Gordon Institute of Business Science
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Leveraging Big Data Analytics for Competitive Advantage in South African Banking

By

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ABSTRACT

Big data is considered a form of capital and source of competitive advantage. This proliferation of data has the promise of transforming business process, altering corporate ecosystems and unlocking business value through the strategic and operational implications of better informed decision making and enhanced organisational responsiveness. Furthermore, the big data era has new implications for understanding consumer behaviour and formulating marketing strategy. Despite the promise of the big data revolution being a source of competitive advantage and superior organisational performance, organisations lack the ability to create difficult to match capabilities to effectively leverage big data for competitive advantage.

The research explores leveraging big data analytics for competitive advantage in South African banking. Data was collected through 11 semi-structured, in depth interviews with experts from the South African banking industry. Thematic analysis of the qualitative interview data provided insights into leveraging big data analytics for competitive advantage in South African banking, particularly, the industries utilisation of big data analytics, the adequacy of the methodologies employed for the processing of big data and the resource and capability requirements.

The research establishes that in strategizing around leveraging big data capabilities, it is imperative that South African banking is cognisant of the key role that top management emphasis, inter-departmental dynamics and organisational design plays in the development and leveraging of these capabilities. Furthermore, the research accentuates the importance of the embodiment of a data-oriented culture to facilitate the organisation to sense, seize and execute on opportunities.

KEYWORDS

Big Data, Analytics, Competitive Advantage, Strategy, Market-orientation, Capability

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DECLARATION

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

Dinesh Ramsunder Buldoo

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1.1 Introduction

Peter Drucker (1954), the father of modern management made the timeless statement that, “There is only one valid definition of business purpose: to create a customer… It is the customer who determines what the business is… any business enterprise has two- and only these two basic functions: marketing and innovation. Marketing and innovation produce results; all the rest are costs” (p. 144).

Marketing and innovation encompasses the capability of organisations to utilise superior skills to extract insights for understanding and satisfying customers (Day, 1994, Kohli & Jaworski, 1990). These functions are at the epicentre of the big data analytics movement since individual consumers generate rich and plentiful data in real time which through advantageous interpretation can result in the extraction of hidden consumer insights that can be exploited for competitive advantage (Erevelles, Fukawa, & Swayne, 2015). The big data revolution is seen as the key platform for innovation, competition and productivity (Lycett, 2013). Premised on big data and big data analytics being perceived as the ultimate marketing and innovation asset in contemporary business, this exploratory research seeks to understand how big data analytics can be leveraged for competitive advantage in South African banking.

1.2 Background to the Research Problem

Superior performance is achieved through conceiving and implementing competitive strategy which enables organisations to acquire and maintain sustainable competitive advantage (Bharadwaj, Varadarajan, & Fahy, 1993; Barney, 1991; Slater & Narver, 1994). Sustainable competitive advantage is accomplished when an organisation is creating more economic value than the marginal organisation in its industry, the benefits of their value creating strategy cannot be duplicated by other organisations in its industry, and when this value creating strategy is not being simultaneously implemented by current or potential competitors in the industry (Barney, 1991; Barney & Clark, 2007; Kozlenkova, Samaha, & Palmatier, 2013).

Traditionally, competitive strategy in pursuit of superior organisational performance and sustained competitive advantage has been externally focussed on opportunities and threats, internally focussed on strengths and weaknesses (Barney, 1991) or focussed on exploiting internal strengths in response to external opportunities while defusing threats and avoiding internal weakness (Barney, 1991; Black & Boal, 1994). Grant (1991) argued that competitive strategy during the 1980's predominantly focussed on the link to the external environment while the focus in the 1990's shifted to looking towards the organisations internal capabilities as a source of competitive advantage. Extant research in the 1990's confirms that the focus of competitive strategy has moved towards leveraging internal capabilities to consistently deliver superior customer value (Barney, 1991; Black & Boal, 1994; Slater & Narver, 1994) and generate higher than average market returns (Moorman & Slotegraaf, 1999).

The focus on leveraging internal capabilities for sustainable competitive advantage led to the emergence of the resource-based view of the organisation and the resultant resource-based theory (Barney, 1991; Barney & Clark, 2007; Grant, 1991; Kozlenkova et al., 2013; Peteraf, 1993; Peteraf & Barney, 2003; Vorhies & Morgan, 2005; Wernerfelt, 1984). Resource-based theory analyses organisations from a resource perspective rather than a product perspective (Wernerfelt, 1984), integrates an economic view with a management view (Peteraf & Barney, 2003) and serves as a framework for predicting and explaining competitive advantage and organisational performance outcomes (Kozlenkova et al., 2013).

The contemporary environment of business is characterised by hyper competition (Erevelles et al., 2015) and rapid changes (Beer, Voelpel, Leibold, & Tekie, 2005). Knowledge is created, acquired, disseminated and rendered obsolete at a constantly increasing rate, therefore knowledge only serves as a momentary competitive advantage (Erevelles, Horton, & Fukawa, 2007). Premised on this high velocity and turbulent business environment, Erevelles et al. (2007) introduced the concept of imaginative intensity, which is defined as the rate at which an organisation generates and utilises ideas. Erevelles et al. (2007) further asserts that the organisations ability to maintain competitive advantage is not based only on their knowledge, but also on their imaginative intensity, which is said to be a key contributor to an organisations innovation capability, product development strategy and future success. These paradigms postulate that external information, particularly market based organisational learning is a fundamental prerequisite for stimulating imaginative intensity and providing the organisation with the opportunity to gain insights from environmental data and respond to environmental changes thereby achieving competitive advantage.

Achievement of competitive advantage therefore necessitates organisations to constantly learn and adapt by updating and reconfiguring resources (Beer et al. 2005; Erevelles et al. 2015). Moorman and Slotegraaf (1999) posited that the most valuable characteristic of organisational capabilities may be their ability to serve as flexible strategic options, which is the ability to adapt to changes in the external environment. The ability to reconfigure, extend and upgrade resources for the organisation to serve as a flexible strategic option aligns to the dynamic capabilities construct (Erevelles et al., 2015; Kozlenkova et al., 2013; Moorman & Slotegraaf, 1999). Asset configuration has applicability to the organisations ability to modify and reconfigure assets with the view of creating new value (Erevelles et al., 2015; Fang, Palmatier, & Grewal, 2011). This is based on the key role that the optimal asset configuration plays in enabling the organisation to dynamically respond to environmental changes and better serve customer needs (Day, 2014; Kozlenkova et al., 2013; Teece, Pisano, & Shuen, 1997).

The organisational learning concept aligns with Gianiodis, Ellis and Seechi's (2010) assertions that inbound and outbound knowledge flows, that is knowledge exchange between the organisation and its environment, particularly systematic knowledge exploration, retention and exploitation are mandatory to the innovation process (Greer & Lei, 2012). Extant research by Han, Kim, and Srivastava (1998) provides empirical evidence that market orientation, particularly market orientation is a key antecedent to innovation and superior organisational performance.

Consistency between these constructs and more recent research is noted, particularly research on market orientation, continuous market-based learning, collaborative innovation with customers and co-creation (Day, 2011; Greer & Lei, 2012; Vorhies & Morgan, 2005). Pertinent examples includes Vorhies and Morgan's (2005) research which evidences the positive correlation between superior organisational performances, market-based learning and marketing capabilities and Day's (2011) research which concludes that organisational focus on marketing capabilities enhances market insights and the capability to anticipate environmental changes and unmet needs. These capabilities promote innovation, sustainable competitive advantage and superior organisational performance (Barney., 1991; Day, 2011; Erevelles et al., 2015; Han et al., 1998; Greer & Lei, 2012; Johnson et al., 2017, Lycett, 2013; Gupta & George, 2016, Slater & Narver, 1994; Vorhies & Morgan, 2005, Wamba, Akter, Edwards, Chopin, & Gnazou, 2015).

Greer and Lei (2012) argued that collaborative innovation with customers is important for the development of innovative products and services. The importance of synthesis between a product or service offering and what the customer really wants is demonstrated by Ries (2011), where the concept of validated learning is introduced as key to start up success and constant innovation in established organisations. Validated learning is premised on empirical data being collected from customers (Ries, 2011). Constant innovation success in organisations is also contingent on reducing and eliminating waste, which is characterised by any effort that is not necessary for learning what the customer wants and adding to the customers value proposition (Ries, 2011).

These arguments suggest that competitive advantage can be achieved through the organisation developing and effectively leveraging the pertinent internal capabilities to respond to the external environment based on market intelligence and foresight. This is contingent on strategy being devised and implemented to facilitate the effective generation, analysis and advantageous interpretation of data to induce the development of innovative products, services and target marketing initiatives which resonates with markets requirements.

Contemporary business is characterised by a proliferation of data, termed “big data”, which is transforming marketing, product and service development, competitive strategy and business in its entirety (Erevelles et al., 2015; Johnson et al., 2017; Junque de Fortuny, Gupta & George, 2016, Martens, & Provost, 2013; Provost & Fawcett, 2013, Wamba et al., 2015). Big data is characterised by an unparalleled volume, variety and velocity of real time structured and unstructured consumer data (Erevelles et al., 2015; Johnson et al., 2017; Lycett, 2013), particularly big data and big data analytics describes large (petabytes, exabytes or zettabytes in magnitude) and complex datasets requiring advanced gathering, storage and analysis technologies (Chen et al., 2012; Erevelles et al., 2015).

Big data is considered a form of capital and source of competitive advantage since it is viewed as a means for facilitating data driven decision making thus enabling managers to align their organisational strategies to market demands (Erevelles et al., 2015; Johnson et al., 2017). Data mining refers the extraction of important environmental information from large quantities of data to facilitate superior organisational decision making (Hormazi & Giles, 2004). Business Intelligence is related to big data (Chen, Chiang, & Storey, 2012) and has technological roots that encompasses the resources required for the effective capturing, analysis and representation of data to facilitate effective decision making (Lycett, 2013). The increased availability of data provides impetus for business intelligence since data is its fundamental resource (Lycett, 2013). Chen et al. (2012) asserts that business intelligence, through leveraging big data and big data analytics can facilitate data driven decision making in high impact and critical areas. Market and customer orientation including consumer purchase and consumption behaviour, post purchase evaluation and engagement and problem identification are the key drivers of interest in big data (Hofacker, Malthouse, & Sultan, 2016).

Hormazi and Giles (2004) argued that the banking industry generates a wealth of data which can be leveraged for competitive advantage through data mining. The effective analysis of trends and patterns in large data sets enables the banking industry to exploit big data to increase the accuracy of their predictive analytics, particularly in the areas of target marketing for cross and upselling, mass customisation, product development based on customer needs, risk management, fraud detection and customer acquisition, retention and attrition analytics (Hormazi & Giles, 2004).

Predictive analytics is one of the best understood methods to utilise data for improved decision making (Junque de Fortuny et al., 2013). Effective analytics has been cited as a differentiator between top performing and lower performing organisations, with the top organisation's decisions being data driven through rigorous analytics (Lavelle, Hopkins, Lesser, Shockley, & Kruschwitz, 2010). Research by Wamba, Akter, Edwards, Chopin and Gnazou (2015) indicates that big data is evolving and therefore it is key for organisations to build the capabilities to leverage the same for competitive advantage.

1.3 Research Problem

Gupta and George (2016), professed that big data literature lacks theoretical foundations due it being published predominantly by technology consultants. This results in the paradox of only a small percentage of organisations being able to realise the benefits of big data and big data analytics despite the promise of the transformative potential of big data (Gupta & George, 2016).

Martens et al. (2016) contended that while there is hype over big data and the success of predictive analytics, most organisations utilise big data in a very aggregated form rather than in a non-aggregated form utilising fine grained data for predictive analytics.

The improvement from moving to big data while aggregating this data into traditional structured data for the purposes of fitting into traditional analytics methods is not appreciable, while there is substantial value when using big data in its fine-grained form (Martens et al., 2016).

Gupta and George (2016) argued that research evidencing the economic benefits of big data is still in the early stages and while a large number of organisations already have invested or have plans to invest in big data capabilities little is known about how organisations should go about building these big data capabilities. Despite significant interest in big data and analytics capabilities, inconsistencies between business intelligence and analytics capabilities and organisational performance have been cited (Torres, Sidorova, & Jones, 2018). In some cases, organisations even experienced declines in competitive performance (Kiron, Shockley, Kruschwitz, Finch, & Haydock, 2011). Organisations are making substantial investments in big data capabilities; however, they largely lack understanding of how to effectively leverage these capabilities to create a competitive advantage (Johnson et al., 2017; Lavelle et al., 2010). The failure of organisations to benefit from big data has been ascribed to their inability to understand the physical, human and organisational capital resource requirements (Erevelles, Fukawa, & Swayne, 2015). While it is important to understand the organisations big data resource requirements, the specific inter relationships between these assets, which lead to effectively exploiting the same for sustainable competitive advantage need also be considered (Black & Boal, 1994; Fang, Palmatier, & Grewal, 2011; Johnson et al., 2017; Moorman & Slotegraaf, 1999).

Martens et al. (2016) argued that while the banking sector is privy to large volumes of structured, semi-structured and unstructured data in the form of the financial transactions they observe; this wealth of big data is generally not being leveraged for target marketing and predictive analytics applications. The traditional analytics methods predominantly employed in the banking sector fails to exploit the wealth of consumer behaviour data gathered since these methods aggregate unstructured behavioural data into traditional structured data comprising a relatively small set of variables suitable for traditional analytics methods (Martens et al., 2016). This inability to effectively leverage big data has been attributed to the volume of data being beyond the capabilities of traditional methods or because data scientists are not convinced of the value in changing their methods (Martens et al., 2016). As per Provost and Fawcett (2013), data science is intricately intertwined with big data and data driven decision making; however, there is confusion as to what exactly data science is.

The paradigms presented above suggests that, while the big data revolution is viewed as a source of competitive advantage, a gap exists in the organisations ability to effectively leverage the same. It is proposed that the key contributors are; (1) organisations generally lack understanding of how to utilise big data and big data analytics for competitive advantage, (2) the methodologies employed for the processing of big data is inadequate since big data is generally aggregated into a few variables to fit traditional analytic methods (Martens et al., 2016), (3) organisations generally lack understanding of the specific big data resource requirements (Erevelles et al., 2015), and (4) organisations generally lack understanding of the inter-relationships between big data assets, specifically they lack understanding of how to create big data capabilities (Gupta & George, 2016; Johnson et al., 2017; Moorman & Slotegraaf, 1999).

The challenges presented above are deemed to be detrimental since they render big data investments unwarranted and foster the inability to achieve sustainable competitive advantage and superior performance. It is proposed that it also results in the organisation becoming static due to its inability to timeously sense and respond to environmental changes in the contemporary dynamic and hyper competitive market place.

1.4 Purpose of the Research

The purpose of the research is to understand the current big data resource and capability challenges in South African banking by exploring the issues identified in the preceding section to gain insights as to how to create the requisite big data capabilities, that can be leveraged for competitive advantage.

In particular, the research aims to; (1) Establish how big data analytics is used in South African banking for competitive advantage, (2) Determine to what extent the methodologies employed for the processing of big data is considered adequate to leverage big data analytics as source of competitive advantage in South African banking, (3) To determine what are the specific big data resource requirements for leveraging it as a source of competitive advantage in South African banking, and (4) Explore the role of the inter-relationships between big data assets in leveraging big data analytics as source of competitive advantage in South African banking.

1.5 Scope of Research

The scope of the research is confined to gaining insights into leveraging big data analytics for competitive advantage in the South African banking industry. This industry was selected based on; (1) big data and analytics being high on their strategic agendas for attaining competitive advantage (Hormazi & Giles, 2004; Martens et al., 2016), (2) the banks being privy to an unprecedented volume, velocity and variety of real time primary data (Erevelles et al., 2015, Martens et al., 2016) resulting in a large amount of applications for big data analytics (Hormazi & Giles, 2004), and (3) the anticipated challenges in migrating banking to big data technologies as a result of various sources of data traditionally being located in decentralised legacy database technologies and on multiple platforms (Krishna, 2016, Wamba et al., 2015). It is expected that the ability to leverage big data analytics in South African banking will require a structured, coordinated and coherent approach. Premised on these complexities it is anticipated that the banking industry would yield rich insights, which may be applicable to the financial services industry as well as other industries. The scope is also confined to understanding the constituents for leveraging big data analytics that are within the organisations control; hence, exogenous factors that are deemed to be beyond the banks control will be cited but not be explored at depth.

1.6 Relevance and motivation for the research

The arguments presented in the preceding sections evidences that organisations are looking to capitalise on the big data analytics movement in their quest for competitive advantage and superior performance. The ability to realise the benefits of stronger customer and market orientation (Day, 2011; Han et al., 1998; Slater & Narver, 1994; Vorhies & Morgan, 2005), making data driven decisions, crafting superior competitive strategy (Barney. , 1991, Erevelles et al., 2015, Johnson et al., 2017, Lycett, 2013, Moorman & Slotegraaf, 1999) and being an agile learning organisation by dynamically attaining alignment between the organisation and the external environment (Barney. , 1991; Black & Boal, 1994; Day, 2014; Fang et al., 2011) results in organisations investing heavily in big data capabilities (Johnson et al., 2017; Gupta & George, 2016, Martens et al., 2016).

Premised on extant literature suggesting that organisations generally lack understanding of big data capability requirements and how this capability can be leveraged for competitive advantage (Johnson et al., 2017, Gupta & George, 2016, Martens et al.,

2016) it can be inferred that organisations are not entirely coherent and strategic in their big data capability investments. Therefore, it is prudent that business gains an understanding of these inadequacies and how to create the requisite capabilities so that they can be leveraged for competitive advantage. Gupta and George (2016) provides empirical evidence that effectively leveraging big data capabilities leads to superior organisational performance.

Through an improved understanding of the above, business can strategically and coherently address these issues to improve their ability to leverage big data analytics for superior performance and sustainable competitive advantage. This will enable them to justify the substantial investments in big data capability from a return on investment perspective as well as to improve the utilisation of their existing big data assets. The resultant enhanced organisational performance is anticipated to ensure that big data remains high on the organisations strategic agenda thus providing impetus for future investments in big data capabilities and research and development initiatives. The research aims to gain insights into how to build big data capability and through these insights provide preliminary guidance for creating and understanding big data capabilities.

The research aims to contribute to theory by exploring extant literature and elucidating how South African banks can create big data capabilities for competitive advantage from a market orientation and dynamic capabilities perspective. This is based on most of the big data literature lacking theoretical foundations, the paucity of published big data literature and the lack of understanding about how organisations build big data capabilities (Gupta & George, 2016). The significance to business is that it offers guidance to South African bank managers for designing and creating big data capabilities, with the objective of leveraging the same for competitive advantage.

1.7 Structure of the Research Report

Chapter 1: Problem definition and purpose

Chapter 1 introduces the research and illustrates its relevance in both the business and academic domains. It illustrates the research problem and the purpose of the research.

Chapter 2: Literature review

This chapter reviews extant literature on big data, big data analytics and sustainable competitive advantage. market orientation, resource-based theory and dynamic capabilities.

Chapter 3: Research questions

Chapter 3 presents the research questions as well as the rationale for each of the research questions.

Chapter 4: Research methodology and design

This chapter discusses the research methodology and design as well as defends the various research methodology and design decisions. Details pertaining to the population, sampling method and size, data gathering approach, analysis approach and limitations are presented.

Chapter 5: Results

Chapter 5 presents the qualitative data collected from the interviews.

Chapter 6: Discussion of results

This section provides a detailed account of the research results against the existing literature on which the research is grounded.

Chapter 7: Conclusion and recommendations

Chapter 7 presents the key findings of the research as well as provides pertinent recommendations for business. Possible future research on the topic is also recommended.

2 CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

The preceding section presented the construct of business intelligence, which is viewed as the platform for innovation, productivity and competition (Lycett, 2013). Business intelligence employs a data centric approach, where the ability to generate appreciable benefits is contingent on data collection, extraction and analysis capabilities (Chen et al., 2012). The knowledge and insights extracted from environmental data is key to decisions pertaining to the evolution of the organisation through devising strategy to align with environmental changes and to develop and acquire the capabilities to respond to these changes (Beer et al., 2005). Barney (1991), posited that integrating environmental knowledge with the organisations internal capabilities is key to competitive advantage.

According to Davenport (2014), the knowledge acquisition and analysis process has evolved from decision support to big data analytics encompassing the gathering, storage and analysis of large volumes of data to facilitate data driven decisions and action (Lycett, 2013). While big data encompasses a proliferation of structured, transactional and unstructured behavioural data (Erevelles et al., 2015), with the requisite attributes to establish competitive advantage, extant literature cites inadequacies in the understanding and general methodologies pertaining to the development (Gupta & George, 2016), deployment and leveraging of big data capabilities (Erevelles et al., 2015; Johnson et al., 2017; Krishna, 2016; Martens et al., 2016).

This chapter reviews extant literature to establish how big data analytics can be leveraged for competitive advantage within the South African banking context. Premised on the research problem and purpose presented in Chapter 1, the research draws on resource-based theory (Kozlenkova et al., 2013), dynamic capabilities theory (Teece, 2007) and the market orientation construct (Jaworski & Kohli, 1993; Kohli & Jaworski, 1990; Narver & Slater, 1990; Slater & Narver, 1994) as theoretical frameworks. Each of these perspectives as they relate to leveraging big data for competitive advantage are presented in the subsequent sections of this chapter.

2.2 Theoretical Frameworks

2.2.1 Resource Based Theory

Grant (1991) postulated that the resource position of an organisation is a key determinant of its's competitive advantage; however, according to Gupta and George (2016), extant literature emphasises that competitive advantage is not derived from investments in resources alone, but rather from organisations creating capabilities that competitors find difficult to imitate. The focus on resources and capabilities as the foundation of strategy formulation is premised on the assertion that the internal attributes of the organisation are responsible for their profits (Barney & Clark, 2007; Kozlenkova et al., 2013; Wernerfelt, 1984).

Resource based theory (RBT) considers organisations to be collections of resources, which in combination can be deployed to generate competitive advantage (Gupta & George, 2016). Kozlenkova et al. (2013) argued that RBT is an important framework, which is utilised extensively for explaining and predicting the organisations competitive advantage and performance outcomes. RBT is widely acknowledged as the most powerful and prominent theory for explaining and predicating organisational relationships, competitive advantage and profits (Gupta & George, 2016). Erevelles et al. (2015) advocated that resource-based theory is a suitable framework for understanding the benefits of big data and how organisations can better leverage it for competitive advantage. These attributes have relevance in the context of the research, since having knowledge of the organisations existing and required big data resources and determining how to advantageously deploy and leverage the same is key to attaining competitive advantage.

Kozlenkova et al. (2013) assert that resources and capabilities are key constructs of RBT. Wernerfelt (1984), in his early works on the resource-based view (RBV) of organisations defined a resource as a strength or weakness of an organisation and advocated that these resources, if effectively leveraged can lead to high profits and can form resource position barriers. In larger organisations strategy involves a balance between the exploitation of existing resources and exploration for the development and acquisition of new resources (Wernerfelt, 1984). Research confirms that resources comprise tangible and intangible assets that are owned and controlled by the organisation and are utilised to conceive and execute the organisations strategies (Day, 1994; Erevelles et al., 2015; Kozlenkova et al., 2013; Gupta & George, 2016). It follows that the four main resource categories encompass physical, financial, human and organisational resources (Erevelles et al., 2015; Kozlenkova et al., 2013).

Capabilities are special types of resources (Kozlenkova et al., 2013), which facilitates the aggregation (Gupta & George, 2016) and efficient deployment of other organisational resources with the objective of enhancing the productivity of those other resources (Kozlenkova et al., 2013). Day (1994) defines capabilities as complex bundles of accumulated knowledge and skills, which are exercised through deeply embedded organisational routines and practices, thereby enabling the advantageous deployment of combinations of organisational resources. Day (1994) emphasises that these bundles of skills utilise tacit knowledge and cumulative learning (Day, 2014) and are deeply embedded in the organisation to the extent that they cannot be easily traded or imitated. Aligning with the above, Kozlenkova et al. (2013) elucidates capabilities as typically information based, tangible or intangible organisational processes. On the premise that capabilities are "organisationally embedded non-transferrable organisation-specific resources" (Kozlenkova et al., 2013, p. 4), which are truly distinctive (Ramaswami, Bhargava, & Srivastava, 2009) and cannot be imitated (Day, 1994), it is inferred that capabilities possess the pertinent attributes of being a source of sustainable competitive advantage.

Barney and Hesterly (2012) asserted that sustainable competitive advantage is obtained when resources simultaneously possess the attributes of being valuable, rare, imperfectly inimitable, and exploitable by the organisation. The VRIO framework encompasses these four key resource attributes and is utilised to assess if organisational resources or combinations thereof have the potential of generating sustainable competitive advantage (Kozlenkova et al., 2013). Kozlenkova et al. (2013) elucidates that in accordance to the VRIO framework a resource is, (1) valuable, if the resource enables the organisation to devise and implement strategy that results in an increase in the organisations net revenues and/or a decrease in the organisations net cost. In addition, a valuable resource enables the organisation to exploit external opportunities, and/or neutralise external threats (Barney & Hesterly, 2012), (2) rare, if the resource is not controlled by a large number of competing organisations, (3) imperfectly inimitable, if the resource is difficult and/or substantially costly to duplicate, substitute, acquire or develop by competing organisations, and (4) Organisation refers to the organisational processes, policies and procedures, that is physical organisational attributes which either enables or inhibits the organisation from fully leveraging a resource that is valuable, rare and imperfectly imitable. Gupta and George (2016) elaborate that the organisation attribute includes history, relationships, trust and culture. Culture encompasses the attributes of individuals associated with the organisation, the organisational structure and management control systems (Gupta & George, 2016).

While a resource which simultaneously embodies the VRIO attributes had been described as source of sustainable competitive advantage, Barney and Hesterly (2012) stipulate that RBT's two key assumptions of resource heterogeneity and resource immobility must be true to explicate how sustainable competitive advantage can be derived. Resource heterogeneity assumes that resources are spread heterogeneously across the industry resulting in some organisations being more skilled at certain activities by virtue of them possessing unique bundles of strategic resources (Barney & Hesterly, 2012; Kozlenkova et al., 2013). These unique strategic resources can serve as a long-lasting source of competitive advantage because of them taking a long time to develop, thus making them inherently difficult to duplicate (Day, 2014). Resource immobility assumes that it is difficult for resources to be traded within organisations in the industry rendering the advantage of resource heterogeneity to persist over time (Barney & Hesterly, 2012; Kozlenkova et al., 2013).

An analysis of the RBT framework presented above and Grant's (1991) resource based approach to strategy evidences that in order to achieve a competitive advantage, the organisation must (1) understand its internal resource capabilities, (2) be able to and be set up to leverage and exploit these capabilities, (3) be able to utilise internal resources and capabilities as the foundation of strategy formulation, and (4) be able to identify resource and capability gaps and replenish the same. Furthermore, Section 1.2 introduced the paradigm of a hyper competitive and rapidly changing business landscape necessitating organisations to constantly learn and adapt by updating and reconfiguring their resources to respond to the environment and achieve competitive advantage (Beer et al., 2005; Erevelles et.al, 2015).

2.2.2 **Dynamic Capabilities**

The contemporary business environment has been described to be fast moving and in constant flux (Beer et al., 2005; Erevelles et al., 2007; Day, 2011; Erevelles et al., 2015; Johnson et al., 2017). Teece (2007) argued that sustaining competitive advantage in dynamic business environments requires that organisations, in addition to owning idiosyncratic and difficult to replicate resources, must also possess unique and difficult to replicate dynamic capabilities.

Dynamic capabilities refer to an organisations ability to respond to environmental change (Erevelles et al., 2015) and has relevance within the paradigm of innovation-based competition, price/performance rivalry and increasing returns (Teece, Pisano, & Shuen, Dynamic Capabilities and Strategic Management, 1997). According to Erevelles et al. (2015) an organisation, which leverages the superior consumer insights extracted from big data to understand and respond to unmet and changing consumer needs enhances dynamic capability.

Teece et al. (1997) posited that competitive advantage is gained through distinctive combinations of the organisations resources and the evolution of these resources. This is facilitated through the identification of new opportunities and the organisation having the capability to efficiently and effectively organise their resources to respond to the opportunity (Black & Boal, 1994; Kozlenkova et al., 2013; Teece, 2007; Teece et al., 1997) and create new value (Erevelles et al., 2015). Resource evolution pertains to creating, upgrading, protecting and keeping relevant the organisations unique resource base (Kozlenkova et al., 2013; Teece, 2007), with the objective of keeping abreast with the rapidly evolving business environment.

According to Teece (2007), dynamic capabilities encompass the ability to adapt to changing customer and technological opportunities and to explain the sources of competitive advantage over time. These capabilities are disaggregated into the ability to (1) sense and shape external threats and opportunities through scanning, searching and exploring across markets and technologies (Day, 2011; Teece, 2007). More specifically, sensing pertains to the acquisition of information about the organisations internal operations and the external environment in which it operates, while shaping opportunities pertains to the analysis and filtering of this information (Teece, 2007; Torres et al., 2018), (2) seize opportunities through the integration and interpretation of the information in order to facilitate decision making, a shared understanding amongst stakeholders and the formulation of strategy in response to the opportunities identified (Teece, 2007; Torres et al., 2018), and (3) transform, which encompasses maintaining competitiveness through the creation, renewal or reconfiguration of the organisations capabilities in accordance to the strategy formulated (Teece, 2007; Torres et al., 2018). Transformation may also require changes to the organisational structure and business model (Day, 2011; Teece, 2007). A recent study concluded by Torres et al., (2018) proved empirically that the dynamic capabilities framework, particularly the sense, seize and transform construct is useful for business intelligence and analytics applications.

Kozlenkova et al. 2013 postulated that dynamic capabilities are similar to capabilities given that their purpose is to accentuate the value derived from resources (Kozlenkova et al., 2013). Day (2014) aligns with the above in arguing that while the essence of RBT encompasses the exploitation of the organisations resources and capabilities, dynamic capabilities sit on the exploratory side of this construct given that it facilitates the augmentation, reconfiguration and expansion of organisational capabilities to pursue new opportunities thereby accentuating the value extracted from resources. While there are two schools of thought pertaining to dynamic capability in that some researchers view dynamic capabilities as an extension to RBT, while others view it as a stand-alone framework (Teece et al., 1997; Teece, 2007; Peteraf & Barney, 2003), this research aligns with the perspectives of Kozlenkova et al. (2013) and Day (2014) and considers dynamic capabilities as an extension to RBT.

Teece (2007) accentuated the importance of dynamic capabilities through the assertion that evolving customer needs and technological advancements result in the opening up of opportunities for newcomers, which effectively puts the profits of the legacy organisations at risk. The dynamic capabilities construct is therefore relevant to the research premised on the fact that South African banking operates in a dynamic business environment characterised by changing customer needs, technological opportunities and new entrants to the market.

2.2.3 **Market Orientation Perspective**

Extant literature posited that market orientation provides organisations with competitive advantage (Day, 1994; Jaworski & Kohli, 1993; Han et al., 1998; Slater & Narver, 1994; Vorhies & Morgan, 2005) and superior financial performance (Morgan, Vorhies, & Mason, 2009; Narver & Slater, 1990; Ramaswami et al., 2009). Market orientation encompasses the collection, co-ordination and utilisation of customer and competitor information to facilitate the building superior customer value (Day, 2011).

Kohli and Jaworski's (1990) research placed emphasis on market orientation encompassing the organisation wide generation and dissemination of market intelligence and the subsequent action in response to this intelligence. The market intelligence generation, dissemination and responsiveness framework prioritise information management (Han et al., 1998) and has been cited in extant literature as the market information processing perspective (Day, 2011; Hult, Ketchen Jr, & Slater, 2005; Morgan, Vorhies, & Mason, 2009). Building on the market information processing perspective, Jaworski and Kohli (1993) postulated that the antecedents to market orientation are; (1) top management emphasis on the orientation and risk aversion, (2) interdepartmental dynamics, comprising conflict and connectedness, and (3) organisational systems, particularly formalisation, centralisation, departmentalisation and rewards systems.

Slater and Narver (1994) elucidate that market orientation has a dependency on the organisational culture being committed to delivering superior customer value and assert that market-orientation comprises three behavioural components, namely customer orientation, competitor focus and inter-function co-ordination. The dependency on organisational culture derives from Narver and Slater’s (1990) research, where market orientation was described as “the business culture that most effectively and efficiently creates superior value for customers” (p. 20). In a study conducted with 225 banks, Han et al. (1998) evidence that of the three behavioural components, customer orientation was the dominant factor driving organisational innovation and performance. Han et al. (1998) postulated that the result is consistent with the tendency to high profiling customer orientation since the marketing concept accentuates putting the interests of the customer first. The results; however, does not detract the importance of competitor focus and inter-function coordination since they have increased significance in conditions of high technological uncertainty (Han et al., 1998).

While the above frameworks evidence commonality on the objective of delivering superior customer value, it is evident that the Kohli and Jaworski (1990) and Jaworski and Kohli (1993) perspectives relate to market information processing, organisational structure and management (Kuada & Buatsi, 2005) and the Narver and Slater (1990) perspective relates to organisational culture and philosophy (Kuada & Buatsi, 2005). Collectively these frameworks are deemed to provide a broad understanding of market orientation and is supported by extant literature stressing that market-oriented organisations require a deeply rooted organisational culture which supports the value of market intelligence and co-ordinated inter functional actions with the objective of gaining competitive advantage (Day, 1994; Moorman, 1995).

Hult et al. (2005) argued that as a result of the difference in the above two perspectives, Strategic management Journal articles debated issues pertaining to market orientation from either a cultural emphasis (Narver & Slater, 1990) or a market information processing emphasis (Kohli & Jaworski, 1990). As a result, Hult et al. (2005) posited that "strategic management may possess an incomplete understanding of how market orientation contributes to performance" (p. 1173). In addressing this gap, Hult et al. (2005) proved empirically that both Narver and Slater's culture centred perspective and Kohli and Jaworski's information process centred perspective are important for a complete understanding of market orientation and must be included in future studies. While the Kohli and Jaworski (1990) and Narver and Slater (1990) market orientation frameworks was developed in the 1990's, Hult et al. (2005) evidences relevance and applicability of these constructs in the 2000's.

Morgan et al. (2009) employs the information processing perspective (Kohli & Jaworski, 1990) of market orientation in an empirical study testing the relationship between marketing capabilities, market orientation and organisational performance. Furthermore, in more recent research aimed at addressing the gap between marketing capabilities and the deluge of data resulting from technology empowered customers, Day (2014) and Day (2011) posited that the vigilant market learning constituent of the adaptive marketing capabilities construct aligns with Kohli and Jaworski's (1990) information processing perspective of market orientation. The referenced study confirmed applicability of the market information processing perspective in hyper competitive business environments, which was one of the key components of the Day (2014) and Day (2011) study. This corroborates Jaworski and Kohli's (1993) postulation that market orientation and the market information processing perspective has relevance and is an important determinant of organisational performance irrespective of market turbulence, technological turbulence and the competitive intensity of the business environment.

The research cited above was conducted by authorities in the strategic management and marketing fields, and published in the prestigious Strategic Management Journal, Journal of marketing and the Journal of the Academy of Marketing Science. The discussion evidences relevance and applicability of the market information processing (Kohli & Jaworski, 1990) perspective in a body of contemporary strategic and market orientation research.

2.3 Leveraging Big Data for Competitive Advantage

Technology has transformed individual consumers into incessant generators of a wealth structured transactional data and unstructured behavioural data (Erevelles et al., 2015). This proliferation of data has the promise of transforming business process, altering corporate ecosystems and unlocking business value through the strategic and operational implications (Wamba et al., 2015) of better informed decision making and enhanced organisational responsiveness (Torres et al., 2018). Accordingly, Ervelles et al. (2015) posited that the big data era has new implications for understanding consumer behaviour and formulating marketing strategy.

It follows, that the effective leveraging of big data capabilities is viewed as the platform for realising superior performance and sustainable competitive advantage (Erevelles et al., 2007; Junque de Fortuny et al., 2013; Provost & Fawcett, 2013; Erevelles et al., 2015; Martens et al., 2016; Johnson et al., 2017). Consistent with the assertions of Chen et al. (2012), Torres et al. (2018) postulated that analytics capability is a component of business intelligence that pertains to the utilisation of analytical techniques to answer organisational questions and facilitate improved decision making. The shift of business intelligence from being reporting centric to analysis centric accentuates the importance of analytics (Torres et al., 2018). This supports Davenport's (2014) assertion that the knowledge acquisition and analysis process has evolved from decision support to big data analytics and data driven decision making. Big Data analytics encompasses the extraction of hidden insights from large structured and unstructured data sets through superior analytics capabilities (Erevelles et al., 2015).

Wamba et al. (2015) argued that several definitions of big data exist due to the emerging nature of the concept and assert that defining big data by the 5 V's corresponding to the attributes of volume, variety, velocity, veracity and value provides a holistic framework for creating actionable insights. Other accounts of big data consider up to 10 V's (Gupta & George, 2016). Premised on the purpose of the research being to gain insights on leveraging big data analytics from a resource and capability perspective, the V's pertaining to value and veracity are not utilised further. The 3V's perspective, which according to Johnson et al. (2017) operationalises big data for analysis is deemed to be aligned to the scope and purpose of this research and shall be considered. Big data is operationalised by the 3V's representative of the unprecedented volume, variety and velocity of data (Zhenning, Frankwick, & Ramirez, 2015; Erevelles, Fukawa, & Swayne, 2015; Johnson et al., 2017). Volume represents the large magnitudes of data available, variety represents the richness of the unstructured behavioural data and velocity represents the real-time rapidity at which data is created (Zhenning, Frankwick, & Ramirez, 2015; Erevelles, Fukawa, & Swayne, 2015). Furthermore, the 3V's differentiate big data from traditional data, which is characterised as structured (Johnson et al., 2017) and comprising a few parameters (Martens et al., 2016).

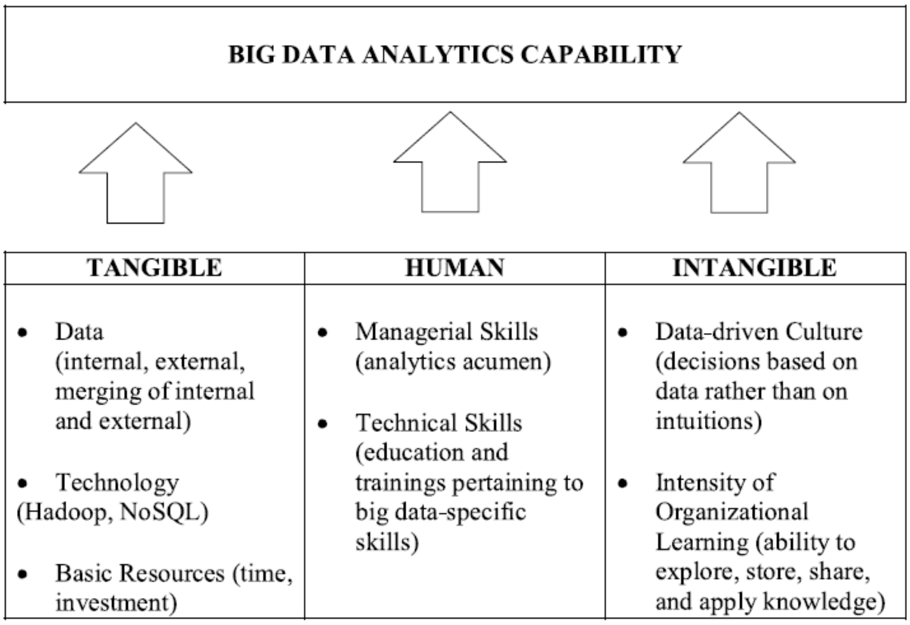
Zhenning et.al (2015) asserts that most of traditional marketing relies on analytics dealing with small structured data sets requiring limited analytic and implementation capacity. Traditional platforms are incapable of ingesting and analysing big data (Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013) since big data describes data sets that are terabytes to exabytes in magnitude, unstructured and complex requiring advanced and unique technologies to store, manage, analyse and visualise (Zhenning et al., 2015). As established in Section 2.2.3, market orientation traditionally refers to a corporate culture dedicated to the creation of superior customer value through the coordinated application of inter-functional resources, the ability to generate, disseminate and utilise superior customer and competitor information, superiority in determining present and future customer needs as well as the factors that influence consumer behaviour (Narver & Slater, 1990; Shapiro, 1988b; Kohli & Jaworski, 1990; Dutta, Narasimhan & Rajiv, 1999).

In cognisance of the strategic intent, the characteristics of big data and the attributes of market orientation as explicated in Section 2.2.3, it is postulated that the principles associated with the development of a contemporary big data market-oriented approach encompasses the traditional market information processing perspective (Kohli & Jaworski, 1990) and culture emphasis perspective (Narver & Slater, 1990); however, in addition dynamic capabilities (Teece, 2007) and the unique big data resource requirements must be considered (Erevelles et al., 2015). Premised on the above it is postulated that the market oriented approach framework, included in Section 2.6, Figure 2 be utilised as the basis for the development of a concept for creating big data capabilities. This concept is detailed in Section 2.5.

2.4 Big Data Resource Requirements

Drawing on RBT, it follows that the four main resource categories encompass physical, financial, human and organisational resources (Kozlenkova et al., 2013). Erevelles et al. (2015) posited that in the big data context; (1) the physical capital resources includes the capital investment and the software and hardware platforms for the collection, storage and analysis of big data, (2) the human capital resources includes the data scientists and strategists who capture, organise and extract insights from big data, and (3) organisational capital resources includes the organisational structure that enables the organisation to be responsive to the insights extracted. Gupta and George (2016) builds on the above in their classification of big data resources as depicted in Figure 1, below.

Figure 1:Classification of Big Data Resources



Source: Adapted from (Gupta & George, 2016, p. 1051)

As illustrated in Figure 1, big data resources have been arranged as tangible, intangible and human resources. When juxtaposed with the Erevelles et al. (2015) classification of big data resources, it is evident that; (1) the tangible resources are analogous to the physical capital resources, (2) the human capital resources are consistent in both classifications, and (3) the intangible resources are analogous to the organisational capital resources.

Barney (1991) asserts that tangible resources are to some extent readily available to organisations of comparable size; hence, tangible resources are unlikely to independently generate competitive advantage. This assertion is premised on comparably sized organisations having the ability to acquire these resources, thus rendering them homogenous and unable to satisfy the “rare” attribute of the VRIO framework. While such tangible resources may not be unique individually, the confluence of these resources with other resources can create unique capabilities to generate competitive advantage (Hult et al., 2005). In support, Gupta and George (2016) assert that competitive advantage is not derived from investments alone, but from the creation of difficult to replicate, organisation specific capabilities through the combination of tangible, intangible and human resources.

The below discusses the big data tangible and human resource requirements in accordance to Figure 1, above. The intangible resources, which include a data driven culture and intensity of organisational learning is discussed under Section 2.5 which deals with creating big data capabilities. This is premised on these resources being deemed to be capabilities since they have the ability to enable or inhibit the organisation from leveraging their big data resources. As per Section 2.2.1, they are constituents of organisation attribute in the VRIO framework.

2.4.1 **Data**

Traditional data encompasses fixed scale structured data characterised by small data sets that are megabytes, gigabytes or kilobytes in order of magnitude (Martens et al., 2016; Zhenning et al., 2015), while big data is characterised by large and complex unstructured data sets that are terabytes and exabytes in magnitude (Erevelles et al., 2015; Gupta & George, 2016; Johnson et al., 2017; Martens et al., 2016; Zhenning et al., 2015). A comprehensive definition of big data is included in Section 2.3. Data includes internal and external data where internal data is generated within the organisation through their process and procedures and external data is gathered from the environment (Erevelles, Fukawa, & Swayne, 2015; Gupta & George, 2016).

Internal data is utilised for improving and optimising internal procedures and operations (Torres et al., 2018), while external data serves as market intelligence which is key to the organisation being market oriented (Day et al., 2011; Erevelles et al., 2015; Hult, Ketchen Jr, & Slater, 2005; Jaworski & Kohli, 1993; Slater & Narver, 1994). In order for organisations to leverage big data analytics, they must integrate their use of internal and external data (Gupta & George, 2016).

Data governance and quality has been cited as an antecedent to extracting superior insight from big data (Isik, Jones, & Sidrova, 2013; Lavelle et al., 2011; Seddon, Constantinidis, Tamm, & Dod, 2016; Torres et al., 2018). According to Isik et al. (2013)

data quality refers to the clean, accurate, consistent, comprehensives and valid data. Data quality issues are responsible for the failure of more than half of analytics projects (Isik et al., 2013). Failures emanate from organisations making decisions on erroneous data (Isik et al., 2013). Data governance and quality requires the pertinent technology and technical expertise (Isik et al., 2013).

Within the banking context, Martens et al. (2016) assert that this sector is privy to wealth of big data in the form of the transactions they observe, however only a few organisations leverage this massive fine-grained data in a non-aggregated form to draw valuable consumer behaviour insights for predictive analytics. This unstructured transactional data is generally aggregated to a summarised form of structured data comprising a few variables permitting analysis thereof utilising traditional analytics (Martens et al., 2016). It is postulated that this approach is a result of the data being too large and complex for traditional methods or due to resistance from the modellers with regards to changing their methods (Martens et al., 2016). Martens et al. (2016) evidence that there is no appreciable improvement from large volumes of big data when it is aggregated into traditional structured data. Consistent with the above, extant literature confirms that the banking sector has access to a wealth of consumer data (Krishna, 2016; Hormazi & Giles, 2004).

2.4.2 **Technology**

While technology alone is not deemed a source of competitive advantage for organisations of a similar size, it is key for the creation of capabilities (Barney, 1991; Gupta & George, 2016). Extant research evidences technical infrastructure to be critical to the success of big data implementation (Torres et al., 2018). Processing of big data requires technology facilitating distributed storage and parallel processing (Junque et al., 2013) with advanced requirements for the efficient storage and retrieval of data (Gupta & George, 2016). Literature cites open source technologies such as Hadoop for distributed storage and parallel processing and Not Only SQL (NoSQL) for efficient storage and retrieval of data (Gupta & George, 2016; Isik et al., 2013). Traditional platforms and methodologies are inadequate for the processing of big data (Isik et al., 2013; Martens et al., 2016; Provost & Fawcett, 2013; Zhenning et al., 2015).

Extant literature asserts that there has been immense augmentation in the development of big data technologies (Kiron et al., 2011; Mcafee & Brynjolfsson, 2012), thus giving organisations the potential to manage the increasing volume, velocity and variety of data (Gupta & George, 2016; Isik et al., 2013). The literature predominantly demonstrates that big data technology is not a hinderance to big data capability development since the pertinent technologies are available in the market, and in addition, is incessantly improving (Gupta & George, 2016; Isik et al., 2013).

2.4.3 Basic Resources (Investment and Time)

Due to newness, the development of big data capabilities requires substantial investment in technology and other big data initiatives related to gaining an understanding of how to develop and implement big data capabilities (Gupta & George, 2016). To realise the benefits of big data many organisations are investing heavily in big data resources (Johnson et al., 2017; Kiron et al., 2011; Lavelle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011; Gupta & George, 2016; Torres et al., 2018). Premised on the newness of big data and the substantial costs associated with implementation thereof, it is asserted that organisations will not realise the envisaged gains immediately; however, organisations must devote time and resources to realise their analytics objectives (Gupta & George, 2016).

According to Kiron et al. (2011) the investment required is dependent on the current status of the organisation infrastructure level of sophistication that the organisation envisages; however, it is key that resources be deployed to ensure mastery in achieving a data oriented culture, particularly in the following competencies; (1) implementing a structured process for applying analytics to business strategy, (2) sharing insights about customer history and value to all relevant people within the organisation, and (3) ensure that analytics guides strategy and operations. Torres et al. (2018) accentuated item (3) through empirical evidence confirming that the positive relationship between business intelligence and analytics and operational efficiency is mediated by process change capabilities.

2.4.4 Human Resources

Big data specific technical and managerial skills are critical to success in big data projects (Gupta & George, 2016; Isik et al., 2013; Torres et al., 2018). According to Gupta and George (2016), big data technical skills includes the ability to extract intelligence from big data utilising new forms of technology. Specific skills include “competencies in machine learning, data extraction, data cleaning, statistical analysis and understanding of programming paradigms" (Gupta & George, 2016, p. 1052). Torres et al. (2018) argued that highly skilled analytics resources must have the ability produce insightful high-quality information in terms of accuracy and usefulness for interpretation by the organisations decision makers. This supports Provost and Fawcett's (2013) assertion that in addition technical skills, analysts are required to understand the business problem to be solved. Furthermore, the organisations decision maker must be skilled in interpreting the information to ensure that opportunities and threats are picked up (Seddon et al., 2016; Torres et al., 2018). Misinterpretation of the information detracts from the quality of insights and ultimately the strategic intent of analytics (Torres et al., 2018). The above suggests that analysts are required to have business acumen and business is required to have data acumen.

According to Provost and Fawcett (2013), the skills listed above are data science and data engineering skills. The role of the data scientist is to guide and support the extraction useful insights and knowledge from data to facilitate data driven decision making (Hormazi & Giles, 2004; Provost & Fawcett, 2013). In addition, the role requires data scientists to articulate business problems from a data perspective, understand analytics and statistics, possess the ability to visualise data and have intuition, knowledge, creativity and common sense (Provost & Fawcett, 2013). It is inferred that the data scientist is required have technical abilities for extracting insights from the data as well as business acumen to ensure that the insights extracted facilitates data driven decision making and addresses a business need. Data engineering is responsible for data architecture and data processing, which includes ingestion of the data into the system, processing of the data to ensure that it is healthy and of adequate quality for the extraction of insights (Provost & Fawcett, 2013).

Provost and Fawcett (2013) postulated that a shortage of data science skills resulted from academic institutions not being able to put together the pertinent data science programs quickly enough to support industries demand for the same. Gupta and George (2016) assert that the big data technical skills gap persists with only a few universities offering the pertinent courses, while the skills demand is on the increase.

In addition to technical resources, Gupta and George (2016) assert that big data management skills are critical to big data success. Big data managers must possess data acumen to interpret the information extracted from the technical teams (Seddon et al., 2016; Torres et al., 2018) and have the foresight to identify business applications as well as predict the future needs of the customer (Gupta & George, 2016). Management is also key for attracting, developing and retaining the requisite big data specific skills (Torres et al., 2018).

Drawing on RBT, Erevelles et al. (2015) assert that big data will serve as a source of sustainable competitive advantage when the organisation is able to effectively leverage their physical capital, human capital and organisational capital resources to the extent that they simultaneously satisfy the VRIO criteria. A body of extant literature asserts that investing and owning resources does not engender competitive advantage; instead competitive advantage is generated when organisations create hard to imitate capabilities through the aggregation and efficient deployment of organisational resources (Barney & Hesterly, 2012; Barney, 1991; Day, 1994; Gupta & George, 2016; Han et al., 1998; Hult et al., 2005; Kozlenkova et al., 2013; Teece, 2007; Torres et al., 2018; Wernerfelt, 1984).

2.5 Big Data Capabilities

Capabilities are ubiquitous with organisational processes and are of strategic importance to creating a market-oriented organisation and competitive advantage (Day, 2014; Day, 2011; Day, 1994; Kozlenkova et al., 2013; Teece, 2007). While market-orientation and the associated increase in organisational performance cannot be gained by simply pulling a lever (Hult et al., 2005), organisations can become more market oriented through the identification and development of superior imperfectly inimitable capabilities which distinguishes them as market driven organisations (Day, 2011; Day, 1994; Dutta et al., 1999; Han et al., 1998; Vorhies & Morgan, 2005). According to Wamba et al. (2015), emphasis must be placed on big data orientations and the related operations and management issues as superior organisational performance is contingent on these orientations, which facilitate competitive advantage. Furthermore, the need for research pertaining to big data asset orientations was accentuated (Wamba et al., 2015). In addition, capabilities must be dynamic to facilitate the efficient and effective reorganisation of resources in response to dynamic environments characterised by evolving customer needs and technological advancements (Teece, 2007).

Within the big data context, Gupta and George (2016) advocated that “gaining competitive advantage from big data is not only about making investments, collecting hordes of data, and having access to sophisticated technology but also to have availability of big data specific technical and managerial skills, an intensity of organisational learning, and an organisation culture where insights extracted from data are valued and acted on" (p. 1061). In accordance to the above, Marr (2015) asserts that strategists and executives are not as much concerned with the technologies and characteristics of big data, they are concerned with how to build capability and make the best use of it.

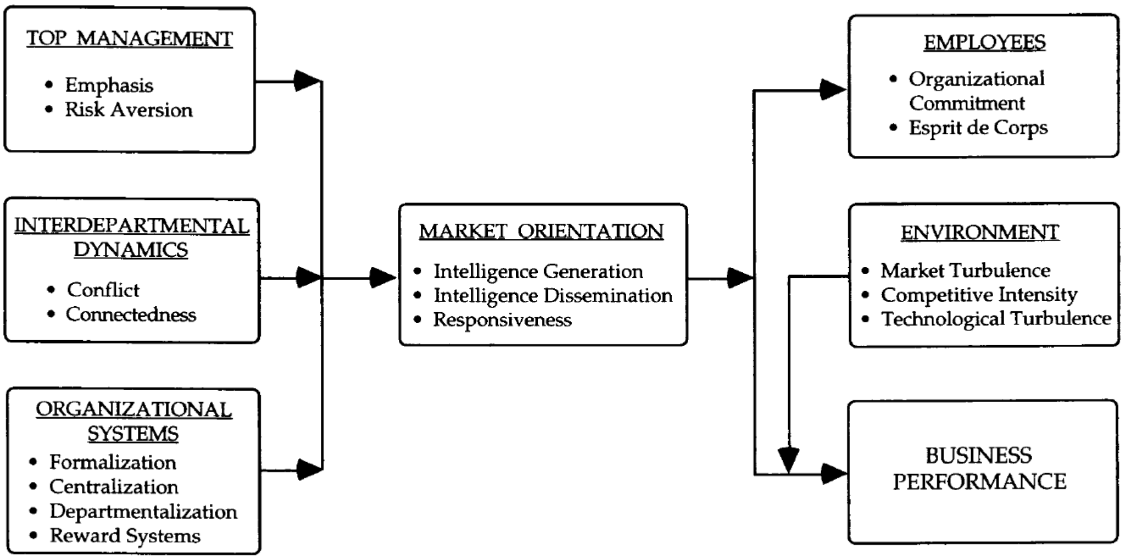
According to Kiron et al. (2011), mastering the capabilities of information management, analytics skills and tools, and a data-oriented culture enables organisations to leverage big analytics. Within the context of the Kiron et al. (2011) research, the following are applicable; (1) information management pertains to "capture, combine and use information from many sources, and disseminate it so that individuals throughout the organisation, and at virtually every level, have access to it" (p. 9). It is also accentuated that the ability to break the barriers of function and business silo's and integrate information across the same is a capability of fully transformed data driven organisations, (2) analytics skills and tools pertains to possessing and deploying superior analytics capabilities in terms of skills and technology, and (3) culture pertains to having "behaviours, practices and beliefs [that] are consistent at every level" (p. 11). More specifically, a data-oriented culture pertains to a culture of data driven decision making at every level. It is evident that items (1) and (3) above aligns with key constituents of the Kohli and Jaworski (1990) and Narver and Slater (1990) market orientation frameworks. Furthermore, the key capabilities required encompasses human resource skills and culture, giving impetus to the Gupta and George (2016) assertion in the preceding paragraph.

As per Section 2.3, it was postulated that premised on the strategic intent, the attributes of market orientation and the characteristics of big data, the traditional market information processing perspective (Kohli & Jaworski, 1990) and culture emphasis perspective (Narver & Slater, 1990) be utilised as a basis for the development of a concept for creating big capability.

2.6 Development Big Data Capabilities

The market information processing perspective is applied as part of Jaworski and Kohli's (1993) framework depicted in Figure 2, below.

Figure 2:Antecedents and Consequences of Market Orientation



Source: Adapted from (Jaworski & Kohli, 1993)

According to Kohli and Jaworski (1990), the framework comprises the following three main pillars, (1) antecedent conditions, which have the ability of enabling or discouraging market orientation, (2) the market orientation construct, which is also referred to as the market information processing perspective. This refers to the organisation wide generation and dissemination of market intelligence and the subsequent action in response to this intelligence, and (3) consequences of market orientation, which refers to the results achieved from a market orientation. The pillars included within points (1) and (2) and the pertinent components included therein are elucidated in the subsequent sections within the context of developing capabilities for leveraging big data analytics for competitive advantage. The consequences of market orientation, included in point (3) is depicted for completeness, however this pillar is not discussed separately since the consequences are beyond the scope of this study.

2.6.1 **Organisational Factors**

Day (2011) asserts that during times of technological disruption, most organisations have trouble keeping pace. The factors resulting in the failure of most big data projects are organisations not being ready or the organisations failure to adopt a data driven culture (Gupta & George, 2016). Day (2011) identifies organisational rigidities, structural insularity and lagging reactions as the key contributors to the above. This accentuates the assertions that failure to benefit from big data derives from not understanding its unique resource requirements (Erevelles et al., 2015) and the lack of understanding that firms have with regards to leveraging big data for innovation success Johnson et al. (2017) in the hyper competitive marketplace (Erevelles, Horton, & Fukawa, 2007). Emphasis is placed on the need for possessing the correct capabilities in the optimal (most enabling) configurations, as these are antecedents for effectively altering and enhancing the organisations resource base to generate new value creating strategies to leverage big data (Moorman & Slotegraaf, 1999; Fang et al., 2011; Johnson et al., 2017).

Kohli and Jaworski (1990) assert that the antecedents to market orientation includes the organisational factors which can enhance or impede the implementation of the business philosophy. Based on these attributes, it is postulated that this is analogous to the organisation constituent of RBT, specifically the VRIO framework (Kozlenkova et al., 2013). As illustrated in Section 2.6, Figure 2, the antecedents to a market orientation includes; (1) top management, (2) interdepartmental dynamics, and (3) organisational systems.

2.6.1.1 Top Management Emphasis and Risk Aversion

According to Jaworski and Kohli (1993), top management emphasis and risk aversion are the key elements that impact the organisations ability to be market oriented. Emphasis refers to the amount of importance and commitment that top management attributes to being market oriented, which also includes embodying this commitment by sending the right signals to the entire organisation (Jaworski & Kohli, 1993; Kohli & Jaworski, 1990). Within this context of management, Torres et al. (2018) proved empirically that big data management capability impacts the success of analytics projects through championing analytics initiatives, reducing political barriers, encouraging organisational acceptance, and the creation of cultural values, particularly an analytical culture wherein decision makers are comfortable to utilise data driven insights and analytic models. Jaworski and Kohli's (1993) study suggested a positive relationship between market orientation and top management emphasis; thus, evidencing the importance of top management embodying market-oriented values and incessantly emphasising the need to be market oriented. According to Narver and Slater (1990), it is the duty of top management and leadership to engender the culture of inter-functional coordination into the organisation. Barton and Court (2012) in support postulated that leaders must invest time to align managers across the organisation to gather support and impetus for big data initiatives.

Wamba et al. (2015), particularly emphasising senior management implementation involvement, gives cadence to the above through the assertion that extant studies prove a strong positive relationship between top management buy-in and support and IT project implementation success. According to Wamba et al. (2015), “the Director of ICT of the NSW SES stated: “the one consistency across the project has been that the CIOs from each agency have had a place on the steering committee, which I think has been invaluable as has the level of executive support. Indeed, the executive support has probably been the most important thing across all of it…So that was a key fundamental and that really came out of the direction from government saying you all come together and do all of this and at that point in time we – and I say the royal ‘we’ and it really was the CIOs who said to the CEOs: we will make this work for you…– so we made that commitment and we have been doing that now for three years and will continue to do that, although it does cause a few grey hairs at times”.” (p. 18)

Risk aversion pertains to the risk appetite associated with launching products and services associated with market intelligence and subsequent insights (Jaworski & Kohli, 1993). According to Day (2011), the traditional decision-making processes are cautious and slow, resulting in marketing initiatives being slower than the movement of the market. This is paradigm is referred to as lagging reactions, which is the speed at which organisations can react to verifiable market shifts (Day, 2011). Empirical evidence demonstrates that risk aversion does not impact the generation and dissemination of market intelligence, however it impacts the responsiveness of the organisation (Jaworski & Kohli, 1993). Most of big data investment failures result from failures to make decisions on the insights extracted from the data. The importance of leveraging big data capabilities by responding through data driven decisions is accentuated by Kiron et al. (2011), where the making of data driven decisions had been identified as key to big data investment success. It is postulated that, while failure to make decisions on the intelligence is influenced by numerous factors, risk aversion is expected to be one of the factors.

2.6.1.2 Interdepartmental Dynamics and Organisational Systems

Barney and Hesterly (2012) posited that the firm must be organised to exploit the full potential of its resources and capabilities to achieve competitive advantage. Within this paradigm, Jaworski and Kohli (1993) posited that interdepartmental dynamics and organisational systems as antecedents to exploiting the organisations marketing resources and capabilities. Section 2.6, Figure 2, evidences that interdepartmental dynamics comprises conflict and connectedness, while organisational systems comprises formalisation, centralisation, departmentalisation and rewards systems.

Jaworski and Kohli's (1993), research on the six constituent's pertaining to interdepartmental dynamics and organisational systems suggests that; (1) interdepartmental conflict, which "refers to the tension among departments arising from incompatibility of actual and desired responses" (p. 55), inhibits market orientation, particularly intelligence dissemination and the responsiveness of the organisation, (2) connectedness, which refers to "the degree of formal and informal direct contact among employees across departments" (p. 56), promotes market orientation since it facilitates the organisation wide dissemination of information, (3) formalisation, which refers to the "degree to which rules define roles, authority relations, communications, norms and sanctions, and procedures" (p. 56) appears not to be related to market orientation, (4) centralisation, which refers to the extent to which decision making is centralised, that is the "the inverse of the amount of delegation of decision-making authority throughout an organisation and the extent of participation by the organisational members in decision making" (p. 56), appears to inhibit market orientation, however the result was inconclusive, (5) departmentalisation, which refers to "the number of departments into which organisational activities are segregated and compartmentalized" (p. 56), appears not to have a relationship with market orientation; that is, market orientation appears not to be dependent on the number of departments, and (6) rewards systems, which refers to measurements and rewards appears to be strongly related to market orientation.

The Slater and Narver's (1994) market orientation perspective comprising the customer orientation, competitor focus, and inter-function coordination behavioural components was introduced in Section 2.2.3. The emphasis on behaviour in these three components evidences the cultural aspect of this perspective. According to Slater and Narver (1995), culture is defined as a "deeply rooted set of values and beliefs that provide norms for behaviour in the organisation" (p. 67). The inter-function co-ordination behavioural component pertains to the organisational coordination and utilisation of its resources to deliver superior customer value (Narver & Slater, 1990). It is postulated that this coordinated behaviour must be to the extent that any individual within any function in the organisation must have the potential to contribute to the creation of customer value (Narver & Slater, 1990). This suggests inter-functional coordination to be predominantly culturally driven as opposed to just structurally driven. According to Jaworski and Kohli (1993), the result suggesting a lack of relationship between market orientation and departmentalisation is contradictory to extant literature, which suggests that departmentalisation inhibits communication flow and, hence the dissemination of market intelligence and ultimately market orientation. This counter intuitive result was explained by departmentalisation being of less importance than connectedness and inter-departmental conflict (Jaworski & Kohli, 1993).

Successful inter-functional coordination is contingent on inter-functional dependency, which is achieved through the alignment of inter-functional goals and incentives, whereby each functional area perceives their own interest through close cooperation with other areas (Narver & Slater, 1990). This gives cadence to Jaworski and Kohli's (1993) assertion that alignment of departmental performance objectives creates shared value and focusses coordinated efforts on the markets, thus reducing inter-departmental conflict. Kohli and Jaworski (1990), posited that connectedness can be facilitated through technology and the physical proximity of departments. This discussion evidences that connectedness and conflict are predominantly culturally driven and can be addressed through organisational systems designed to drive the desired behaviours. Premised on Jaworski and Kohli's (1993) assertion that connectedness and conflict explain the lack of relationship between departmentalisation and market orientation, it is inferred that departmentalisation will have little or no impact on market orientation if the culture of connectedness and reduced conflict is established. Furthermore, Jaworski and Kohli's (1993) research confirmed a strong relationship between rewards and market orientation, which suggests support for the Narver and Slater's (1990) notion pertaining to aligning infer-functional incentives to drive inter-functional coordination.

Dutta et. al (1999) assert that close coordination between marketing and R&D are important determinants of new product development and success, more specifically they have concluded that firms with a strong R&D base are the ones with the most to gain from strong marketing capability. Hult et al. (2005) confirms this assertion through their study evidencing that market orientation does not directly improve performance, but rather increases performance when deployed together with other functions. Morgan et al. (2009) also proved the importance of inter-functional coordination by empirically proving that the value of market orientation is only fully realised when it is deployed with complementary organisation capabilities.

According to (Day, 2011), structural insularity inhibits organisations from adopting a market-oriented culture. Structural insularity results from what Aaker (2010) refers to as the “silo crisis” (p. 315), resulting from legacy product, country and functional silos. Silos ultimately slows adaption (Day, 2011) as a result of the independent operations, which inhibits knowledge and information sharing, limits cross functional collaboration (Aaker, 2010) and the ability to transform and align to the environment (Day, 2011). Aaker (2010) argued that in the silo structures there is a lack of desire to share information or work with other silos. It can be inferred that the silo structure is engrained in the cultures and mindsets of the employees operating within such systems. Kiron et al. (2011) argued that organisational leaders with silo mindsets retain control of information within their functional areas with the objective of driving functional goals to the detriment of the organisation, since this inhibits collaboration and the ability to integrate and share organisational data. The need to break down product, country and functional silos and mindsets is key to permit information sharing, coordination, dynamic capabilities and market-orientation (Aaker, 2010; Day 2011; Jaworski & Kohli, 1993; Kiron et al., 2011; Slater & Narver, 1995).

According to Kiron et al. (2011), mastering the capability of possessing a data-oriented culture is a key attribute of top performing organisations in terms of leveraging big data for competitive advantage. Big data projects are either unproductive or fail due to organisational culture issues rather than technological or data related issues (Gupta & George, 2016). Furthermore, the ability of organisations to leverage and benefit from big data investments can either be inhibited or enabled by organisational culture (Gupta & George, 2016). A data-oriented culture defines the extent to which decisions are driven and guided by insights extracted from data (Erevelles et al., 2015; Gupta & George, 2016; Kiron et al., 2011).

As elucidated above, the arguments pertaining to a culture of inter-functional coordination (Narver & Slater, 1990) is key to enabling the coordinated organisation wide generation, dissemination and response to the insights extracted from external and internal information. Furthermore, effective advocacy and leadership has been identified as key to engender inter-functional coordination and the reduction of isolation between functional areas (Jaworski & Kohli, 1993; Narver & Slater, 1990). The literature above evidences the need to align inter-functional goals and incentives to drive inter-functional coordination (Jaworski & Kohli, 1993; Narver & Slater, 1990), thus it is inferred that this is a key attribute to leveraging big data for competitive advantage. Organisations that master the capability of a data-oriented culture are postulated to excel at innovation and strategy development, this differentiates them from competitors and drives competitive advantage (Kiron et al., 2011). In addition to adopting a data-driven culture the pertinent organisational structure is of importance to support and facilitate the same (Jaworski & Kohli, 1993; Narver & Slater, 1990).

2.6.1.3 Organisational Design

It was established that the organisation wide generation and dissemination of information is an antecedent for facilitating a shared understanding of the information, and the formulation and execution of a coordinated strategy. According to Mintzberg (1993), the structure of an organisation pertains to the way in which labour is divided amongst organisational members and the manner in which coordination is achieved. Achieving and sustaining market-orientation necessities organisations to adopt structures that enhances their ability to navigate dynamic and uncertain environments (Kuada & Buatsi, 2005).

The concept of formalisation pertaining to the extent to which formal rules and regulations are enforced by the organisation (Jaworski & Kohli, 1993) was introduced in the preceding section. Formalisation is said to reflect the degree of standardisation and the extent to which deviation from these standards are permitted (Engelen, Brettel, & Heinemann, 2010). It is expected that a high degree of formalisation results in rigidity, which impedes the organisations ability to respond quickly to market information and changes (Kuada & Buatsi, 2005). While Jaworski and Kohli’s (1993) empirical study reflects a lack of relationship between formalisation and market orientation, Jaworski and Kohli (1993) argued that an emphasis on rules makes organisations rigid and less adaptive to external change. The attribute of rigidity is counter the requirements of the dynamic capabilities framework, which accentuates the need for flexibility to permit organisations to adapt to changes in the environment, thus enabling them to achieve and sustain competitive advantage (Kozlenkova et al., 2013; Fang et al., 2011; Teece, 2007). Torres et al. (2018) identified and proved empirically that the ability to effect organisational process change is key to leveraging analytics capability.

Kuada and Buatsi’s (2005) empirical study, conducted in an emerging market environment produced a result which was contradictory to Jaworski and Kohli’s (1993) study and their hypothesis, that according to extant literature formalisation and market orientation should be inversely related (Jaworski & Kohli, 1993). Kuada and Buatsi (2005) argued that the positive relationship between these variables was achieved due to the context of the study, that is in the emerging market environment organisations were in the early stages of transitioning from non-market-oriented strategies to market oriented strategies, therefore formalisation was key to organisational members attaining the skills and routines for achieving a market-oriented design. Engelen et al. (2010) anticipated that the benefits of formalisation will not be appreciable at the early stages of the organisational life cycle in comparison to that of the later stages. The Engel et al. (2010) hypotheses was contradictory to the Kuada and Buatsi (2005) result; however, their result confirmed a positive relationship between market orientation and formalisation throughout the organisational life-cycle. This result confirmed the Kuada and Buatsi (2005) study, that in the early stages formalisation is required. According to Engelen et al. (2010); while the result was contradictory to Jaworski and Kohli's (1993) expectations, their result aligned with the argument that increased formalisation facilitated efficient market orientation (Engelen et al., 2010). While the results included in extant literature is not conclusive, it is evident that some degree of formalisation is required.

The concept of decentralisation was also introduced in the preceding section, where Jaworski and Kohli's (1993) empirical study produced an indecisive result. When decision making is decentralised, decision making authority is transferred to lower levels within the organisational hierarchy (Engelen et al., 2010), with the objective of facilitating improved responsiveness (Jaworski & Kohli, 1993). Gupta and George (2016) assert that organisations in which decision making is restricted to higher levels of management, are unlikely to leverage big data for competitive advantage. Extant literature suggests that centralisation is inversely related to information utilisation for decision making (Jaworski & Kohli, 1993). In support of this argument Gupta and George (2016) posited that centralised decisions are based on prior experience, intuition and the opinions of top executives as opposed to it being data driven. Extant literature asserts that decentralised structures are more suitable to enable organisations the flexibility and speed required to navigate complex, unpredictable, dynamic and hyper competitive environments (Day, 2011; Kuada & Buatsi, 2005; Jaworski & Kohli, 1993).

According to Kuada and Buatsi's (2005) empirical research, centralisation in the emerging market context was positively related to market orientation. This result was substantiated by the cultural and economic factors prevalent in the context of the study (Kuada & Buatsi, 2005).The Engelen et al. (2010) result indicated that decentralisation had a stronger positive effect on organisational responsiveness in the early stage of the organisation life cycle compared to the later stages. The Engelen et al. (2010) result was elucidated by the assertion that in the early stages of development, because of the prevailing uncertainty, markets not being fully identified and the product offering not being completely aligned to the customer's needs; fast and innovate reactions facilitated by decentralisation is required; however, when the environment stabilises the importance of decentralisation decreases. The results pertaining to formalisation and decentralisation appear mixed and context dependant. It is inferred that decentralisation is required in dynamic environments demanding flexibility, innovation and quick organisational responsiveness.

Mintzberg (1987), suggested a matrix structure entailing the grouping of experts into functional units for the purposes of formalisation, but deploying them into project teams for specific projects and tasks. Within this structure decentralised decision making is adopted to accentuate efficiency and innovation; however, ambiguity and uncertainty of the work environment engenders frustration (Slater & Narver, 1995). The mixed results pertaining to the extent of formalisation and decentralisation required (Engelen et al., 2010; Jaworski & Kohli, 1993; Kuada & Buatsi, 2005) suggested that organisational structures have dual needs for autonomy and structure (Slater & Narver, 1995). Predicated on this Slater and Narver (1995) cite an evolution of the "organic organisational structure" comprising an underlying formal structure supplemented by an upper layer of temporary project teams and multi-functional groups. The objective of the two-layer structure is to achieve the efficiency of a formalised structure and the flexibility of an autonomous decentralised structure, which facilitates the effective sharing of information, rapid awareness and response to the market, and reduction in lagging reactions (Miles & Snow, 1992). Under this two-layer organisational structure, temporary teams are deployed to work on various projects including new product development, process design and strategic assessments (Slater & Narver, 1995). This organisational design facilitates connectedness through leveraging technologies such as electronic mail and shared data bases (Slater & Narver, 1995). According to Miles and Snow (1992), the "organic organisational structure" and the evolved two-layer version engenders inter-functional coordination since, by design it creates interdependence between team members facilitating cooperation and information sharing. Aaker (2010), in support of the above postulated that leveraging technologies and the effective use of teams is fundamental when breaking down traditional silos.

As alluded to above, the leveraging big data analytics requires a shared platform for collecting, storing and sharing of intra-organisational and inter-organisational market and customer data, historical data from legacy systems and organisational internal process data (Wamba et al., 2015). According to Barton and Court (2012), legacy information technology (IT) structures hinders data sourcing, storage and analysis. Additionally, existing IT systems typically have silo typologies across various functional units rendering integration of traditional and new systems very challenging (Barton & Court, 2012). Kiron et al. (2011) accentuated that the ability to break the barriers of function and business silo's and integrate information across the same is a capability of fully transformed data driven organisations. Isik et al. (2013) stresses that integration between analytics systems is critical to analytics success and proved empirically that a strong positive relationship exists between business intelligence success and integration with other systems.

In support of the above, Barton and Court (2012) argued that to leverage value from big data investments it is imperative that organisations upgrade IT infrastructure to facilitate data integration and the interconnectivity between systems. In the case of legacy systems with compatibility issues, such projects take years, therefore the prioritisation of IT projects to ensure that the most important data sources are identified and upgraded (Barton & Court, 2012). This suggests an incremental approach to upgrading traditional infrastructure to big data infrastructure.

2.6.2 **Sense, Seize, Execute**

The below, also referred to as the market information processing perspective (Day, 2011; Hult et al., 2005; Morgan, Vorhies, & Mason, 2009) is based on the market orientation component of Section 2.6, Figure 2. According to Kohli and Jaworski (1990), market orientation encompasses the organisation wide; (1) generation of market intelligence pertaining to the present and future customer needs, including an analysis of the exogenous factors that may affect these needs, (2) communication and dissemination of this intelligence across the organisation, and (3) responsiveness, which pertains to the utilisation of this intelligence to develop plans and execute on them (Jaworski & Kohli, 1993). Furthermore, responsiveness encompasses the selection of target markets, aligning the design and offering of services and products to market requirements and distributing and promoting products on the right channels (Kohli & Jaworski, 1990).

A review of the above evidences that Jaworski and Kohli's (1990) definitions for the generation, communication and response to market intelligence pertains to the gathering and dissemination of environmental data in order to determine the markets current and future needs, thereby enabling the organisation to respond by aligning service and product offerings accordingly.

The strategic intent of big data encompasses leveraging big data to drive decision making, deliver superior customer value as well as to enhance the organisations dynamic capability (Erevelles et al., 2015). The above depicts that utilising the market information processing perspective in its current form detracts from the strategic intent of big data since it does not permit for dynamic capabilities. As mentioned in Section 2.4.1, organisations must integrate their internal and external data to leverage big data capabilities (Gupta & George, 2016).

Torres et al. (2018), proved empirically that a positive relationship exists between analytics capability and the efficiency and effectiveness of an organisations business process. This relationship was mediated by the organisations ability to effectively alter its business processes, thereby optimising the same in accordance to opportunities and threats identified through analytics (Torres et al., 2018). This accentuates the importance of the organisation being configured to serve as flexible strategic options (Moorman & Slotegraaf, 1999), which is the capability to adapt to changes in the external environment by reconfiguring, extending and upgrading resources (Erevelles et al., 2015; Kozlenkova et al., 2013; Moorman & Slotegraaf, 1999). According to Torres et al. (2018) the above serves as a source of competitive advantage and requires that organisations plan and design their value creating processes in a modular manner. The organisational attribute of the VRIO framework (Kozlenkova et al., 2013) is a key factor , particularly the organisational rigidity and structural insularity barriers (Day, 2011) detailed in Section 2.6.1.

As per Section 2.2.2, the transformation constituent of the dynamic capabilities construct, encompasses maintaining competitiveness through the creation, renewal or reconfiguration of the organisations capabilities in accordance to the outputs from the "seize" component of the dynamic capabilities construct (Teece, 2007; Torres et al., 2018). This may require changes to the organisational structure and business model (Day, 2011; Teece, 2007). It is inferred from the above, that to realise the strategic intent of big data, the responsiveness and transformation definitions must converge. The resulting “execute” component and associated definition is included below.

Hult et al. (2005), proved empirically that the organisation wide generation and dissemination of market intelligence is positively related to organisational responsiveness. Reference is made to the sense and seize constituents of the dynamic capabilities construct as defined in Section 2.2.2. Torres et al. (2018) provided empirical evidence that a positive relationship exists between the “sense” and “seize” and “transform” constituents of the dynamic capabilities construct. Both Jaworski and Kohli (1993) and Torres (2018) explain that this relationship to exist because access to more data exposes the organisation to more insights and access to competitive actions.

Premised on the definitions for the “sense” and “seize” constituents of the dynamic capabilities construct aligning with the strategic intent of big data and being more comprehensive than the “generation” and “dissemination” constituents of the market information processing perspective it is proposed that “sense” and “seize” replace the “generation” and “dissemination” components of the market information processing perspective. The definition of seize (Teece, 2007; Torres et al., 2018), below incorporates the attribute of engendering a shared understanding amongst stakeholders. This attribute addresses, the Hult et al. (2005) contention that organisations only effectively respond to information if a common understanding of that information exists.

In the context of this research, the conceptual model augments of the market information processing perspective with proposed changes to the following components and terms; (1) Sense and shape external threats and opportunities through scanning, searching and exploring across markets and technologies (Day, 2011; Teece, 2007). More specifically, sensing pertains to the acquisition of information about the organisations internal operations and the external environment in which it operates, while shaping opportunities pertains to the analysis and filtering of this information (Teece, 2007; Torres et al., 2018), (2) Seize opportunities through the integration and interpretation of the information in order to facilitate decision making, a shared understanding amongst stakeholders and the formulation of strategy in response to the opportunities identified (Teece, 2007; Torres et al., 2018). For clarity, integration refers to the coordinated organisation wide effort in interpreting the information, identifying the opportunities and threats and the subsequent formulation of a coordinated strategy (Jaworski & Kohli, 1993; Narver & Slater, 1990), (3) Execute, through the integrated implementation of the strategies pertaining to delivering superior customer value or effecting organisational changes to exploit opportunities and avoid threats.

An analysis of the sense, seize and execute functions as defined above, and within the big data context evidences that these functions require the following big data specific resources (Gupta & George, 2016; Isik et al., 2013; Torres et al., 2018; Wamba et al., 2015); (1) human resources with the requisite technical and management expertise, (2) technology infrastructure, and (3) organisational support. Each of the above resources was discussed in Sections 2.4 and 2.6.1.

Organisational rigidity, which refers to an organisation refusing to transform as a result of them mastering a capability and persisting with the same beyond the point of obsolescence has been identified as key barrier to adapting (Day, 2011). It is postulated that the sense, seize and execute function as elucidated above assists in addressing organisational rigidity by virtue of its dynamic capabilities attributes. Mastering the capabilities of information management, is one of the three key skills that top performing organisations, in terms of leveraging big data analytics possess (Kiron et al., 2011). It is postulated that the capability to effectively sense, seize and transform enables the organisation to master information management capability.

2.7 Conclusion

Ervelles et al. (2015) asserted that big data is considered a form of capital and source of competitive advantage since it is viewed as a means for gaining deeper insights into consumer behaviour and for facilitating data driven decision making, thus enabling managers to align their organisational strategies to market demands (Johnson et al., 2017). Effective analytics had been identified as a differentiator between top performing and lower performing organisations, where the top organisation’s decisions were data driven through leveraging rigorous analytics (Kiron et al., 2011; Lavelle et al., 2010).

Extant literature suggested that there is a lack of understanding of how organisations can leverage big data capability to generate competitive advantage in the dynamic marketplace (Johnson et al., 2017; Martens et al., 2016). Gupta and George (2016) argued that while a large number of organisations have already invested or are planning to invest in big data capabilities little is known about how organisations should go about building these capabilities. Premised on the above and the research purpose, this chapter presented a review of extant literature pertaining to big data, big data analytics, sustainable competitive advantage and market orientation. Literature evidenced that investments alone were inadequate to engender competitive advantage, instead difficult to match capabilities through unique combinations of tangible, intangible and human resources was required (Gupta & George, 2016; Torres et al., 2018). In addition, the hyper competitive and dynamic market place dictates that capabilities are dynamic to ensure competitive advantage is sustainable (Day, 2011; Kozlenkova et al., 2013; Teece, 2007). Mastering the capabilities of information management, analytical skills and tools and a data-oriented culture was identified as key for leveraging big data analytics for competitive advantage.

While big data technological infrastructure requires substantial investments, and skilled human resources are scarce, literature identified key challenges to emanate from a lack of understanding of how to build big data capabilities, a lack of understanding of the unique resource requirements, organisations not being ready for big data and the inability to adopt a data-oriented culture (Erevelles et al., 2015; Gupta & George, 2016; Kiron et al., 2011; Lavelle et al., 2011; Torres et al., 2018). Gupta and George (2016) asserted that organisational culture issues were responsible for a larger number of failed big data projects than technological or data related issues.

The research utilised resource-based theory (Kozlenkova et al., 2013), dynamic capabilities theory (Teece, 2007) and the market orientation construct (Jaworski & Kohli, 1993; Kohli & Jaworski, 1990; Narver & Slater, 1990; Slater & Narver, 1994) as theoretical frameworks. Premised on the strategic intent of big data and the attributes of market orientation (Jaworski & Kohli, Narver & Slater, 1990), it was postulated that the principles associated with the development of a contemporary big data market-oriented approach encompasses the traditional market information processing perspective (Kohli & Jaworski, 1990) and culture emphasis perspective (Narver & Slater, 1990); however, in addition the unique big data resource requirements (Erevelles et al., 2015) and dynamic capabilities were considered to devise a concept, which is to be used as a tool for analysing the research presented in the subsequent chapters.

3 CHAPTER 3: RESEARCH QUESTIONS

3.1 Research Questions

Research Question 1

How is big data analytics used in South African banking for competitive advantage?

Lavelle et al. (2010) asserted that data driven decisions resulting from rigorous and effective analytics is a key differentiator between top performing and lower performing organisations. As per Martens et al. (2016), organisations are making large investments into big data assets, however they lack understanding of how to effectively leverage these big data capabilities for competitive advantage.

Following from the above, Research Question 1 aims to understand the status quo of how big data is being used for competitive advantage in South African banking and if it is perceived to be a source of sustainable competitive advantage.

Research Question 2

To what extent are the methodologies employed for the processing of big data considered adequate to leverage big data analytics as a source of competitive advantage in South African banking?

Research advocated that the methodologies employed for the processing of big data is inadequate, thus organisations lack the capability of effectively harnessing the benefits of big data for competitive advantage (Erevelles et al., 2015; Johnson et al., 2017; Lycett, 2013; Martens et al., 2016; Kozlenkova et al., 2013). The objective of research question 2 is to investigate this assertion and to understand; (1) the perceived adequacy or inadequacy of the methodologies employed to leverage big data analytics for competitive advantage, and the key factors justifying the same, (2) how the quality of the insights extracted from big data can be improved to leverage big data analytics for competitive advantage.

Research Question 3

What are the specific big data resource requirements for leveraging big data analytics as a source of competitive advantage in South African banking?

As detailed in Chapter 1, organisations generally lack understanding of the specific big data resource requirements; therefore, they are unable to leverage the same for competitive advantage (Erevelles et al., 2015; Johnson et al., 2017; Lycett, 2013; Martens et al., 2016).

In cognisance of the above, research question 3 seeks to establish; (1) what are the specific big data resource requirements, (2) what are the gaps between the envisaged resource requirements and the resources that are available, (3) the proposed solutions for addressing the identified resource gaps, and (4) the impediments to implementing the proposed solutions.

Research Question 4

What is the role of the inter-relationships between big data assets in leveraging big data analytics as a source of competitive advantage in South African banking?

As detailed in Chapter 1, organisations generally lack understanding of the inter-relationships between big data assets, specifically they lack understanding of how to create big data capabilities (Gupta & George, 2016; Johnson et al., 2017; Moorman & Slotegraaf, 1999).

In cognisance of the above, research question 4 seeks to establish; (1) what is the role of the inter-relationships between big data assets in being able to effectively leverage big data analytics for competitive advantage in South African banking, (2) what are the challenges in terms of these inter-relationships that inhibits big data analytics from being leveraged as a source of competitive advantage, (3) the proposals for addressing these challenges, and (4) the impediments for executing the recommended proposals.

4 CHAPTER 4: RESEARCH METHODOLOGY AND DESIGN

4.1 Introduction

This chapter discusses the research methodology and design that was selected for the research. The research was grounded by the literature presented in Chapter 2. Data was collected through one on one semi-structured, in-depth interviews with experts from the South African banking industry. Thematic analysis was adopted to gain insights from the qualitative interview data.

4.2 Choice of Methodology

The research philosophy predominantly fits in the interpretivism domain. This was based on the nature of the questions which the research sought to answer. The research questions are subjective in nature, within a social context and does not focus on quantifiable and measurable variables. Qualitative research is non-numeric research is focussed on the generation and analysis of non-numeric data (Quinlan, Babin, Carr, Griffin, & Zikmund, 2015). According to Quinlan et al. (2015), qualitative business research, specifically addresses “business objectives through techniques that allow the research to provide elaborate interpretations of phenomena without depending on numerical measurement; the focus is on discovering inner meanings and new insights” (Quinlan, Babin, Carr, Griffin, & Zikmund, 2015, p. 124).

The research initially developed a conceptual model based on the literature review evidencing a deductive approach (Creswell, 2014), and then followed the inductive approach as per (Williams, 2012). According to Saunders and Lewis (2012), combining inductive and deductive methods into the same research is not unusual and comprises initial analysis based deductively on literature, followed by further development from the researcher’s experience. The evidences that the research followed a combined deductive and inductive approach. The research adopted an emergent and flexible methodology in line with Staller (2012).This research is consistent with Stebbins (2012) definition of exploratory data analysis, which is “the set of steps that qualitative researchers follow in exploring a new area […] generate new concepts and generalizations about that area.” (p. 2).

The scope of this research is consistent with Vogt’s (2011) description of a cross sectional study in that it employed the use of once off interviews conducted over a short period of time. Saunders et al. (2009) and Ayres (2012) suggested that when an exploratory study is being conducted then it is likely that interviews comprising open ended questions will be used. The research objectives and research questions required that semi structured interviews be conducted. This was achieved through one on one personal interviews, which provided the opportunity to explore and answer the "how?", "what?" and "why?" questions as well as the opportunity to observe and record the body language and tone of the interviewee.

4.3 Population

Population is defined as the complete set of group members and need not only be people but can also be organisations and places (Saunders & Lewis, 2012). As of 2016 the South African banking sector comprised 32 registered banks, of which 17 are locally controlled and 15 are foreign controlled (Business Monitor International Ltd, 2017). The population for the study is the 17 locally controlled South African banks.

4.4 Unit of Analysis

Vogt (2005) defines the unit of analysis as "the person or things being studied" (p. 2). Based on the above and the purpose of the study, the sample comprised executives, senior managers and analysts with the requisite expertise and direct involvement with big data and big data analytics in various organisational roles. Premised on these attributes, rich data providing a holistic view and big data insights at the strategic level, the data and architecture management level, data analysis level and data user level was obtained.

4.5 Sampling Method and Size

As per Saunders et al. (2009, p. 223), if sampling is required and if statistical inferences need not be made from the sample then non-probability sampling must be utilized. Saumure and Given (2008) posited that that non-probability sampling is common in qualitative research and it entails the selection of the sample in accordance to the researcher's judgement. Based on this discussion and the nature of the research questions, non-probability sampling was employed.

Purposive sampling is a non-probability sampling technique that enables the cases which will best enable the researcher to answer the research questions (Saunders, Lewis, &

Thornhill, 2009). As per Marshall (1996), purposive sampling is the most common sampling technique. Based on the exploratory nature of the research, the semi-structured interview approach and the anticipated small sample sizes, the purposive sampling method was applied.

As per Dworkin (2012), saturation is achieved when gathering new data does not introduce new theoretical insights nor reveals new properties of your core theoretical categories. A total of 11 interviews comprising 12 participants was conducted over a 3-week period. The interviews comprised 10 one on one interviews and 1 interview with participants 7 and 12 together. Saturation was reached by the ninth interview, since it appeared no new insights were gained. The remaining interviews were conducted nonetheless to confirm that saturation was in-fact reached. Table 1, in Section 5.2 describes the study participants.

4.6 Measurement Instrument

The measurement instrument is defined as the measurement device in the research process (Stebbins, 2012). The researcher conducted one on one, in depth, semi-structured interviews in accordance to the interview guide included in Appendix C: Interview Guide. The interview guide followed a semi-structured format wherein a number open ended questions linked to each of the overarching research questions.

4.7 Data Gathering Process

In line with the Given's (2008) definition of semi-structured interviews, the setting up of the themes was done based on the literature review. Semi-structured interviews facilitated probing answers and building on and exploring the themes of interest. Open ended, non- leading questions included in Appendix C: Interview Guide, was be used for the interviews.

The research focussed on the South African Banking industry, most of these headquarters are based in Johannesburg, and therefore personal interviews were conducted with each of the participants. Interviewer administered surveys are advantageous in that that they have a much higher response rate in comparison to self-administered surveys (Persaud, 2012). Being in close locality to the sample addressed the accessibility and cost issue.

Participants were initially identified and contacted through LinkedIn. Once contract was established, the interviews were confirmed through electronic mail. The interviewees were invited to participate in the study utilising the invitation included in Appendix A: Invitation to Participate in Study. The interviews were voice recorded with the permission of the participants, as evidenced by a signed consent form. An example of the consent form is in Appendix B: Interview Consent Form. The interviews were later be transcribed for analysis.

As per Quinlan (2015), qualitative research is sometimes prone to being subjective, non-representative and non-systematic. As a result, trustworthiness in terms of reliability and validity will have to be considered. According to Quinlan (2015), reliability refers to the "dependability of the research, to the degree to which the research can be repeated while obtaining consistent values" (p. 24), and validity refers to "the accuracy of a measure or the extent to which a source truthfully represents a concept" (p. 24).

Within the context of qualitative research reliability and validity pertain to interviewer bias, interpreter bias and response bias (Saunders & Lewis, 2012). Cognisance was taken of potential data quality issues to ensure that the data gathered was valid and useful for analysis. Saunders et al. (2009) details the issues around data quality. Some key issues that the researcher was aware of included interviewer bias, interviewee bias and having the correct interviewing competence. While the researcher did not have any formal training, cognisance of the above issues enabled the researcher to remain as unbiased as practicable. The interviews were also standardised in accordance to the interview guide included in Appendix C: Interview Guide order to promote validity and reliability.

The five Ps approach of non-structured interview, i.e. "prior planning prevents poor performance" (Saunders, Lewis, & Thornhill, 2009) was always followed to assist in ensuring good quality of data. As per Shenton (2004), provisions were made in accordance to Guba's four criteria for trustworthiness, i.e. Credibility, Transferability, dependability and confirmability. These provisions were adopted as far as practicable and as per the relevance to the research.

4.8 Analysis Approach

The qualitative data collected from the interviews was in the form of voice recordings which were transcribed for analysis. Thematic analysis, which is the analysis of data through the use of themes (Quinlan et al., 2015) was utilised. As per the above, the themes were analysed from the qualitative data gathered. The identification and analysis of patterns or themes in the qualitative date is referred to as thematic analysis (Braun & Clarke, 2006).

4.9 Limitations

Since the data was collected by semi structured interviews, there are biases such as interviewer and interviewee bias (Saunders, Lewis, & Thornhill, 2009) which comes into play. The researcher not being independent from the data collection process introduces biases. Because of the qualitative nature of the research special care had to be taken to ensure trustworthiness of the data (Shenton, 2004). With regards to the data collection there may have been shortcomings in the researchers interviewing skills, which may impact the quality of the data.

5 CHAPTER 5: RESULTS

5.1 Introduction

This chapter presents the results from the analysis of 11 semi-structured, in-depth interviews conducted with experts from the South African banking industry. Thematic analysis of the qualitative interview data provided insights into leveraging big data analytics for competitive advantage in South African banking, particularly, the industries understanding of how to utilise big data analytics, the adequacy of the methodologies employed for the processing of big data and the resource and capability requirements.

The subsequent sections of this chapter include an overview of study participants and presents the results for each of the four overarching research questions introduced in chapter 3. These research questions provide the framework for the presentation of the results.

5.2 Description of the Study Participants

A total of 11 interviews comprising 12 participants was conducted over a 3-week period. The interviews comprised 10 one on one interviews and 1 interview with participants 7 and 12 together. It was agreed that participants 7 and 12 be interviewed together since one of the participants had time constraints and was unable to honour the time slot originally booked. Table 1 below, represents the participant identifiers, role in the bank, bank age and durations of the interviews. The bank age is noted since the implementation and role of big data is different when considering banks with legacy systems and newer banks.

Table 1: Description of Study Participants

Identifier	Role in Bank	Bank age	Duration
Participant 1	Customer and Market Insights Manager	> 100 years	38:07 min
Participant 2	Regional Head	< 50 years	37:26 min
Participant 3	Chief Information Officer	> 100 years	39:55 min
Participant 4	Data Analyst	< 100 years	44:56 min
Participant 5	Chief Information Officer	> 100 years	57:29 min

Identifier	Role in Bank	Bank age	Duration
Participant 6	Regional Chief Data Officer, Previously Head Data Product Development	> 100 years	55:23 min
Participant 7	Digital Marketing Manager	> 100 years	48:18 min
Participant 8	Chief Data Officer	> 100 years	52:19 min
Participant 9	Marketing Manager	> 100 years	37:22 min
Participant 10	Head: Home Services	> 100 years	41:47 min
Participant 11	Actuary: Data Science Lab	< 50 years	36:00 min
Participant 12	Digital Consultant	> 100 years	48:18 min

In the interests of the banks and participants anonymity, no names are disclosed, and all the participants are identified as tabulated above. Heterogeneity was obtained through the varying levels of maturity of the banks and the array of big data skillsets and roles of the participants. The sample comprised executives, senior managers and analysts with the requisite expertise and direct involvement with big data and big data analytics in various organisational roles. Premised on these attributes, rich data providing a holistic view and big data insights at the strategic level, the data and architecture management level, data analysis level and data user level was obtained. Purposive sampling was employed to best facilitate the answering of the research questions. The 11 interviews utilised for the study were conducted face-to-face either at the Gordon Institute of Business Science or at the premises of the participant.

5.3 Results for Research Question 1

Research Question 1: How is big data analytics used in South African banking for competitive advantage?

The objective of Research Question 1 was to establish if big data analytics is considered a source of competitive advantage, and to understand how big data analytics is currently being utilised for competitive advantage in South African banking. Table 2 below, depicts the codes and the emergent themes for Research Question 1. The themes resulted from the aggregation of these codes.

Table 2: Themes and Codes Research Question 1

Themes	Codes
RQ1: T1 - Competitive Advantage	CA: Create Operational Efficiency
	CA: Credit Risk Management
	CA: Customer Centricity
	CA: Customer Personalisation
	CA: Data Driven Decisions
	CA: Predictive Analytics
	CA: Product Development
	CA: Target Marketing
	CA: Value in using big data
RQ1: T2 - Customer Information	CI: Customer Behavioural Data_Primary
	CI: Customer Credit Data
	CI: Customer DNA
	CI: Customer Journey
	CI: Customer Transactional Data_Primary
	CI: Life Events_Primary Data
	CI: Real Time Insights
	CI: Social Profiling
	CI: Third Party Partnerships
	CI: Voice to text from customer calls

The emergent themes pertaining to big data analytics as a source of competitive advantage relates to the ability to leverage the proliferation of client information currently available to create a single customer view with the objective of increasing customer value by driving a customer centric philosophy predominantly grounded on target marketing, personalisation and customisation.

The pertinent qualitative data supporting the above assertions is presented in Sections 5.3.1 to 5.3.3 below.

5.3.1 Big Data Analytics as a Source of Competitive Advantage in South African Banking

In all cases, the study participants considered big data analytics to be a source, or a potential source of competitive advantage in South African banking. In six cases the participants confirmed big data analytics to be a definite source of competitive advantage. Participant 8 asserted, “a source, yes, definitely it should be, you know, to fully understand why it's a competitive advantage, you've got to unpack what big data is and what it can do…find intelligent information and let's make a decision on it…we sit on a wealth of information “. Participant 11 concurred with the above and introduced the dimensions utilising big data as a platform for innovation and differentiation by stating, “Ya, definitely [it is a source of competitive advantage]…I think it is absolutely essential for you to bring something different and innovative into that space just to differentiate yourself and we see big data analytics has quite a big role to play to differentiate yourself.”

Six participants argued that big data analytics was a potential source of competitive advantage, since they shared the sentiment that big data analytics was in the early stages of augmentation in South African banking with substantial development prior to them being able to effectively leverage it for competitive advantage. Participant 5 acknowledged big data analytics to be a potential source of competitive advantage and emphasised that, “If you look at the maturity of using big data in the context of South African banks, I think we probably like twenty, thirty percent majority… so even if you asked me if there's value in using big data, absolutely there's been value.” Participant 10 supported the notion that while big data is a potential source of competitive advantage, it is not yet mature in South African banking and asserted, “I think it [big data] is in theory, a source of sustainable competitive advantage. I think in terms of actually executing on it, I think we still got a long way to go as an industry.”

While the arguments presented above evidenced a difference in perspective in terms of big data analytics being a definite or potential source of competitive advantage, the common thread was that big data analytics was positively associated with competitive advantage. None of the participants suggested big data not to be a source of competitive advantage.

Two participants introduced legislation as an area of uncertainty and concern to leveraging big data analytics for competitive advantage. Legislation was deemed to present restrictions on the utilisation of customer information and was therefore viewed as an inhibitor to the augmentation of big data analytics in South African banking. Participant 6 succinctly captured the essence of the discussion above, through the assertion that “I think, we’re still in the early phases, so it's interesting because banks are in a bit of a tricky situation because of the legislative requirements… while the ideas of getting into big data and using big data for competitive advantage are very, very high on people's priority lists, the ability to use it or not use [it] is becoming challenging…I suppose to sum up there is intent for companies to use big data [for competitive advantage]".

5.3.2 The current utilisation of Big Data Analytics as a Source of Competitive Advantage in South African Banking

The qualitative data presented in the preceding section established that the bank has access to a myriad of transactional data, which through advantageous analytics, potentially can be leveraged for competitive advantage. This section builds on this sentiment as most of the participants explained that currently competitive advantage is derived by utilising the wealth of data to increase customer value through various applications including personalisation and customisation, target marketing, assisting customers better and achieving operational efficiencies. The data in support of this assertion in presented in the subsequent sections.

The concept of the proliferation of data is reinforced by Participant 5's assertion that big data encompasses "internal data, external data, the bureau related data plus social data". In answering this research question most of the participants initiated the discussion by defining big data. Participant 6 indicated that big data is high volume and can be structured and unstructured data. Participant 8 defined big data as "basically just lots of data that either comes at you too fast, too big to churn through normal size computers, so to speak of, or [a] combination of it…. sometimes [characterised by the] five v's…variety, velocity, veracity, volume and value."

5.3.2.1 Personalisation and Customisation

Personalisation was a dominant code that emerged in the explanations of how big data is currently utilised for competitive advantage. Participant 10 accentuated the concept of personalisation by asserting that, "[big data is being used] to provide more upfront value to the customers and that's where sort of phrases like "my bank knows me", become a lot more important rather than saying "I got home loan" or "I got this", or "I got that". Participant 8 explained that big data analytics is currently used as a source of competitive advantage by "understanding our customers a lot better, at understanding what they want to do, when they want to do it, how they want to do it".

Most of the participants understood personalisation to include delivering the right solution at the right time to the right customer and through the right channel. Participant 5 elucidated that “personalisation is based on personal events…called life events or life triggers…. there's certain things that I can use in terms of what is available to [the] bank…to be able to build life events…to be able to personalise things to the customer…we do look at what's currently available to us in order to deduce certain things... I think the advantage of using the big data is that we can be more specific and customised and personalised to the consumers, to the benefit of the consumers.”

Most of the participants shared consensus that personalisation was requisite on the bank utilising transactional data to understand the customer. Two participants explained that customer behavioural data comprised “transactional data, credit information and social information,” thus clarifying transactional data to be a subset of behavioural data. Participant 5 elaborated that “[the] behavioural side is quite important…a lot of the time when you tap into social media, tap into your own current account transactions, you can easily pick behavioural trends around customers…it really complements to take the data to the next level that it really can add value to the consumer and our understanding of the consumer.”

Participant 5 illustrated the concept of personalisation utilising customer behavioural data, in particular credit card transactional data to deduce life events by way of the following example, “I can troll through your credit card history and find out if you have been to a, I don’t know, two regular meetings with a doctor…and I can use that information to deduce certain things…because obviously if your wife is pregnant…and there are certain cycles that you need to go in terms of meeting a certain type of doctor; you would use that information to deduce as to maybe there's a child on the way”. Participant 6 acknowledged that big data analytics has current applicability “to create competitive advantage in sales and product choice and through customisation…there are a myriad of use cases that can enable use of big data for determining product choice for somebody and therefore increasing sales, knowing what product to give somebody at the right time based on a life stage or a moment”, but indicated that there may be limitations due to concerns over legislation.

Customisation was introduced by two participants. Participant 5 defined customisation as, “looking at the product configuration and adjusting them to fit you.” Customisation was understood by most of the participants to be synonymous with product development driven by trends in consumer behaviour. Participant 4 articulated the customisation concept through an illustration of how competitive advantage was created by designing and launching a customised product based purely on observation of customers behaviours. According to Participant 4, “if you can see what your clients are doing, you can easily create products that the other banks are not offering. This was the case for us when we created…it was purely from just noticing that our clients like…so it created a competitive advantage for us…we created a new business from it.”

5.3.2.2 Target Marketing

Target marketing was identified by all the participants as an extensive application area for leveraging big data analytics for competitive advantage. According to Participant 1, target marketing pertains to “target[ing] the right people for the right product. Participant 9 stressed the importance of accurate target marketing and predictive analytics and emphasised that “where we going to with artificial intelligence, becoming more predictable in terms of timing, campaigning as well as change in campaigning and targeting clients at the correct space… I think it’s really important for target marketing… so I think if we are going to get the necessary ROI, we have to make sure every contact is a very valuable [contact]…and the only way we can identify or do that is through data so, everything is driven through data…we are using a lot of modelling right now to predict next purchase.” Participant 6 argued that target marketing is not leveraged effectively as it is “spray and pray a lot of the time”; however, “[when] data has been used to come up with analytics, intelligent analytics, the increase in rates is over three hundred percent.” This example illustrates a substantial return on investment can be derived from effective data driven target marketing.

The participants assertions quoted in this section emphasised the importance of targeting the right client, with the right product at the right time and on the right platform. Premised on the above description of target market it is inferred that target marketing is an application area and subset of the personalisation and customisation application discussed in Section 5.3.2.1.

5.3.2.3 Big Data Analytics for Competitive Advantage – Platform for better Assisting Customers

Three participants identified utilising big data analytics as a platform for assisting customers as a differentiator. According to Participant 3, “if you can assist your customers to better spend their money or to better track their spend budget, those kinds of things, and protect themselves, especially with finances, that is what sets you apart.”

All three participants provided the same example of a low balance alert function based on predictive analytics and customer behaviour.

5.3.2.4 Operational Efficiencies

In addition to personalisation, customisation, having contextually relevant conversations with the customer and the overall ability to provide the right solution at the right time and through the right channel, two participants identified big data analytics as a platform to save operating costs through efficiencies while increasing customer value.

Participant 6 indicated that this was being achieved through the automation of manual processes and explained that “our AI team is doing a lot around voice recognition, cognitive type analytics around looking at how somebody moves around a branch and how long they wait at each point, so that type of data is obviously very unstructured. That's mostly to create efficiencies in branches and less so to provide somebody individually with the product… there's a lot of places where there is still manual work done and documents captured, and I think the biggest competitive advantage that the bank will get in the next couple of years around big data is creating operational efficiency. So, taking some processes are that are currently manual and automating them.”

5.3.3 Summary of findings for Research Question 1

In answering Research Question 1, it was established that the proliferation of structured and unstructured data, termed big data, is seen as an avenue to gather client information, which can be analysed with the objective of identifying trends and patterns to drive personalisation, customisation, target marketing and providing the right product at the right time utilising the right platform. The envisaged outcome of this customer centric approach is an increase customer value and competitive advantage. Reduction of the banks operating costs through the automation of manual processes and the attainment of operational efficiencies also emerged as a key area for competitive advantage through leveraging big data.

The utilisation of big data in South African banking is seen to be in the infancy stages of development with a long way to go prior to it being leveraged to its full potential. Regulation featured as an inhibiting factor for the enhancement of big data in South African banking. Regulation as a theme is discussed in Section 5.4.4.5.

5.4 Results for Research Question 2

Research Question 2: To what extent are the methodologies employed for the processing of big data considered adequate to leverage big data analytics as a source of competitive advantage in South African banking?

This research question aimed to establish the deemed adequacy of the methodologies employed for the processing of big data to leverage it as a source of competitive advantage as well as to identify the key inadequacies and areas for improvement. The term processing was explained to the participants to encompass the gathering, storage, analysis or utilisation of big data. Due to the heterogeneity of the sample the participants were prompted to provide insights on the components of processing that was most applicable to their area of application and expertise.

The research question was developed from extant literature suggesting that the methodologies employed for the processing of big data is inadequate predominantly because of big data being aggregated to fit traditional analytics methods (Martens et al., 2016). Table 3 below, depicts the codes and emergent themes for Research Question 2. The themes resulted from an aggregation of these codes.

Table 3 Themes and Codes for Research Question 2

Themes	Codes
RQ2: T1 - Human Resources	HR: Translator
RQ2: T2 - Technology	TECH: Technology
	TECH: Open Source - Distributed Storage and Processing
	TECH: Machine Learning
	TECH: Data Gathering
	TECH: Artificial Intelligence
	TECH: Algorithms
	TECH: Advanced Hardware
RQ2: T3 - Investment	INV: Organisational Buy in
	INV: Investment in Resources
	INV: High Cost
	INV: Customer Value Increase
	INV: Commercial Value
RQ2: T4 - Data Health	DQ: Data Health
RQ2: T5 - Legacy	LEG: Product Silos
	LEG: Legacy

Themes	Codes
	LEG: Incompatible Systems
	LEG: Challenge to Leverage BDA without a single customer view
RQ2: T6 - Regulation	REG: Rethink Regulation
	REG: Restriction on how Social Data is used
	REG: Regulation Uncertainty
	REG: Regulation restricts how Transactional Data is used
	REG: POPI
	REG: Consumer Protection Act
RQ2: T7 - Maturity Level	MAT: Maturity Level

Table 3, evidences that Human Resources, Technology, Investment, Data Quality, Legacy, Maturity and Regulation were the seven emergent themes for Research Question 2. Sections 5.4.1 to 5.4.4 presents the relevant qualitative data.

5.4.1 Difference in the Methodologies for the Processing of Big Data versus Traditional Data

As per Section 5.3.2, four participants understood big data to be characterised by large volumes of structured and unstructured data. Two participants provided their understanding of traditional data and traditional data analytics. According to Participant 5, traditional data "basically means that the customer's age group is this, this is what the income is" and what "big data does is that it compliments [traditional data] with very qualitative customer centric information that also includes [the] behavioural side of things." Participant 11 explained traditional data analytics to encompass "traditional teams who know how to do structured data in a structured database". Premised on the above and the overall conversations with the participants it was evident that the basic underlying understanding of traditional data was that it primarily comprised structured data including demographic and geographic type customer information stored in structured databases.

While nine participants acknowledged that there are differences between the methodologies required for the processing of traditional data and big data, four of the participants who were technically experienced on big data and traditional data elucidated the differences at a more granular level. Participant 11 asserted that "it's [big data analytics and traditional analytics] quite different…. the process is quite different, we need to get familiar with new types of databases where you can incorporate more unstructured data…you need a completely new skills base when it comes to analysts."

In line with the data quoted above, seven participants postulated that the differences emanating from the characteristics of big data being fundamentally different from traditional data translated into different human resource and technology requirements.

Participant 11 eloquently summarised the fundamental difference between traditional analytics and big data analytics through the following example, “in the traditional method, you would create the structure of the data first and then you would put the data in that structure so you would define the column headings…define how many rows you put in…when all that structure is in place do you bring in all the data whereas now with big data, you want to dump all the data into the database first, it doesn’t matter what it looks like and then from there…you start looking for patterns and then once you find the patterns, you can create the structure out of it so it’s that kind of mind-shift that”. This elucidation highlights a unique methodology moving away from a predominantly structured approach based on prior knowledge to a more unstructured and exploratory approach guided principally by the data.

Building on Participant 11’s assertion that “you need a completely new skills base when it comes to analysts”, Participant 5 argued that “the resource capabilities that [we] require [are] fundamentally different. Historically we need a DBA [data base administrator], now I need data engineers, now I need a data scientist…so, the type of resources and the type of skills that are required transitioning from normal conventional analytics into big data [analytics are] fundamentally different.”

Participant 6 elucidated the technological requirements as “storage size, so you've got to have technologies that allow you to store efficiently and process…the volume and speed are the two big considerations. If you can't get that out of it and you, you generally can't get that out of the traditional warehouse” In addition to the hardware requirements, five participants elaborated on the software, algorithms, artificial intelligence and machine learning requirements. According to Participant 1, “you need systems to store that data and you also need algorithms to process the data. So, you need artificial intelligence algorithms to process the data…you can’t talk of big data unless you talk of machine learning or artificial intelligence.” Participant 5 explained that “the actual software construct that we need to use is also different…artificial intelligence plays a massive role in the big data environment…need the capability to be able to predict based on what is currently available…these algorithms and stuff has to be quite quick in predicting certain things, historically if you look at like an Arima model that that takes a lot of time to crunch numbers versus what we need to do in terms of big data, is to use the artificial intelligence side of things. So neural networks, artificial intelligence means that all of that gets used in the construct of the big data."

It is evident that from a technological perspective that the shift is predominantly focussed on hardware and software to efficiently store, retrieve and process large volumes of data. The result of these requirements is the migration from traditional data warehouses to open source platforms for distributed storage and processing. According to Participant 5, "in the transition [from traditional analytics to big data analytics], there's other software that we will need to look at, you know, things like that kind of runs on the server instead of using your memory on your machine, like things like Tableau and a lot of stuff." Participant 6 elaborated that "on the later technologies…because it's open source, the integration into other technologies is much easier as well as the types of tools that you can build on top of it…tools like [name of open source platform] that can handle volume and then do your work there."

One participant introduced the need for a change in mindset when organisations transition from traditional analytics to big data analytics. Participant 11 asserted that "the biggest challenge is sort of the cultural shift and a change of mind-set…they [traditional analysts] need to break away from the old ways of doing things and start to think of things in a new direction…so it's that kind of mindset shift"

The assertions of Participants 5 and 11 above confirms that the skills set required for big data analytics is entirely different from the skills sets of traditional analysts, where traditionally data base administrators were required and now data scientists and data engineers are required. The need for a complete cultural shift and mindset change in addition to a different technical skillset implies that, for big data it may be viable to train and introduce new resources into the system as opposed to attempting to transform traditional analysts to big data analysts. The organisational cultural aspect is discussed further in Section 5.6.4.

Three participants indicated that there is still a need for traditional analysts. Participant 3 indicated that "a traditional data analyst [is] still in high demand". Participant 5 postulated that "there's going to be a transition period…I think probably a good ninety percent of the work that we do is so based on the traditional side of it probably and ten percent [on the big data side], but over time it's going to transition…So in that interim period, there's no pressure for the traditional analyst to become a data scientist, right. But we've created the environment as to who wants to go there that will facilitate that. But we're not forcing everybody to go into the data science and when you look at the banking side, even at the highest maturity of the data world, right. We would still have conventional analytics in a bank because that is still required, right…" In line with the above, Participant 6 shared the above sentiment that while some resources will like to transition to big data analytics, there is no pressure to convert traditional analysts to big data analysts. Participants 6's argument that "it depends on the person and whether it's something they want to explore or not…some people are quite comfortable doing their old traditional - they good at (name)…they understand business and that's what they want to stick to. And then there are the guys that are like, no, I want to start going into the different types of technologies" confirms this. These arguments are indictive of the maturity level of South African banks in terms of transitioning to big data.

One participant provided a view contrary to the general consensus. This contrary perspective aligns to the previous section where it was established that South African banking is still in the developmental stages of big data analytics adoption. Participant 10 argued that "for the most part today, they don't differ and that's because we are still trying to solve the same problem, so we use the same sort of logistical regression techniques and all of those things. I think somewhat in a world where there is bigger data, you have to start thinking more with a scientific mind-set and of course we employ those people but there is almost always a view of the methodologies… In actual fact we have our information management set up but that hasn't translated well into new methodologies of analysing data yet so we almost started the journey on the one side, I think on the other side, if you were honest about it you would have to be a bit more aggressive to push the guys…so I think it's immature at the moment, very immature across the industry."

Table 2, in Section 5.3 evidences Customer Transactional Data as a key component synonymous with big data and explaining the contrast between big data analytics and traditional data analytics. Two participants confirmed that the level of aggregation of transactional data is dependent on the application, where applications requiring high level information can utilise aggregated data comprising a few parameters and applications requiring detailed information relating to life events for personalisation, customisation and customer contextual conversations requires analysis of more granular transactional data comprising a multitude of parameters. Participant 5 articulated the concept of data aggregation as “it depends as to what you need to do…customer information is always at a transaction level. So, we need to keep the full history of the customer information. There are certain things that you can do at an aggregate level, like for example, if you have a client…that we think that his car is four years old and he needs to have a new car, you don't really need to know the transactional history of the client level because the aggregated, we will tell you that based on the history of this customer can qualify for a vehicle of a million Rand, so we can use that level of information. But the moment you want to go into life events or triggers right, you have mill through the full transaction history… when you do analytics on a portfolio level, you can rely more on the aggregate side of it right, but the moment you go into the world of customer level right, we need to have the full history at a customer level.”

Participants 5 and 8 also suggested that the ability to hone down to the more granular transactional level or zoom out to the aggregate level as per the requirements of the application exists to a large extent and can be achieved. Participant 5 confirmed this through the elucidation that “A lot of the time we prefer to have everything at a detailed account level or detailed customer level [transactional level] and then aggregate as and when required rather than to use aggregated information… we don't just build an aggregate level … we’d rather prefer to build it at a customer level so that even if you have aggregate view, you can actually filter down into the customer.” Participant 8, however argued that while the above is possible to some level of granularity, the data is to a lesser extent stored at a very granular level. Participant 8’s assertion that “let's keep some information in the shape, but let's keep another piece of information a bit more deeper level. Hardly ever to the very granular level because it's just too much. Otherwise you have to have a massive infrastructure to be able to churn through it” confirms that data is stored in various layers at different levels of granularity, however not at a very granular level due to a need for the same not being established and the large infrastructure requirements.

5.4.2 **Adequacy of the Methodologies for processing of Big Data for Competitive Advantage**

Four participants deemed the methodologies to be generally inadequate due to the existence of legacy issues and the fact that big data is deemed immature and in the early stages of augmentation in South African banking. Participant 6 confirmed this through the assertion that “we're in a buildout phase at the moment, so we know it's not adequate and we're in the process of getting it onto platforms that are adequate and it's all about just getting one product at a time because in the banking environment there are hundreds of legacy systems… to get the data feeding into big data platforms is a very difficult process and it takes years but it's something that has to be done” Participant 10 argued that, “they’re [the methodologies for processing big data] not [adequate], I think its immature, I definitely think it’s immature.”

In two cases, the participants cited the methodologies to be adequate based on the status of big data development South African banking. Participant 3 postulated that “it's adequate for what we know right now…I think [we are] in [the] very early stages within the organisation, processing and collecting this big data…I think we have a basic idea at the moment of what we want to get out of the data... but the more you explore, the more you gather…maybe your methodology has to change too to fit to what you want to get out in the end… I think for now we're at a good place for what we know.” Participant 8 shared a similar sentiment in the assertion “because it's a new field, as you're uncovering things and at the same speed you [are] realising how inadequate you are with it, if you asked me, are we doing well? I can say on the one end yes, we've done better than the rest” It is noteworthy that Participants 3 and 8 acknowledged that as big data augments in the industry, inadequacies are uncovered and therefore the methodologies will have to evolve. Consistent with this assertion, Participant 11 stated that “we actually don’t know to what extent they are adequate, we all learning still as we go along”

The above quotations evidence the sentiment that big data methodologies are in a state of flux and there is need for these methodologies to evolve as big data capabilities augments in South African banking.

5.4.3 **Maturity of Big Data Analytics in South African Banking**

Section 5.3.1 and the insights from Participant 3, 5, 8 and 11 in Sections 5.4.1 and 5.4.2 above confirms big data analytics to be in the early developmental stages in South African banking. The general consensus amongst participants was that big data capability is currently approximately 10% to 30% developed with the majority of augmentation still to occur. No additional qualitative data pertaining to the big data maturity level in South African banking is provided in this section as the pertinent data has been cited in the preceding sections referenced above.

5.4.4 Improving the Quality of Insights Extracted from Big Data Analytics to Leverage it as a Source of Competitive Advantage

In addition to the gaps and new requirements presented in Sections 5.4.1 and 5.4.2 as a result of transitioning from traditional analytics to big data analytics the participants unpacked additional key areas requiring improvement in order in improve the quality of the insights extracted from big data analytics. The emergent themes included upskilling of resources and bridging the gap between business and data analytics. The participants also identified of investment and data quality as an enablers and legacy issues and regulation as major inhibitors. The qualitative data in support of the above themes is presented in the sections below.

5.4.4.1 Enabler: Human Resources

Upskilling of human resources had been identified as an antecedent to improving the insights extracted from big data. As presented in Section 5.4.1, this need follows from the vastly different skill sets and mind sets required for big data analytics. In support of Participant 5 and 11's assertions in the above referenced section that fundamentally different skillsets are required, Participants 6 and 8 communicated the need for "upskilling of your teams to be able to do the right analytics" and "get[ting] better analysts that know the assumptions" respectively. Participant 10 asserted that "I think number one is that skill set wise…I think there's a skill issue"

Nine participants indicated that the quality of the insights extracted from big data is to a large extent diluted because of (1) the scope of analytics being poorly defined by business, (2) analysts not understanding the business need, (3) business not understanding the data component, and (4) the insights not being presented in a format suitable to address business needs. Participant 1 indicated that "data is processed by IT Developers or Business Intelligence Analysts, but the data is meant for the business, the business users, the managers, the execs who have ideas. It must be in a form that is understandable to them." Similarly, Participant 4 indicated that "one thing that many people struggle with is you might get all these guys that are cod[ing] out the algorithms and stuff like that, but can they translate the results from there to business speak…there is a huge gap here in South Africa…we are struggling to get the technical guys…and when you do get the technical guy, you need someone who will be able to translate it into business value…those are some of the skills that you need."

Participants 6 and 9 spoke of the importance of business adequately articulating the scope and problem to be solved. Participant 9 stressed that “there is that gap, so you give either a too narrow scope or too big a scope and…you can go round and round and you can find whatever it is, whether or not it’s relevant, leaves much to be desired” Participant 6 advised that “what we've been trying to do as a data organisation…is force business to start asking the right questions…in the past is they would go and say, I want to know the difference between this and this. They wouldn't say, oh, well I want to understand the difference between this and this because I want to be able to do x, y. They don't articulate their problem statements very well and because of that, the wrong types of analytics get done.” These quotes evidence the need for business to ensure that the data analytics resources understand the problem that business is attempting to solve through analytics.

Participant 3 proposed that “consultation between the techies doing the work and the business who needs to get the insight out of the data needs to come close and needs to come way earlier in the project…what ends up happening then is techies get frustrated and they just run with something” [which may not be responding to the business need].” Bridging the communication and knowledge gap between data science and business emerged as a key issue requiring resolution for the improvement the insights extracted from big data. Most of the participants identified the role of a Translator, whose function is to translate the business need to the technical team. According to Participant 5, “a translator takes a business need [and] translates [it] to the technical team…but in the new world it cannot work like that, right, because what happens is that a lot of the time the messages get lost [in translation] and you end up doing what you interpret it to be.”

In order to address the communication and knowledge gap, Participant 6 proposed that “step one is getting business and training them… to think about data and not just ask for data extract.…a lot of time they ask for data instead of providing the problem statement… there are translators…that's one of the key points is that that role is not technical. It is there to make sure you unpack the business use cases to make sure they properly understood and checked back with business on a continuous basis and then it's translating to the technical teams to make sure they know what they need to build.”

Participant 3 elucidated the deemed attributes of the Translator as “that person who can bridge the gap and translate the - business requirement for the technology guys and actually let them implement it and review…so some techies can do it, not all of them, but that person who really drives the strategy and can translate that both ways is key." It is noteworthy that Participant 3's articulation is predominantly consistent with that of Participants 5 and 6, however in addition a need for the translator to have the ability to translate both ways had been identified.

5.4.4.2 Enabler: Investment

In all cases big data has been characterised as a costly exercise requiring substantial investment in human and technological resources. Participant 3 emphasises this need for large investment in the assertion that "getting the program off the ground is a massive investment…you have to have the right infrastructure. If you want to drive proper big data, you have to [have a] real strategy around that, you will have to be able to invest in it…your infrastructure is going to cost you money, your people obviously basic salary is going to cost you money, but over and above that your people are probably going to cost you double because you have to train them… everyone wants a big data warehouse, not everyone can afford it." Participant 5 also stressed that big data required substantial investment commitments "everybody wanted to do the big data, but you have to pump money behind it because the cost of running big data is also quite expensive… I mean these skills are highly scarce…highly traded skills [and] highly paid skills…I can't switch off traditional analytics…there's a transition period…in the transition period, you're running double the cost because you're building a team that's going to do big data, data scientists, plus you've got the existing [resources] that keeps the lights on…you need to be ready to be able to absorb that cost to the extent that it transitions you into the next cycle…your cost is going to be significantly higher than the revenue side of it, but we can see that curve is going to start there…probably in a year's time will break even and then from there to be incremental profit, because of the initial investment side."

The first key point from the arguments presented above is the substantial costs on the human resource component, which entails the basic salary plus training costs of scarce and "highly traded skills [and] highly paid skills. The second point is that the way forward is deemed to entail a transition phase where big data analytics will have to run in parallel with traditional analytics resulting in double costs. The transition period argument was presented in Section 5.4.1 and the sentiment of incremental change in transitioning to big data was shared amongst six participants.

Premised on the substantial investment requirements, the ubiquitous consensus amongst participants was that evidence of value is a key antecedent to stimulate organisational buy in and unlocking future big data capability investments. To this point Participant 4 argued that “the management needs to buy into data…the biggest complaint many people have is management buy in…they're struggling to really see where they can extract value…it ties into them not understanding the value, because if they understood the value they would invest into it, like if it's machines, if it's the people or whatever it is, they would invest in that” In support of this argument, Participant 5 cautioned that “organisational buy in is very important…you can't have big data as a sideshow… if the organisational buy in is not there, you always going have this cottage industry that's running on the side that's never going to really be able to scale up or to add real value the business.”

Participant 5’s assertion that “commercial outcomes are going to be quite important. It [Big data] shouldn't be done for entertainment purposes. There has to have a customer outcome and a commercial outcome and then it's quite easy to get the organisation to go with it” gives impetus to the argument that organisational buy in is obtained through evidence of value. Two participants postulated the need to demonstrate early wins and focussed goals to engender organisational buy in. According to Participant 11, “the biggest success is just to illustrate your wins early on…if you can focus on a handful of projects initially with very clear goals or outcomes that you want to achieve, and then if you can get to that point where you can start feeding that success back to business, you know, showcasing that around business, then you start getting people interested.” Demonstrating value to the business in terms of quick wins, successes in focussed big data projects with clear goals and outcomes and commercial value in terms of increase in customer value and return on investment have been identified as the drivers for organisational buy in and additional investments.

5.4.4.3 Enabler: Data Quality

Participant 8 summed up the concept of data quality as “garbage in is garbage out”. In addition to Participant 8’s assertions, three other participants confirmed data health, particularly data accuracy, completeness and validity as key constituents to extracting superior insights from the data ingested into the system. Participant 6 argued that “the quality of insights is going to be driven by two things, the accuracy of your model and the accuracy of your data…anytime [that] your data quality is poor, it's going to impact your quality of insights." Aligning to this argument, two participants identified data quality as the first thing that needs to be ensured in order to improve the insights extracted.

Participant 5 consolidated the arguments pertaining to the importance of data quality and provided insights into the data quality process through the explanation that "one of the things that we have to get around the data side is that it's as good as the cleanliness of the data…making sure that the piece of information that I get from the customer right on the front, it goes through certain health configurations to the extent that that information can be relied on… first of all, it has to be complete; it has to be accurate, if there's any missing information that has to be populated… we set up a team that's going to make sure that all the data that we ingest are actually accurate type of information… we set up a data architecture team, so what the architecture team would do is to take the full governance around the data… they can issue us a health certificate before the guys like the data scientist ingest the data and work on it."

5.4.4.4 Inhibitor: Legacy

Seven participants cited legacy to be an inhibitor to leveraging big data analytics. Market newcomers were identified to possess the advantage of capitalising on the big data and big data analytics by virtue of the fact that they are predominantly digital and don't have legacy issues.

Two participants presented the legacy aspect from a technological or resource perspective. Participant 4 argued that "with the legacy issues that many banks are facing…have been around for hundreds of years…it probably makes it difficult for them to leverage BDA [big data analytics] as effectively as new banks...that are coming up now because those guys are purely digital, no legacy issues and stuff." Participant 5 shared this notion and postulated that "analytics is always a leading edge in terms of the banking side and you'll see the newcomers to the market…like the…bank and all of those guys, they're going to always work on the digital platform sites in order to give that cutting edge technology side of things…remember banks were first built, banks were built on products…so, the silos that all the banks would run with is a product cycle… a bank that is built around products is very hard to transition to a customer centred bank."

Participant 10 articulated the legacy argument from a process or capability perspective in the statement that "these are not start-ups, they've got a hundred and fifty to two hundred years' worth of history of engrained process and procedure and that is a massive challenge to overcome, huge, all banks. That is what makes us worry obviously about start-up related ones because we know that our business system needs a lot more work."

The arguments presented above evidences that all three participants identified newcomers as a threat to the legacy banks. Participant 11, from the perspective of a bank which is less than 50 years old and not considered legacy gives cadence to this notion in the statement that "I think that it's going to give us a competitive advantage as well because I think…the big four are sort of sitting with very well-developed models [legacy models] already. It's harder to change course when you've already invested so much in your current way of doing things. Yes, I think we are starting off. We don't sit with those legacy systems problems. Now we can, we can start designing the systems around – in such a way that we are more dynamic…be able to change."

One of the key insights from the above is the fact that banks were traditionally built around products, resulting in a siloed organisational design. Participant 5 as quoted above, asserted that "as a bank that is built around products is very hard to transition to a customer centred bank". The qualitative data and relevant discussions pertaining to these issues is continued in Sections 5.6.3 and 5.6.4.

5.4.4.5 Inhibitor: Regulation

Regulation emerged as a dominant theme, particularly because of the restrictions it places on the utilisation of customer transactional and behavioural data. Section 5.3 identified both data types as key constituents for leveraging big data analytics for competitive advantage as they are required for customisation and personalisation applications. Premised on the above, all participants deemed regulation to inhibit the augmentation of big data and big data analytics in South African banking. Regulation is outside the scope of this research; however, the results are presented below to facilitate the formulation of future research questions.

Four participants confirmed that regulation is challenging when personalisation applications require the utilisation of fine grained behavioural data, however when data is utilised at the aggregated level regulation is not restrictive. Participant 12 elaborated on this point through the assertion that "if you're using very broad, vague data, there's less compliance…because it's anonymous, it's vague, it's broad, and it’s not applicable. The minute you start using first party data and more niche data and starts becoming a bit more tricky and your source also becomes a little bit less, so your campaigns aren’t that effective” Participant 3 provided a summary of the inhibiting impact of regulation on the utilisation of behavioural data in the statement that “with the POPI Act, [we are] just very cautious about how we use [behavioural data] …it's real family events…we can pick up from your spending patterns, but then how you use that data…that then becomes special personal information and there's very strict regulations about what you're allowed to do with that, especially if you then want market to someone.“ Participant 6 gave cadence to this argument and introduced the concept of consent in the assertion that “in terms of determining the right product for the right person, that's where there is that fine line between what somebody has consented their data to be used for and what not …So, while there are a myriad of use cases that can enable use of big data for determining product choice…knowing what product to give somebody at the right time based on a life stage or a moment…that becomes a little bit tricky because people have to know that that is what the data's being used for”

Two participants introduced the impact of regulation uncertainty to the discussion. To this point, Participant 3 argued that “the models are there, capabilities are there, but what we're allowed to do with that is still a bit grey, we're figuring that out. Regulatory, because it’s so unclear at the moment, we’re still figuring it out, it is a challenge” Participant 6 stressed that “nobody wants to be made an example of as the first company to have an action against them due to privacy… POPI is a concern…there is definitely uncertainty around it because there are teams that are looking at it in a lot of detail and assessing the way they interpret it”

Phrases such as “your campaigns aren’t that effective”, “what we're allowed to do with that is still a bit grey, we're figuring that out”, “But regulatory, because it’s so unclear at the moment” and “nobody wants to be made an example of as the first company to have an action against them due to privacy” demonstrates the deemed impeding effects of regulation and regulation uncertainty on the development of big data in South African banking.

Two participants indicated that regulation required rethinking. Participant 5 proposed that “the thing that inhibits in a banking construct as to what you can do is the regulatory side and the customer side … I think that regulatory side as an industry; we need to sit down with the regulators to basically show the difference between personalised messaging versus spam messaging. They're fundamentally different" Participant 10 also proposed that the banking industry needs to work together with the regulators and argued that "since 2008 we've had more regulation…the regulation statistically is based on models of ten, fifteen years ago… I think culturally we…all need to come together a little bit more regulation wise. Culturally, I think - how do you get the regulators to also be pushing the boundaries of these things with us [the banking industry]? I just feel that it's a fence paradox, right…everybody's standing on the cliff, one or two people might fall, sure if there's no fence there. So, what we do is we put a big fence there, then when the fence breaks, everybody falls, right? So how do you be more agile?"

5.4.5 Summary of findings for Research Question 2

In answering Research Question 2, seven primary overarching themes, namely, Human Resources, Technology, Investment, Data Health, Legacy, Maturity and Regulation emerged. Human resources and technology featured strongly when participants elucidated the differences between big data analytics and traditional analytics. Due to the high volume, velocity and variety of big data in contrast to traditional data, it was established that big data had unique resource requirements in the form of data scientists, data engineers, quicker algorithms, artificial intelligence and advanced platforms for data ingestion, storage and analysis. Data health, which encompasses data accuracy, completeness, validity and compliance was recognised as a key factor in increasing the quality of the insights derived from big data.

The South African banking industry is transitioning into big data analytics; however, they are in the early stages of development. As a consequence of the maturity level, the unique human resource and technology requirements and the fact that big data analytics will have to run in parallel with traditional analytics during the transition phase, big data has been established to be an investment intensive exercise. Investment and data health were confirmed to be key enablers for scaling up on big data assets, extracting superior insights and delivering organisational value. Organisational buy in emerged as a sub theme and an enabler to obtaining investment in big data assets. Evidence of commercial and customer value were cited as antecedents to organisational buy in.

Legacy and regulation emerged as inhibitors to leveraging big data analytics for competitive advantage. Legacy was identified to have a more profound impact on older banks by virtue of them not being purely digitised and having a predominantly siloed organisational architecture. The traditional silo structure suffers compatibility issues between the various systems and inherently inhibits communication flows and knowledge sharing. Regulation and regulation uncertainty poses challenges for the utilisation of customer transactional and behavioural data at a granular level. Restrictions on the use of granular data is deemed to greatly impede the organisations ability to derive value from big data since personalisation and customisation is the basis of leveraging big data for competitive advantage.

A gap between the business need and the outputs from analytics had been discovered. The issue originated because of business providing the data scientist with inadequately defined scopes, business not having an appreciation of the data science perspective and the data scientists not understanding the business problem that the data analytics is attempting to solve. Translators, whose role is to bridge the knowledge and communication gap between business and the data science team had been defined. The experts deemed this solution to be sub optimal since messages were lost in translation resulting in the quality of insights being sub optimal.

The methodologies for the processing of big data were generally deemed inadequate for leveraging big data analytics for competitive advantage. In some cases, premised on the maturity level and resultant incremental learning occurring as South African banking augments their big data analytics capabilities and uncovers inadequacies, the methodologies were cited to be generally adequate for the current developmental stage.

5.5 Results for Research Question 3

Research Question 3: What are the specific big data resource requirements for leveraging big data analytics as a source of competitive advantage in South African banking?

Extant literature suggests that organisations generally lack understanding of the specific big data resource requirements and as a result are unable to leverage the same for competitive advantage (Erevelles et al., 2015; Johnson et al., 2017; Kozlenkova et al., 2013; Lycett, 2013; Martens et al., 2016). One of the primary objectives of this study was to understand the big data resource requirements, the gaps between the perceived requirements and the status quo and what is required for South African banking to transcend these gaps. Research Question 3 and the pertinent sub questions were designed on this basis. Table 4 below, depicts the codes and emergent themes for Research Question 3. The themes resulted from the aggregation of these codes.

Table 4 Themes and Codes for Research Question 3

Themes	Codes
RQ3: T1 - Human Resources	HR: Big Data Engineering Team
	HR: Data Architecture Policy
	HR: Data Architecture: Chief Data Officer
	HR: Data Engineers
	HR: Data Scientist
	HR: Data Scientist must be able to navigate multiple software and technologies
	HR: Data Scientist Role is Complex
	HR: Human Resources at the cutting Edge of Technology
	HR: Source System Knowledge
	HR: Human Resources
RQ3: T2 - Technology	TECH: Need Software to Process - Structure and Unstructured data
	TECH: Speed of Data Storage, Extraction and Processing
	TECH: Technology is available on the Market - not the biggest challenge
RQ3: T3 - Education and Training	ED: Bank work together with university
	ED: Business Data Science Degree
	ED: Data Ingestion: Hadoop Skills
	ED: Inadequate Skills in South Africa
	ED: Internal Training vs External Training
	ED: International Data Science Degree
	ED: Level of Insights needs to be improved
	ED: Specific Data Science Degree is required from SA University
	ED: Upskilling Resources is needed
RQ3: T4 - Partnerships	PRT: International Partners more advanced on the data Science Side
	PRT: Partnerships with specialists
	PRT: Proximity is important: Limit to Outsourcing

Human Resources, Technology, Education and Training and Partnerships emerged as the four dominant teams for Research Question 3. Within the Human Resources theme, Data Scientist and Data Engineer were dominant sub themes. For the purposes of consistency, resources were explained to the participants to encompass tangible and intangible assets including capital, human and technology resources. The most pertinent insights to this question was provided by the participants whose experience encompassed the technical aspects of big data. Sections 5.5.1 to 5.5.4 includes the discussion and pertinent qualitative data.

5.5.1 The Specific Big Data Resource Requirements to Effectively Leverage Big Data Analytics for Competitive Advantage

Participants predominantly elucidated the deemed human resource and technology requirements for leveraging big data analytics for competitive advantage. The responses built on the resource requirements presented for Research Question 2, Section 5.4. Participant 5 provided an overview of the big data resource requirements as "if we talk about the individual resource inside it is the data scientists are key, data engineers are key and then data architecture side is quite key."

Participant 6 provided a detailed account of the human resource requirements, which included "making sure you've got people with the right understandings to make sure the organisation, employs the right tools and platforms…I mean if you get your tools and platforms wrong, it's going to be wrong all the way through…So, from a technical capability, people with more experience in assessing tools, platforms, etcetera, understanding of warehouse, data lakes and then data quality tools, you know, so, what data quality tool is the best…we've got big data engineering [team] and within there is a data ingestion team. There's a team that decommissions old platforms, this team that decides on new tools and platforms, there's a team that builds the data quality and data management standards…there's a team that looks at governance - standards and governance, and is everything we doing around our big data or our data compliant with all regulation and standards, then there's data architecture team. So are the data flows flowing in the right way and that's just getting your foundation right once your foundation's right…Then data science teams that look at your, big data components and start processing structured and unstructured data…and then there's the data product managers that help build a data product tool or translates - be the translators between business and data. So, there's a lot of different skills that you need. And making sure you've got the right mix of all of that as well." While the job titles between organisations may differ, the above evidences the key functions to include data scientists, data engineers, data architecture teams, data ingestions teams, data governance and compliance teams and translators.

Participant 8 focussed predominantly on the technology aspects, which encompassed platforms for data ingestion, storage and processing. The speed of saving or ingesting the data, the speed of extracting the data and the capability of expanding the system by adding more processing capability without downtime was cited as important technology attributes. Open source platforms were identified to be solutions to this issue.

According to Participant 8, “hardware wise, you've got to store the data…we want to have more data stored quicker as it flows through the system…now there’s better and better compression techniques where they can store more data in less physical hardware space….you've got to consider two things; the speed at which is going to be saved and the speed at which you can extract it as well because otherwise later on you can't use that effectively….the second thing in the speed of processing, this is where this parallel processing is taking place is, is key and then with that, the ability to add more either processing or speed to a system without having to rip the whole system apart, you know, I almost want to say in engineering terms, [be] able to add another two cylinders to a v-six to make that a v-eight…literally on the fly…that is the challenge and to be honest, the guys have come up with solutions in the open source world of being able to buy commodity hardware, you add it to the stack and relatively quickly telling it there's more resources available, so you can go either store or use it for processing. So that is the hardware side and then with the people side…I think there is training to be had on the data science side.”

It was noted that most of the participants mentioned the technology resources; however, their focal point when elucidating the specific big data resource requirements was the human resources aspect. This phenomenon suggested that human resource issues may be more prevalent than the technology issues. The assertions by five participants that the technology required is readily available on the market and that it is a matter of selecting the correct options and putting it in place gave cadence to the above notion.

As per Participant 11, “I think in terms of architecture everything is there, it’s just a question of going out and putting it into place” Participant 6 confirmed this notion through the assertion that “The hardware is available so it's not getting the hardware that’s the hard piece that is - there are so many different options nowadays with hardware...the hardware, software is available, there's actually so much available to choose from. So, I'd definitely say it's the resources, understanding that hardware and software, that is the challenge without a doubt.”

Premised on human resources being defined as the constraint, the subsequent section details the perceived attributes of the data scientist and data engineer, both of which emerged as key roles.

5.5.1.1 Data Scientist

The data scientist emerged as a dominant sub theme within the big data human resources area. All the participants accentuated the importance of this role in enabling their respective organisations to leverage big data analytics for competitive advantage. The below elucidates the complexities and expectations of the data scientist function.

Participant 6 provided a high-level description of data science to include "look[ing] at your, big data components and start processing structured and unstructured data." Participant 1 described the data scientist function to encompass the ability to "manipulate the data and also extract insights from it and also I think the data scientist role for me- it's a complex role because you need someone who understands the data, the software, who can do all that and also someone who can interpret the data…also they need to understand business, so they take the right insights to business." Participant 5 also deemed the data scientist role to be complex and further elaborated that "what the data scientists would do is a combination of a very deep analytical but with a good knowledge around the data and the structures around data…these are the guys that could use multiple data and pick up trends…run models around the data to pick up certain things, so the level of insights that have just to be improved…you always look for resources that are the cutting edge of technology to the extent that they self-learn and do things… I think there's a fundamental important kind of component or attribute of a data scientist, they're generally very self-taught guys… data science, you should be able to navigate across multiple versions, multiple technologies, and multiple software… Data scientists has first, got the technical background but also got a business acumen side of it, commercial acumen side of it so they can easily decipher insights"

The above articulated the data scientist as a key multi-disciplined resource encompassing deep technical knowledge in terms of software technologies and the structures around the data. The data scientist is expected to manipulate structured and unstructured data and have the business acumen to extract and present the pertinent insights to business in an understandable format; thereby, solving a business problem.

5.5.1.2 Data Engineer

Participant 6, in Section 5.5.1 described some of the attributes of the data engineer and data engineering team. These attributes incorporate the responsibility for assessing and designing the correct big data solutions, which includes the selection of the right architecture in terms of hardware, tools and platforms as well as the decommissioning of the old architecture for replacement with new architecture. Participant 11 explained that "…in the architecture you also need data engineers that know how to get the data into the architecture and get it analytics ready… you obviously need the technicians that know how to run the database and get data into the database…" The above suggests that the data architecture team comprises data engineers. Participant 5 further elaborated that what the "…data architecture team…would do is to take the full governance around the data…there's a whole governance framework that we set up in order to make sure that the data is housed correctly. They can issue us a health certificate…"

Premised on the above the data engineer's responsibility encompasses technology selection, architecture interface design, installation and maintenance, data ingestion and processing to ensure that the data is in a healthy form and ready for analysis by the data scientists.

5.5.1.3 Chief Data Officer (CDO)

The chief data officer appeared to be a data engineering profession as this role had been described to be an executive position responsible for the governance of the data, architecture design and system integration.

According to Participant 4, "the CDO will be someone in charge of the data that making sure that the data is clean and ready to be analysed all the way up to the analysis…they are involved in strategy and stuff…I would say the data officer should be someone who understands the data…from it being generated, being analysed and being presented to business and be involved in the strategy of the business" Participant 6 provided a detailed account of the role as "educating [the] organisation around data, that firmly sits within the CDO and there are plans in place to make sure businesses get more skilled around data and the - what data can do for the organisation… chief data officer…what should our landscape look like or what functions should sit where, what needs to be housed as essential function within the data environment and controlled and managed in a single place, and what do you allow to sit in business…because then it's a lot more in tune with what business requirements are and we are going through that process at the moment"

As per the above the function of training and raising the profile of big data also rested with the CDO. Furthermore, it suggests that the CDO is the executive member leading and representing the big data team.

5.5.2 Gap between the Resource Requirements identified and the available Big Data Resources

It was established in Section 5.5.1 that the sentiment amongst most of the participants was that the gap in big data resource requirements was in fact human resources with the requisite big data skillsets as opposed to the availability of technology on the market. Serious shortages in data scientists, data engineers and resources possessing the required ICT technical knowledge in big data tools and platforms were cited. Five participants provided an account of the above.

As per Participant 4, "I think the thing that happens here in SA is the skills are difficult to really find people…who can really analyse the data itself …you need people who will even understand what to do. Understand how to extract information not getting into big data, just simple data even structured…there is a huge gap here in South Africa. We are struggling to get the technical guys. And on top of that, when you do get the technical guy, you need someone who will be able to translate it into business value. So those are some of the skills that you need." Participant 8 in citing an extant study asserted that "we did a study many, many years ago, like two, three years ago now, but Harvard Business Review published that I think every year it's a hundred thousand data scientists, there'll be a shortage growing in a hundred thousand data scientists every single year." Participant 3 cited a more recent survey with a South African context and accentuated that "resources are scarce…they said per annum, in South Africa there would be seventy odd thousand additional ICT roles available every annum and then, the throughput of candidates from universities that we get into the market was then at about twenty odd thousand."

The quotations provided below include statements such as, "a lack of formal education" and "only probably one or two universities that would offer a proper data science degree" evidences the sentiment that South African universities played a role in the data science skills shortages that the industry is experiencing. This issue coupled with the yearly resource deficit cited above evidences the criticality of the situation and illustrates that little evidence of it being addressed exists.

Participant 5 indicated that “there are only probably one or two universities that would offer a proper data science degree. So, I think Potchefstroom got a data science type of degree, right. Other universities are no longer there…I think that from a South African context or even from an education point of view, we tend to hire guys who have done computer science and stuff, but it's a bit different when you go into the world of data science…for us to go and train our individuals has been a challenge.” Participant 6 further elaborated that “the two-key skill sets that are lacking…in the South African market at the moment are people that understand the big data platforms and tools so that can ingest the data. So, people that can understand Hadoop [open source] and building of the tools onto Hadoop. I think that's one of the big skills shortages … the second big category is data science skills… there is not a lot of formal education around data science just yet. They’re starting to be a little bit more and more, but a lot of it is still very maths and stats focused or engineering…I mean, a couple of the universities are starting it now doing an actual data science degree in qualification…So, until you get that as a more formal - and I think it's not publicised enough.”

The above culminates the consensus of an inadequacy of formal training for data science and data engineering, with restricted availability of “a proper data science degree” in South African universities. The discussion also suggests that the banks have to onboard people with computer science and engineering backgrounds and train these resources to be data scientists, however the banks are experiencing capacity and capability challenges in this regard.

5.5.3 **Addressing the Resource Gaps for Leveraging Big Data Analytics for Competitive Advantage**

In addition to a skills scarcity, participants identified inadequacies in the skillsets of South African data scientists and data engineers. Education and Training and Partnerships were the emergent themes for transcending the gaps and leveraging big data analytics for competitive advantage. Education and training and partnerships are outside the scope of this research, however the results are presented in Sections 5.5.3.1 and 5.5.3.2 below, to facilitate the development of future research questions.

5.5.3.1 Education and Training

The preceding section established that the South African university curriculum for data scientists and data engineers was inadequate. Due to these inadequacies some banks are forced to either send successful candidates to international institutions for a formal data science education or remain heavily reliant on internal training. While seven participants cited the issue, four participants provided valuable insights.

Participant 3 accentuated the above in stating that “I think there is a bit of a gap [in South African university curriculums], basic skills are there which helps. So, they have the basic understanding of how data is stored, they the basic understanding about the structures of the data. When you get to real big data analytics, there's very few institutions that actually go into that and that's why the internal training again becomes so critical.” Two participants advised that as a result of the inadequacies of South African training, their respective organisations are training their resources internationally.

Participant 5 advised that “what I'm more interested [in]…is to send the teams to China and India for them to enrol in a proper data science type of course. So that when they come back they are equipped in terms of what they need to learn…” Similarly, Participant 6 indicated that “…for our data scientists, we have a program that we run with New York Data Science Academy once a year, where there is a handful of people that get selected, they do a pre-assessment and get selected and go and do an intensive training course in the US to get a data science qualification. That is the only formal training that is provided, everything else is still very reliant on people doing what they need to do, what they feel they need to do and…there's a lot of on the job training…”

The above suggests that the “handful” of candidates afforded the international opportunity is not sufficient to address the prevalent human resource scarcity issue, hence there remains a substantial reliance on internal training. While the preceding section highlight capacity and capability challenges for the provision of internal training, the below illustrates that a need for internal training programs still exists. Internal training emerged as a prominent theme amongst many participants, particularly because internal training was deemed to facilitate a better understanding of the organisational culture and the organisations data, data culture and technology architecture.

A per Participant 3, "…get someone with that core skill. We can manage the internal training or coaching, mentoring whatever you want to call it program because there's going to be nuances in your business, there's going to be nuances in the way you implemented the technology in your business as well. So even if you get experts from another company, they do have to go through a process of understanding your company, your data and your environment.…" Participant 5 built on this notion by indicating that "A lot of the time, right, we prefer to train them in house because you know…the fact that you know, data science side of it, then you qualified, but for you to be able to effective, you need to be able to navigate the organisation as well. So, it's a quite important thing… a lot of the time that each corporate has a different culture, everything is different."

While the benefits for internal training were noted, the below evidences that this does not diminish the need for specific data science and data engineering formal training. Obtaining candidates with the requisite formal training was also cited to reduce the internal training period which meant that value could be extracted earlier from trained resources. Participant 5 gives cadence to the above in the assertion that "…a lot of people who take like six to nine months to adopt, but in order to avoid that I would rather invest six to nine months in training the individual that are already has the right credentials to take them… but to get the skills here, for us to go and train our individuals has been a challenge." Participant 6 acknowledged the need for internal training, but accentuated the importance of formal training by stressing that "I think the more formal training at the university, like more specific curriculums there, will definitely help…you see, internally it's quite difficult because you already have quite a skill shortage, how much you know, and it's very difficult for us to become a learning organisation when you're a bank, so you have to deliver value to business first and foremost. Education and training is very important for our employees, but it cannot outweigh [operations]. So, you can't have, for example, someone whose job it is to just sit and train people the whole time. So, it is a bit tough. I think if there [were] more courses out on the market, I think it would definitely be beneficial so that you could send employees on…ya, a data course, absolutely."

Premised on the above and as well as the gaps identified between data science and the business, the sentiment amongst participants is that it is imperative for South African universities to relook at their curricula and offer data science specific degrees as well as business data science degrees. Participant 4 asserts that "…there's not even one MBA with data science in South Africa, there's none, all the MBA with data science they're in the US or the UK. So, there's a huge skills gap there, imagine they [are] doing MBA with data science. That's you understanding the technical side and understanding the business and putting them together. We don't have that… I'll do my MBA, but I want to the one with data science, it will probably be an international university online because here they don't offer it." Participant 5 in alignment with the notion of the business data science qualification proposed that "…[we] look at like MIT's international markets…probably about two, three years ago they brought up a degree which is a business science in data science, business data science…there will be a requirement for universities to re look at in terms of what they offer so that we have a pipeline of people that can come straight from campus to site and start working on the data science…there is a massive demand for these kinds of skills… I think universities definitely need to think around it because the world is definitely moving towards it, it's never going to go the other way and they need to be able to structure the relevant courses…"

5.5.3.2 Partnerships

Partnerships between the banks, local and international specialists and universities were proposed as solutions to assisting with skills shortages and enhancing the skill set of South African data scientists and engineers. In some cases, the banks were engaged in international partnerships with countries that are more developed in terms of data science capabilities.

Two cases evidenced international partnerships as a platform for training and developing human resources. Participant 3 advised that "[they] do partner with a company in India as well for development. It's a little bit easier to get the resources there." Participant 5 elaborated on international partnerships and asserted that "…we are partnering with international companies… I think India has got a very advanced data science side…and consultant side and in States …because these two countries are a bit more advanced than we are South Africa…so we want to get them on board in order to train the data scientists that we have on site to the extent that…they are always at the edge of the technology side…But to get the skills here, for us to go and train our individuals has been a challenge. So, we have to reach to other countries to be able to get specialists like from

Germany for example, to come and train our guys on the latest technology and the latest software." One of the benefits with the proposal of engaging international resources assists in addressing the training capacity and capability issues identified in the preceding section. The above acknowledges India as a data science authority, Participant 6 gives cadence to this in the statement that "if you compare us to somewhere like India, where there are more qualified people than anywhere else in the world. We outsource a lot of our stuff to India."

One participant indicated that private companies must be proactive by designing specific data scientist graduate recruitment programs through partnerships with international universities. These programs facilitate the conversion of maths, science and statistics graduates to data scientists without placing the entire burden on South African universities. Participant 5 advised that "the education is quite important…it doesn't help for…[the] bank to always complain…I think private companies have a role to play. We can't always point at the universities and say you guys are not giving us the right skills…we also need to be able to build that…going forward [we] would need to be able to build that to the extent that…you create a graduate program for data scientist. So that's exactly what we did, is that we have our normal graduate program, we created the graduate program for data scientists. We [are] partnering with China in terms of getting them the right skills, with India and with other organisations and universities and stuff in order to get them to become data scientists, data analysts."

Two participants indicated that their organisations are collaborating with South African universities to develop data science specific skills. Participant 8 postulated that "universities has got a part [to play] there and we personally collaborate with various universities where we try and influence the curriculum"

Participant 10 similarly indicated that "I know we do one I think it's University of Free State…where there's a data scientist type of program specific, where we do a lot of sponsorship of that to push people through that sort of outcome...what I really am hoping is that it gives people a good, strong technical background but doesn't give them too many sort of - I always believe in - you must know the technical of it."

5.5.4 Impediments for Addressing the Resource and Capability Gaps for Leveraging Big Data Analytics for Competitive Advantage

The themes for addressing the resource and capability gaps were identified to be legacy, mindset shift, organisational culture, organisational structure, evidencing value, organisational buy in and investment. Each of these factors emerged as dominant themes for the research; however, these themes have not been specifically included in Table 4 for Research Question 3. This is attributable to the fact that in accordance to applicability; legacy, organisational buy in and investment were included in Table 3 for Research Question 2 and organisational culture and structure in Table 5 for Research Question 4. The below provides some of the pertinent qualitative data, however the detailed data and discussions are presented in Sections 5.4.4.2, 5.4.4.4 and 5.6.4 which are dedicated to each of these factors.

Participant 1 emphasised the legacy and organisational cultural aspects by stating that "we have created big IT systems and we have also created ethos within the business so for instance, I talked about taking people from different areas, if you go to IT, they will think it's their project, they will run with it and they will know what to do and if you go to the business, they will say it's their project and they'll know what to do. I think the history and the legacy of the banks it's a big hindrance to get into the right skills, the right systems, remember we already have systems- we have paid a lot of money for systems so ya." Participant 8 spoke of organisational culture and design in the postulation that "our multi matrix organisation structure is probably a key issue in doing it faster and quicker…and however stupid it sounds, but often personalities gelling is the biggest success factor. People getting together and feeling yes, we want to work together. We - no matter what, what the executives say, they make it happen because they just have a good relationship, you know"

Building on the assertions of the preceding sections, Participant 5 again highlighted the need for investment and the resource constraint by postulating that "you need to be ready to be able to absorb that cost to the extent that it transitioned you into the next cycle. Resources is a big challenge. I had to be very honest around it. That to finding readily available resources that can easily plug into the environment is a challenge" Participant 6 stressed that "Funding always, and prioritisation…there's always pressure on delivering value in showing value…you've got to first and foremost show that you're delivering value, so how much time you have to dedicate to building a training program or data education for the organisation versus showing value [meaning the normal operations]…you've got to have the right balance, but you often pushed on the delivering value piece [that is usual business operations]"

5.5.5 Summary of findings for Research Question 3

Human Resources, Technology, Education and Training and Partnerships emerged as the primary overarching themes for Research Question 3. In addition, the themes of legacy, mindset shift, organisational culture, organisational structure, evidencing value, organisational buy in and investment specifically emerged in answering the sub question pertaining to the impeding factors to implementing the proposed solutions for addressing resource gaps.

It was established that the scarcity of skilled data scientists, data engineers and business data scientists in South Africa is a key factor impeding the augmentation of big data in South African banking. The technology required for leveraging big data for competitive advantage was cited to be available on the market; however, the technology skills to implement an overall system design and select the right architecture in terms of hardware, tools and software platforms was available, but scarce and inadequate. As presented in Research Question 2, the participants again cited that evidencing commercial value was key to ensuring organisational buy in and investment in big data resources.

The scarcity of the requisite big data skills in South Africa was predominantly attributed to inadequacies in the South African education system, particularly South African universities being inadequate, slow and limited in offering "proper" and "specific" data science and data engineering courses. One participant indicated that South African institutions still do not offer any business data science degree, which has been identified to dilute the insights extracted from big data as a result of the gap between data science and business. It was proposed that the skills gap be addressed through the South African universities reviewing and redesigning their curriculum to include relevant and specific data science, data engineering and business data science degrees. The participants also believed that collaboration between the banks and the universities was required to design these degrees to ensure that their needs are met.

Partnerships with international specialists had also been identified as a platform for supplementing the skills shortage as well as for the purposes of training and knowledge transfer.

5.6 Results for Research Question 4

What is the role of the inter-relationships between big data assets in leveraging big data analytics as a source of competitive advantage in South African banking?

Research Question 4 was derived from extant literature suggesting that in addition to understanding the big data resource requirements, it is also important to understand the inter-relationships between these assets to facilitate the creation of big data capabilities, which can be leveraged for competitive advantage (Gupta & George, 2016; Johnson et al., 2017; Moorman & Slotegraaf, 1999).

In cognisance of the fact that the major South African banks are predominantly in excess of 100 years old with legacy systems in place, big data asset configuration was deemed to play an important role in this industries ability to leverage big data analytics for competitive advantage. Premised on the above, Research Question 4 aims to establish the role of the inter-relationships between big data assets, the challenges in terms of these inter-relationships, that inhibits big data analytics from being leverage for competitive advantage, and the proposed solutions for addressing these challenges to better facilitate the leveraging of big data analytics in South African banking. Table 5 below, depicts the codes and emergent themes for Research Question 4. The themes resulted from the aggregation of these codes.

Table 5 Themes and Codes for Research Question 4

Themes	Codes
RQ4: T1 - Organisation Operating Model	OM: Central Customer Information
	OM: Asset Config_What Functions Should sit where
	OM: Incremental Integration of Assets
	OM: Data architecture: Policies around the data and Compatibility
	OM: Built a Bank and found customers

Themes	Codes
RQ4: T2 - Organisational Culture	OC: Exco_Board must push big data_Top down approach
	OC: Break silo mentality
	OC: Mindset Shift
	OC: Organisational Culture
	OC: Communities of Practice across the organisation
RQ4: T3 - Organisational Structure	OS: Organisational Structure Issues
	OS: Integrated Teams
	OS: Representation at the right forums
	OS: Business Engagement Team - Translate Business need to technical
	OS: Business Background and Technical Background
	OS: Message is lost in translation
	OS: Balance between strategic and to do operations_Functional work and project work
RQ4: T4 - Bank Strategy	BS: Bank Strategy

Organisation Operating Model, Organisational Culture, Organisational Structure and Bank Strategy emerged as the four dominant themes for Research Question 4. Note that the participants understood the inter-relationships between big data assets to be asset configuration.

Two participants asserted that asset configuration is a key aspect for leveraging big data analytics for competitive advantage. Participant 8 expressed the significance of asset configuration in leveraging big data analytics through the statement that, “It’s [asset configuration is] absolutely the start of everything and as I said early on, I think we didn't realise how bad ours [asset configuration] were to leverage big data two years ago, three years ago, and that is why we're not where we want to be with the insights pieces.”

In discussing the role that asset configuration plays in leveraging big data analytics for competitive advantage, maturity and the silo effect were the two key challenges cited by the participants. It was noted that most of the participants, when asked about the role of asset configuration in leveraging big data analytics for competitive advantage predominantly discussed asset configuration challenges.

5.6.1 Asset Configuration and Maturity

It was established in Sections 5.3.1 and 5.4.3 that big data analytics was in the early stages of augmentation in South African banking with substantial development required prior to it being effectively leveraged for competitive advantage. Three participants cited maturity in the elucidation of the role of asset configuration in leveraging big data analytics for competitive advantage. Participant 11 evidenced the perception of immaturity through the assertion that "I think ten years from now someone will do an MBA to look back at what the optimal configuration is, I don't think we know yet. So, we're still trying to find that out as we go along." Both participants 3 and 5 shared this sentiment and indicated that banking was in an exploratory phase in terms of asset configuration. Participant 5 illustrated this point through the statement that "the stage that we are in [right now] we first starting to explore around what can be achieved on the big data platforms, so we haven't really gone into the extent of coordinating and orchestrating across all the areas in order to get that right."

Participant 11 succinctly captures South African banking's maturity level by stressing that "what the optimal configuration is, I don't think we know yet …by being sort of device agnostic, architecture agnostic"

5.6.2 **Asset Configuration and Legacy**

It was established in Section 5.4.4.4 that legacy organisational design resulting from banks traditionally being built on products was the root of the silo effect. Six participants cited organisational silos as a key asset configuration challenge negatively impacting the ability to leverage big data analytics for competitive advantage in South African banking. These challenges relate to three of the dominant asset configuration themes, namely organisation operating model, organisational structure and organisational culture.

5.6.3 **Organisation Operating Model**

The organisation operating model relates to the configuration of the technology assets. Section 5.4.4.4 established that product silos resulted in technology assets being disconnected and concentrated to within each of these product silos. It was also established that the extant silo structures and the associated way of working is engrained in the mature banks rendering it a challenge to change course and modify their architecture and way of working for the purposes of leveraging big data analytics.

Participant 8 expressed extreme frustration on the issue and stated that, "We've got a massive problem with the data sitting all over the show, different clusters, different servers." Three participants articulated the challenges related to data being distributed across multiple product silo's. Participant 4 built on the above and indicated that, "I think it's been probably like legacy systems, just the systems themselves. Data sits in multiple systems…So putting together a picture of a client might be difficult because some systems cannot communicate with another system, so that sucks. Like it sometimes really sucks or the way, the way one department defines a client is different from the way another department defines a client."

Two participants spoke of the importance of interconnectivity and compatibility between technologies. Participant 9 postulated that, "there's no integration or the data systems are so disparate …systems necessarily don't speak to each other…you don't ever get a complete view of the client…you have a very one-dimensional view of the client, so I think that…getting those systems to talk to each other is very important [for] getting a full picture [of the client].". This view was supported by Participant 4's assertion that, "trying to get like a one on one view of a client can be difficult…so you wouldn't be able to leverage big data…because the systems just…don't talk to each other… we cannot leverage the data that sits in those silos, but if we could, if all of those are interconnected, then it'll be easier to create new products, easier to do marketing campaigns easier for the bankers to go hunt for new Info for new business out there."

The general consensus amongst all the participants was the urgent need to break away from the silo models to more centralised models which facilitated data sharing and the creation of a single customer view. To this point, Participant 12 stressed that, "brands need to understand that they need one central place for all their data to kind of better understand their consumers within each category of business offerings that they have." Participant 4 indicated that "one thing that I think people at one of the banks, at the conference were saying…each product…sort of has analysts for each product…so they work in silos…I think the problem is they cannot cross pollinate…they cannot communicate because they are in multiple silos, the configuration …that has worked very well here at [bank name] is having one central location…so we get a better view of the client." Two participants shared the notion that integration of assets was required. Participant 5 indicated that "I mean the biggest advantage, the first integration that we need to do with the big data side of things is with the credit world…credit sits with a universe of information and we sit with a universe information, when you put them together…it gives a different profile around the customer, but that level of integration has to happen as we advance."

Two participants in recognition of the challenges elucidated above, indicated that their respective banks were in the process of consolidation. Participant 6 stated that, “You've got to be able to get your data into a single place where you can start using information across different spectrums. So, at the moment…there there's a big push to understand some of these channel behaviours…if you don't get all the data and get it linked to a single customer record, you’ll never understand how that data can be used.” Participant 3 eloquently encapsulates the assertions pertaining to the need for consolidation and the level of maturity of South African banks in terms of big data augmentation by explaining that “…the drive that we're in now is really about consolidation…we don't know what data we have at the moment…in pockets we do... there's a lot of pockets within the greater group that we can tap into…but it's not all in the same place …the infrastructure is very segregated across the whole the business…so, to get a view of which customer is represented by which brands within the group or even the subdivisions within the group...that's where we are at the moment…collecting all that data because I don’t want to go sell you an insurance product if you already have something. But I don't know because I don't have access to your data. I don't know where the data is…once we get all of that data points, obviously there's massive more value we can add.”

The quotations presented above as well as in Section 5.4.4.4 accentuated the need for South African banking to break away from the legacy technology setups and to consolidate data into a central system. These attributes are key to creating the single customer view, which as per Section 5.3, is one of the antecedents to leveraging big data analytics for competitive advantage.

5.6.4 **Organisational Culture**

Legacy and silo architecture also resulted in what participants described to be silo mentality and a silo organisational culture. To the point pertaining to organisational culture, the discussions emphasised the fact that culture and the way of working and thinking required to leverage big data analytics for competitive advantage was substantially different from that of the traditional mindsets and ways of working and thinking.

Participant 11 highlighted this point when illustrating the difference between big data analytics and traditional analytics as “it’s quite different; the first challenge is to start implementing that cultural shift …it is possible to re-skill your existing people in that [the technical skills] but I think the biggest challenge is sort of the cultural shift and a change of mind-set." Participant 4 shared the notion of the cultural shift being the biggest challenge in the postulation that, "the biggest challenge [is] where even personnel themselves…want to be in silos. They don't want to be in a central place" This statement emphasised the point that silo mentality is engrained in personnel. Participant 9 built on this point by stating that, "The silo culture would be the biggest problem or hindrance, people are like what's mine is mine, collaboration is one of every organisation's key values, I don't think you have ever come across an organisation where collaboration or some form of it is not a value but the implementation thereof is another story though, I think it's about people letting go of this- it's my team, it's more our team, it's more collaboration I think." Participant 1 reinforced these sentiments and introduced the notion of ownership into the discussion through the argument that, "I think they think that this is an IT project, and it's not [that] it is going to change [or] it has potential of changing…the way we do our work…and also as we get data from people, from systems then we get insights and then we can redesign or reengineer our products." Participant 6 succinctly encapsulates the discussion above through the assertions that, "you do get the whole mentality of its my landscape, I want to protect my zone. Don't come and take my people…they are more hoarders and protectors of their little empires rather than doing what's best for the organisation around data."

The above quotations reflect the need for breaking away from silo mentality and adopting a more collaborative approach and mindset. Three of the participants further emphasised the need for an organisational view and made a link to organisational performance. Participant 4 asserted that, "if we are in silos it's going to be difficult to really drive the overall business. We might drive our strategies in the silos, but it's one share price, if it is one share price you need to be, you need to be central to inform all these strategies." Two of the three participants alluded to divisional performance measurements being substantial contributors to silo cultures and mindsets. Participant 6 indicated, "It's that one level down where the struggle happens, but those [are] the guys that are very, very revenue focused and driven, so it's very hard to get them to prioritize stuff [the overall organisational goals]." This point was indicating that big data was bought into at the EXCO level, however the disintegration or silo mentality occurred at the senior management, which was [one] level down from EXCO, where the teams were more divisional revenue focussed as opposed to having a holistic organisational view. Participant 9 concurs with the notion that integration is present at the EXCO level and disintegration occurs a level down. The assertion that, "It is, very much so [integrated at

EXCO level], when I think it just gets lower level down, that's where the disintegration happens" evidences this. Participant 9's statement that, "It's very difficult because every product house will drive their own agenda and they will want to make their system work the best… time to market is extremely important so I don't think necessarily they are worried about system integration, as long as we can sell that product."

Five participants identified leadership to play a key role in addressing the asset configuration issues pertaining to leveraging big data for competitive advantage. Participant 1 accentuated that it is the responsibility of leadership to drive big data, and asserted, "I don't think they are doing enough to make sure the configuration is right… I think it needs to go to the top, say the EXCO. The message needs to come from there. They need to take it as a project of their own and put their signatures on it that we are running with big data analytics…they can get assistance from IT and the quants guys, but it needs to be driven from the leadership, so they get the configuration right."

5.6.5 **Organisational Structure**

Issues pertaining to organisational structure was established to originate from legacy silo mindsets as well as specific big data requirements. Participant 3 explained that "even in our small area we have our own EXCO, our own data teams our own IT teams…the infrastructure is very segregated across the whole the business." This example evidences the fragmented silo structures resulting from banks being traditionally built around products. The discussions revealed that this issue was present in all the legacy banks as four other participants shared similar sentiments.

The specific organisational structure issue pertinent to big data originates from the knowledge and communication gap that exists between the business side and the data science side. This issue was explored in Sections 5.4.4.1 and 5.5.1.1 where it emerged as a dominant theme. Inability to transcend this gap was established to dilute the quality of insights extracted from big data. Participant 4 indicated that "you just need someone who can translate the technical aspects into business, who understands the business levels, how to extract the information and translate it into business value" Participant 10 also accentuated this issue through the statement that, "So, typically…and I think it happens in most banks is like the data analysis is kind of separate to the business…so what happens is, is that we're not clear on the problem as business and so the guys try to solve everything and then on the other hand, if you're not linked to the business and you don't necessarily understand it, you almost have a utopian view of how this is going to work. So, I do see a disconnect and I know [colleague name – CIO] is working hard to try and break that down."

A key finding in the above referenced sections was that the potential human resource fulfilling this role was scarce and was expected to have a data science background coupled with strong business acumen. Participant 5 elucidated that this role should be filled by a data scientist with "very deep analytical…but with good knowledge around the data…got the technical background but also got a business acumen side of it, commercial acumen side." According to Participant 11, " someone with a very wide range of skill sets ..you don't really get that in the market, you get a computer scientist that knows a bit of stats or a statistician that knows a bit of computers or a scientist or a great database administrator…to get [a] sort of Jack of all trades is kind of impossible." Participant 6 provided a contrary view to Participant 5 in stating that, "there are translators in my previous data product management role, that's one of the key points is that that role is not technical." Irrespective of whether the translator is a technical role or not, the data evidences that the gap is not filled, and suboptimal results are being achieved. Participant 5 encapsulates the above through the statement that, "what happens is that a lot of the time the messages get lost [in translation] and also you end up doing…what you interpret for it to be."

To the point that a single resource has the ability to bridge the gap between business and data science, Participant 8 asserted that, "everybody is like this is the perfect data scientist and I don't believe it exists…I don't think you are ever going to get it. My strategy has always been to build a team where I've got strong computer science guys, strong stats guys and strong business people…everybody strong at least in some direction, but they've got to overlap into the rest of it. The stats guy that knows computer science…business guys that know computer science storage systems and so forth and stats and so you make up a team that can actually function well together. …build the team that leverage off one another" Participant 6 also subscribed to a team fulfilling this function and indicated that, "there are teams of people that are business engagement people that their job is to take something that the business has said and translate it into a data need." The business engagement team is understood to be an intermediary between the business and data science.

Two participants proposed a hub and spoke model comprising a central data science team serving the business. Participant 11 indicated that, “some of it is silos but a way to overcome it is to try and implement a hub and spoke model, where the central IP sits, with the data scientists – and then you have connections, you build up relationships with the business unit and then we work on collaborative models of working together with the business units so we try and collaborate on that project.” Participant 4 also subscribes to the hub and spoke model, this is evidenced by the assertion that, “the configuration that would work, that has worked very well. I think here at [bank name] is having one central location for analysts, for the data scientists and our team, our team we feed into product development, we do work for marketing, we do work for private banking, for private capital” Premised on these quotations, the hub and spoke model comprises a central team of data scientists and analyst who serve each of the business units.

Two other participants subscribe to embed data scientists into each of the business, with the objective of the data scientist ultimately getting an understanding of each of the businesses into which they have been embedded. The premise for the solution is that by them gaining an understanding of the business as well as the business problems they are trying to solve with the data analytics they are in a position to extract superior insights from the data. Participant 5 elucidates this solution as, “what we do is that we embed individuals in the business…for example, in my team, the person who looks after business banking insights…is embedded in the business banking environment…they get to understand the problems that the people are trying to solve, the problems that the customers are trying to solve. So, they're part of the business environment and they also have the skills to be able to provide the insights like not to have this, these handoffs that happens because things get lost in that translation...in the construct of the new world and the data scientist world they would solve for that plus.” Participant 9’s concurrence with the approach of embedded data scientists or analysts in the teams they serve is evidenced by the assertion that, “In a dream world, I would love to have analysts in my team just so that they are close to the campaigning and so that they understand what we are trying to achieve.”

Three participants asserted that big data required representation at the correct forums and levels with the objective of getting buy in from top management as well as ensuring that the data agenda is a priority and is driven by top management. Participant 11 articulates this through the assertion that “The first thing I think is to get more buy in from senior level, they have a seat at the table…the best way we’ve done it is to connect at the very highest level within each business unit…so that you start tapping into the questions that the CEO is asking…it's easier to have a sort of top-down directive to implement some of the solutions…the trick is to make big data…one of the CEO's priorities." To this point Participant 4 indicates that "involving the CDO in, in strategy business strategy, having a secure a seat on the EXCO."

5.6.6 **Bank Strategy**

Bank Strategy was one of the emergent themes in the discussion pertaining to the role of asset configuration in leveraging big data analytics for competitive advantage. Two participants made direct reference to strategy, while three participants alluded to solutions and issues of a strategic nature in the discussion.

From an asset configuration perspective, Participant 3 articulated strategy to be the starting point of big data development and emphasised, "So again, the biggest thing for me there is do you have a strategy of what you want to do with your big data? I think if you have a clear strategy…so, get to something, get that result and then see what's the next thing. Key with any sort of project is know what you want to get out of it…don't just go and build it for the sake of it, the moment you have that clear vision…you can configure those assets…to make sense for what you want to achieve…configuration is a function of what your strategy is with that data." Participant 6 concurred that asset configuration is of importance and asserted, "Absolutely [asset configuration is considered] … we have a new Chief Data Officer…he spent between then and now and still not even finished. Sorting out exactly that. What should our landscape look like or what functions should sit where, what needs to be housed as essential function within the data environment and controlled and managed in a single place…what do you allow to sit in business or do you should sit in business because then it's a lot more in tune with what business requirements are and we are going through that process at the moment." These quotations elucidate the importance of asset configuration being synonymous with big data strategy.

Three participants alluded to the need for a focussed and coherent big data strategy. Participant 10 supports this notion through the assertions that, "so I think you need to choose specific problems and actually pull in people from outside the banking environment into the bank to try and solve them… my personal view on this, there are so many problems to solve, we want to solve all of them." Participant 11, in support of the above also argued that, “if you can focus on a handful of projects initially with very clear goals or outcomes that you want to achieve, and then if you can get to that point where you can start feeding that success back to business, you know, showcasing that around business.” This sentiment was shared by participant 10 in the assertion that “I know that at the moment he [the CIO] needs quick wins…more than he needs longer to plays…I think first thing is quick wins. I think we've got to have a few more quick wins on this, build some sort of confidence around it”

Participant 5 was quoted in a discussion Section 5.4.4.2 pertaining to the organisational buy in and investment being antecedents to big data being leveraged for competitive advantage. Within the above referenced quotation, it was stated that, “you can't have big data as a sideshow… if the organisational buy in is not there, you always going have this cottage industry that's running on the side.” This quotation reinforces the importance of the bank having a clear, coordinated and coherent strategy to leverage big data for competitive advantage. Participant 5 appeared to build on the concepts of clear goals and quick wins cited above by alluding to “quantifying as to what should be the Rand value or the commercial outcome of the…data sets that we have. So, every like six months odd, we will look at all the analytics that were produced, all the insights that were produced, how did the increment either to improve the experience of the customer, improve the take-up ratios of customer, what was the ultimate commercial outcome” This suggests that measurable goals must be part of the big data strategy.

According to Participant 3 one of the biggest impediments to leveraging big data is strategy. To this point Participant 3 asserted that “if there’s a lack of vision, it’s going to fail.”

5.6.7 **Summary of findings for Research Question 4**

In answering Research Question 4, four dominant themes emerged; namely, Organisation Operating Model, Organisational Culture, Organisational Structure and Bank Strategy. It was established that the extant silo structures and the associated way of working is engrained in the mature banks rendering it a challenge to change course and modify their architecture and way of working for the purposes of leveraging big data analytics. The participants expressed an urgent need to break away from the silo models to more centralised models which facilitated data sharing and the creation of a single customer view.

Legacy and silo architecture also resulted in what participants described to be silo mentality and a silo organisational culture. To the point pertaining to organisational culture, the discussions emphasised the fact that culture and the way of working and thinking required to leverage big data analytics for competitive advantage was substantially different from that of the traditional mindsets and ways of working and thinking. The participants accentuated the need to break away from silo mindsets and cultures and transition to a more collaborative approach and mindset. Participants spoke of having an organisational view as opposed to a functional view, which was characteristic of product silos.

The participants did not explicitly cite physical proximity or organisational hierarchy issues. The most prominent issue pertaining to the organisational structure from a big data perspective was the knowledge and communication gap between the business and the data science team. There was emphasis on this issue since it was reported to diminish the quality of insights extracted from the data. The participants tabled three distinct proposals to address the issue; (1) to implement a business management team as the interface between data science and the business.,' (2) a hub and spoke model, comprising a central data science team, that feeds into the different parts of the business as required, and (3) to integrate data science personnel into the businesses they serve. Bank Strategy was one of the emergent themes in the discussion pertaining to the role of asset configuration in leveraging big data analytics for competitive advantage. The banks big data strategy was identified as one of the biggest impediments to leveraging big data. The participants alluded to the need for a vision and a focussed and coherent big data strategy.

5.7 Conclusion

Chapter 5 presented the research findings based on the research questions included in Chapter 3. The utilisation of big data in South African banking is seen to be in the infancy stages of development with a long way to go prior to it being leveraged to its full potential. Regulation featured as an inhibiting factor for the enhancement of big data in South African banking. The methodologies for the processing of big data were generally deemed inadequate for leveraging big data analytics for competitive advantage. In some cases, premised on the maturity level and resultant incremental learning occurring as South African banking augments their big data analytics capabilities and uncovers inadequacies, the methodologies were cited to be generally adequate for the current developmental stage.

It was established that the scarcity of skilled data scientists, data engineers and business data scientists in South Africa is a key factor impeding the augmentation of big data in South African banking. The technology required for leveraging big data for competitive advantage was cited to be available on the market; however, the technology skills to implement an overall system design and select the right architecture in terms of hardware, tools and software platforms was available, but scarce and inadequate.

Legacy was identified as a major inhibitor and threat to the traditional banks as it allows opportunity for new entrants into the market. Legacy emanates from banks traditionally being built around products, which renders transitioning from a traditional bank to a market orientated bank very challenging. The silo effect, referring to technology and employees being concentrated within functional areas emerged as the key issue emanating from legacy, resulting in technology and data being concentrated within silo's and employees not collaborating with colleagues from other silos.

The emergent themes appear to predominantly support the literature reviewed in Chapter 2, however a detailed analysis of the findings contrasted with the literature follows in Chapter 6.

6 CHAPTER 6: DISCUSSION OF RESULTS

6.1 Introduction

This chapter includes a detailed discussion of the results from the analysis of the qualitative interview data presented in Chapter 5. These results are contrasted with extant literature presented in Chapter 2 and provides insights into leveraging big data analytics for competitive advantage in South African banking. The research findings in this chapter aims to build on the current body of knowledge by analysing leveraging big data analytics for competitive advantage from a resource-based, dynamic capabilities and market orientation perspective. The research questions presented in Chapter 3 provides the framework for the discussion of the results in this chapter.

6.2 Discussion of Research Question 1

How is big data analytics used in South African banking for competitive advantage?

Extant literature suggests that organisations make substantial investments into big data assets; however, they largely lack understanding of how to leverage these assets for competitive advantage (Martens et al., 2016). Research Question 1 sought to establish if big data analytics was considered to be a source of competitive advantage and how big data analytics is used in South African Banking for competitive advantage.

6.2.1 Big Data Analytics as a Source of Competitive Advantage in South African Banking

Big data is characterised by a proliferation of structured and unstructured data, which is considered a form of capital and a source of competitive advantage (Erevelles et al., 2015; Gupta & George, 2016; Johnson et al., 2017). The findings in support of the above confirmed big data to be a source, or a potential source of competitive advantage with participants citing access to a wealth of data to be the foundation of this competitive advantage. According to Gupta and George (2016), big data and its related technologies are new with many organisations still developing an understanding of how to implement these capabilities. Furthermore, projects comprising legacy systems with compatibility issues and requiring IT infrastructure upgrades takes years (Barton & Court, 2012), with the envisaged gains from big data investments not being realised immediately (Gupta &

George, 2016). These assertions were supported by the participants that believed big data was a potential source of competitive advantage since big data analytics was cited to be in the very early stages of augmentation in South African banking with substantial development prior to them being able to effectively leverage it for competitive advantage. The finding in Section 5.4.1 asserts that approximately 90% of analytics is still traditional analytics. This accentuates Martens et al. (2016) argument that while the banking sector is privy to a wealth of structured, semi-structured and unstructured data in the form of the financial transactions they observe; it is not being leveraged for target marketing and predictive analytics since traditional analytic methods are predominantly employed in the banking sector.

Most of the participants explained that competitive advantage is derived by utilising the wealth of data to increase customer value through various applications including personalisation and customisation, target marketing, assisting customers better and achieving operational efficiencies. Operational efficiencies pertained to improving the customer journey in the branches and automating manual processes thereby reducing the banks operating costs. The above and an analysis of the results in Table 2, Section 5.3 evidences that the current applications for big data is predominantly focussed around customer centricity and business process optimisation. These results mostly support literature, particularly for the marketing applications aimed at better understanding consumer behaviour (Erevelles et al., 2015) and making improvements to business process (Gupta & George, 2016; Torres et al., 2018). In addition to these applications, literature asserts that big data enhances the organisations ability to be dynamic, thus enabling organisations to align their strategies to the environment (Erevelles et al., 2015; Johnson et al., 2017). The findings did not make any reference to big data informing organisational strategy or efforts of attaining alignment with the environment.

Additionally, while the findings identified customisation, personalisation and target marketing as key application areas for leveraging big data for competitive advantage in South African banking, participants cited legislation as a major inhibitor based on the restrictions it places on the utilisation of fine grained customer transactional and behavioural data. As per Section 5.4.4.5, one of the participants indicated that compliance is very restrictive and challenging when attempting to utilise fine grained data, however there are less compliance issues when utilising vague, broad and highly aggregated data. According Martens et al. (2016), there is no appreciable improvement in predictive analytics when big data is aggregated to the extent that it resembles traditional data comprising a few general parameters. This assertion is supported by the finding that target marketing is still ‘spray and pray;’ that is, it is still predominantly mass marketing.

6.2.2 **Relevance of Findings for Research Question 1**

Research question 1 investigated how big data is being utilised for competitive advantage in South African banking. The results suggest that big data is currently more a potential source of competitive advantage than it is a definite source of competitive advantage in South African banking. This is premised on big data being in the early stages of development and legislative restrictions detracting from value adding applications of personalisation, customisation and target marketing, all of which derive impetus from fine grained customer transactional and behavioural data. Legislation is identified as a major inhibitor because of the restrictions it places on the utilisation of fine grained transactional and behavioural data. Premised on the assertions of Martens et al. (2016), it is inferred that the current form of legislative restrictions limits the applicability of big data to business process optimisation only.

6.3 Discussion of Research Question 2

To what extent are the methodologies employed for the processing of big data considered adequate to leverage big data analytics as a source of competitive advantage in South African banking?

This research question aimed to establish the deemed adequacy of the methodologies employed for the processing of big data to leverage it as a source of competitive advantage as well as to identify the key inadequacies and areas for improvement.

6.3.1 **Adequacy of the Methodologies for processing of Big Data for Competitive Advantage**

Due to big data being in the early stages of augmentation, the findings predominantly established the methodologies for the processing of big data to be inadequate. Legacy issues pertaining to getting all the data from traditional data warehouses onto big data platforms was identified as a key issue that takes years to resolve, with one system at a time being transitioned to these new platforms. This supports Barton and Courts (2012) assertion that projects comprising legacy systems and compatibility issues takes years, thus requiring that these projects be prioritised such that the most important data sources are identified and upgraded first. Most of the participants supported this incremental methodology for transitioning from traditional analytics to big data analytics, as upgrading one system at a time was cited by most of the participants. One of the participants indicated that during the transition phase traditional analytics and platforms must run in parallel with big data analytics and platforms.

The findings indicated that 'we all learning still as we go along' and the 'more you explore, the more you gather…maybe your methodology has to change too to fit to what you want to get out in the end.' This evidences that that the industry is in an exploratory phase of incremental learning. As per the previous section this accentuates the maturity level of the industry and supports Gupta and George's (2016) assertion that there is little knowledge of how organisations build big data capabilities.

6.3.2 **Maturity of Big Data Analytics in South African Banking**

The preceding sections established that big data analytics is in the early stages of development in South African banking. The findings revealed that big data capabilities are approximately 10 to 30% developed. As eluded to in the preceding section, the transitioning to big data is occurring incrementally. According to the findings, because of big data capability being immature in the industry, there is a requirement to run these platforms in parallel, therefore is a large scope for traditional analysts. While this may support Martens et al. (2016) assertion that predictive analytics predominantly employs highly aggregated data to fit traditional methods, it is however a consequence of the maturity level as well as the legislative restrictions discussed in Section 6.2.2, as opposed to being intentional.

Furthermore, Martens et al. (2016) postulation that data is highly aggregated due to resistance from traditional analysts to change their methods is refuted as the findings indicated that there is a large scope for traditional analysts and that data scientists have a fundamentally different skillset and mindset compared to traditional analysts, therefore there is no pressure for traditional analyst to migrate to being a data scientist. According to most participants, in the cases that traditional analysts choose to develop into data science, the same is supported and facilitated.

6.3.3 Enabler: Human Resources

The findings emphasised the industries and countries need for upskilling human resources. All the participants indicated that upskilling of human resources is key to improving the insights extracted from big data. This supports extant literature, which emphasises the incessant worldwide shortage of data science skills (Gupta & George, 2016; Provost & Fawcett, 2013).

Most of the participants stressed that the quality of insights extracted from big data was to a large extent diluted due to; (1) analysts not understanding the business need, (2) the insights not being presented in a format suitable for interpretation by business, (3) business not understanding the data components, and (4) the scope of analytics being poorly defined by business. According to literature, the role of the data scientist is to guide and support the extraction of useful insights and knowledge from the data to facilitate data driven decision making (Hormazi & Giles, 2004; Provost & Fawcett, 2013). Data scientists must have the ability to articulate business problems from a data perspective (Provost & Fawcett, 2013; Torres et al., 2018), thus necessitating a combination of technical skills and business acumen to facilitate the production of insightful high-quality information in terms of accuracy and usefulness for interpretation by the organisations decision makers (Torres et al., 2018). Items (1) and (2) above, supports literature in terms of the expectations of the skillset required from a data scientist. Items (3) and (4) supports the assertion that the organisations decision makers must possess data acumen to interpret the information extracted from the technical teams (Seddon et al., 2016; Torres et al., 2018). The need for the organisations decision makers to possess data acumen (Seddon et al., 2016; Torres et al., 2018) is accentuated by the fact that misinterpretation of the information detracts from the quality of insights and ultimately the strategic value that can be derived from analytics (Torres et al., 2018).

The findings indicated that in the South African context, the requirements discussed above are scarce and predominantly unavailable, because the country "is struggling to get the technical guys…and when you do get the technical guy, you need someone who will be able to translate it into business value.' The role of a Translator, whose function is to articulate the business need and problem statement to the analysts emerged from the findings. This function was not evident in the literature, however based on the participants elucidations, the role was developed by upskilling a business manager with data acumen skills.

6.3.4 Enabler: Investment

The findings indicated that big data capability requires substantial investments and organisational buy in. This is consistent with assertions in extant literature that developing big data capabilities requires heavy investments (Johnson et al., 2017; Kiron et al., 2011; Lavelle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011; Gupta & George, 2016; Torres et al., 2018). Kiron et al. (2011) postulated that the investment required is dependent on the status of the organisations existing infrastructure and the level of sophistication that the organisation envisages. The participants did not speak about the level of envisaged sophistication or investment.

Participants spoke of organisational buy in being key for unlocking investments for big data project support. According to the findings. organisational buy in is engendered through the demonstration of value and project successes. Obtaining organisational buy in through the demonstration of commercial value may prove challenging based on Gupta and George’s (2016) assertion that, due to the newness of big data and the substantial costs associated with implementation, organisations will not realise the envisaged gains immediately. Gupta and George (2016), however stressed that organisations must devote time and resources to realise their analytics objectives. Aligning to the above, some of the participants spoke of the initial costs being substantially higher than the revenues generated, with indications of approximately a year to break even.

The need for organisational buy in aligns to the Wamba et al. (2015) assertion that, extant studies prove a strong positive relationship between top management buy-in and support and IT project implementation success. The findings supported this through identifying that big data required representation at the correct forums and levels, particularly EXCO level to gain access to the CEO. Participants indicated that this was required to align big data to the organisations goals and priorities. Literature did not elucidate the link between demonstrating project successes and organisational buy in, in the big data context, however there was consensus in the findings that developing a strategy comprising a handful of big data projects with focussed and measurable goals facilitated the demonstration of quick wins, engendered organisational support and unlocked further investment. Organisation buy in and leadership is detailed in Sections 6.4.1.3 and 6.5.4.

6.3.5 Enabler: Data Quality

Data quality refers to clean, accurate, consistent, comprehensive and valid data (Isik et al., 2013). Data governance and quality is an antecedent to extracting superior insights from big data (Isik, Jones, & Sidrova, 2013; Lavelle et al., 2011; Seddon, Constantinidis, Tamm, & Dod, 2016; Torres et al., 2018). Consistent with the above, most of the participants cited good quality data as one of the key antecedents to extracting superior insights from the data. Participants spoke of ensuring cleanliness, completeness, accuracy and validity of the data ingested into the system prior to the data being certified for analysis. The importance of data quality is accentuated by literature confirming that data quality issues are responsible for the failure of more than half analytics projects (Isik et al., 2013).

6.3.6 Inhibitor: Legacy

All participants from the large banks in excess of 100-years old cited legacy as a major inhibitor to big data augmentation. Participant 5 explicated that legacy emanated from banks traditionally being built around products, resulting in product silo's. Furthermore, a bank that is built around products is very hard to transition to a customer centred bank.' Day (2011) identified structural insularity as one of the key factors that prevent organisations from adopting a market-oriented culture. Aaker (2010), elucidated that structural insularity or "silo crisis" (p. 315) results from traditional product, country and functional silo's. The above evidences that the findings align with literature in this regard.

Extant literature asserts that capabilities are ubiquitous with organisational process and are key to creating a market-oriented organisation and competitive advantage (Day, 2014; Day, 2011; Day, 1994; Kozlenkova et al., 2013; Teece, 2007). Furthermore, capabilities must be dynamic to facilitate the efficient and effective reorganisation of resources in response to dynamic environments characterised by evolving customer needs and technological advancements (Teece, 2007). According to the findings, a major challenge for traditional banks is that 'they've got a 150 to 200 years' worth of history of engrained process and procedure and that is a massive challenge to overcome.' Analysis of this statement with the literature presented above, evidences that engrained processes and procedures have the impact of rendering legacy banks rigid and unable to transform, thus preventing them from aligning with the dynamic requirements of the environment. This inhibits the sustainability of competitive advantage (Day, 2011; Erevelles et al., 2015; Kozlenkova et al., 2013; Teece, 2007). The other issue emanating from engrained process and procedures is what Day (2011) refers to as organisational rigidity, that is the tendency of organisations to refuse transformation and continue to exploit engrained capabilities to obsolescence. Organisational rigidity is a major barrier to obtaining a market-orientation (Barton & Court, 2012; Day, 2011; Wamba et al., 2015).

It was interesting to note that legacy and engrained process was identified by all the legacy banks as a major threat, which the start-up banks had the opportunity to exploit. Conversely, aligning with the theory and the discussion above, the participant from the start-up bank saw the structural insularity and organisational rigidity of the tradition banks as an opportunity and indicated that “I think that it's going to give us a competitive advantage…the big four are sort of sitting with very well-developed models [legacy models] already. It's harder to change course when you've already invested so much in your current way of doing things. Yes, I think we are starting off. We don't sit with those legacy systems problems. Now we can, start designing the systems around – in such a way that we are more dynamic…be able to change.”

6.3.7 **Inhibitor: Regulation**

Regulation is considered to be an exogenous factor, which is beyond the scope of the study. Premised on this, literature pertaining to regulation had not been reviewed. This section presents a high-level overview of the findings only and suggests that regulation and consumer protection in the banking context be an area for future research.

Legislation had been identified a major inhibitor to leveraging big data analytics for competitive advantage. The legislative restrictions pertaining to the utilisation of fine grained consumer transactional and behavioural data was discussed in Sections 6.2.1 and 6.2.2. The data presented in Section 5.4.4.5 emphasises these issues. It was evident that a solution pertaining to legislation is required in order to permit big data to be leveraged for competitive advantage and to augment big data within the South African banking sector. Two participants proposed that the banking industry collaborates with regulators to discuss and demonstrate how consumer personal data is utilised, protected and to differentiate between personalised messaging and spam. Legislation will not be discussed further and is suggested as an important area for future research.

6.3.8 Relevance of Findings for Research Question 2

In answering research question 2, it was established that the methodologies employed for the processing of big data is not adequate for leveraging big data analytics for competitive advantage in South African Banking. Skilled human resources, investment, organisational buy in and quality data were established to be key enablers for the extraction of superior insights from big data, while regulation and legacy was established to be the inhibitors. A key finding is that the industry, in terms of big data capability building, is learning as they go along, which indicates incremental learning but an area of weakness, since according to extant literature competitive advantage is derived from capabilities as opposed to independent resources (Barney & Hesterly, 2012; Day, 2011; Kozlenkova et al., 2013).

South African banking is 10% to 30% developed in terms of big data capabilities, resulting in a transition period as big data capability is incrementally developed. The consequence of the above is that analytics is currently predominantly done on traditional platforms utilising traditional data. Legacy was identified as a major inhibitor and threat to the traditional banks as it allows opportunity for new entrants into the market. Legacy emanates from banks traditionally being built around products, which renders transitioning from a traditional bank to a market orientated bank very challenging. Structural rigidity and structural insularity, resulting from engrained processes and the silo effect respectively, are consequences of the traditional banking architecture and are key inhibitors to developing dynamic capabilities and a market-oriented culture (Aaker, 2010; Day, 2011). Opportunity for new entrants to disrupt the South African banking industry emanates from new banks being on purely digital platforms and them not having to navigate the legacy issues, which traditional banks are finding challenging. New banks also possess the ability to adopt an organisational design that enhances their ability to be dynamic, which complemented with big data capabilities will make them more responsive to evolving customer needs and environmental changes (Day, 2011; Erevelles et al., 2015; Kozlenkova et al., 2013; Teece, 2007). The findings pertaining to legacy issues supported extant literature.

The findings predominantly supported literature in terms of the human resource requirements, however within the South African banking context, the additional role of a translator was identified. This role encompasses translating the business need to the data science team to fill the knowledge and communication gap between data science and the business, thus elucidating the business problem and requirements and ultimately improving the quality of insights extracted from big data. The literature and findings support the sentiment that there is an incessant scarcity of data science skills.

Regulation had been identified as the other key inhibitor due to the restrictions it places on consumer transactional and behavioural data, both of which give big data impetus in personalisation, customisation and target marketing applications. Legislation is outside the scope of this study and is not explored further beyond this point.

6.4 Discussion of Research Question 3

What are the specific big data resource requirements for leveraging big data analytics as a source of competitive advantage in South African banking?

Extant literature suggests that organisations generally lack understanding of the specific big data resource requirements and as a result are unable to leverage the same for competitive advantage (Erevelles et al., 2015; Johnson et al., 2017; Kozlenkova et al., 2013; Lycett, 2013; Martens et al., 2016). One of the primary objectives of this study was to understand the specific big data resource requirements.

6.4.1 **The Specific Big Data Resource Requirements to Effectively Leverage Big Data Analytics for Competitive Advantage**

The findings revealed that while most of the participants made mention of the technology resources, their focal point when elucidating the specific big data resource requirements was the human resources aspect. The findings confirmed that the software and 'the hardware is available so it's not getting the hardware that's the hard piece,' it is the 'resources, understanding that hardware and software, that is the challenge without a doubt.' This notion supports literature which asserts that big data technologies have developed to a large extent (Kiron et al., 2011; Mcafee & Brynjolfsson, 2012), thus providing organisations with the ability to manage the increasing volume, velocity and variety of big data (Gupta & George, 2016; Isik et al., 2013). Furthermore, literature confirms that technology is not an inhibitor to building big data capabilities as the required technologies are readily available on the market (Gupta & George, 2016; Isik et al., 2013).

According to Participant 5, the fundamental big data resources encompasses data scientists, data engineers and data architecture. An evaluation of these resources against Gupta and Georges (2016) classification of big data resources included in Section 2.4, Figure 2 evidences that the tangible and human resources have been cited. Drawing on RBT, according to Erevelles et al. (2016) and Gupta and George (2016) the physical, financial, human and organisational resources includes; (1) physical capital resources including the capital investment, technology and the data. As indicated in Section 2.4, the physical capital resources are analogous to the tangible resources, (2) the human capital resources comprises the data scientists, data engineers and big data managerial skills with data acumen, and (3) organisational capital resources includes the organisational structure that enables the organisation to be responsive to the insights extracted. As indicated in Section 2.4, the organisational capital resources are analogous to the intangible resources.

The findings revealed that all the participants shared a common understanding of the big data resource requirements from a technology and human resource perspective. Participant 6's detailed account of the human resource requirements is included in Section 5.5.1. While job titles differed between organisations, the findings explicated that the data engineering team comprised data engineers and the following key areas; (1) Data ingestion team, responsible for the platforms for the ingestion and retrieval of the data, (2) Data governance team, responsible for data quality and data health, (3) Data architecture team, responsible for the overall architecture design and implementation including tools and platforms. The data science team comprised data scientists, responsible for the analysis of the structured and unstructured data. The translators, comprised business managers who are trained with data acumen and serve as the interface between business and data science. An analysis of the above against Gupta and Georges (2016) classification of big data resources included in Section 2.4, Figure 2, evidences alignment between literature and the findings for the technical human resources, however the managerial skills in literature appears to be analogous with the translator role as both have been established to be managers with data acumen. The role of the data scientist and data engineer is discussed in Sections 6.4.1.1 and 6.4.1.2 respectively.

Participant 8's detailed account of the big data technology requirements is included in Section 5.5.1. From a technology perspective the findings identified requirements for platforms for data ingestion, storage and processing. The speed of saving or ingesting the data, the speed of extracting the data and the capability of expanding the system by adding more processing capability without downtime was cited as important technology attributes. Open source platforms were identified to be solutions to this issue. According to participant 8, parallel processing is implemented to provide high speed processing as required in big data applications. The elucidation of the big data technology requirements above, aligns with extant literature, which identifies open source technologies such as such as Hadoop for distributed storage and parallel processing and NoSQL for the efficient storage and retrieval of data (Gupta & George, 2016; Isik et al., 2013). In support of the above, Section 5.4.1 evidences that the findings refer to 'new types of databases where you can incorporate more unstructured data.' This references the NoSQL databases mentioned above. Furthermore, the findings make specific reference to the open source platform Hadoop. Section 5.4.1 of the findings explicates that the hardware, and software requirements for big data applications is fundamentally different in terms of storage, retrieval and processing. This supports the assertions in extant literature that, traditional platforms and methodologies are inadequate for the processing of big data (Isik et al., 2013; Martens et al., 2016; Provost & Fawcett, 2013; Zhenning et al., 2015). The above suggests that the technical experts from the sample have a deep understanding of the big data technology resource requirements.

6.4.1.1 Data Scientist

According to the findings, the data scientist is a key multi-disciplined resource encompassing deep technical knowledge in terms of software technologies and the structures around the data. The data scientist is expected to manipulate structured and unstructured data and have the business acumen to extract and present the pertinent insights to business in an understandable format; thereby, solving a business problem. This supports literature in terms of the data scientist role as explicated in Section 6.3.3.

6.4.1.2 Data Engineer

According to Provost and Fawcett (2013), data engineers are responsible for data architecture and data processing, which includes ingestion and processing of the data to ensure that it is healthy and of adequate quality for the extraction of insights (Provost & Fawcett, 2013). The findings mostly support literature in the explication that the data engineer's role encompasses technology selection, architecture interface design, installation and maintenance, data ingestion and processing to ensure that the data is in a healthy form and ready for analysis by the data scientists. The findings appear to extend the data engineers role to also include technology selection, architecture interface design, installation and maintenance.

6.4.1.3 Chief Data Officer (CDO)

The findings defined the role of the Chief Data Officer (CDO) as an executive role responsible for (1) developing and driving the big data strategy in terms of data architecture and the data landscape. Data landscape was explained to be which functions sit where in the business; that is which data functions are centralised and which data functions are decentralised, (2) raising the profile of big data to engender organisational buy in, (3) aligning the big data agenda with the organisation requirements and, (4) educating the organisation around data and demonstrate what data can do for the organisation.

According to Jaworski and Kohli (1993), top management emphasis is one of the key elements that impact the ability of the organisation to be market oriented. Emphasis pertains to the amount of importance and commitment top management attributes to being market oriented, which also includes embodying this commitment by sending the rights signals to the entire organisation and incessantly emphasising the need to be market oriented (Jaworski & Kohli, 1993; Kohli & Jaworski, 1990). Furthermore, the literature review in Chapter 2 explicated the importance of a culture of inter-functional coordination, particularly Narver and Slater (1990) emphasised that it is the duty of top management to engender this culture into the organisation. The findings demonstrate that the participants understand the importance of top management and leadership in big data implementation success. Specifically, items (2), (3) and (4) of the findings aligns with the literature presented above, since the CDO is an executive role that is required to raise the profile of big data at the executive level and to the rest of the organisation. Furthermore, items (3) and (4) of the findings also aligns with driving a data-oriented culture through educating the organisation about data and what data can do for the organisation, which Kiron et al. (2011) identified to be key attribute of top performing and transformed big data organisations.

The finding in item (1) above, aligns with the tenets of theory pertaining to organisational culture, this is detailed in Section 6.5.4.

6.4.2 Gap between the Resource Requirements identified and the available Big Data Resources

Support between the findings and literature was established in Section 6.4.1, where the gap in big data resource requirements was concluded to be human resources with the requisite big data skillsets as opposed to the availability of big data technology on the market. The findings further establish that participants predominantly attribute the serious shortages in data scientists, data engineers, and resources possessing the required ICT technical knowledge in big data tools and platforms to universities, particularly South African universities. Participants indicated that there remains an inadequacy of formal training for data science and data engineering, with very restricted availability of a proper data science degree. While the above elucidates the skills shortage in a South African context, Provost and Fawcett (2013) postulated that the shortage of data science skills initially resulted from academic institutions not being able to put together the pertinent data science programs quickly enough to support industries demand for the same. Gupta and George (2016) further confirmed that the big data technical skills gap persists with only a few universities offering the pertinent courses, while the skills demand is incessantly increasing. This confirms that the findings support literature in terms of the availability of data science and data engineering specific curricula and qualifications.

In addition to data science and data engineering specific curricula, the findings identified a need for a business data science degree, which participants referred to as a Master of Business Administration (MBA) for data science to assist in improving the quality of insights extracted from big data by bridging the knowledge and communication gap between business and data science. Participant 4 asserted that such course is not offered in South Africa. The findings revealed that as a result of the skills gap, South African banking has much reliance on (1) international higher education institutions, (2) international partnerships to facilitate the planning and execution of big data projects and assistance in training local skills, and (3) in-house training.

The specifics pertaining to education and the related theoretical paradigm for addressing the same is outside the scope of this study. It is suggested that this be conducted as future research. The detailed findings are presented in Sections 5.5.3, 5.5.3.1 and 5.5.3.2.

6.4.3 Impediments for Addressing the Resource Gaps for Leveraging Big Data Analytics for Competitive Advantage

According to the findings, the themes for addressing the resource and capability gaps were identified to be legacy, mindset shift, organisational culture, organisational structure, evidencing value, organisational buy in and investment. Each of these factors, as per applicability are discussed in Sections 5.4.4.2, 5.4.4.4 and 5.6.4 which are dedicated to each of these factors.

6.4.4 Relevance of Findings for Research Question 3

In answering research question 3, it was established that the participants have a deep understanding of the specific big data resource requirements as the findings closely aligned to literature. This was evidenced by the participants having identified and explicated all the resources, which aligns with the tangible and human resource components of Gupta and Georges (2016) classification of big data resources included in Section 2.4, Figure 2. The data constituent of tangible resources was discussed in Section 6.3.5. The intangible constituents pertaining to culture and information sharing are discussed in Section 6.5, as they align to the organisational aspect of RBT, specifically the VRIO framework (Erevelles et al., 2015; Kozlenkova et al., 2013).

It was also established that there is an incessant skills shortage, which has the impact of impeding the augmentation of big data analytics in South African banking. Participants identified inadequacies in the formal training, particularly the curricula in South African universities, which do not offer adequate data science, data engineering and business data science degrees. This was established to be key factor, which is outside the scope of this study and is suggested for future research.

The key role of leadership was identified. Within the big data context, it seems that this leadership role resides with the Chief Data Officer. The importance of this role is accentuated by literature asserting that big data projects are either unproductive or fail due to organisational culture issues rather than technological or data related issues (Gupta & George, 2016). The findings evidenced that driving a data-oriented culture is one the key responsibilities of the Chief Data Officer.

Culminating the finding that the participants have a deep understanding of the specific big data resource requirements with the finding from research question 2, that the industry is learning as they go along; that is in the process of incrementally learning how to build big data capability evidences that, competitive advantage, if developed will not be sustainable. This is premised on the assertion that comparably sized organisations have the ability to acquire tangible resources thus eventually rendering them homogenous and unable to satisfy the “rare” attribute of the VRIO framework (Barney, 1991). Similarly, while human resources are scarce, acquiring skilled human resources may serve as a temporary competitive advantage, however as skills become more prevalent in the industry or resources are traded, homogeneity will prevail together with a loss of competitive advantage (Barney, 1991; Gupta & George, 2016; Torres et al., 2018). Gupta and George’s (2016) assertion that competitive advantage is not derived from investments alone, but from the creation of difficult to replicate, organisation specific capabilities through the combination of tangible, intangible and human resources accentuates the above. This translates to the need for South African banks to acquire knowledge on how to build difficult to copy, organisation specific big data capabilities through the confluence of their big data resources (Gupta & George, 2016; Hult et al., 2005). The building of capabilities is discussed under research question 4 below.

6.5 Discussion of Research Question 4

What is the role of the inter-relationships between big data assets in leveraging big data analytics as a source of competitive advantage in South African banking?

Extant literature suggests that in addition to understanding the specific big data resource requirements, it is also important to understand the inter-relationships between these big data assets to facilitate the creation of capabilities, which can be leveraged for competitive advantage (Gupta & George, 2016; Johnson et al., 2017; Moorman & Slotegraaf, 1999).

In cognisance of the fact that the major South African banks are predominantly in excess of 100 years old with legacy systems in place, big data asset configuration was deemed to play an important role in this industries ability to leverage big data analytics for competitive advantage. Premised on the above, Research Question 4 aims to establish the role of the inter-relationships between big data assets, the challenges in terms of these inter-relationships, that inhibits big data analytics from being leverage for competitive advantage, and the proposed solutions for addressing these challenges to better facilitate the leveraging of big data analytics in South African banking

6.5.1 Asset Configuration and Maturity

Maturity emerged as a dominant theme in the findings pertaining to asset configuration. Section 6.3.2 concluded that big data is in the early stages of augmentation in South African banking and that the industry is in the process of incrementally learning how to implement big data projects and build big data capability. As explicated in Section 2.2.1, capabilities refer to special types of resources, which facilitates the aggregation and efficient deployment of other organisational resources with the objective of enhancing their productivity (Gupta & George, 2016; Kozlenkova et al., 2013). According to Wamba et al. (2015), emphasis must be placed on big data orientations as superior organisational performance is contingent on these orientations, which facilitate competitive advantage. The findings confirmed that there is a knowledge gap pertaining to how to build big data capabilities. Most of the participants shared sentiments such as "what the optimal configuration is, I don't think we know yet."

Participant 5 eloquently captured the status of quo in terms of capability development through the assertion that "the stage that we are in [right now] we first starting to explore around what can be achieved on the big data platforms, so we haven't really gone into the extent of coordinating and orchestrating across all the areas in order to get that right." In addition to confirming Gupta and Georges (2016) postulation that organisations don't know how to create capabilities, it confirms Marr's (2015) argument that contemporary executives are still concerned about how to build big data capabilities and how to make the best use out of it. The inability to understand and implement the big data orientations that Wamba et al. (2015) refers to above, detracts from the value of big data and the ability to leverage it for competitive advantage and superior performance.

6.5.2 Asset Configuration and Legacy

Section 6.3.6 concluded that legacy is a major inhibitor and threat to South African traditional banks as it impedes big data capability augmentation and presents opportunity for new entrants into the market. As detailed in the above referenced section, structural insularity and structural rigidity (Aaker, 2010; Day, 2011) emanates from legacy issues. Legacy has been included in this section as it emerged as a dominant theme and to reinforce the impact that it has on big data capability augmentation. The subsequent sections discuss the organisational operating model, organisational culture and organisational structure, all of which are dominant themes associated with organisational design and big data capability development and have challenges emanating from legacy.

6.5.3 **Organisation Operating Model**

The organisation operating model relates to the configuration of the technology assets. As discussed above, legacy is a key issue, which traditional banks are finding challenging to transcend. The findings revealed that a consequence of traditional silo architecture is that technology assets are disconnected and concentrated within each of the product silos, along with the associated data. Most of the participants expressed extreme frustration when elucidating the consequences of this paradigm as, 'we've got a massive problem with the data sitting all over the show, different clusters, different servers' and 'putting together a picture of a client might be difficult because some systems cannot communicate with another system, so that sucks.' According to the above, the findings also evidenced that data sharing is severely restricted, and the banks are not able to create a single customer view. On this point, participants shared the notions that 'if you don't get all the data and get it linked to a single customer record, you'll never understand how that data can be used' and that 'we cannot leverage the data that sits in those silos.' The findings also indicated that consolidation of the systems and associated data was recognised to be of extreme importance.

The findings support literature, which asserts that leveraging big data analytics capability requires a shared platform for collecting, storing and sharing intra-organisational and inter-organisational market and customer data, historical data from legacy systems and organisational internal process data (Wamba et al., 2015). This is a key concept of the organisation wide generation and dissemination of market intelligence according to the Kohli and Jaworski (1990) market orientation perspective explicated in Section 2.6.2. As elucidated above and in extant literature, in addition to external data, the data must also encompass internal organisational data (Day, 2011; Gupta & George, 2016; Isik et al., 2013; Teece, 2007; Torres et al., 2018; Wamba et al., 2015). According to Kiron et al. (2011), the above, which pertains to the capability of capturing and combining information from many sources for dissemination so that individuals throughout the organisation has access to it, is one of the three key capabilities of successfully transformed big data organisations. Furthermore, the same literature accentuated the importance of breaking down the barriers introduced by silo to permit the integration of information (Kiron et al., 2011). The findings above support these assertions as it is evident that the criticality and consequences of breaking down silos and barriers have been elucidated by the participants.

As discussed in Section 6.3.8 big data capability is being incrementally developed. In the case of integrating the technology and data, Participant 5 indicated that 'the first integration that we need to do with the big data side of things is with the credit world…credit sits with a universe of information and we sit with a universe information.' This is in support of Barton and Court's (2012) postulation that in the case of legacy systems with compatibility issues prioritisation of upgrades to ensure that the most important data sources are identified an upgraded first. In terms of the organisation operating model, the finding seems to suggest that the data and technology is required to be linked onto a single platform. This suggests a decentralised and integrated system.

6.5.4 **Organisational Culture**

The findings indicated that legacy and silo architecture also resulted in what participants described to be silo mentality and a silo organisational culture. Participants indicated that silo mentality encompassed personnel wanting to remain in silos and not being amenable to collaboration. This supports Aaker's (2010) assertion that in silo structures, there is a lack of desire to share work or collaborate with other silos. The findings further revealed that silo culture manifested behaviours of ownership and protectionism. This encompassed profound non-collaborative behaviours such as, 'people are like what's mine is mine' and 'I want to protect my zone, don't come and take my people…they are more hoarders and protectors of their little empires.' Participants also spoke of 'where the teams were more divisional revenue focussed as opposed to having a holistic organisational view.' These findings strongly support the Kiron et al. (2011) assertion that organisational leaders with silo mindsets retain control of information within their functional areas with the objective of driving functional goals to the detriment of the organisation.

The findings alluded to divisional interests driving silo behaviours, particularly the notions that 'silo mentality occurred at the senior management, which was [one] level down from EXCO, where the teams were more divisional revenue focussed as opposed to having a holistic organisational view' and 'I don't think necessarily they are worried about system integration, as long as we can sell that product.' While this was identified in the findings, the notion to align divisional goals to break silo type mentalities did not emerge.

According to Narver and Slater (1990), successful inter-functional coordination is contingent on inter-functional dependency, which is achieved through the alignment of inter-functional goals and incentives. This requires that goals and incentives be structured such that each functional area's interest must be realised through close cooperation with other areas.

Most of the participants perceived leadership to have a key role in driving big data and culture. Participants strongly asserted that 'it is the responsibility of leadership to drive big data' and 'they need to take it as a project of their own and put their signatures on it that we are running with big data analytics.' The impetus of leadership involvement was detailed in Section 6.4.1.3. In addition, literature supports the above and accentuates that effective advocacy and leadership is key to engender inter-functional coordination and the reduction of isolation between functional areas (Jaworski & Kohli, 1993; Narver & Slater, 1990).

It was noted that, while the participants placed emphasis on organisational culture, there was little emphasis on a data oriented-culture. As per Section 6.4.1.3, one participant alluded to the CDO having the responsibility of educating the organisation around data and to demonstrate how data can help them. This aligns with the concept of a data-oriented culture; however, it was not explicitly stated. This was surprising in cognisance of the importance of a data-oriented culture. Culture pertains to having behaviours, practices and beliefs that are consistent throughout the organisation; however, a data-oriented culture complements the above with specific emphasis on it being a culture of data driven decision making at every level (Kiron et al., 2011). The value of a data-oriented culture is accentuated by it being identified amongst the top three capabilities to be mastered for leveraging big data analytics for competitive advantage (Kiron et al., 2011). Furthermore, Gupta and George (2016) advocate that the ability of organisations to leverage and benefit from big data investments can either be inhibited or enabled by organisational culture. This aligns to the Organisational aspect of the VRIO framework (Barney & Hesterly, 2012; Kozlenkova et al., 2013).

The findings indicated a strong need to break down silos and silo mentality. To this point Participant 4 argued that 'if we are in silos it's going to be difficult to really drive the overall business, we might drive our strategies in the silos, but it's one share price.' The findings support literature in that a culture promoting inter-functional coordination is required to drive big data and a market-oriented culture (Aaker, 2010; Day 2011; Jaworski & Kohli, 1993; Kiron et al., 2011; Slater & Narver, 1995). Section 2.6.1.2 provides a detailed argument pertaining to the importance of inter-functional coordination, specifically that a culture of inter-functional coordination (Narver & Slater, 1990) is key to enabling the coordinated organisation wide generation, dissemination and response to the insights extracted from external and internal information.

6.5.5 **Organisational Structure**

In terms of organisational structure, the findings did not explicitly reveal physical proximity or organisational hierarchy issues. The organisational structure issues appeared to emanate from the silo mentality and the resultant divisionally segregated culture discussed in Section 6.5.4. This paradigm is clarified by Jaworski and Kohli's (1993) explication that departmentalisation is of less importance than connectedness and inter-departmental conflict; that is, the number of departments an organisation has is of less relevance, if the personnel are connected either physically or through technology and there is less interdepartmental conflict. Interdepartmental conflict pertains to the tension that arises between departments due to incompatibility of actual and desired responses (Jaworski & Kohli, 1993). According to Narver and Slater (1990), inter-function coordination engenders the integrated interpretation of the information and the subsequent integrated response to the insights from the information. This is detailed in Section 2.6.2 under the "seize" and "execute" tenets of the conceptual model, derived from a culmination of Jaworski and Kohli's (1990) market orientation perspective, Narver and Slaters (1990) cultural emphasis perspective and Teece's (2007) dynamic capabilities framework. Premised on the above, a culture of inter-functional coordination comprising integrated interpretation and integrated execution reduces inter-departmental conflict since it engenders a shared understanding amongst stakeholders (Jaworski & Kohli, 1993; Narver & Slater, 1990; Teece, 2007).

The most prominent issue pertaining to the organisational structure from a big data perspective was the knowledge and communication gap between the business and the data science team. The findings evidenced emphasis on this issue since it was reported to diminish the quality of insights extracted from the data. This challenge was detailed in Section 6.3.3, where the translator role was identified. While the role is required, the findings revealed that the complexities and wide skill set that this role demands is predominantly unavailable in the market. This was evidenced through statements such as, 'someone with a very wide range of skill sets...you don't really get that in the market' and ‘to get [a] sort of Jack of all trades is kind of impossible.’ An additional consequence of having a translator is that ‘these handoffs that happens because things get lost in that translation.’ The findings evidenced three distinct proposals to address the issue; (1) to implement a business management team as the interface between data science and the business. This team was proposed to comprise ‘strong computer science guys, strong stats guys and strong business people,’ (2) a hub and spoke model, comprising a central data science team, that feeds into the different parts of the business as required, and (3) to integrate data science personnel into the businesses they serve. This was described to entail ‘embed[ding] the individuals in[to] the business…for example…the person who looks after business banking…is embedded into business banking environment…they get to understand the problems that the people are trying to solve, the problems that the customers are trying to solve.’

It was interesting to note that the hub and spoke model was suggested by both the participants from the newer banks. While each of the various models proposed have benefits and deficiencies, a review of the pertinent literature in Section 2.6.1.3 reveals mixed results pertaining to formalisation and decentralisation. These parameters appear to be context dependant; that is, dependant on the dynamism of the environment (Engelen et al., 2010) and the culture, such as power distance ratio (Kuada & Buatsi, 2005). The mixed results pertaining to the extent of formalisation and decentralisation required (Engelen et al., 2010; Jaworski & Kohli, 1993; Kuada & Buatsi, 2005) suggested that organisational structures have dual needs for autonomy and structure (Slater & Narver, 1995). In order to address these dual needs, Slater and Narver (1995) proposed the two-layer structure which, according to Miles and Snow (1992) attempts to achieve the efficiency of a formalised structure and the flexibility of an autonomous decentralised structure to facilitate the effective sharing of information, rapid awareness and response to the market with a reduction in lagging reactions. These attributes align with the objectives of being a market-oriented organisation in a dynamic marketplace and as per Section 2.2.3 is analogous to building big data capability. As elucidated in Section 2.6.1.3, the two-layer structure comprises temporary multifunctional teams that are deployed to work on various projects (Slater & Narver, 1995). This organisational design is said to facilitate connectedness through leveraging technologies such as electronic mail and shared data bases (Slater & Narver, 1995). The two-layer structure appears to be a culmination of the three proposals presented in the findings.

6.5.6 Bank Strategy

The findings revealed that creating a coordinated big data strategy encompassing the goals, objectives and measurable outcomes was important to the participants. Furthermore, as discussed in Section 6.3.4, the packaging of big data project milestones and goals to report successes and garner organisational buy in for future investments was also identified as key. While the interview did not direct specific questions towards strategy, when the discussion around strategy emerged, it was observed to be broad with little detail. This may be attributable to the fact that big data is still in the infancy stages of development within South African banking industry and the industry incrementally learning during implementation. The detailed discussions pertaining to maturity and incremental project implementation and learning is included in Sections 6.3.2 and 6.3.2. The absence of deeper strategic insights into; (1) the planned utilisation of big data resources as a foundation of strategy development (Barney & Clark, 2007; Kozlenkova et al., 2013; Wernerfelt, 1984), (2) the development of dynamic capabilities in cognisance of the contemporary dynamic market place (Teece, 2007; Teece et al., 1997), and (3) how insights from big data may inform strategy (Kiron et al., 2011) was inferred to be evidence of the level of infancy and the incremental development of knowledge into the building of big data capabilities. This was seen to give cadence to the Gupta and George's (2016) assertion that organisations don't know how to build capabilities.

6.5.7 Relevance of Findings for Research Question 4

Research question 4 pertained to the organisational constituent of the VRIO framework (Barney & Hesterly, 2012; Kozlenkova et al., 2013). As explicated in Section 2.2.1, the organisational constituent possesses the attribute of enhancing or inhibiting the organisations ability to leverage their valuable, rare and imperfectly inimitable resources for competitive advantage. In answering research question 4, it was established that the inter-relationships between big data assets is key for leveraging big data analytics for competitive advantage. This finding supports literature, that competitive advantage is not derived only by making investments, collecting data, and possessing technology but, through the combination of tangible, intangible and human resource assets to create difficult to match capabilities (Gupta & George, 2016). The findings specifically indicated that the organisational operating model, organisational culture and organisational structure are key constructs for leveraging the organisations big data resources for competitive advantage.

From the findings for research questions 2 and 3, which carried over to research question 4, South African banking is incrementally developing their skills for building big data capability. While the specific components, in terms of organisational operating model, culture and organisational structure have been identified, it appears that putting these components together to build difficult to replicate dynamic capabilities for sustainable competitive advantage is a challenge, particularly due to legacy issues and the incremental knowledge development that is occurring.

There are concerns that the solutions being developed may be sub optimal and not sustainable. This is premised on the findings in Section 6.5.6, which suggests that in depth strategy pertaining to big data capability development is not taking place, particularly with regards to building dynamic capabilities to ensure sustainability of their solutions, competitive advantage and profits. Furthermore, while organisational culture had been identified as a key construct, the concept of a data-oriented culture was not prominent in the findings. The findings supported literature regarding the key role that top leadership and inter-functional coordination has in engendering emphasis on market orientation and organisation culture; however, the concept of risk aversion did not feature in the findings. According to Jaworski and Kohli (1993), risk aversion impacts the organisation responsiveness and hence their ability to leverage the insights from the gathering, dissemination and interpretation of information. The importance of leveraging big data capabilities by responding through data driven decisions is accentuated by Kiron et al. (2011), where the making of data driven decisions had been identified as key to big data investment success. It is postulated that, while failure to make decisions on the intelligence is influenced by numerous factors, risk aversion is expected to be one of the key factors. It is inferred, that risk aversion did not feature in the findings since, as indicated above, the concept of a data-oriented culture, which pertains to data driven decision making did not feature prominently.

While the intention is not to propose a specific organisational design, it is key to ensure that the design adopted is an enabler for the effective sharing of information, rapid awareness and response to the market, reduction in lagging reactions and is dynamic to enable the reconfiguration of assets to facilitate alignment with the environmental and changing customer needs (Engelen et al., 2010; Jaworski & Kohli, 1993; Kuada & Buatsi, 2005; Narver & Slater, 1990; Teece, 2007; Torres et al., 2018). This is of importance considering the opportunities that structural insularity and structural rigidity presents for new entrants into the market. Traditional banks must specifically consider if the speed of the incremental augmentation is adequate considering the threats of new market entrants.

6.6 Conclusion

The findings from research questions 1, 2 and 3 culminated in research question 4. Research question 1 identified how big data analytics is utilised for competitive advantage in South African banking, while research questions 2 and 3 identified the gaps and the requisite unique big data resources. Research questions 2 and 3, specifically focussed of the VRI components comprising the tangible and human resource constituents of Gupta and Georges (2016) classification of big data resources included in Section 2.4, Figure 2. Research question 4, being the organisational constituent aligned to the intangible component of Gupta and Georges (2016) classification of big data resources. The organisational learning component included in the above referenced classification refers to the process adopted by the firm for exploring, sharing and applying knowledge (Gupta & George, 2016).

It was established that big data capability is in the early stages of augmentation in South African banking. In strategizing around the development of big data capabilities, it is imperative that South African banking is cognisant of the antecedents to the development of these capabilities. As detailed Section 2.6.1, these comprise (1) top management emphasis, (2) interdepartmental dynamics, and (3) organisational design. As detailed in Section 2.6.2, satisfying the antecedents equips the organisation with the capability to (1) Sense, (2) Seize and (3) Execute, thereby leveraging big data capabilities for sustainable competitive advantage.

7 CHAPTER 7: CONCLUSION AND RECOMMENDATIONS

7.1 Introduction

The purpose of the research was to explore the current big data resource and capability challenges in South African banking, to gain insights as to how to transcend the gaps and create the requisite capabilities, that can be leveraged for competitive advantage. The study was premised on leveraging big data analytics being high on the banks strategic agendas (Hormazi & Giles, 2004; Martens et al., 2016), the banks being privy to a proliferation of structured and unstructured data (Martens et al., 2016), and the anticipated challenges associated with transitioning from decentralised legacy systems to big data analytics (Krishna, 2016; Wamba et al., 2015). Furthermore, extant literature suggests that organisations fail to capitalise on big data investments due to a lack of understanding of the specific big data resource requirements (Erevelles et al., 2015) and organisations not knowing how to build big data capabilities (Gupta & George, 2016; Johnson, Friend, & Lee, 2017). Predicated on the substantial investments associated with the implementation of big data capabilities (Johnson et al., 2017; Lavelle et al., 2010), and the strategic implications in terms of sustainability, competitive advantage and superior organisational performance (Erevelles et al., 2015), it is paramount that these contemporary challenges be understood and addressed.

This chapter concludes the research on ‘leveraging big data analytics for competitive advantage in South African banking,’ through a presentation of the research findings and the implications for business and theory. Additionally, this chapter details the research limitations and suggests areas for future research.

7.2 Research Findings

The exploratory research confirmed that while there is a deep understanding of the specific big data resource requirements, the inter-relationships between these tangible, intangible and human resource assets are key build big data capabilities for competitive advantage. This finding supported Gupta and George’s (2016) assertion competitive advantage is not derived from investments only, but from the combinations of big data assets to create difficult to match capabilities. While the concept of dynamic capabilities did not feature, literature asserts that dynamic capabilities is key to ensuring that competitive advantage is sustainable in the contemporary hyper-competitive marketplace (Torres et al., 2018; Teece et al., 2007).

Legacy was identified as a major inhibitor and threat to the traditional banks as it allows opportunity for new entrants into the market. Legacy emanates from banks traditionally being built around products, which renders transitioning from a traditional bank to a market orientated bank very challenging. Structural rigidity and structural insularity, resulting from engrained processes and the silo effect respectively, are consequences of the traditional banking architecture and are key inhibitors to developing dynamic capabilities and a market-oriented culture (Aaker, 2010; Day, 2011).

It was established that big data capability is in the early stages of augmentation in South African banking. In strategizing around the development of big data capabilities, it is imperative that South African banking is cognisant of the antecedents to the development of these capabilities. As detailed Section 2.6.1, these comprise (1) top management emphasis, (2) interdepartmental dynamics and organisational systems, and (3) organisational design. As detailed in Section 2.6.2, satisfying the antecedents equips the organisation with the capability to (1) Sense, (2) Seize and (3) Execute, thereby leveraging big data capabilities for sustainable competitive advantage. The antecedents and the sense, seize and execute criteria above have been identified through a confluence of extant literature and the research findings.

Extant research pertaining to big data focussed on (1) leveraging big data through business intelligence and dynamic capabilities (Torres et al., 2018). The focal point of the research being configuring business process based on analytics utilising internal process information, (2) big data specific resource from an RBT perspective (Erevelles et al., 2015), and (3) an empirical study to validate that big data analytics capabilities lead to superior organisational performance by examining the resources that are required to create big data analytics capability utilising RBT (Gupta & George, 2016). The Gupta and George (2016) research, specifically stated that there is a need to further research on how to create big data capabilities.

This research is a confluence of the extant research cited above, in that it considers leveraging both internal and external information, through considering leveraging big data analytics from a combination of RBT, dynamic capabilities and the market orientation framework. Jaworski and Kohli’s (1993) market information processing perspective and Narver and Slaters (1990) cultural emphasis perspective has been uniquely utilised to form the basis of a conceptual framework for developing big data capabilities in the South African banking context. The conceptual framework is presented in Section 7.3 below.

7.2.1 Big Data Analytics as a Source of Competitive Advantage in South African Banking

The research confirmed big data and big data analytics to be a potential source of competitive advantage, with the proliferation of data that the banks have access to being cited as the foundation of this competitive advantage. Premised on big data being in the infancy stages of augmentation in South African banking it is seen as a potential source of competitive advantage rather than a definite source. Competitive advantage was perceived to be derived from utilising the wealth of data to increase customer value through various applications including personalisation and customisation, target marketing and achieving operational efficiencies through business process optimisation.

7.2.2 Big Data Resource and Capability Requirements

It was established that the participants have a deep understanding of the specific big data resource requirements as the findings closely aligned to literature. This was evidenced by the participants having identified and explicated all the resources, which aligns with the tangible and human resource components of Gupta and George's (2016) classification of big data resources included in Section 2.4, Figure 2.

The key role of leadership was identified. Within the big data context, it seems that this leadership role resides with the Chief Data Officer. The importance of this role is accentuated by literature asserting that big data projects are either unproductive or fail due to organisational culture issues rather than technological or data related issues (Gupta & George, 2016). The findings evidenced that driving organisational culture and market emphasis is one the key responsibilities of the Chief Data Officer.

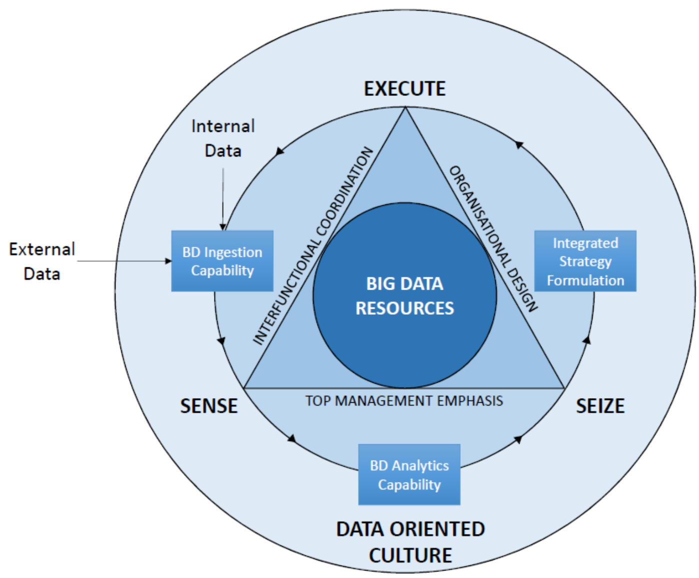
The findings confirmed that the organisational operating model, culture and organisational structure are antecedents to developing big data capabilities; however, it appears that combing big data assets that simultaneously satisfy the VRIO criteria is challenging. Within the South African banking context, legacy has been identified to be a key inhibitor, which impedes the augmentation of big data capabilities. This is predominantly due to structural insularity and structural rigidity, which emanates from legacy organisational architecture being built around products.

7.3 A Proposed Framework for the Development of Big Data Capabilities

Figure 3 below, presents a proposed model for the development of big data capabilities. The model was developed through the review and amalgamation of the pertinent extant literature. As elucidated in Section 2.3, the model was developed based on the strategic intent of big data and the attributes of market orientation.

The strategic intent of big data according to literature encompassed; (1) the transformation of business process and unlocking business value through operational implications (Wamba et al., 2015), (2) new implications for better understanding consumer behaviour and formulating marketing strategy (Erevelles et al., 2015), and (3) the development of dynamic capabilities to facilitate the efficient and effective reorganisation of resources in response to dynamic environments characterised by evolving customer needs and technological advancements (Teece, 2007). In cognisance of the above, it was postulated that the principles associated with the development of a contemporary big data market-oriented approach encompassed the traditional market information processing perspective (Kohli & Jaworski, 1990) and culture emphasis perspective (Narver & Slater, 1990); however, in addition dynamic capabilities (Teece, 2007) and the unique big data resource requirements had to be considered (Erevelles et al., 2015).

Figure 3: Big Data Capability Development Model



The Big Data Capability Development model was based on a confluence of the above mentioned theories and tested through the key insights derived from the research findings detailed in Chapters 5 and 6. The resultant model is explained in Sections 7.3.1 to 7.3.3.

7.3.1 **Big Data Capability Development Model - Big Data Resources**

The findings established that the participants have a deep understanding of the specific big data resources requirements, which was consistent with Gupta and George (2016) and Erevelles et al. (2015) and encompassed (1) physical capital resources including the capital investment, technology and internal and external data, (2) the human capital resources including the data scientists, data engineers and big data managers with data acumen, and (3) organisational capital resources including the organisational structure that enables the organisation to be responsive to the insights extracted.

As elucidated in Section 2.4, item (1) pertains to the tangible resources, item (2) pertains to the human resources and item (3) pertains to the intangible resources. The big data resources included in the centre of the Big Data Capability model encompasses the tangible and human resources. These resources align to the VRI constituents of the VRIO framework, which requires that a resource must simultaneously possess the VRIO attributes to be a source of competitive advantage (Barney & Hesterly, 2012). In order to be a source of sustainable competitive advantage the organisational constituent discussed in Section 7.3.2 is simultaneously required.

7.3.2 **Big Data Capability Development Model – Antecedent Conditions**

The Jaworski and Kohli (1993), Antecedents and Consequences of Market Orientation framework included in Section 2.6, Figure 2 provided the basis for the development of the proposed framework. According to Kohli and Jaworski (1990) the antecedent conditions have the ability of enabling or discouraging market orientation. Based on the above referenced framework, Narver and Slaters (1990) cultural emphasis perspective to market orientation and the research findings, it was established that the antecedents, as depicted in Figure 3 above, includes; (1) Inter-functional Coordination, (2) Organisational Design, (3) Top Management Emphasis, and (4) Data Oriented Culture.

Where; (1) Inter-function co-ordination pertains to the organisational coordination and utilisation of its resources to deliver superior customer value (Narver & Slater, 1990), (2) Organisational design pertains to the way in which labour is divided amongst organisational members and the manner in which coordination is achieved Mintzberg

(1993), (3) Top Management emphasis refers to the amount of importance and commitment that top management attributes to being market oriented, which also includes embodying this commitment by sending the right signals to the entire organisation (Jaworski & Kohli, 1993; Kohli & Jaworski, 1990), and (4) Data-oriented culture pertains to a culture of data driven decision making at every level.

These antecedents constitute the organisational constituent of the VRIO framework and possesses the attribute of enhancing or inhibiting the organisations ability to leverage their valuable, rare and imperfectly inimitable resources for competitive advantage (Barney & Hesterly, 2012). Antecedents (1), (2), (3) and (4) above, make up the organisational constituent, which according to Barney and Hesterly (2012), when combined with the VRI big data resources, serve as a source of competitive advantage. Organisational constituents (1), (2) and (3) are included are included around the triangle to depict that they combine with the big data resources to form capabilities; that is the big data ingestion capability and big data analytics capability.

The data-oriented culture is included in the outermost ring as the big data analytics capabilities have impetus and is driven within a data driven culture (Kiron et al., 2011). The big data ingestion capability and the big data analytics capability mentioned above, pertains to the “sense” and “seize” functions respectively. This is discussed in Section 7.3.3, below.

The risk aversion constituent originally included in Jaworski and Kohli’s (1993) antecedents to market orientation, has not been explicitly depicted in the proposed model based on the it not being identified in the findings. Furthermore, according to Jaworski and Kohli (1993), risk aversion impacts the responsiveness of the organisation to the insights extracted from the data, it is proposed that the responsiveness is inherent in the organisations data-oriented culture, the function of which is to give data driven decision making impetus.

7.3.3 Big Data Capability Development Model – Sense, Seize, Execute

As explicated in Section 2.6.2, premised on the definitions for the “sense” and “seize” constituents of the dynamic capabilities construct (Teece, 2007) aligning with the strategic intent of big data, as detailed in Sections 7.3 above, and being more comprehensive than the “generation” and “dissemination” constituents of Jaworski and

Kohli's (1993) market information processing perspective it was proposed that "sense" and "seize" replace the "generation" and "dissemination" components of the market information processing perspective. The definition of seize (Teece, 2007; Torres et al., 2018), below incorporates the attribute of engendering a shared understanding amongst stakeholders, which according to Jaworski and Kohli (1993) had been identified as key to reduce inter-functional conflict, thereby enhancing connectedness, inter-functional coordination and ultimately market orientation. This attribute addresses, the Hult et al. (2005) contention that organisations only effectively respond to information if a common understanding of that information exists.

In the context of this research, the conceptual model augments of the market information processing perspective with proposed changes to the following components and terms; (1) Sense and shape external threats and opportunities through scanning, searching and exploring across markets and technologies (Day, 2011; Teece, 2007). More specifically, sensing pertains to the acquisition of information about the organisations internal operations and the external environment in which it operates, while shaping opportunities pertains to the analysis and filtering of this information (Teece, 2007; Torres et al., 2018), (2) Seize opportunities through the integration and interpretation of the information in order to facilitate decision making, a shared understanding amongst stakeholders and the formulation of strategy in response to the opportunities identified (Teece, 2007; Torres et al., 2018). Integration refers to the coordinated organisation wide effort in interpreting the information, identifying the opportunities and threats and the subsequent formulation of a coordinated strategy (Jaworski & Kohli, 1993; Narver & Slater, 1990), (3) Execute, through the integrated implementation of the strategies pertaining to delivering superior customer value or effecting organisational changes to exploit opportunities and avoid threats.

An analysis of the sense, seize and execute functions as defined above, and within the big data context evidences that these functions require the following big data specific resources (Gupta & George, 2016; Isik et al., 2013; Torres et al., 2018; Wamba et al., 2015); (1) human resources with the requisite technical and management expertise, (2) technology infrastructure, and (3) organisational support. Each of the above resources was part of the research findings and discussed in Sections 6.3, 6.4 and 6.5.

7.4 Recommendations for Managers

The research has provided a practical framework for managers to conceptualise and understand the key constituents for leveraging big data analytics for competitive advantage. Through an improved understanding, managers can strategically and coherently diagnose big data resource and capability issues to improve their ability to leverage these capabilities for competitive advantage. Furthermore, the insight provides preliminary guidance for creating and understanding big data capabilities. Managers, specifically transitioning from traditional analytics to big data analytics utilising an incremental approach need to consider the viability of how quickly these increments occur as new entrants have the potential of capturing competitive advantage and market share through disruptive innovation.

7.5 Recommendations for Future Research

Based on the research findings, the following are suggested for future research;

- The Big Data Capability Model can be validated quantitatively utilising a large sample of executives, directors and senior managers in banking with knowledge and expertise on big data specific technology, information management and processing, market and development and strategy development.
- A qualitative comparative analysis to understand which combinations of organisation design are optimum for the South African context and other contexts. This is based on the theoretical results pertaining to formalisation and decentralisation appearing to be mixed and context dependant as discussed in Section 2.6.1.3.
- As per Section 5.4.4.5, regulation was found to be a major inhibitor of the augmentation of big data analytics in South Africa. An exploration of regulation and consumer protection within the context of the utilisation of consumer transactional and behavioural data for personalisation and customisation in banking is suggested. Specific interest will be in how amenable people are to permit the use of this information for banking specific personalisation and customisation applications.
- A follow on from the regulation topic is how regulators and the banks can work together to protect the consumer as well as leverage the benefits on consumer data.

- As per Section 5.5.3.1, the lack of availability of big data specific degrees in South Africa was found to be a major inhibitor of the augmentation of big data analytics in South African. These degrees include data science, data engineering and business data science. Future research into how the banks and universities can collaborate to create these skills and offer the pertinent education.

7.6 Research Limitations

The limitation of the qualitative study included;

- Generalizability of the results based on the small sample size.
- Qualitative research is subjective by nature, therefore the biases of the researcher and the interviewee may be impact the data and the interpretation thereof.
- The researcher did not have prior training on conducting interviews for research purposes. This could have the potential of impacting the results.
- The researcher not being independent from the data collection process introduces biases.

7.7 Conclusion

The research comprised 11 semi-structured, in-depth interviews conducted with experts from the South African banking industry. Thematic analysis of the qualitative interview data provided insights into leveraging big data analytics for competitive advantage in South African banking, particularly, the industries understanding of how to utilise big data analytics, the adequacy of the methodologies employed for the processing of big data and the resource and capability requirements.

The research established that big data capability is in the early stages of augmentation in South African banking, with legacy issues presenting a major challenge to traditional banks. Structural rigidity and structural insularity emanating from traditional organisation architecture is impeding the development of big data analytics, which presents opportunity for new market entrants. Education and regulation were found to be key inhibitors to leveraging big data analytics and are recommended as areas for future research.

In strategizing around the development of big data capabilities, it is imperative that South African banking is cognisant of the antecedents to the development of these capabilities. As detailed Section 2.6.1, these comprise; (1) top management emphasis, (2) interdepartmental dynamics, and (3) organisational design. As detailed in Section 2.6.2, satisfying the antecedents equips the organisation with the capability to (1) Sense, (2) Seize and (3) Execute, thereby leveraging big data capabilities for sustainable competitive advantage.

Emphasis on must be placed on organisational design to ensure that it is an enabler for the effective sharing of information, rapid awareness and response to the market, reduction in lagging reactions and is dynamic to enable the reconfiguration of assets to facilitate alignment with the environmental and changing customer needs.

8 REFERENCES

Aaker, D. (2010). Marketing Challenges in the next decade. *Journal of Brand Management, 17*, 315-316. doi:10.1057/bm.2010.2

Ayres, L. (2012). *Semi-Structured Interview.* Thousand Oaks: SAGE Publications, Inc.

Barney. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management, 17*(1), 99-120. doi:10.1177/014920639101700108

Barney, J., & Hesterly, W. (2012). *Strategic Management and Competitive Advantage.* New Jersey: Pearson.

Barton, D., & Court, D. (2012). Making Advanced Analytics Work for You. *Harvard Business Review*, 78-83.

Beer, M., Voelpel, S. C., Leibold, M., & Tekie, E. B. (2005). Strategic Management as Organizational Learning: Developing Fit and Alignment through a Disciplined Process. *Long Range Planning*(38), 445-465. doi:10.1016/j.lrp.2005.04.008

Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (2013). Digital Business Strategy: Toward a next generation of insights. *MIS Quarterly, 37*(2), 471-482.

Bharadwaj, S. G., Varadarajan, R. P., & Fahy, J. (1993). Sustainable Competitive Advantage in Service Industries: A Conceptual Model and Research Propositions. *Journal of Marketing, 57*(4), 83-89. Retrieved from http://www.jstor.org/stable/1252221

Black, J. A., & Boal, K. B. (1994). Strategic Resources: Traits, Configurations and Paths to Sustainable Competitive Advantage. *Strategic Management Journal, 15*, 131-148.

Braun, V., & Clarke, V. (2006). Using Thematic Analysis in Psychology. *Qualitative Research in Psychology, 3*(2), 77-101. doi:http://dx.doi.org/10.1191/1478088706qp063oa

Business Monitor Internation Ltd. (2017, November 21). *BMI Industry View - Banking - South Africa - Q1 2018.* Retrieved from Business Monitor International: https://bmo-bmiresearch-com

Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business Intelligence and Analytics: From Big Data to Big Impact. *MIS Quarterly, 36*(4), 1165-188.

Creswell, J. W. (2014). *Research Design - Qualitative, Quantitative, and Mixed Methods Approaches.* London: Sage.

Davenport, T. H. (2014). How strategists use “big data” to support internal business decisions, discovery and production. *Strategy & Leadership, 42*(4), 44-50. doi:https://doi.org/10.1108/SL-05-2014-0034

Day, G. S. (1994). The Capabilities of Market-Driven Organisations. *Journal of Marketing, 58*(4), 37-52.

Day, G. S. (2011). Closing the Marketing Capabilities Gap. *Journal of Marketing*, 183-195.

Day, G. S. (2014). An outside-in approach to resource-based theories. *Journal of the Academy of Marketing Science, 42*(27), 27-28. doi:10.1007/s11747-013-0348-3

Drucker, P. F. (1954). *The Practice of Management.* New York: Harper and Row Publishers.

Dutta, S., Narasimhan, O., & Rajiv, S. (1999). Success in High-Technology Markets: Is Marketing Capability Critical? *Marketing Science, 18*(4), 547-568.

Dworkin, S. L. (2012). Sample Size Policy for Qualitative Studies Using In Depth. *Arch Sex Behav, 41*, 1319-1320.

Engelen, A., Brettel, M., & Heinemann, F. (2010). The antecedants and consequences of a market orientation: the oderating role of organisational life cycles. *Journal of Marketing Mangement, 26*(5-6), 515-547.

Erevelles, S., Fukawa, N., & Swayne, L. (2015). Big Data consumer analytics and the transformation of marketing. *Journal of Business Research*, 1-8. doi:10.1016/j.jbusres.2015.07.001

Erevelles, S., Horton, V., & Fukawa, N. (2007). Imagination in Marketing. *Marketing Management Journal, 17*(2), 109-119.

Fang, E., Palmatier, R. W., & Grewal, R. (2011). Effects of Customer and Innovation Asset Configuration Strategies on Firm Performance. *Journal of Marketing Research, XLVIII*, 587-602.

Gianiodis, P. T., Ellis, S. C., & Seechi, E. (2010). Advancing a typology of open innovtion. *International Journal of Innovation Management, 14*, 1-64. doi:10.1142/S1363919610002775

Grant, R. M. (1991). A Resource Based Theory of Competitive Advantage. *California Management Review*, 114-135.

Greer, C. R., & Lei, D. (2012). Collaborative Innovation with Customers: A Review of the Literature and Suggestions for Future Research. *International Journal of Management Reviews, 14*, 63-84. doi:10.1111/j.1468-2370.2011.00310.x

Gupta, M., & George, J. F. (2016). Toward the development of big data analytics capability. *Information & Management, 53*, 1049-1064.

Han, J. K., Kim, N., & Srivastava, R. K. (1998). Market Orientation and Organizational Performance: Is Innovation a Missing Link. *Journal of Marketing, 62*(4), 30-45. Retrieved from http://www.jstor.org/stable/1252285

Hofacker, C. F., Malthouse, E. C., & Sultan, F. (2016). Big Data and consumer behavior: imminent opportunities. *Journal of Consumer Marketing, 33*(2), 89-97. doi:https://doi.org/10.1108/JCM-04-2015-1399

Hormazi, A. M., & Giles, S. (2004). Data Mining: A Competitive Weapon for Banking and Retail Industries. *Information Systems Management, 21*(2), 62-71.

Hult, G., Ketchen Jr, D. J., & Slater, S. (2005). Market Orientation and performance: an integration of disparate approaches. *Strategic Management Journal, 26*, 1173-1181.

Isik, O., Jones, M. C., & Sidrova, A. (2013). Business intelligence success: The roles of BI capabilities and decision environments. *Information & Management, 50*, 13-23.

Jaworski, B. J., & Kohli, A. K. (1993). Market Orientation: Antecedents and Consequences. *Journal of Marketing, 57*, 53-70.

Johnson, J. S., Friend, S. B., & Lee, H. L. (2017, September). Big Data Facilitation, Utilization and Monetization: Exploring the 3V's in a New Product Development Process. *Journal of Product Innovation Management, 34*(5), 640-658.

Junque de Fortuny, E., Martens, D., & Provost, F. (2013). Predictive Modeling with Big Data: Is Bigger Really Better? *Big Data, 1*(4), 215-226.

Kiron, D., Shockley, R., Kruschwitz, N., Finch, G., & Haydock, M. (2011). Analytics: The Widening Divide. *MIT Sloan Management Review*, 1-22.

Kohli, A. K., & Jaworski, B. J. (1990). Market Orientation: The Construct, Research Propositions, and Managerial Implications. *Journal of Marketing, 54*, 1-18.

Kozlenkova, I. V., Samaha, S. A., & Palmatier, R. W. (2013). Resource-Based Theory in Marketing. *Journal of the Academy of Marketing Science*, 1-21. doi:DOI 10.1007/s11747-013-0336-7

Krishna, D. (2016). Big Data in risk management. *Journal of Risk Management in Financial Institutions, 9*(1), 46-52.

Kuada, J., & Buatsi, S. N. (2005). Market Oientation and Management Practices in Ghanaian Firms: Revisiting the Jaworski and Kohli Framework. *Journal of Internation Marketing, 13*(1), 58-88.

Lavelle, S., Hopkins, M. S., Lesser, E., Shockley, R., & Kruschwitz, N. (2010). *Analytics: The new path to value, How smart organizations are embedding analytics to transform insights into action.* North Hollywood, CA: MIT Sloan Management Review. Retrieved from https://sloanreview.mit.edu/projects/analytics-the-new-path-to-value/

Lavelle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2011). Big Data, Analytics and the path from Insights to Value. *MITSloan Management Review, 52*(2), 20-31.

Lycett, M. (2013). 'Datafication': making sense of (big) data in a complex world. *European Journal of Information Systems, 22*, 381-386. doi:doi:10.1057/ejis.2013.10

Marr, B. (2015). *Big Data: Using SMART Big Data, Analytics and Metrics to Make Better Decisions and Improve Performance.* Chichester: Wiley and Son Ltd. Retrieved from https://books.google.co.za/books?hl=en&lr=&id=OfglBgAAQBAJ&oi=fnd&pg=PA1&ots=e0PYU7XVu4&sig=eDTHktt45_I2sWgOD64NY2Dn2bw&redir_esc=y#v=onepage&q&f=false

Marshall, M. N. (1996). Sampling for Qualitative Research. *Family Practive, 13*(6), 522-525.

Martens, D., Provost, F., Clark, J., & de Fortuny, E. J. (2016). Mining massive fine-grained behavor data to improve predictive analytics. *MIS Quarterly, 40*(4), 869-888.

Mcafee, A., & Brynjolfsson, E. (2012). Big Data: The Management Revolution. *Harvard Business Review*, 1-9.

Miles, R. E., & Snow, C. C. (1992). Causes of Failure in Network Organisations. *California Management Review, 34*, 53-72.

Mintzberg, H. (1987). Crafting Strategy. *Harvard Business Review*, 66-74.

Mintzberg, H. (1993). *Structure in fives: Designing effective organizations.* New Jersey: Prentice-Hall.

Moorman, C. (1995). Organizational Market Information Processes: Cultural Antecedents and New Product Outcomes. *Journal of Marketing Research, 32*(3), 318-335.

Moorman, C., & Slotegraaf, R. J. (1999, May). The Contingency Value of Complementary Capabilities in Product Development. *Journal of Marketing Research, 36*(2), 239-257.

Morgan, N. A., Vorhies, D. W., & Mason, C. H. (2009). Market Orientation, Marketing Capabilities, and Firm Performance. *Strategic Management Journal, 30*, 909-920. doi:10.1002/smj.764

Narver, J. C., & Slater, S. F. (1990). The Effect of a Market Orientation on Business Profitability. *Journal of Marketing*, 20-37.

Persaud, N. (2012). *Encyclopedia of Research Design.* (N. J. Salkind, Ed.) Thousand Oaks: Sage Publications, Inc. doi:http://dx.doi.org/10.4135/9781412961288

Peteraf, M. A., & Barney, J. B. (2003). Unraveling The Resource-Based Tangle. *Managerial and Decision Economics, 24*, 309-323. doi:10.1002/mde.1126

Provost, F., & Fawcett, T. (2013). Data Science and its relationship to big data and data driven decision making. *Big Data, 1*(1), 51-65.

Quinlan, C., Babin, B., Carr, J., Griffin, M., & Zikmund, W. G. (2015). *Business Research Methods* (First ed.). Hampshire: Engage Learning EMEA.

Ramaswami, S. N., Bhargava, M., & Srivastava, R. K. (2009). Market-based capabilities ad financial performance of firms: Insights into marketings contribution to firm value. *Journal of the Academy of Marketing Science, 37*(2), 97-116.

Ries, E. (2011). *The Lean Startup - How Constant Innovation Creates Radically Successful Businesses.* Great Britain: Portfolio Penguin.

Saumure, K., & Given, L. M. (2008). *The Sage Encyclopedia of qualitative research methods.* Thousand Oaks: Sage Publications Ltd. doi:10.4135/9781412963909

Saunders, M., & Lewis, P. (2012). *Doing Research in Business & Management - An essential guide to planning your project.* Essex, England: Pearson Education Limited.

Saunders, M., Lewis, P., & Thornhill, A. (2009). *Research methods for Business Students.* Essex: Pearson Education.

Seddon, P. B., Constantinidis, D., Tamm, T., & Dod, H. (2016). How does business analytics contribute to business value. *Information systems journal, 27*, 237-269. doi:10.1111/isj.12101

Shenton, A. K. (2004). Strategies for ensuring trustworthiness in qualitative research projects. *Education for Information, 22*, 63-75.

Slater, S. F., & Narver, J. C. (1994). Market Orientation, Customer Value, and Superior Performance. *Business Horizons*, 22-28.

Slater, S. F., & Narver, J. C. (1995). Market Orientation and the Learning Organisation. *Journal of Marketing, 59*, 63-74.

Staller, K. M. (2012). *Encyclopedia of Research Design.* (N. J. Salkind, Ed.) Thousand Oaks: Sage Publications, Inc. doi:http://dx.doi.org/10.4135/9781412961288

Stebbins, R. A. (2012). *The SAGE Encyclopedia of Qualitative Research Methods.* Thousand oaks: Sage Publications, Inc. doi: http://dx.doi.org/10.4135/9781412963909

Teece, D. J. (2007). Explicating Dynamic Capabilities: The Nature and Microcfoundations of (Sustainable) Enterprise Performance. *Strategic Managment Journal, 28*, 1319-1350. doi:DOI: 10.1002/smj.640

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic Capabilities and Strategic Management. *Strategic Management Journal, 18*(7), 509-533.

Torres, R., Sidorova, A., & Jones, M. C. (2018). Enabling firm performance through business intelligence and analytics: A dynamic capabilities perspective. *Information & Management, 55*, 822-839.

Vogt, W. P. (2005). *Dictionary of Statitics and Methodology.* Thousand Oaks, CA: Sage Publications Ltd. doi:10.4135/9781412983907

Vogt, W. P. (2011). *Cross-Sectional Study.* Thousand Oaks: SAGE Publications, Inc.

Vorhies, D. W., & Morgan, N. A. (2005). Benchmarking Marketing Capabilities for Sustainable Competitive Advantage. *Journal of Marketing, 69*, 80-94.

Wamba, S. F., Akter, S., Edwards, A., Chopin, G., & Gnazou, D. (2015). How "big data"can make big impact: Findings from a systematic review and a longitudinal case study. *International Journal of Prodcution Economics*, 1-33.

Wernerfelt, B. (1984). A Resource-based View of the Firm. *Strategic Management Journal*, 171-180.

Williams, J. P. (2012). *Emergent Themes.* Thousand Oaks: SAGE Publications, Inc.

Zhenning, X., Frankwick, G. L., & Ramirez, E. (2015, October). Effects of big data analytics and traditional marketing analytics on new product success: A knowledge fusion perspective. *Journal of Business Research*, 1-5.

Gordon Institute of Business Science
University of Pretoria

Appendix A: Invitation to Participate in Study

Dear Sir/Madam

I am currently working towards completing my Masters of Business Administration (MBA) degree at the Gordon Institute of Business Science (GIBS). The completion of an Integrated Business Research Project forms a large component of the success criteria.

In the current age Business Intelligence and Big Data are viewed to be key factors for attaining and maintaining sustainable competitive advantage. In line with current trends, my research project is titled “Leveraging Big Data Analytics for Competitive Advantage in South African commercial banking.” The objective of my study is to gain insights into the commercial banking industries views on leveraging big data for sustainable competitive advantage as well as to explore the enabling and inhibiting factors for leveraging big data.

The data to facilitate the above study shall be collected through one on one semi-structured in-depth interviews with experienced experts like yourself. Note that the interview does not intend to gather data specific to your organisation but to gain your expert opinion on the topic with specific focus on the commercial banking industry. It is anticipated that the interview will last approximately 1 hour. Please find attached the consent form for your perusal. Participation is voluntary, and your anonymity and confidentiality are guaranteed.

The research aims to gain insights into the following with regards to leveraging big data for sustainable competitive advantage in South African commercial banking; (1) Investigate the role of big data in South African commercial banking, (2) Investigate the key inadequacies in the methodologies employed for the gathering storage and analysis of big data, (3) Explore the understanding of the specific big data resource and capability requirements for attaining a sustainable competitive advantage, (4) Understand the role of big data asset configuration in leveraging big data as a source of sustainable competitive advantage.

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University of Pretoria

Kindly confirm your willingness to participate in my research and advise your availability between the 26th July 2018 and the 7th August 2018. Should your available time fall outside these requested times, I will be happy to schedule as per your convenience.
I look forward to your participation and gaining invaluable insights from you.

Thank you,

Dinesh Buldoo
082 859 3985
20033682@mygibs.co.za

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of Business Science
University of Pretoria

Appendix B: Interview Consent Form

Topic: Leveraging Big Data Analytics for Competitive Advantage in South African Banking

Researcher: Dinesh Buldoo, MBA Student, Gordon Institute of Business Science, University of Pretoria, 2018

I am conducting research on "Leveraging Big Data Analytics for Competitive Advantage in South African Banking," and am trying to gain insights into the banking industries views on leveraging big data for sustainable competitive advantage as well as to explore the enabling and inhibiting factors for leveraging big data.

Our interview is expected to be an hour in duration. Your participation is voluntary, and you can withdraw at any time without penalty. All data shall be treated with the greatest confidentiality ensuring anonymity to both your organisation and yourself. All data shall be reported without identifiers. If you have any concerns, please feel free to contact my supervisor or myself. Our contact details are provided below.

Thanks,

Dinesh Buldoo
MBA Student
Email: 20033682@mygibs.co.za
Tel: 082 859 3985

Danie Petzer
Professor | Director of Research
The University of Pretoria's Gordon Institute of Business Science
Email: petzerd@gibs.co.za
Direct Tel: +27 11 771 4242

Participants Details

Name: ____________________

Signature: ________________

Date: ___________________

Researchers Details

Name: ____________________

Signature: ________________

Date: ___________________

Appendix C: Interview Guide

Role in Organisation:	
Date:	
Time:	

I would like to thank you for agreeing to be a participant in my research. You may have some insight into my research topic and the research objectives, however should you require I am happy to take you through it.

Prior to commencing with the interview, may you please sign the consent form and please confirm that you are comfortable if I record our discussion with an audio recording device? The recording is for the purposes of my research and shall be handled with the strictest confidentiality.

RQ1: How is big data analytics (BDA) used in South African banking for competitive advantage (CA)?	
Sub-Question No.	**Sub-Question**
1.1.	Do you consider BDA to be a source of CA in South African banking? Please motivate your answer?
1.2.	How is BDA used as a source of CA in South African banking? Please explain with examples?
RQ2: To what extent are the methodologies employed for the processing of big data considered adequate to leverage BDA for CA in South African banking?	
2.1.	To what extent are the methodologies employed for the processing of big data considered adequate to leverage BDA for CA? Please motivate your answer.
2.2.	How do you propose that the quality of the insights extracted from big data can be improved to more effectively leverage BDA as a source of CA in South African banking? Please explain.
RQ3: What are the specific big data resource requirements for leveraging BDA as a source of CA in South African banking?	
3.1.	In your view, what are the specific big data resource requirements to effectively leverage BDA as a source of CA in South African banking?

3.2.	Is there a gap between the resource requirements identified in 3.1 above and the available big data resources? Please motivate your answer.
3.3.	How do you propose that these resource gaps be addressed? Please explain
3.4.	In your view, what are the key impediments to implementing each of the solutions presented in 3.3 above? Please explain
RQ4: What is the role of the inter-relationships between big data assets in leveraging BDA as a source of CA in South African banking?	
4.1.	What is the role of the inter-relationships between big data assets in being able to effectively leverage BDA as a source of CA in South African banking? Please explain with examples.
4.2.	Are there currently challenges in terms of these inter-relationships that inhibits BDA from being leveraged as a source of CA? Please motivate your answer.
4.3.	How do you propose that these challenges be addressed? Please explain.
4.4.	In your view, what are the key impediments to implementing the solutions presented in 4.3 above? Please motivate your answer

Appendix D: Ethics Clearance Letter

Gordon Institute of Business Science
University of Pretoria

21 August 2018

Buldoo Dinesh

Dear Dinesh

Please be advised that your application for Ethical Clearance has been approved.

You are therefore allowed to continue collecting your data.

Please note that approval is granted based on the methodology and research instruments provided in the application. If there is any deviation change or addition to the research method or tools, a supplementary application for approval must be obtained

We wish you everything of the best for the rest of the project.

Kind Regards

GIBS MBA Research Ethical Clearance Committee

Gordon Institute of Business Science
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Appendix E: ATLAS.ti Code Book

Code
CA: Data Driven Decisions
CA: Value in using big data
CA: Credit Risk Management
CA: Product Development
CA: Target Marketing
CA: Customer Personalisation
CA: Create Operational Efficiency
CA: Customer Centricity
CA: Predictive Analytics
CA: Competitive Advantage
CI: Real Time Insights
CI: Customer DNA
CI: Customer Journey
CI: Third Party Partnerships
CI: Life Events_Primary Data
CI: Customer Credit Data
CI: Customer Behavioural Data_Primary
CI: Voice to text from customer calls
CI: Social Profiling
CI: Customer Transactional Data_Primary
Methodologies are Inadequate
EN: Quality of Insights
HR: Translator
TECH: Advanced Hardware
TECH: Open Source - Distributed Storage and Processing
TECH: Machine Learning
TECH: Artificial Intelligence
TECH: Algorithms
TECH: Technology
TECH: Data Gathering
INV: Investment in Resources
INV: High Cost
ORG: Organisational Buy in
INV: Customer Value Increase
INV: Commercial Value
DQ: Data Health
LEG: Challenge to Leverage BDA without a single customer view
LEG: Product Silos
LEG: Legacy
LEG: Incompatible Systems
REG: Regulation Uncertainty
REG: Restriction on how Social Data is used
REG: Regulation restricts how Transactional Data is used
REG: Consumer Protection Act
REG: POPI
REG: Rethink Regulation
MAT: Maturity Level

AGG: Level of Data Aggregation depends on the application
CONF: Big Data Analytics has to run in parallel with TDA
AGG: Too much Infrastructure required for fine grained transactional
DEF: Big Data Definition and Big Data Analytics
DEF: Traditional Data and Traditional Data Analytics
HR: DE_Data Architecture: Chief Data Officer
HR: DE_Data Engineers
HR: DE_Big Data Engineering Team
HR: Data Scientist
HR: Source System Knowledge
HR: DE_Data Architecture Team - Governence and Data Health
HR: Human Resources
HR: Data Scientist Role is Complex
HR: DE_Data Architecture Policy
HR: Data Scientist must be able to navigate multiple software and technologies
TECH: Speed of Data Storage, Extraction and Processing
TECH: Need Software to Process - Structure and Unstructured data
TECH: Technology is available on the Market - not the biggest challenge
ED: Upskilling Resources is needed
ED: Specific Data Science Degree is required from SA University
ED: Inadequate Skills in South Africa
ED: International Data Science Degree
ED: Level of Insights needs to be improved
ED: Data Ingestion: Hadoop Skills
ED: Internal Training vs External Training
ED: Bank work together with university
ED: Business Data Science Degree
PRT: International Partners more advanced on the data Science Side
PRT: Partnerships with specialists
OM; Asset Config_What Functions Should sit where
OM: Incremental Integration of Assets
OM: Built a Bank and found customers
OM: Data architecture: Policies around the data and Compatibility
OM: Centeral Customer Information
OC: Exco_Board must push big data_Top down approach
OC: Communities of Practice across the organisation
OC: Mindset Shift
OC: Organisational Culture
OC: Break silo mentality
OS: Business Engagement Team - Translate Business need to technical
OS: Business Background and Technical Background
OS: Representation at the right forums
OS: Message is lost in translation
OS: Integrated Teams
OS: Organisational Structure Issues
OS: Balance between strategic and to do operations_Functional work and project work
BS: Bank Strategy