENTIAL	
INFLUENTIAL	

B. DATA CAPABILITIES

DATA

1. From your experience, how accessible are extensive datasets for analysis within organisations?

VERY LIMITED	
LIMITED	
EXTENSIVE	

2. In your opinion, how effectively do organisations integrate various data sources for analysis purposes?

NOT EFFECTIVE	
SOMEWHAT EFFECTIVE	
EFFECTIVE	

3. How valuable do you think internal and external data integration is for deriving insights in business environments?

NOT VALUABLE	
SOMEWHAT VALUABLE	
VALUABLE	

TECHNOLOGY

From your experience, how common is the adoption of parallel computing approaches like Hadoop for big data processing?

NOT COMMON	
SOMEWHAT COMMON	
COMMON	

1. In your opinion, what level of importance do organisations place on utilising data visualisation tools for analysing big data?

NOT IMPORTANT	
SOMEWHAT IMPORTANT	
IMPORTANT	

2. How prevalent is the use of new forms of databases like NoSQL for storing and managing data in your experience?

NOT PREVALENT	
SOMEWHAT PREVALENT	
PREVALENT	

HUMAN SKILLS

Technology Skills

Based on your observations, how equipped are big data analytics staff with the necessary skills for their roles?

LACKING	
PARTIALLY EQUIPPED	
EQUIPPED	

1. How effective do you believe the training programs provided to big data analytics staff are?

INEFFECTIVE	
SOMEWHAT EFFECTIVE	
EFFECTIVE	

Managerial Skills

In your experience, how well do big data analytics managers understand the business needs and collaborate with other functional managers, suppliers, and customers to explore opportunities?

POOR UNDERSTANDING	
PARTIAL UNDERSTANDING	
GOOD UNDERSTANDING	

1. How efficiently do big data analytics managers coordinate activities to support other functional managers, suppliers, and customers in your opinion?

INEFFICIENT	
SOMEWHAT EFFICIENT	
EFFICIENT	

2. How proficient are big data analytics managers in understanding and evaluating the insights extracted from big data?

NOT PROFICIENT		
SOMEWHAT PROFICIENT		

PROFICIENT		

Data-Driven Culture

1. From your perspective to what extent do organisations prioritise data-driven decision-making over intuition or gut feelings?

LOW PRIORITY	
MEDIUM PRIORITY	
HIGH PRIORITY	

2. How receptive do you find organisations to changing decisions based on data-driven insights, even if they contradict existing viewpoints?

NOT RECEPTIVE	
SOMEWHAT RECEPTIVE	
RECEPTIVE	

3. To what degree do organisations encourage employees to base their decisions on data-driven insights?

NOT ENCOURAGED	
SOMEWHAT ENCOURAGED	
ENCOURAGED	

C. Operationalising Sense, Seize, and Transform

Sensing

In your experience, how proactive are organisations in identifying new business opportunities through data analysis?

NOT PROACTIVE	
SOMEWHAT PROACTIVE	
PROACTIVE	

1. How frequently do organisations review their product development efforts based on customer insights derived from data analysis?

RARELY	
OCCASIONALLY	

FREQUENTLY	

2. To what extent do organisations use established processes to identify changing market trends and customer needs through data analysis?

NOT EXTENSIVELY	
SOMEWHAT EXTENSIVELY	
EXTENSIVELY	

Seizing

When opportunities or threats are identified through data analysis, how effectively do organisations explore potential solutions?

NOT EFFECTIVE	
SOMEWHAT EFFECTIVE	
EFFECTIVE	

1. How proficient are organisations in evaluating and selecting potential solutions derived from data analysis?

NOT PROFICIENT	
SOMEWHAT PROFICIENT	
PROFICIENT	

2. Once a potential solution is selected based on data analysis, how efficiently do organisations plan and execute its implementation?

INEFFICIENT	
SOMEWHAT EFFICIENT	
EFFICIENT	

Transforming

1. In your opinion, how successful are organisations in innovating and implementing new strategies based on insights derived from data analysis?

NOT SUCCESSFUL	
SOMEWHAT SUCCESSFUL	
SUCCESSFUL	

2. How adaptive are organisations in adjusting their business processes based on shifts in market trends identified through data analysis?

NOT ADAPTIVE	
SOMEWHAT ADAPTIVE	
ADAPTIVE	

3. To what extent do organisations reconfigure their business processes to capitalise on new opportunities identified through data analysis?

NOT EXTENSIVELY	
SOMEWHAT EXTENSIVELY	
EXTENSIVELY	

D. Operationalising Marketing Capabilities

1. How well do organisations utilise market knowledge derived from data analysis to inform their marketing strategies?

POORLY	
SOMEWHAT WELL	
WELL	

2. How effectively do organisations leverage their control and access to distribution channels based on insights derived from data analysis?

INEFFECTIVELY	
SOMEWHAT EFFECTIVELY	
EFFECTIVELY	

3. To what extent do organisations capitalise on advantageous relationships with customers identified through data analysis?

NOT MUCH	
MODERATELY	
SIGNIFICANTLY	

4. How established are the customer bases of organisations in your experience,

considering insights derived from data analysis?

NOT ESTABLISHED	
SOMEWHAT ESTABLISHED	
ESTABLISHED	

5. How efficient and effective are the production/services of organisations based on insights derived from data analysis?

INEFFICIENT/INEFFECTIVE	
SOMEWHAT EFFICIENT/EFFECTIVE	
EFFICIENT/EFFECTIVE	

E. Operationalising Technological Capabilities

1. On a scale of 1 to 7, how effectively do organisations leverage their technological capabilities to enhance big data processing and analysis?

1 (Not Effective) - 7 (Highly Effective)

1	2	3	4	5	6	7

2. On a scale of 1 to 7, how would organisations utilise advanced technologies for data visualisation and interpretation?

1 (Poor) - 7 (Excellent)

1	2	3	4	5	6	7

3. On a scale of 1 to 7, how proficiently do organisations implement and optimise various databases, such as NoSQL, to store and manage large datasets?

1 (Not Proficient) - 7 (Highly Proficient)

1	2	3	4	5	6	7

4. On a scale of 1 to 7, how actively do organisations stay updated with emerging technologies and trends in big data analytics?

1 (Not Active) - 7 (Highly Active)

1	2	3	4	5	6	7

F. Operationalisation of Competitive Performance

On a scale of 1 to 7, how successfully do organisations achieve higher profitability compared to competitors?

1 (Not Successful) - 7 (Highly Successful)

1	2	3	4	5	6	7

1. On a scale of 1 to 7, how effectively do organisations measure and enhance their return on investment (ROI) compared to competitors?

1 (Not Effective) - 7 (Highly Effective)

1	2	3	4	5	6	7

2. On a scale of 1 to 7, how would you rate an organisation's ability to gain a larger market share compared to competitors?

1 (Poor) - 7 (Excellent)

1	2	3	4	5	6	7

3. On a scale of 1 to 7, how well do organisations achieve significant sales growth compared to competitors within your industry?

1 (Not Well) - 7 (Very Well)

1	2	3	4	5	6	7

4. On a scale of 1 to 7, how promptly do organisations respond to changing market demands compared to competitors?

1 (Slowly) - 7 (Very Quickly)

1	2	3	4	5	6	7

5. On a scale of 1 to 7, how efficiently do organisations reduce operating costs compared to competitors?

1 (Inefficiently) - 7 (Very Efficiently)

1	2	3	4	5	6	7

6. On a scale of 1 to 7, how effectively do organisations prioritise and enhance customer satisfaction compared to competitors?

1 (Not Effective) - 7 (Highly Effective)

1	2	3	4	5	6	7

Please rate each question according to the provided scale. Your feedback is appreciated!

Thank you for your cooperation! Your insights are invaluable to our research.

APPENDIX D: CONSENT FORM FOR SEMI-STRUCTURED INDIVIDUAL INTERVIEWS

Title of project: **A COMPREHENSIVE FRAMEWORK FOR BIG DATA ANALYTICS CAPABILITIES AND COMPETITIVE ADVANTAGE IN SOUTH AFRICA**

Name of researcher: Sivakumarie Subramoney (Mrs)

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

I agree to the following:

(Please circle the relevant options below)

The research study was explained to me. I understand what this study is about.	Yes	No
I understand that I can volunteer to take part in the study	Yes	No
I agree that the focus group interview may be audio recorded	Yes	No
I agree that direct quotations from the focus group interview may be used by the researcher in their PhD Thesis	Yes	No
I agree that my participation will remain anonymous (my name or other identifying data will not be used by the researcher in their PhD thesis)	Yes	No
I agree that other researchers may use the information I provide in the focus group interview (depending on their own ethics clearance being obtained) but my name and any personal information will not be used or passed on	Yes	No

Signature

Name of Participant

Date

Signature

Name of researcher/person seeking consent

Date

APPENDIX E: PARTICIPANT SHEET FOR INDIVIDUAL SEMI-STRUCTURED INTERVIEWS

Dear Respondent

I am currently pursuing a PhD in the Graduate School of Business and Leadership at the University of South Africa, under the supervision of Prof. Rabelani Dagada. My research focuses on developing **"A Comprehensive Framework for Big Data Analytics Capabilities and Competitive Advantage in South Africa."**

I am writing to invite you to participate in an individual interview as part of this study. Your involvement would require approximately one hour of your time. Depending on your preference, the interview can be conducted either at your office or through an online meeting platform such as MS Teams, Google meet or Zoom.

For academic rigour, I would like to record the interview with your permission. The audio recordings will be securely stored on a password-protected computer and may be used for future secondary analysis by authorised researchers only.

During the interview, I will inquire about your professional background, including your job title, academic qualifications, and relevant experience. Please rest assured that all information shared will be treated confidentially and anonymously. Any data used in reporting the study results will be anonymised, ensuring your privacy is protected.

Your participation in this study is entirely voluntary, and you are free to withdraw at any time without consequence. There are no direct benefits for participating, nor will there be any costs incurred, including travel expenses. The risks associated with this study are minimal, akin to those encountered in everyday life.

Upon completion, the findings from this research will form the basis of my PhD thesis, which will be accessible through the university library website. If you would like, I would be happy to provide you with a summary of the thesis upon its completion.

Should you have any questions or require further clarification about the research study, please do not hesitate to contact me or my supervisor using the details provided below. For ethics-related inquiries within Unisa's Graduate School of Business

Leadership (SBL), you may also contact the Unisa Ethics Hotline at 0800 075 278 or via email at unisa@thehotline.co.za

Thank you for considering this invitation. I look forward to your favourable response.

Yours sincerely,

SIVAKUMARIE SUBRAMONEY (Student Number: 38027429)

PhD Candidate in Digital Transformation, UNISA

Department of Digital Transformation and Supply Chain Management

Graduate School of Business and Leadership, UNISA

Email1: 38027429@mylife.unisa.ac.za

Cell: + 27 730830125

Prof. Rabelani Dagada

Chair of Department: Digital Transformation and Supply Chain Management

Associate Professor: ICT

Graduate School of Business and Leadership, UNISA

Email2: dagadr@unisa.ac.za

Cell: +27 73 214 0174

APPENDIX F: SEMI-STRUCTURED INDIVIDUAL INTERVIEWS GUIDE

Project Title: A COMPREHENSIVE FRAMEWORK FOR BIG DATA ANALYTICS CAPABILITIES AND COMPETITIVE ADVANTAGE IN SOUTH AFRICA

Introduction (2–3 minutes)

Interviewer to say:

“Thank you for agreeing to participate. This interview will take approximately 30 minutes. All information you share will be kept confidential and used only for academic research. You may withdraw at any time or skip questions if you are not comfortable answering. Do I have your permission to record this session for transcription purposes?”

✓ Confirm informed consent ✓ Confirm audio recording

QUESTIONS

1. What resources do you utilise or have access to in facilitating the use of big data?
2. Can you elaborate on how you utilise these resources to support big data initiatives?
3. Could you expand on your personal experiences with data analytics and how you perceive its value-adding properties?
4. How would you define competitive performance from your perspective as a business leader, and how do you personally measure this?
5. In your role as a business leader, do you employ dynamic capabilities, and if so, how do you apply them within your big data initiatives?
6. What resources, both internal and external, do you personally utilise to build and enhance operational capabilities related to big data analytics, and how do you incorporate them into your leadership approach?
7. Can you provide specific insights into how you utilise big data analytics within your decision-making processes and strategic planning efforts?
8. Specifically, what types of data do you find most valuable, and how do you ensure the quality and durability of this data in your analysis?
9. From your perspective, how do technological advancements, such as analytical tools and advanced data visualisation (ADV) tools, contribute to the success of big data initiatives?

10. As a business leader, what roles do you see yourself and your colleagues playing in driving a data-driven culture within, and what challenges and strategies have you encountered or implemented in this regard?
11. How do you personally assess the potential benefits of big data analytics, and what different usage scenarios have you observed or implemented?
12. Additionally, how agile is your organisation in adopting new insights derived from data analytics?

FINAL WORDS

Thank you for your time and for sharing your insights. These questions aim to delve into your personal experiences and perspectives as a business leader in the realm of big data analytics. Your insights are invaluable to our research, and we appreciate your participation. If you would like to receive a summary of the findings, please let me know.

APPENDIX G – RESEARCH ETHICS CLEARANCE

Graduate School of Business Leadership, University of South Africa, PO Box 392, Unisa, 0003, South Africa
Cnr Janadel and Alexandra Avenues, Midrand, 1685, Tel: +27 11 652 0000, Fax: +27 11 652 0299
E-mail: sbl@unisa.ac.za Website: www.unisa.ac.za/sbl

SCHOOL OF BUSINESS LEADERSHIP RESEARCH ETHICS REVIEW COMMITTEE (GSBL CRERC)

03 May 2024

Ref #: 2022_SBL_DBL_022_FA
Name of applicant: Ms S Subramoney
Student #: 38027249

Dear Mrs S Subramoney

Decision: Ethics Approval

Student: Mrs S Subramoney (38027249@mylife.unisa.ac.za ; 073 083 0125)

Supervisor: Prof R Dagada, (rdagadr@unisa.ac.za ; 073 214 0174)

Project Title: Big data analytics capabilities and competitive advantage.

Qualification: Doctor of Business Leadership (DBL)

Expiry Date: April 2027

Thank you for applying for research ethics clearance, SBL Research Ethics Review Committee reviewed your application in compliance with the Unisa Policy on Research Ethics.

Outcome of the SBL Research Committee:
Approval is granted until April 2027.

The application was reviewed in compliance with the Unisa Policy on Research Ethics by the SBL Research Ethics Review Committee on the 03/05/2024.

The proposed research may now commence with the proviso that:

- 1) The researcher will ensure that the research project adheres to the relevant guidelines set out in the Unisa Covid-19 position statement on research ethics attached
- 2) The researcher/s will ensure that the research project adheres to the values and principles expressed in the UNISA Policy on Research Ethics.
- 3) Any adverse circumstance arising in the undertaking of the research project that is relevant to the ethicality of the study, as well as changes in the methodology, should be communicated in writing to the SBL Research Ethics Review Committee.
- 4) An amended application could be requested if there are substantial changes from the existing proposal, especially if those changes affect any of the study-related risks for the research participants.
- 5) The researcher will ensure that the research project adheres to any applicable national legislation, professional codes of conduct, institutional guidelines and scientific standards relevant to the specific field of study.

45
years

Building leaders who go beyond



Graduate School of Business Leadership, University of South Africa, PO Box 392, Unisa, 0003, South Africa
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E-mail: sbl@unisa.ac.za Website: www.unisa.ac.za/sbl

Kind regards,

NBW Mitwa

Prof N Mitwa

Chairperson: SBL Research Ethics Committee

011 - 652 0000 / niltonb@unisa.ac.za

P Msweli

Prof P Msweli

Executive Dean: Graduate School of Business Leadership

011- 652 0256 / mswelp@unisa.ac.za

45 Building leaders who go beyond



ANNEXURE H: TRANSCRIPT OF QUALITATIVE INTERVIEWS

Data analysis meeting (2024-07-17 12:35 GMT+2) – Transcript

Attendees

Researcher and Participant 3

Transcript

This editable transcript was computer generated and may contain errors. People can also change the text after it was created.

Researcher:

Good afternoon and thank you so much for joining me today. Before we begin, I want to confirm that this interview forms part of my doctoral research on Big Data Analytics Capabilities in South African organisations. Everything you share will remain confidential, and you're welcome to pause or stop the interview at any time. With your permission, I would like to record our session for accuracy. Is that okay with you?

Participant 3:

Yes, that's perfectly fine. You can go ahead and record.

Researcher:

Thank you. To start us off, could you briefly tell me about your current role, the organisation you're working in, and how long you've been in this position?

Participant 3:

Sure. I'm currently a manager in the retail sector. I've been with the company for just over two years, and I've been in this specific role for the same amount of time. What I handle mainly are customer engagement activities, campaign performance analytics, and the broader sales insights for our retail operations. It's a very data-intensive role, even though my background is actually in law, I have an LLB but in retail, data drives almost everything now.

00:10:00

Researcher: Thank you. Let's move to the first interview question.

Question 1: What resources do you utilise or have access to in facilitating the use of big data?

Participant 3: We use a wide range of data sources. In retail, data comes from everywhere. And honestly, *"we collect data from everywhere but there is no formal roadmap for what happens next."*

We collect loyalty card behaviour data, online browsing data, mobile app interactions, in-store transaction data, and even store-movement analytics in some branches. But after collecting all that, there really isn't a structured process outlining who uses the data, how quickly insights should be escalated, or which business unit owns the next step.

That's why I've said before: *"the insights do not flow up to inform business units in real time, which defeats the purpose of predictive analytics."*

Retail moves fast, and without a coordinated data pipeline, we lose time and competitive edge.

00:15:00

Researcher: Thank you.

Question 2: Can you elaborate on how you utilise these resources to support big data initiatives?

Participant 3: We try to make the best of what we have. When insights reach us timeously, we use them for campaign planning, stock optimisation, customer segmentation, and to understand behavioural shifts. For example, we often use purchase frequency data and loyalty metrics to adjust promotions.

However, because the flow of insights is inconsistent, a lot of our work becomes reactive instead of proactive. We are acting on what happened, not what is likely to happen next.

Researcher: Thank you.

Question 3: Could you expand on your personal experiences with data analytics and how you perceive its value-adding properties?

Participant 3: When analytics work, it's incredibly powerful. For example, *"improved segmentation through clustering techniques helped us increase our campaign hit rates. That had a direct impact on our sales."*

Another strong example is our new loyalty platform. *"Without our analytics capabilities, we would not have been able to develop our new customer loyalty platform it's now a key differentiator."*

So yes, when analytics is used well, the value is obvious. The challenge is maintaining that value consistently across departments.

00:30:00

Researcher: Let's go to the next question.

How would you define competitive performance from your perspective as a business leader, and how do you personally measure this?

Participant 3: In retail, competitive performance is basically the ability to stay ahead of shifting customer needs. If you understand your customer faster than your competitor does, you survive. So, for us, competitive performance includes campaign success, revenue lift, growth in returning customers, engagement on digital platforms all of that.

It's really about being responsive to what the data is showing.

Researcher:

Thank you. And now **Question 5: In your role as a business leader, do you employ dynamic capabilities, and if so, how do you apply them within your big data initiatives?**

Participant 3: We try, but it's difficult. To be honest, *"we spend more time repairing data than analysing it."*

The reason is that *"there are no enterprise-wide data ownership frameworks, so nobody is responsible for data quality."*

Before we can sense or respond in the dynamic capabilities sense, we're still fixing foundational issues like duplicate entries, missing values, inconsistent store codes, things that shouldn't be happening at this scale. So yes, dynamic capabilities are the goal, but data quality slows us down significantly.

00:40:00

Researcher: Thank you.

Question 6: What resources, both internal and external, do you personally utilise to build and enhance operational capabilities related to big data analytics?

Participant 3: People are the most important resource, if we can retain them. Right now, *"we are losing talent to Europe and the US. Local business can't compete on salaries for top data scientists."*

Externally, we sometimes rely on consultants, but that becomes expensive. And even when the right tools are available, *"if your people are not open to using data in their daily decisions, then it all collapses."*

So operational capabilities are a mix of tools, systems, and the right mindset.

Researcher: Thank you.

Can you provide specific insights into how you utilise big data analytics within your decision-making processes and strategic planning efforts?

Participant 3: I use data to monitor weekly sales patterns, campaign performance, customer movement, loyalty activity, and even store-level operational metrics. Data shapes almost every decision.

But the biggest limitation is timing. If we had consistent real-time insights, we could prevent losses instead of responding to them.

Researcher: Thank you. You are doing great.

And let's move to question 8. We are getting there. Specifically, what types of data do you find most valuable, and how do you ensure the quality and durability of this data?

Participant 3: Behavioural data is the most valuable. Things like purchasing patterns, store visitation frequency, and product affinity.

Quality is the challenge. As I mentioned, we still spend huge amounts of time fixing errors. There's no unified data governance structure.

Researcher: Thank you so much.

From your perspective, how do technological advancements such as analytical tools and advanced data visualisation contribute to the success of big data initiatives?

Participant 3: The tools themselves are great. Dashboards, predictive models, segmentation tools help a lot.

But again, *"the tools are there, but if your people are not open to using data in their daily decisions, then it all collapses."*

So, the tools help, but they don't create a data-driven culture by themselves.

00:55:00

Researcher: Thank you.

As a business leader, what roles do you see yourself and your colleagues playing in driving a data-driven culture?

Participant 3: I think leadership needs to set the example by using data visibly and consistently. If leaders don't use data, others won't either. But cultural change is slow in many South African companies people are still comfortable doing things as they've always been done.

Researcher: Thank you. I will now ask you the two final questions together.

How do you personally assess the potential benefits of big data analytics, and how agile is your organisation in adopting new insights derived from data analytics?

Participant 3: Big data can absolutely transform retail. But agility is limited by both internal and external factors.

For example, *“compliance with data protection regulations held back our analytics deployment by six months.”*
And on top of that, *“load-shedding disrupts our data centres; it’s hard to run real-time analytics when the power isn’t stable.”*

So, agility is compromised by things that are sometimes beyond the organisation’s control.

Researcher: Before we close, is there anything else you’d like to add about how big data could be improved in the retail sector?

Participant 3: Just that the potential is definitely there, the data is there, but unless we sort out the fundamentals like quality, accountability, culture, and infrastructure, we won’t unlock the full value. A proper data governance framework would make a massive difference.

Researcher: Thank you very much. I really appreciate your time and your insights. They will be very valuable for the study.

Participant 3: It’s a pleasure. Happy to assist.

Meeting ended after 00:55:00 🙌