BIG DATA ANALYTICS AND OPERATIONS DECISIONS: A CASE STUDY OF BANKS IN KENYA

BY

DOUGLAS OMBATI MITIEKA

A RESEARCH PROJECT SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR AWARD OF THE DEGREE OF MASTER OF SCIENCE IN OPERATIONS AND TECHNOLOGY MANAGEMENT OF THE UNIVERSITY OF NAIROBI

OCTOBER, 2019

DECLARATION

I declare that the Research Project titled: Big Data Analytics and Operations Decisions: A Case Study of Banks in Kenya is my original work and has not been presented for award of a degree in any University.

Signature: ____________________ **Date:** ____________

Registration Number: D68/10517/2018

STUDENT NAME: DOUGLAS MITIEKA

This Research Project has been submitted with our approval as the University Supervisors

Signature: ____________________ **Date:** ___________

SUPERVISOR: DR. WAINAINA GITHII

Signature: ____________________ **Date:** ___________

MODERATOR: DR. OMBATI THOMAS

ACKNOWLEDGEMENT

First, I give thanks to God the Almighty who has gifted me with life, gave me the energy to combine studies, work and family. This project would not have been easy without the direct support of my family, friends and the University of Nairobi staff.

In particular, I would like to thank:

Dr. Wainaina Githii, my supervisor who introduced me to the concept of behavioral management and was kind enough to accept my request for project supervision. His support, academic advice and guidance to relevant literature sources greatly shaped this project.

Dr. Ombati Thomas, who has been my mentor, and more so inspired and encouraged me to take the challenge of this program in the first place. He has always been available, and I mean this literally so whenever I am stuck, he helped me stay on the course. It is incredible his grasp of intellectual problems and ability to give constructive input expeditiously.

The staff and organization of the four banks where I collected my data as well as the top managers who allowed access to the banks, enabled me to conduct my research.

To all I say, Asante!

DEDICATION

This Thesis is dedicated to two groups of people:

My parents: Hudson Kereni & Ann Kwamboka, who instilled in me the virtue of hard work and ambition.

My own family: Teresa and John-Francis for being a strong pillar

TABLE OF CONTENTS

List of Tables

List of Figures

ABSTRACT

Big Data Analytics is emerging as technology that re-defines how companies compete through development of capabilities and new business models. In the era of Big Data decisions can be automated in a way that guarantees speed, quality and flexibility. Despite this rush and the push to have enterprises embrace BDA, empirical evidence shows that majority of the firms have not been successful from their BDA initiatives. Those who have built their operational capabilities by developing their organizational knowledge and skills have shown some degree of success. The study applied knowledge based view to understand how firms build their capabilities necessary to operate in the presence of Big Data. An exploratory multiple case study research was conducted to establish how Big Data is used in making operations decisions. Data was collected using semi-structured interviews as the primary method and document review as the secondary method. The findings indicate that operations capabilities, skilled workforce, team cohesion, culture and cognitive capability have a role in shaping the use of Big Data Analytics for operations decisions. Overall the results point to the significance of operational capabilities, cognitive capabilities and team cohesion in designing operations that facilitate decisions that are of high quality, adaptable and fast.

Keywords: Big Data Analytics, Operations Decisions, Team Cohesion, Operations Capability, Cognitive Capability.

CHAPTER ONE: INTRODUCTION

1.1 Background of Study

Emerging technologies are increasingly gaining potential of 'disrupting' business operations (Chiang & Abbasi, 2016). For instance, Storey, Chen and Chiang (2012) argued that Big Data Analytics (BDA) and other emerging technologies such as artificial intelligence and machine learning could aid organizations to: 'better understand their businesses and markets' and therefore 'leverage opportunities presented by big data' (pp.1166–1168). The emergence of BDA as source of information has triggered operations managers to re-think their firm's operations capabilities in response to changes in the external environment (Wamba, Akter, Gunasekaran, Dubey, & Childe, 2016).

The explosion of data generated from diverse sources has taken an exponential trajectory (McAfee & Brynjolfsson, 2012; Provost & Fawcett, 2013; Verschiedene, 2014) in a world that is volatile, uncertain, complex and ambiguous. This exponential growth of data has called for enhanced capabilities to process large sets of data, obtain insights, relationships and trends to enable decision making for the benefit of operations.

This study is an exploration of how banks in Kenya are using BDA for decision making with a focus on four established banks namely: Kenya Commercial Bank (KCB), Equity Bank, Barclays Bank (BBK) and Co-operative Bank of Kenya (Coop). Whereas KCB, Co-operative and Equity the largest local banks in Kenya in terms of core capital, market capitalization, market share and revenue, BBK is a large bank, well established and with a global presence. All these four banks are unique in their own way having harnessed the power of BDA to launch innovative products (CBK, 2018).

In anchoring this study, three relevant theories have been considered. The theories are: Prospect theory (Kahneman & Tversky, 1974), Dynamic Capabilities theory (Teece, Pisano & Shuen, 1997) and Knowledge Based View theory (Grant, 1996). Of the three theories, Knowledge Based View (KBV) emerges as the most suitable because BDA is about generating information or knowledge. Knowledge is a resource that can be used it to build dynamic capabilities which will facilitate operations decisions. In business operations, knowledge can be located at three distinct levels; managerial level which encompass cognitive capabilities, employee level which deals with behavior and processes level which deals with tacit knowledge and dynamic capabilities. All the three capabilities aspire to unpack knowledge and therefore KBV becomes the most appropriate theoretical framework on which this study will be built upon.

1.1.1 Big Data Analytics

Big Data Analytics has been applied in organizations to enhance operations efficiency, customer satisfaction and new product development (Jeseke, Grüner, & Wei, 2013) hence attaining operational flexibility, speed and quality.

Big data (BD) refers to large volumes of data of different types that are growing at a high velocity (McAfee & Brynjolfsson, 2012; Provost & Fawcett, 2013; Verschiedene, 2014). Data collected by organizations is growing exponentially in terms of volume, velocity, value, veracity and variety (Verschiedene, 2014). For it to be called big data it must have acquired all these five characteristics.

Big Data Analytics, on the other hand is a capability to process large sets of data to obtain insights, relationships and other vital information. This data comes from multiple sources, assembled with the aid of smart devices (Zaslavsky, Perera, & Georgakopoulos, 2012). The category of data is as diverse as the sources themselves and is processed through analysis by computer software algorithms.

1.1.2 Operations Decisions

There are five approaches of making decisions; the rational approach, satisficing approach, personal approach, procedural approach and political approach (Keen & Morton, 1978). Big Data Analytics is founded on the basis of rational models of decision making. A rational model assumes that operations are deterministic and produces error-free results (Boudreau, et al., 2003). A rational model employs a stepwise approach of data collection, weighing and analyzing evidence then choosing among many alternatives that emerge (Crozier, Ranyard, & Svenson, 2002).

Big Data Analytics facilitates decision-making, by providing a choice of actions to take from an array of possibilities. Big Data Analytics is the source of insight, knowledge, information and insights that reduces uncertainty in decision making (Chiang & Abbasi, 2016). Insights refer to deep and intuitive comprehension of constructs and phenomena that can be leveraged by practitioners (Sharma, Reynolds, Scheepers, Seddon, & Shanks, 2010; Lycett, 2013) leading to better decisions (Storey, Chen, & Chiang, 2012).

While operations that have invested in big data have been found to be high achievers, competitive advantage comes from data transformations and gaining insights from analysis (Davenport, 2006). Thus, operations decisions will be enhanced when managers understand how to derive insights from BDA (LaValle, et al., 2011). Operations invest in BDA to enable managers make swift and high quality decisions about business models and processes (Meissner & Wulf, 2014; Wieder & Ossimitz, 2015). Thus, BDA may have a role in creating operations that are agile with positive impact on the quality of operations decisions. To realize this, managers who make the ultimate decisions should have the ability and willingness to unearth and use insights from BDA (Deloitte, 2014).

1.1.3 Selected Commercial Banks in Kenya

In Kenya, there are a total of 43 licensed commercial banks and 13 microfinance institutions as per attached appendix. Commercial banks in Kenya are categorized into three tiers based on an index computed from net assets, total deposits, core capital, number of accounts and loans. A bank whose score is more than 5 percent is tier 1 or large bank, while a score between 1percent and 5 percent is a tier 2 or medium bank and less than 1 percent is a tier 3 or small bank (CBK, 2018).

Banks in Kenya have taken advantage of digital platforms and embraced emerging technologies such as Block chain, Artificial Intelligence (AI) Chatbots, Video Teller Machines (VTMs) and psychometric credit scores. This has enabled the banks to drive their strategies and new business models that have made them render efficient services. Currently, banks are digitizing their processes such as loan applications and Know your Customer (KYC) procedures. This digital moves will enable them access a wider clientele and deliver services with efficiency (CBK, 2018).

In this section, an overview of four selected banks, three of which are tier 1 (large banks) and one tier 2 bank will be considered. All these banks are actively engaged in digital innovations and emerging technologies such as BDA.

The first case is Equity bank which is the largest in market capitalization at 148 billion (Cytonn, 2018), its uniqueness lying in its ability to embrace innovation over 10 years ago, which disrupted the banking industry and set it on a positive growth trajectory. With 170 branches, it is second in market share controlling 9.3 percent. At the moment, Equity bank is training data scientists to enhance its BDA capabilities (iLabAfrica, 2019).

The second case is Barclays Bank of Kenya which is a global bank and a subsidiary of Absa Group. Barclays is a contrast of Equity bank, since it has traditionally targeted high end customers. However, recently it has ventured down market and embraced BDA that has seen the bank come up with innovative products such as Timiza. To bolster the organization's capabilities, Barclays has also introduced a position of Chief Data officer in its organization structure (Alushula, 2019).

The third case is Kenya Commercial Bank, which is unique in being Kenya's oldest and most established bank. In terms of branch network, it has 199 branches and a market share of 13.1 percent making it number one in the tier 1 category. In terms of market capitalization, it is number two at Ksh122 billion (Cytonn, 2018).

The fourth case is Cooperative bank of Kenya, which is a tier 1 bank that has successfully implemented a turnaround strategy, that saw it move from a loss of Ksh. 2 billion in 2002 to sustainable profitability. The bank has also embraced BDA to launch innovative products like Mcoop cash and Coopnet. With only 147 branches, it is number 3 overall and among the top in tier 1 banks.

1.2 Research Problem

Big Data Analytics has potential to change how companies compete through new business models, where decisions are automated in a way that guarantees speed, quality and flexibility (Bughin, Catlin, Hirt, & Willmott, 2018). As the new 'oil and refinery' (Hartmann, Zaki, Feldmann, & Neely, 2014), enterprises who have made investments in BDA do so with the belief that the technology would support business models where operations decisions are fully automated and driven by analytics (Bughin, et al., 2018). Despite this rush and the push to have enterprises embrace BDA, empirical evidence shows that majority of the firms have not benefited from their investments in BDA (Bughin et al., 2018; Manyika, et al., 2015).

In Kenya, the advent of big data has presented both opportunities and challenges especially for established firms. Not to be left behind, Kenya banks in particular are increasingly adopting emerging technologies and integrating BDA into their operations (CBK, 2018). The aftermath of this has been new and innovative products such as Fuliza by Kenya Commercial bank (KCB) and Timiza by Barclays Bank of Kenya. These innovative products have been conceived after analysis of large volumes of transactions from customers and discovering trends and behaviors. Using records of customer transaction behavior, the firms are able to project customers' creditworthiness thus lowering risk of default (Muthui, 2019).

Despite the available research, little is known about how and under what circumstances BDA can lead to improved decision making. In particular, there is a paucity of research investigating how established firms re-configure their operations processes, re-organize their people and expertise in the era of BDA to enhance improved decisions-making (Nutt & Wilson, 2010).

The purpose of this study is to explore how Banks in Kenya use Big Data Analytics for operations decisions. Using a case study design of selected banks in Kenya, the study will seek to establish the extent to which BDA has impacts their operation decisions. To address the research problem, two questions have been proposed namely: First, to what extent do Banks in Kenya use BDA for operations decision-making? Secondly, how do banks in Kenya use Big Data Analytics for operations decision-making?

1.3 Objectives of the study

The overall objective is to explore how and to what extent banks in Kenya use Big Data Analytics for operations decisions. The specific objectives of this research are:

i) To determine the extent to which Banks in Kenya are using Big Data Analytics.

ii) To establish how Banks in Kenya use Big Data Analytics for operations decisions.

1.4 Value of the Study

The researcher intends to make two contributions. First, the findings from the study will provide insight into BDA and operations decisions processes of established firms. Secondly, the researcher intends to demonstrate empirically how operations may position themselves to respond to an evolving BDA environment. This study will benefit to operations managers and big data practitioners in banks who seek to understand the circumstances under which BDA can have a positive impact on decisions.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

This chapter will lay the theoretical basis for the study. It will explore decision making in operations and its enablers such as insights from big data and the tension due to cognitive factors. It will then assess the implication of decisions based on BDA and the role played by human cognition. The chapter will conclude with a framework that conceptualizes the study.

2.2 Theoretical Foundations

A theoretical background provides the lens of viewing the different concepts of a research study (Gibbert & Ruigrok, 2010). Theories are statements of causality which helps in understanding phenomena in terms of what causes what and why. A good theory will therefore help managers know what may happen if certain actions are taken, thereby providing a good basis for predicting the future (Christensen, 1997).

2.2.1 Theories reviewed in the study

This research anchors on the Knowledge Based View (RBV) theory which was arrived at upon reviewing three theories that are relevant to the topic of study. The theories are: Prospect theory (Kahneman & Tversky, 1974), Dynamic Capabilities theory (Teece, Pisano & Shuen, 1997), Knowledge Based View theory (Grant, 1996).

A KBV approach holds the view that data is a critical resource in operation decisions as articulated in the resource based view (RBV) theory. The RBV theory underscores the criticality of inside resources to an operation. Operations optimize their internal resources which are of value, scarce, and difficult to substitute (Barney, 1991). In the context of BDA knowledge or information is viewed as resource, which however keeps changing in volume, velocity, value, veracity and variety (Verschiedene, 2014). Therefore, in terms of approach, the researcher is influenced by McAfee and Brynjolfsson (2012) who characterize big data as possessing volume, velocity and variety attributes.

Knowledge or information that resides in operations can be found in three places namely: the individual or managerial level in form of cognitive capabilities, at employee level in the form of behaviors and in operations processes level in form of dynamic capabilities. As shown by Helfat and Peteraf (2015), the three capabilities influence decision quality by facilitating timely response to any signals from the external environment that might be a threat to the operation decision-making proceses (Erevelles, Fukawa, & Swayne, 2016). Therefore, the three operation capabilities fit within the KBV framework because they all aspire to unpack knowledge (Amit & Schoemaker, 1993).

2.2.2 Applicability of the Theories to the Research Study

In this study, decision making is considered as a process of choosing among diverse alternatives during uncertain circumstances (Milliken, 1987) and absence of information contributes to even greater uncertainty (Nutt & Wilson, 2010). In the era of big data, knowledge and information are abundant and these have potential of reducing errors that lurk in decision making processes (Filatotchev & Nakajima, 2010).

However, the impact of BDA on the behavior of people like operations managers who make costly decisions on occasion, has not been established. Although the benefits of BDA have been highlighted by McAfee and Brynjolfsson (2012), it is not clear the process by which these benefits accrue. This means decision making in the era of big data is complex and riddled with uncertainty (Camillus, 2008).

Extant literature suggests that when faced with a decision, people may on occasion ignore evidence from BDA and use simplifying rules of thumb commonly known as heuristics and biases to make choices. Further, a growing stream of research has found that people are a major factor in operations decision making (Boudreau, et al., 2003) and that automating operations processes using technologies like BDA will make practical sense if they account for human cognitive limitations and biases (Kahneman, 2013). Similar studies conducted point that majority of the established firms tend to have a problem transitioning to BDA and stick to routines that are rigid and held back by strong cognitive forces. As a result, adapting their operation to be more data-driven requires them to re-learn and re-configure their operations (Chesbrough & Rosenbloom, 2002). The challenges of re-learning and re-configuring their operations are evident despite the enormous resources controlled by established firms which have unlimited access to data, expertise and a wider clientele.

However, there have been conflicting results from other scholars who have empirically argued that companies which employ BDA can develop more effective operations than those which do not (Gillon, Brynjolfsson, Griffin, Gupta, & Mithas, 2012; Mithas, M., Earley, Murugesan, & Djavanshir, 2013) and firms that utilize the potential of emerging technologies like BDA obtain important insights that may potentially increase the quality of their decisions. In addition, some scholars have come to suggest that BDA may enhance decision making in ways that will drive innovation, productivity and how firms compete generally (Manyika, et al., 2016) with empirical evidence pointing that BDA could lead to improved decisions which may ultimately drive innovation, enhance relationships with clients and improve risk management within operations (Kiron, 2013).

2.3 Decision-making in Operations

Bellman and Zadeh (1970) defined decisions as choices among many alternatives. When faced with many alternatives, Kahneman and Tversky (1974) argued that humans tend to use simplifying assumptions or rules of thumb known as heuristics and biases to arrive at a decision. The two psychologists also demonstrated that humans do not choose the same way, when faced with a similar situation at different time and context. This, they argued was because of 'bounded rationality' in humans as advanced by Simon (1947). Kahneman (2013) also found out that "expert judgement" is inferior to a simple algorithm and that algorithms are very accurate and always outdo people in decision making due to what he referred to as human cognitive limitation. In later research Kahneman discovered 'noise' in organizations due to what he described as managers inability to make consistent decision when a similar issue is presented at a different time (Kahneman, Rosenfield, Gandhi, & Blaser, 2016).

The model of decision making process as proposed by Herbert Simon is in three stages namely: intelligence gathering, design (or data analysis), and making a choice (Simon, 1947). Behavioral theory of the firm offers a range of explanations why managers may ignore analytic evidence or advice (Edwards, 1961; March, 1978) and use their simplifying rules of thumb.

In operational settings, people are an important aspect of operations and cannot be ignored (Boudreau, et al., 2013). This presents a tension in operations decisions where managers will choose between reliance on BDA insights or simplifying ‘rules of thumb’ known as heuristics and biases. Operation decisions can be structured or unstructured. Structured decisions are based on standard operating procedures and therefore by their very nature are repetitive. Unstructured decisions on the other hand do not have definite responses and therefore cannot be programmed (Simon,1976). This gives rise to five approaches of making decisions; the rational approach, satisficing approach, personal approach, procedural approach and political approach (Keen & Morton, 1978).

In rational approach, the decision maker has all the information, is aware of the available alternatives and hence can select optimally.

The satisficing approach is employed when the decision maker doesn’t have full information. The outcome are decisions that are based the normative model of decision making and is predicated on the fact that operations managers are confronted with constraints and barriers whenever they need to make a decision. Among them are limited cognitive abilities and ‘bounded rationality’ which causes them to use mental shortcuts also known as heuristics and biases to make decisions (Kahneman, 2013).

Procedural approach is based on standard rules or operating procedures. Operations standardize decision making rules to ensure consistency in decision outcomes. However, Sutcliffe and McNamara (2001) warn that standardized rules can operations ignore people behavior in designing and running of operations. Political approach employs negotiations, power play and influences from organizational politics while personal approach is individual specific that depends on the character of the decision maker.

All these approaches are applicable whenever decisions are to be made implying that decision making is not an event but rather a process; a series of activities. Furthermore, several paths can be followed in arriving at the most optimal decision (Benders & Van Nunen, 1981). In general decision making follows a sequence of steps. It begins by identifying the decision that is to be made then collecting the relevant data. Thereafter, the available alternatives are determined and evidence gathered to enable selection of a choice (Crozier, et al., 2002).

Operations employ several tools to standardize their decision-making processes. Among them are decision rules, information maps, decision trees and algorithms (Sutcliffe & McNamara, 2001). The quality of their decisions are determined by the efficiency and effectiveness of their operations and their extent to which people behavior is accounted for in disparate operational environments (Boudreau, Hopp, McClain, & Thomas, 2003).

2.4 The Role of Big Data Analytics in Operations decisions

Big Data Analytics had been used to enhance operations efficiency, customer satisfaction and new product development (Jeseke, Grüner, & Wei, 2013). New product development is a series of steps that a firm takes in turning ideas into products and eventually deciding to commercialize them (Cooper, 2010). Furthermore, BDA can be used to analyze consumer behavior so as to know what products to launch (Yu & Yang, 2016). Big Data Analytics can enable an operation to be efficient and effective which can confer competitive advantages (Prahalad & Hamel, 1990).

Big Data Analytics may help in market discovery which is at the end of the products chain where value is being generated. The smiling curve is a tool that can assist to identify activities along the value chain which may add more value to customers and help the firm grow quickly. Examples of these activities are research and development (R&D), standardized services, advertising, brand management, logistics and after sale services. (Shih, 1996). Although it was initially applied in a manufacturing context, it has could have applications in the services industry as well. An operation's core competence can be used to inform the decision on the choice of activities that can add value in any industry. This means if an activity fits a firm's core competence, it can be done in-house. If it is not a core activity, it can be done by another firm (Sanchez & Mahoney, 1996).

2.5 Big Data Analytics and Operations Decisions

Having anchored this study on KBV, the human cognitive capabilities of managers, employee behavior and dynamic capabilities of the operations processes will pay a major role in operation decisions. The researcher is able to examine how BDA contribute to the operation capabilities needed to make decisions. For instance, inadequate cognitive capabilities may lead to biases such as anchoring adjustment and dissonance (Bendoly, 2015). Using the cognitive approach, it is possible to explain why people tend to cling to old processes even in the era of big data. At the process level, routines due to tacit knowledge can cause employees be conservative by clinging to what they know (Winter, 2003). As cautioned by Kahneman (2011), operations decision makers from time to time rely on rules of thumb and simplifying assumptions and will ignore BDA leading to errors.

The dynamic capability approach ensure new knowledge is accommodated by adjusting the operation's competencies in response to change in external environment (Teece, Pisano, & Shuen, 1997). Thus, for the operation to acquire new knowledge, it will develop its learning abilities, managerial cognitive capabilities and behaviors.

It is not enough how to generate meaningful insights but equally important how insights can be transformed into good decisions that can create value for a firm. Business analysts use insights to develop a deep comprehension of phenomenon which can then be used as basis for decision making in an organization (Sharma, Reynolds, Scheepers, Seddon, & Shanks, 2010; Lycett, 2013). Therefore attaining good insights can influence the quality of decisions (Storey, Chen, & Chiang, 2012). For instance, Gangadharan and Swami (2004) found out that the use of data analysis enabled a clear understanding of business issues and opportunities which subsequently created new revenue sources and cut cost.

There is no relationship between an insight and actions taken. While BDA can be used to generate insights, decision based on evidence is not an obvious choice (Sharma, Reynolds, Scheepers, Seddon, & Shanks, 2010).

In operations decision making, the process of generating insights from data involves multiple players and teams from diverse parts of the organization. The composition and structure of those teams is often an outcome of managerial decisions that are taken within existing decision-making processes. These processes can both enable and constrain the ability of those teams to generate insights. Team composition and existing structures have a far reaching effect on decisions and decision making. As an example, Henderson and Clark (1990) analyzed a case in which research and development teams were unable to figure out the significance of emerging technologies for their new products even after being furnished by useful information. The teams' composition was found have a direct impact on the success or failure.

2.6 Proposed Conceptual Framework

The proposed conceptual framework was developed based on the theoretical background in section 2.2

The BDA constructs are operationalized through variables that are categorized into tangible resources, intangible resources and human skills. Tangible resources are those which can be traded in a market like data, technology and time. Data collected by banks is both in structured and unstructured format. Structured data is internal and firm-specific and can be measured by customer transactions, number loans and human resources. Unstructured data is external to the firm and may not have a relationship with firm's business but can provide additional insight about customers. Examples of external data are websites, internet searches, social media and calling records. The existence of technologies to process big data are like data warehouses, data marts, Hadoop and Spark can be measured. In addition, time devoted to big data initiatives can be measured as resource.

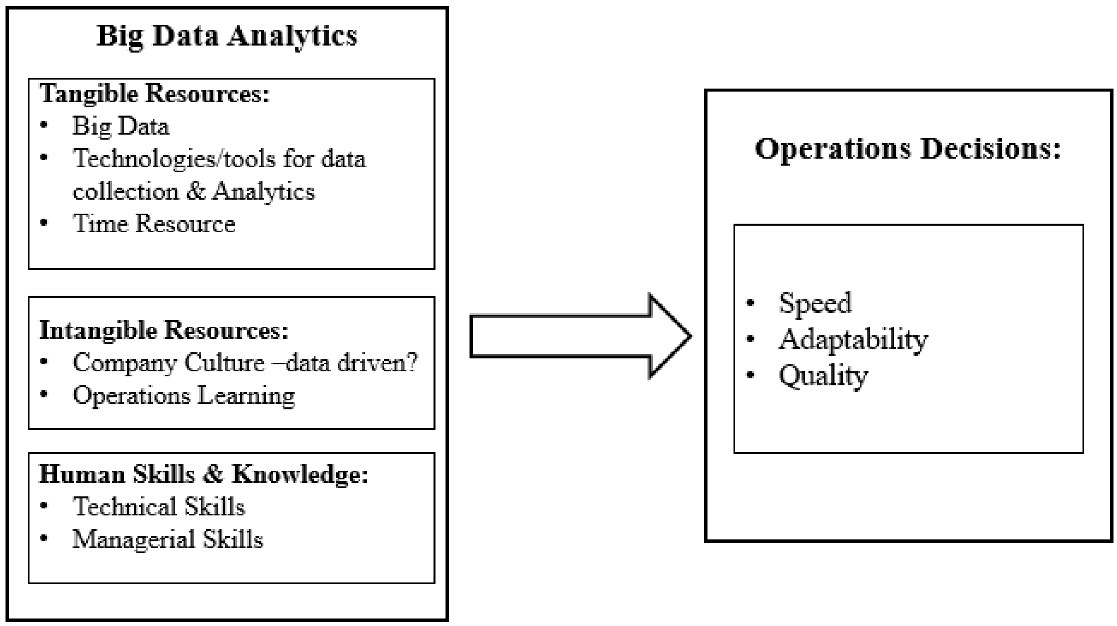
Humans skills and knowledge is categorized into tow: technical and managerial skills. In terms of technical skills, the number of people trained in big data analytics and their levels such as basic, associate and expert can be measured. Managerial skills, behaviors and tacit knowledge are acquired by working in a firm for a long period of time. This can be measured by determining the employee turnover at the middle management level (Gupta & George, 2016).

Finally, intangible resources comprise company culture and operations learning. Culture of the organization can be measured through number of employees at different levels who use BDA verses those who use intuition (McAfee & Brynjolfsson, 2012). Operations learning can be measured by how fast the firms adapt their operations in response to changing external environment with BDA (Teece, Pisano, & Shuen, 1997).

Operations decisions can be measured by quality, adaptability and speed (Hajirezaie & Husseini, 2009). In this study, while quality of decisions was measured through reduction in number of errors due to BDA, speed was measured by additional number of customers served with BDA enabling technology. Lastly, flexibility or adaptability was measured in terms of how long it takes an operation to modify its activities to cope with the unexpected circumstances and requests (Slack et al., 2013).

Operations decisions are considered adaptable, quality and fast if they lead to an operations strategy that has ability to 'align the requirements of the market with the operations resources' (Slack & Lewis, 2011). In the context of this research, requirements of the market are discovered through big data. On the other hand, operations decisions prioritizes operations resources including big data to address the requirements of the market and achieve the measures of flexibility, speed and quality (Hajirezaie & Husseini, 2009).

Figure 2. 1: Proposed Conceptual framework



Source: Adapted from Gupta and George (2016).

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Introduction

The previous chapter reviewed literature on theoretical foundation, Big Data Analytics, operations decisions as well as the explanation of the conceptual framework that guides the study. This chapter discusses the methodology that was used in the study. It comprises of three elements namely; philosophical assumptions, research design and research methods (Creswell, 2007). In particular, this chapter covers philosophical underpinning, research design, selection of the cases, data collection, data analysis, reliability and validity tests and concludes with ethical issues.

3.2 Philosophical Underpinning

The philosophy adopted in a research study is based on two important questions namely: an ontological question which focusses on truth in realism or relativism and an epistemological question that is concerned with how knowledge about the world is viewed from the researchers' point of view (Bryman, et al., 2014). There are two philosophical approaches that have prevailed while addressing these questions namely, positivism and phenomenology or social constructionism. Positivism takes a natural scientist philosophical while phenomenology takes the interpretivist view.

In positivism approach, development of a research strategy entails data collection and then applying an existing theory to generate hypotheses. These hypotheses are then tested and confirmed, or challenged, leading to the more exposition of theory which may then be empirically tested using another research study (Gill & Johnson 2002).

Interpretivism on the other hand advocates for the researcher to view humans as social actors by distinguishing them from objects such as machines and computers. This philosophical stance emanates from two intellectual artifacts: phenomenology and symbolic interactionism. Phenomenology defines how humans make sense of the world. It has been argued that business fields like organizational behavior, marketing and human resource management are suitably studied using an interpretivism philosophy (Saunders, 2011). In addition, Creswell (1998) argues that interpretivism or phenomenology is appropriate in situations where knowledge or phenomenon is developed through observations that are subjective with the aim of building theories from case study. Accordingly, the reality and knowledge of the world thereof is seen through subjective lenses.

There are four models for qualitative study comprising of positivism, post-positivism, critical theory and constructivism (Guba & Lincoln, 1994). However, qualitative study is not necessarily interpretive and so a decision as to whether a qualitative research study is interpretive or not depends on the researcher's philosophical leaning (Myers, 1997). A researcher can employ a positivist or interpretive approach depending on the philosophical underpinning. This study leans more towards social constructionism paradigm so as to incorporate the real life and behavior when it comes to decision making (Creswell, 2007). Since social constructionism is anchored on qualitative research, this study followed a qualitative approach.

3.3 Research Design

In order to answer the research question, the study employed a multiple case study that is exploratory in nature and based on the real life experiences of respondents (Myers, 2013). A case study was adopted since it enables a researcher comprehend how individual elements behave in different settings (Eisenhardt, 1989).With the aid of a variety of data sources, such as interviews, reports and documents, phenomenon was explored within its context (Yin, 2003).

A case study approach avails an opportunity for researchers to see the real issues in the phenomenon that is being investigated (Yin, 2003). Indeed, a case study is a better approach when in-depth information concerning a complex issue is being sought (Eisenhardt, 1989; Eisenhardt & Graebner, 2007). In order to investigate and answer unambiguously (Vaus, 2005) how Big Data Analytics are used for operations decision-making a case study design emerges as the appropriate approach. As shown in Table 3.1, the type of research question (whether "how", what and "why") influences the type of research design to be adopted (Miles, Huberman, & Saldana, 2014; Yin 2003).

Table 3. 1: Research design and format of research question

Research Design	Format of research question
Experiment	How, Why
Survey	Who, What, Where, How many
Archival Analysis	Who, What, Where, How many
History	How, Why
Case Study	How, Why

Source: Yin, 2003

While case studies lack the rigor, it can produce better results by carrying out an in-depth study of a complex issue. This was realized by careful selection of unit of analysis and setting the boundary for the case study. By so doing, it ensured structure to the procedure of conducting the case research and reliability of data collected from the selected cases (Seuring, 2008). However, case study has many benefits such as ability to withstand complex situations with many variables, makes use of multiple sources of evidence and good in theory development (Yin, 2003). This is the main reason why case study was the preferable design in this study.

3.4 Selection of the cases

The selection of a case for study from a population of large banks in Kenya used replication logic. The four banks that were selected and participants sampled to achieve 'maximum variation.' In bounding the cases, components that lie inside the case and some that lie outside the case are considered since both define the environment and context of the cases (Stake, 2006).

The cases were selected on the basis of their ability to provide rich information and also minimize chance of extraneous variables (Eisenhardt, 1989). Thus, after a case has been selected and studied, new cases that can replicate the cases before them and extend emerging theory were subsequently chosen. Selection of cases from different banks was done in order to enable cross case comparison to enhance generalizability (Pettigrew, 1998).

In this study, well-established firms with enough experience and requisite resources to undertake big data transformations were selected. Four banks were progressively selected for study as this number was found sufficient to furnish the researcher with relevant data to reach saturation (Corbin & Strauss, 2008). In addition, due to resource constraints, the number four was a compromise, yet sufficient in achievement of the research objective (Isaksson, Johansson, & Fischer, 2010).

The first one is Kenya Commercial Bank (KCB) whose uniqueness lie in being the most established banking institution in terms of branch network (199 branches). Through its innovativeness and aggressive marketing, it has become the largest bank in market share at 13.1 percent. In addition, KCB is a tier 1 bank with market capitalization of 122 billion, making it number two overall (Cytonn, 2018).

The second is Equity Bank which although is relatively new has been the most innovative and disruptive bank whose initiatives have seen it grow from a small building society to number one bank in market capitalization of Ksh148 billion (Cytonn, 2018). Apart from its stellar performance, Equity bank is the first bank to train Data scientists in partnership with Strathmore University (iLabAfrica, 2019).

The third one is Barclays Bank that was selected to achieve maximum variation (Strauss & Corbin, 2008). This is because unlike the first three other banks which have grown or maintained their trajectory, Barclays slid from top 5 as it was overtaken by Equity and Coo-operative banks. By choosing Barclays bank, which is multi-national company of a global operations chain the researcher attained maximum variation among cases. Previously it has targeted high end customers, a sharp contrast to Equity bank which targeted the bottom of the pyramid. Recently the bank launched ‘Timiza’ a big data analytics-based product for mobile bankers that resulted in growth of loan portfolio (Alushula, 2019).

Finally, Co-operative bank of Kenya was selected due to its turnaround strategy implemented in 2002 (Cooperative Bank Integrated Report, 2018) that resulted into phenomenal growth and overtaking bigger banks like Barclays bank. In terms of growth, co-operative bank shares some peculiarities with equity bank share and so it provided theoretical replication (Yin, 2003). In addition, it is the most innovative in the and trailblazer in embracing emerging technologies resulting in products such as Mcoop cash and Coopnet.

3.5 Data Collection

Data collection methods used semi-structured interviews as the primary source while reports and archival documents provided secondary data. Sampling of participants was done purposively and through snowballing instead of employing rules of statistics like random sampling (Yin, 2003). Further, multiple sources of data were collected to enable triangulation of study findings (Yin, 2003). The nature of data collected was qualitative, which was considered appropriate in understanding the reason behind an observed phenomenon (Miles, et al., 1994).

In order to capture the rich understanding from real life experiences of respondents, the researcher administered semi-structured interviews from already predefined questions to stimulate the conversation, and subsequently adapting the interview protocol based on the responses obtained from the interviewee (Myers, 2013). The field study proceeded with seven (7) main questions as per the attached appendix (Appendix 1). The interviews were carried out face to face so as to capture all the questions while allowing the participants to have reasonable degree of flexibility to add more or ask unplanned questions hence enabling informants and the researcher to provide additional insights. As more and more data was being collected, at some point it would reach the saturation point. The essence of saturation point was to be confident that enough data has been gathered and that any additional data adds little value or does not add value at all (Corbin & Strauss, 2008).

Data was collected from various departments of the banks under study through recording transcribing and then coding. Whenever something was not clear, the interviewer would go back to the interviewee at source bank to obtain more clarity. The researcher chose participants from different levels of the firms who were primarily users of BDA and those tasked with big data initiatives. They were selected based on their expertise and ability to provide the required data. At the operational level professionals like data scientists, business analysist, information technology specialist, computer engineers, operations managers and the heads of technology were selected. At executive levels, Chief Information Officer (CIO) and Chief Data Officers (CDO) were interviewed. The rationale behind multiple respondents being interviewed was to allow the researcher to look inside the many aspects within firms that work collaboratively in order to make big data decision. The number interviewees for each case are summarized in table 3.2

Table 3. 2: Number of interviewees in each case

Title	**KCB**	**BBK**	**EQTY**	**COOP**	**TOTAL**
Data Scientist	1	2	3	2	8
Data Analysts	4	5	4	3	16
Operations Managers	3	2	3	3	11
Business Analysts	4	5	3	4	16
IT Specialists	3	3	6	5	17
Computer Programmers	2	3	4	2	11
CIO/CDO	-	1	1	-	2

Source: Author's Interviews

3.6 Data analysis

Data collection and analysis was managed concurrently in an iterative manner (Hartley, 1994). This was necessary to give way for emerging theory that may be founded on empirical evidence. Data collected through observation of phenomena, was described and classified into categories highlighting the differences between big data-based operations and traditional operations that run on basic information technology platforms. The process enabled visualization of how and to what extent BDA are being used in bank operations. On the other hand, data collected from interview responses was first be transcribed, then organized systematically in order for the researcher to obtain overall insight. This was then condensed and tabulated to allow for themes to emerge and ease of interpretation (Miles, et al., 1994).

Besides, the data was coded to get a feel of the data and comprehend the responses from the respondents (Bryman, et al., 2014). Data analysis employed qualitative content analysis technique which involved examining, categorizing, tabulating and testing the evidence gathered in order to answer the initial propositions (Yin, 2003). Since data produced by the case studies was enormous, the analysis had to be broken down into within-case and cross-case analysis. To achieve this, Nvivo 12 software tool was used to handle large amounts of data and facilitate deeper analysis.

The main strategy that was used to analyze the case evidence was case descriptions. Initially, 'within case analysis' was undertaken followed by 'cross-case synthesis' so as to pick similarities and difference (Yin, 2003). According to Eisenhardt (1989), within-case analysis can be undertaken through explanation building of a case to establish a logical chain of evidence through in-depth analysis of the situation under investigation.

The researcher undertook cross-case analysis of qualitative data and cross-case comparison to build a novel theory that is based on empirical findings (Eisenhardt, 1989). Cross-case analysis enabled identification of patterns in the data collected hence making the study findings adaptable. Based on evidence and results from the first case, initial propositions were generated. The emergent results from the first case were compared to findings from the next case and the process was repeated iteratively. Multiple within case analyses and cross case comparisons were carried out so as to bolster the validity of a theory that evolved (Charmaz, 2006; Corbin & Strauss, 2008; Yin, 2003).

3.7 Dependability and Validity

Dependability in a research study implies an instrument would yield consistent results at all times if the same procedure is followed (Siverman, 2005; Yin, 2009). Even though it is difficult to generalize exploratory research findings, research ought to be carried in such a way that another person could repeat the steps followed and arrive at same findings (Paré, 2004). In this study, dependability was enhanced by careful recording, transcription, coding and refining of interview protocols.

On the other hand, validity required the study findings to be credible and trustworthy. Validity was achieved by performing internal, external and construct validity tests (Yin, 1994). In this study, validity was achieved through selection of multiple cases, use of multiple sources of evidence and pattern matching from cross-case analysis as illustrated in Table 3.2

Table 3. 3: Dependability and Validity

Criterion	Blueprint from Literature	How they were be actualized in the study
Dependability	Proposes the use of case study database	Field notes were taken on each interview
		Every interview was carefully recorded, transcribed to text and stored. Further, the interviews were reviewed by the Project Supervisor and Moderator.
		A case narrative was drawn for each case
	Needs a case study protocol	Case study protocol as per Appendix 1 was used
Internal Validity	Employ Explanation-Building	A logical chain of evidence was established
	Use of Pattern-Matching	Empirical patterns from cross-case analysis
Construct Validity	Triangulation of study results	Multiple sources of evidence was used
	Chain of evidence to be established	Was achieved through careful tracking to ensure no evidence is lost
External Validity	Theoretical sampling for cases using replication logic	Multiple cases (firms) were selected
		Purposive and snowball sampling were used
	More latitude to respond through larger degrees of freedom	Multiple interviews were conducted per case
		Researcher allowed respondents freedom to respond and illustrate concepts

Source Yin, 2003

3.8 Ethical issues in Study

Through the study, the researcher sought informed consent from the firms where data was collected (Singer & Vinson, 2002). The researcher ensured confidentiality was upheld at all times especially as it appertains to data collected and interview responses.

CHAPTER FOUR: DATA ANALYSIS, RESULTS AND DISCUSSION

4.1 Introduction

This chapter comprises two sections. The first section presents description of the four cases and their operating context. Erickson, (1986) suggests that description and interpretation of cases are important components required during data analysis. In similar logic, Yin (2009) asserts that case description is an analytic strategy required in data analysis.

The second section of this chapter presents an analysis of data within cases, data analysis within the conceptual framework and cross-case analysis. The aim of analysis is to ensure that case descriptions are organized in a format that is manageable and easy to comprehend. For a qualitative case study, a good balance between description, analysis and interpretation must be maintained (Merriam, 2009).

The chapter concludes with the study findings derived from themes and patterns that are presented together with the discussion of results.

4.2 Description of Cases

The data used in case description relied on interviews, observation and other archival information such as company documents and reports. Description of cases focusses on four thematic areas: the background and context, BDA technology and tools, operations learning and culture and human and technical skills.

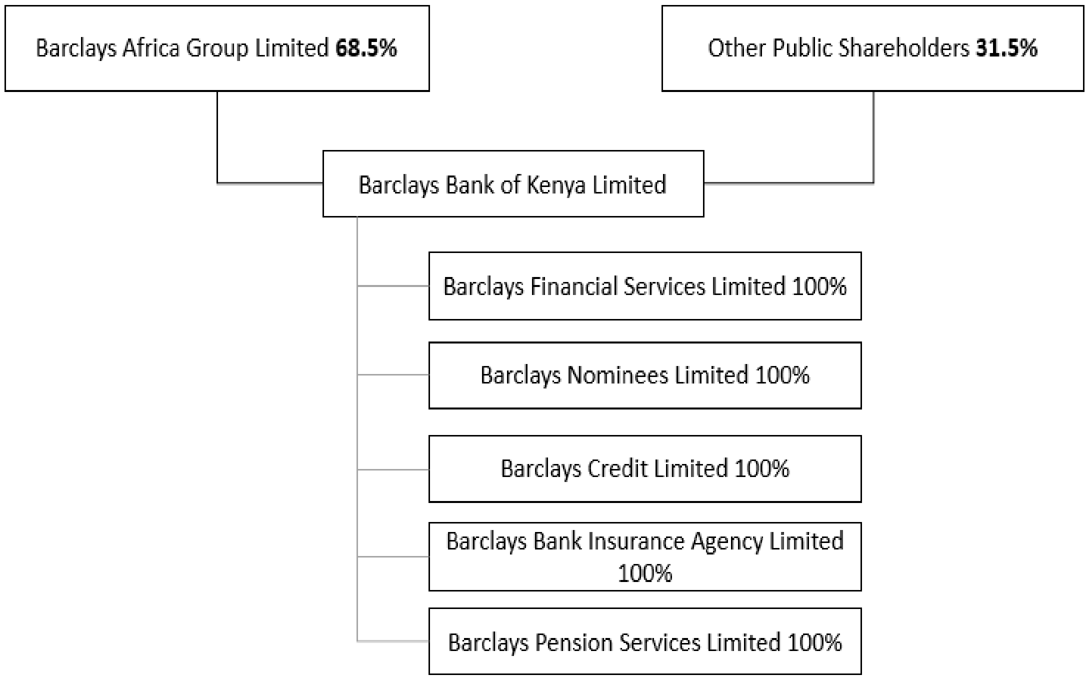
4.2.1 Barclays Bank of Kenya

4.2.1.1 Background and Context of the case

Barclays Bank of Kenya (BBK) is owned by Barclays Africa Group, now trading as Absa Group (68.5 percent) and other public shareholders (31.5 percent) as illustrated in figure

4.1. There are five wholly owned subsidiaries operating under Barclays Bank of Kenya, namely: Financial services, Nominees account, Credit/deposit taking, Insurance Agency and Pension Services Fund (BBK Integrated Report, 2018).

Figure 4. 1: Barclays Bank Shareholding structure



Source: Barclays Bank Integrated Report, 2018

Barclays Bank of Kenya prides itself of 3 million new customers through its Timiza virtual banking product served through 107 branches as shown in Appendix 2. On a daily basis, these customers generate millions of transactions that are increasing in volume, velocity and variety. The bank has for a long time aspired to develop capacities for data collection and analysis to extract insight and monetary value from data. In the last two years, the emphasis of data analytics has been acknowledged up to the board strategy level culminating in the creation of the Chief Data Office (BBK Integrated Report, 2018).

4.2.1.2 Big Data Analytics Technology and Tools

Barclays Bank of Kenya has embraced digital technologies like BDA and customer obsession among its strategic themes for the year 2017 to 2022. Instead of relying on traditional models and structures, it is building an agile structure that is putting it closer to its customers. Furthermore, digitization through BDA is enabling the bank get insights about its customers, while ensuring closer relationships. The bank has made significant investments in emerging technologies such as automation, big data analytics, robotics and artificial intelligence. This was clearly captured as:

> The first step in this quest has been the rolling out CaseWare IDEA Analytics System, a BDA tool the bank launched one…two years ago. We are investing in this technology because we can bet with big data to drive operational excellence (Informant 2).

4.2.1.3 Human and Technical skills

The bank introduced the offices of Chief Data Officer and Chief Customer Officer to leverage BDA and technology innovations for customer experience transformation. Other than this, there was no evidence of training specifically targeting on data analytics skills. The face to face interviews confirmed movement of incumbent staff from different stations to the new Data Office. However, automation and BDA rendered some positions redundant as evidenced by reduction of back-office staff from 35 percent to 32 percent in table 4.1

To respond quickly to emerging needs, the bank needs data analytics team who are well trained on advanced customer analytics and scenario analysis. This has been captured as follows:

> …now they need to get the right people on board, not recycling the same old people. Even within the organization there are people who are eager to learn analytics skills… (Informant 1).

4.2.1.4 Operations learning and Culture

Operations learning is achieved by enhancing dynamic capabilities through a high retention rate of key staff. In this regard, the average turnover declined to 8.5 percent in 2018 down from 13.3 percent in 2017 as shown in table 4.1.

Further, introduction of new culture and culture transformation have been identified as enablers of the strategic plan. As part of culture change, the bank has trained more than 100 staff on 'Unwritten Ground Rules' to confront emerging challenges posed by BDA (BBK Integrated Report, 2018). Table 4.1 presents learning and culture as well as human and technical skills key performance indicators for the year 2017 and 2018. From the table, staff retention has improved indicating strong dynamic capabilities while a shift of front office and back office staff indicates re-organization of skillsets.

Table 4. 1: Learning and Culture Key Performance Indicators

Key Performance Indicator	2017	2018	Status
Retention of high value employees	97%	97%	Unchanged
Staff turnover	13.5%	8.5%	Improved
Front office staff	65%	68%	Increased
Back office staff	35%	32%	Reduced

Source: Barclays Bank Integrated Report, 2018

To be build competencies and capability, the bank considers training of its data scientist and analyst a prime duty as explained by this informant:

> This job requires skill and experience. There is so much data, in coming in different formats. At times you get overwhelmed, but the moment you learn how to make sense from the messiness, you are good to go. The key here is training and retaining the good people (Informant 11).

One of the challenges identified is shortage of people with deep analytics skills who are conversant with the organization culture. There is tension in integrating the new hires with incumbent staff who have gotten used to the old way of doing things. The jobs of the incumbents are at risk and the threatened response is to fight back ferociously.

> The biggest barrier has got to do with the old folks. Doing stuff that makes them uncomfortable, different from what they are used to. The this is how we have always done mentality slows down decision-making. But all this is progressive, you cannot impose your habits on older people (Informant 8).

Another Informant also observed presence of cognitive dissonance due to conservative lending approach even when BDA show strong evidence of potential customers.

> …these people, blatantly ignore evidence from analytics and still go ahead to deny customers loans. You surely don't grow that way (Informant 11).

4.2.1.5 Impact of Big Data Analytics on Bank's Operations Decisions

As a result of predictive analytics, customer engagement has gone up as evidenced through introduction of personalized pricing strategy which is flexible and aligned to customer needs as well as Timiza virtual banking product. Embracing BDA has resulted in optimal number of staff, improved quality of customer experience and service levels (BBK Integrated Report, 2018). Table 4.2 presents the impact of Big Data Analytics on the bank's operations decisions. As depicted, decisions that impact on complaint resolutions have improved over the last three years all of which have a positive impact on service level agreement (SLA) at customer contact center.

Table 4. 2: Service Levels

Key Performance Indicator	Target	2016	2017	2018	Status
First line complaint resolution	>=80%	80.4%	86.5%	84%	Declined
Complaint Resolution under 5 days	>=85%	94.4%	96.4%	97%	Improved
Complaints Backlog over 40 days	<=2%	3.0 %	0.92%	0.87%	Improved
Complaint quality index	>=95%	99.02%	98.91%	98.94%	Improved
Service level at contact center (SLA)	>=80%	64%	77%	79%	Improved

Source: Barclays Bank of Kenya Integrated Report, 2018

Globally, there is a move towards convergence of technology and financial services, commonly called FinTechs and TechFins. At the group level, Barclays Bank has prioritized use of BDA for risk management to help in collections and loan recoveries across its operations in different countries. In Kenya, the operations of the firm are formulated around a strategy of big data analytics to enable it provide customer-centric services as observed by this Informant:

> In today’s world, do we have a choice but to embrace change? The use of emerging technologies, like …robotics, artificial intelligence and business analytics is indispensable. They actually help us get good insights of what our customers think or want (Informant 2).

The prevailing perception is that the bank’s decision making process has improved significantly after embracing BDA. One of the respondents had this to say:

> Through BDA we have been able to build deeper customer insights. We can actually monitor operational trends and as management we are able to monitor and respond quickly to any threats across all business processes. It is actually much better now (Informant 6).

Further, there was evidence of improvement in speed of decision making and reduction in requests processing time. This was captured by one respondent as follows:

> …with great big data analytics tools, we can actually handle large volumes of data, you know it is easier to pick abnormal trends like fraudulent transaction. This is a pain in the neck. Now decisions can be rather faster, if you can flag an irregular transaction and act quickly (Informant 12).

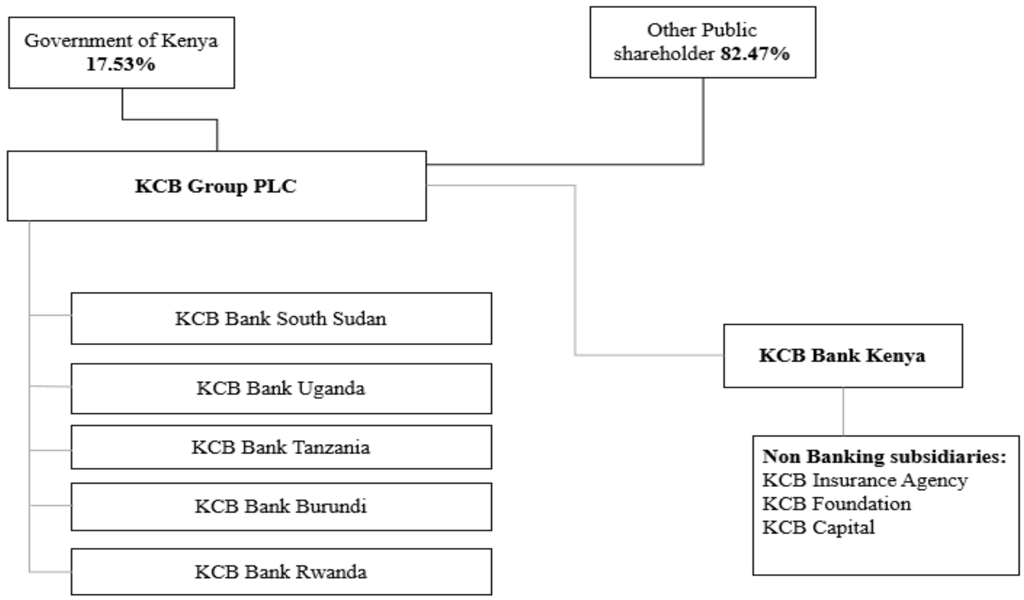
4.2.2 Kenya Commercial Bank

4.2.2.1 Background and context of the case

Kenya commercial Bank (KCB) is the largest and most established bank in Kenya. The bank is owned by the government of Kenya (17.53 percent) and other individual and institutional investors (82.47 percent) as illustrated in figure 4.2. KCB operates under the umbrella of KCB Group plc which also owns regional subsidiaries in Rwanda, South Sudan, Uganda, Tanzania and Burundi as well as the KCB insurance Agency, KCB Capital and KCB Foundation (KCB Integrated Report, 2018).

With a total equity of Ksh 113 billion, the group has 258 branches 6220 staff and 17.4 million customers spread across the six countries. The Kenyan operation is served through 199 branches as shown in Appendix 2.

Figure 4. 2: KCB Ownership Structure



Source: Kenya Commercial Bank Integrated Report, 2018

The bank's large customer base generates millions of transaction that increases in volume, velocity and variety. In terms of operations, the bank processes over 140 million transactions across its different channels. The percentage of branch transactions has gone down from 36 percent in 2016 to 12 percent in 2018 while non-branch transactions went up from 64 percent to 88 percent as illustrated in table 4.3

Table 4. 3: Transaction type and performance

Transaction type	2016	2017	2018	Status
Branch Transaction	36%	23%	12%	Reduced
Non-branch transaction	64%	77%	88%	Increased

Source: KCB Integrated Report and Financial Statements, 2018

4.2.2.2 Big Data Analytics Technology and Tools

Kenya Commercial Bank has deployed Credit Quest an analytics tool for analyzing, reviewing and managing loan applications. Through tracking of credit applications, the tool enhances faster and accurate decision making.

However, there challenges in integrating the new system to the legacy system were mentioned by a number of respondents. For instance, this respondent had this to say:

> There is a lot of technology legacy in this bank, which I believe will take some time to transform (Informant 23).

In addition, the banking's procurement cycle has been speeded up through the procure-to-pay process that has been enhanced by BDA. These are initiatives are decisions that drive operational excellence across the bank's operations.

At the organization strategy level, focus is shifting to data analytics as this informant observed:

> …beginning this financial year, the board has been categorical on the criticality of embracing big data technology. Since it is coming from the top, it kind of makes things easier (Informant 21).

4.2.2.3 Human and Technical Skills

Kenya Commercial Bank is investing in organization-wide programs that are designed to enhance its skillset and human capital base. The bank has also tapped into data analytics skills by recruiting data scientists who assist in modelling scores using customer behaviors and patterns.

The management is particularly bullish about the emerging technologies as observed by one top manager.

> Our BDA strategy aims to understand the different touchpoints in the customer journey. We want to know and experience our customers. Our business model is based on shared value and we want to see our customers making progress (Informant 25).

It's been evident that through insights from BDA, it has informed the decision to introduce popular mobile lending products with differentiated pricing points ranging from a minimum of Ksh 5,000 to an excess of Ksh 100,000. The bank has equally acknowledged that transparency in pricing and credit scoring has greatly influenced the speed of delivering products and services to the customers (KCB integrated Report, 2018).

4.2.2.4 Impact of Big Data Analytics on Bank's Operations Decisions

Big Data Analytics has played a major role in achieving the bank's materiality goals. The bank has identified customer centricity and operational efficiency among the top value creating processes and materiality issues. Materiality issues enable the bank to prioritize its strategies and operational plans. Table 4.4 shows KCB's operations Key Performance Indicators (KPIs) for the year 2017 and 2018.

Table 4. 4: KCB Operations Key Performance Indicators

Key Performance Indicator	2017	2018	Status
Net Promoter Score (NPS)	42	43	Improved
Customer Complaints	729,676	972,439	Increased
First Contact Resolution (FCR) of complaints	83.8%	86.1%	Improved
Net Loan and advances (Ksh billion)	422	455	Improved
Non-Performing loans (Ksh billion)	38	32	Improved

Source: Kenya Commercial Bank Integrated Report, 2018

As shown in table 4.4, in 2018, the bank achieved a net promoter score (NPS) of 43 percent, an indicator of customer centricity while operational efficiency improved by 3 percentage points from 48 percent to 51 percent (KCB Integrated Report, 2018). Further, the bank has identified some operational risks arising from people, processes, incidents and loss of data. Accordingly, emerging technologies and BDA in particular have been implemented to mitigate risk.

> The data is massive…but it has to be processed in a way that can solve business challenges. And who knows….it might provide insight for new business models (Informant 25)

Further the bank has adopted a FinTech strategy by launching new digital platforms that has enabled net more customers and consequently reduction in operating costs. Through BDA the bank has been able to use customer behaviors and patterns to model scores and different pricing points. This has enabled the bank to flexibly serve customers at the low end (borrowing less than Ksh. 5,000) as well the high end customers (borrowing over Ksh. 100,000).

4.2.3 Equity Bank Kenya

4.2.3.1 Background and Context of the case

Equity bank Kenya is a subsidiary of Equity Bank Group plc that is owned by a group of institutional and individual investors. Established in Kenya, in 1984, the bank has grown in leaps and bounds from a small building society to a large bank, boasting over 13.5 million customers. The customer base in the Kenyan operation stands at 10.9 million, served by 176 branches and 35,630 agents as shown in table 4.5. With a market capitalization of Ksh.132 billion, it is the market leader in the banking industry.

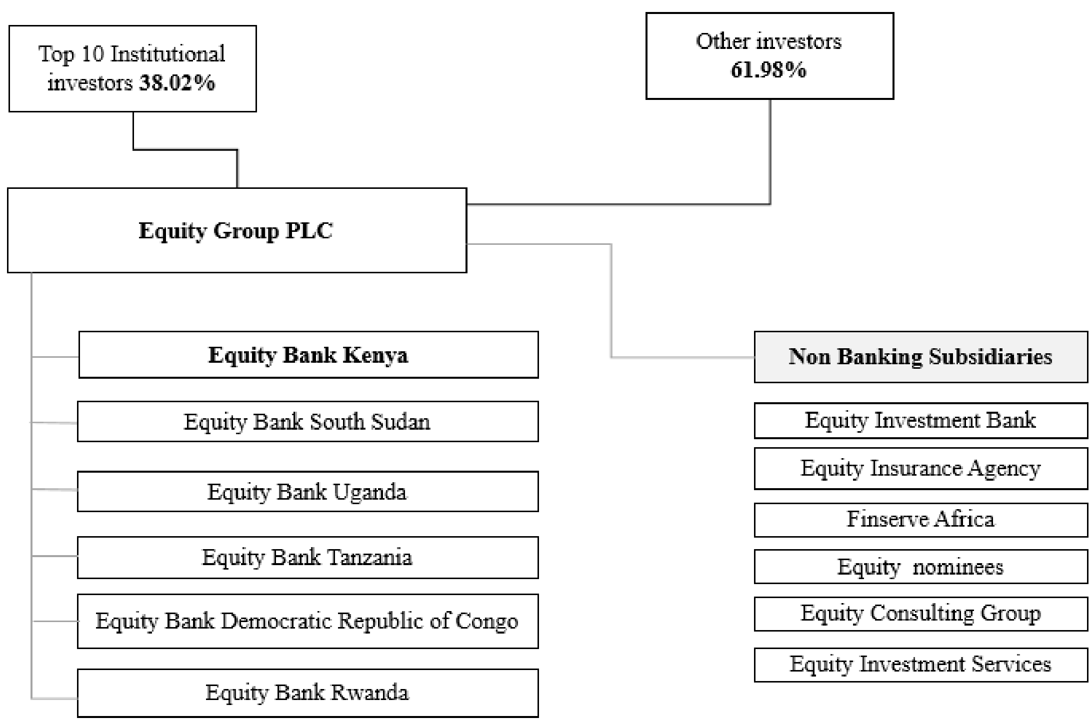
Table 4. 5: Equity Bank Kenya Numbers

Performance	2017	2018	Status
Revenue	47,727	49,372	Growing
Customer numbers	10,141,831	10,920,271	Growing
Branches	177	179	Growing
Agents	31,280	35,630	Growing

Source: Equity Bank Group Integrated Report, 2018

The group has regional presence in five other countries namely Rwanda, Uganda, Tanzania, South Sudan and Democratic Republic of Congo.

Figure 4. 3: Equity Bank Ownership structure



Source: Equity Bank Group Integrated Report, 2018

4.2.3.2 Big Data Analytics Technology and Tools

Equity bank has defined two objectives related to emerging technologies and BDA to enable it execute its strategy. First is adoption of technologies and innovation in its products, services and processes. In addition, the bank has committed to operational control which entail redefining its operating model to achieve efficiency and effectiveness. By leveraging on third party technologies and investment in building own BDA capabilities, the bank is able to use its operating model to deliver operational efficiency and effectiveness. (Equity Bank Integrated Report, 2018).

The bank is continuously improving its technology offering to achieve agile operations and delivering services to customers quickly. In Kenya, the bank has pioneered integration of an Application Program Interface (API) for third parties to interface with the bank and deliver a variety of experiences to customers.

> Our data is now stored centrally, and furthermore we are seeking to add external data sources through the bank's APIs. This is a sure way to develop and promote Kenyan business and that way we have come to lean about our customers in a deeper way (Informant 18).

4.2.3.3 Human and Technical Skills

In terms of data analytics, the bank is investing in training its workforce to acquire necessary skills that will enable improvement of operations processes, risk reduction, mitigate fraud and provision of innovative services that are above traditional banking offerings. The bank is cognizant that data analytics is a core competency that can be leveraged to provide personalized services and hence confer competitive advantages.

Equity has been developing a robust data analytics team and data scientist trained in collaboration with universities.

> …in the era of big data, we see opportunities to interact with our customers than never before. Customer communicate with us through the available digital channels and social media platforms. Paying attention to what they say has enabled us to know their different experiences (Informant 19).

The increasing role of data analyst and data scientists was evident in the bank's operations. They help managers visualize situations before making decisions. They are expected to observe abnormal trends and do a deep dive to establish root cause then advise managers. In this situation, the analyst need to have good mastery of scenario analysis skills.

> Our job here is basically to support management to make better decisions. Is all about slice and dice, providing a detailed view of the operation and explanations. You really must get your numbers right, otherwise you are screwed. But…. but I think our job is really valued… (Informant 14).

4.2.3.4 Operations Culture and Learning

The bank has embarked on re-training of all staff on culture and understanding of the corporate philosophies that made Equity be what it is now. All new employees are inducted into this program and introduced to a performance driven culture.

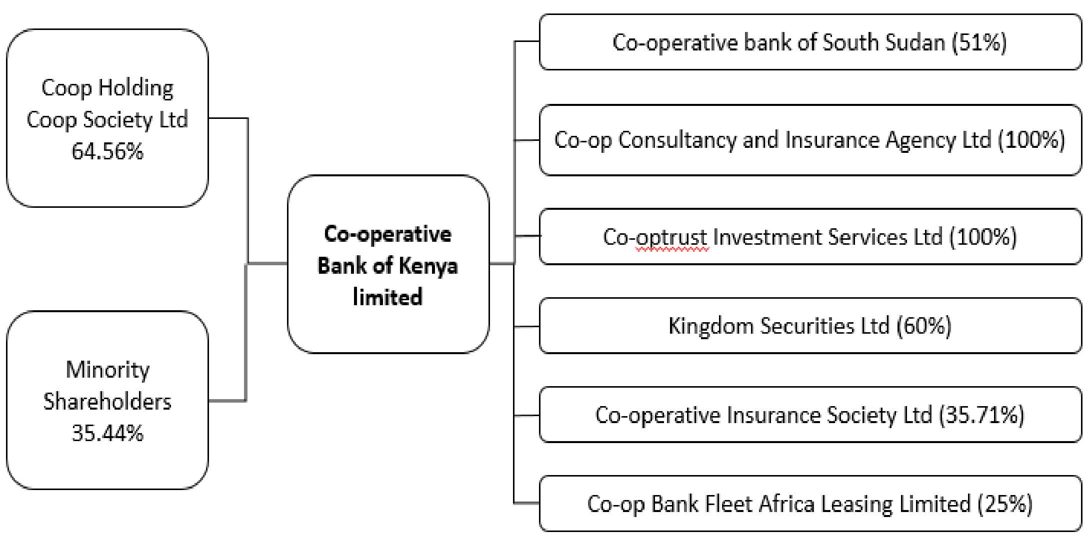
> …our culture is the fabric that holds the bank and its stakeholders together. We have noble aspirations for people and society. This is what makes us Equity, ….it is who we are and it defines how we execute our strategy… (Informant 17).

4.2.4 Co-operative Bank of Kenya

4.2.4.1 Background and context the case

The Co-operative Bank of Kenya is owned by Coop Holding Coop Society Limited (64.56 percent) and other minority shareholders (35.44 percent) as illustrated in figure 4.4. The bank has been in existence since 1968 when it operated as a Cooperative Society. It converted into a full bank in 1994 to serve more customers beyond Cooperative societies. In 1998, the bank was hit by a terror attack and afterwards operations were moved to several rented premises in town. In 2002, the bank recorded a record loss of 2.3 billion. The bank however returned to profitability in 2002 and has been growing since then to occupy the top 3 slot of bank rankings in Kenya (Co-operative Bank Integrated Report, 2018).

Figure 4. 4: Cooperative Bank Ownership Structure



Source: Co-operative Bank Integrated Report, 2018

With 8 million customers, the bank is served by 147 branches (shown in Appendix 2), 4251 employees, 580 automated teller machines (ATMs) and over 12,000 Co-op agents. Co-operative bank provides services to individual customers, institutional customers, Co-operative societies and Banc-assurance products. Some of the drivers of the bank's strategy are digital customer journey and operational efficiency. Digital customer journey has been realized through digital channels such as Mcoop cash, Coopnet and Coop kwa Jirani agency banking.

4.2.4.2 Big Data Analytics Technology and Tools

As a source of manufactured capital, the bank has invested in the most current Information Communication Technologies (ICT) capabilities in its core banking platform, Enterprise Resource Planning (ERP) and Customer Relationship Management (CRM) systems.

> For us big data entails tools, processes and skills. The data we work with is unstructured, unlike the traditional relational databases. This means additional strain on our IT resources and platforms. That is why we are moving to the cloud (Informant 29).

The bank's transformation agenda dubbed 'the Soaring Eagle' is underpinned by investments in big data analytics as a key pillar and business intelligence capabilities. To supplement these capabilities, the bank has employed data analysts, data strategists, data architects, data scientists and data engineers. As one respondent noted,

> …we want to drive our decisions on the basis of what data tells us. The current configuration did not fit what we wanted to do and where we wanted to go. You know, we had to do stuff…. (Informant 27).

4.2.4.3 Human and Technical Skills

Some of the relevant BDA training the bank has embarked on include training on design thinking and agile.

> To succeed in BDA environment, you need a different set of skills and mindset. We are looking for people who are T-shaped, people who can handle multiple duties not the rigid types. We also training our existing resources. (Informant 28).

In addition, the bank has endeavored to retain as far as possible critical skills in data science and business analytics as depicted in table 4.6

4.2.4.4 Operations Culture and Learning

The bank has also invested in dynamic capabilities that is deemed to provide competitive advantage. In this regard, the bank employs right talent that possess specialized skills like data analytics and data science. This is complemented by tacit knowledge of existing employees who the bank has managed to retain.

Table 4. 6: Key Performance Indicators year on year comparison

Key Performance Indicator	2017	2018	Status
Total staff	4069	4251	Reduced
Staff attrition (%) – Voluntary	4.9%	3.8%	Improved
Staff attrition (%) – Involuntary	3.8%	3.2%	Improved
% of our staff who have a tenure of more than 5 years	53.3%	54.9%	Improved

Source: Co-operative Bank Integrated Report, 2018

The KPIs for operations learning and culture is evidenced by reduction in staff attrition from 4.9 percent in the year 2017 to 3.8 percent in 2018. Further the percentage of staff whose tenure is more than 5 years has risen from 53 percent in 2017 to 54 percent in 2018 as shown in table 4.6.

As observed by one respondent, proper governance framework is needed in order to integrate BDA into the bank’s operations.

> It is needless to undertake huge technology projects if the staff are not adequately prepared. This requires a change of mindset and I think is a big cultural shift needed here (Informant 26).

4.3 Within-Case Analysis

In conducting data analysis, initial codes are generated, classified into categories which are then used to establish themes and patterns. The memos are formed from the data collected through a continuous reflection on the raw data. Memos highlight the reflexive thinking about the situation or problem, incorporating participant observation, their reactions as well as hunches of the researcher. Each memo has a code, which are then grouped into thematic categories (Corbin & Strauss, 2008). From thematic categories the outcome follows what Stirling (2001) refers to as basic themes, organizing themes and global themes which constitute the main findings of this case study (Creswell, 2018).

The emerging patterns (LeCompte & Preissle, 1993) are derived by sorting of data into factor clusters (Stake, 2006). Initial codes that are assigned to data are based on a list of provisional codes from the proposed conceptual framework (Miles and Huberman,1994).

4.3.1 Barclays Bank of Kenya

The case study evidence presented arises themes generated when qualitative data is coded based on the research question. Table 4.7 shows emergent theme, their relative importance and the contribution of the case in advancing the theme.

Table 4. 7: Emergent themes in Barclays Bank case

Description	Particulars	Evidence Status
Case Code	BBK	
Analyst's Synopsis	Among pioneer banks to launch BDA technology	
Situational Constraints	None	
Uniqueness among other Cases:		Foreign brand, was initially among top 5 bank before it was relegated by Equity Bank and Co-operative bank
Prominence of themes in case	Prominence of theme 1: Dynamic Capabilities	High
	Prominence of theme 2: Operations Adaptability	Moderate
	Prominence of theme 3: Skilled Workforce	High
	Prominence of theme 4: Decision making	Moderate
Utility of Case in developing themes	Utility of Case in developing theme 1	High
	Utility of Case in developing theme 2	Moderate
	Utility of Case in developing theme 3	High
	Utility of Case in developing theme 4	Moderate
Unique Contextual factors		Rebranding, changing ownership structure from Barclays to Absa
Findings/Evidence	1 Staff Retainability improved, reduced back office employees	Strong
	2 BDA tools have been deployed (Caseware)	Strong
	3 Training for new skills, recruitment of data analysts	Moderate
	4 Evidence based decision making, cognitive biases present	Moderate

Key:

High Utility Case is the one that appears most prominently in generation of the Emergent Theme

Low Utility Case is the one that appears least prominently in the generation of the Emergent Theme

Strong Evidence means strong evidence available to support finding.

4.3.2 Kenya Commercial Bank

The analysis in Table 4.8 shows the emergent themes in KCB bank case, their relative importance and the contribution of the case in producing the theme.

Table 4. 8: Emergent themes in Kenya Commercial Bank case

Description	Particulars	Status
Case Code	KCB	
Analyst's Synopsis		
Situational Constraints		
Uniqueness among other Cases:		Has maintained in top 3 banks
Prominence of themes in case	Prominence of theme 1: Dynamic Capabilities	Moderate
	Prominence of theme 2: Operations Adaptability	High
	Prominence of theme 3: Skilled Workforce	High
	Prominence of theme 4: Decision making	Moderate
Utility of Case in developing themes	Utility of Case in developing theme 1	High
	Utility of Case in developing theme 2	High
	Utility of Case in developing theme 3	High
	Utility of Case in developing theme 4	Moderate
Unique Contextual factors:		
Findings/Evidence	1 Top leadership support for BDA	Moderate
	2 Deployed CreditQuest BDA tool	Strong
	3 Recruited BDA skilled people	Strong
	4 Faster and accurate decision making on loan applications	Strong

Key:

High Utility Case is the one that appears most prominently in generation of the Emergent Theme

Low Utility Case is the one that appears least prominently in the generation of the Emergent Theme

Strong Evidence means strong evidence available to support finding.

4.3.3 Equity Bank Kenya Limited

The analysis in Table 4.9 shows the emergent themes in Equity Bank case, their relative importance and the contribution of the case in generation of the theme.

Table 4. 9: Emergent theme in Equity Bank case

Description	Particulars	Status
Case Code	EQTY	
Analyst's Synopsis		
Situational Constraints		
Uniqueness among other Cases:		Grew to dethrone Barclays Bank and Standard Chartered Bank from top 3 slots
Prominence of themes in case	Prominence of theme 1: Dynamic Capabilities	High
	Prominence of theme 2: Operations Adaptability	High
	Prominence of theme 3: Skilled Workforce	High
	Prominence of theme 4: Decision making	Moderate
Utility of Case in developing themes	Utility of Case in developing theme 1	High
	Utility of Case in developing theme 2	High
	Utility of Case in developing theme 3	High
	Utility of Case in developing theme 4	High
Unique Contextual factors		
Findings/Evidence	1 BDA Integrated at strategy level	Strong
	2 API integration results in agile operations	Strong
	3 Trained and recruited data scientists and analysts	Strong
	4 BDA believed will aid decision making	Moderate

Key:

High Utility Case is the one that appears most prominently in generation of the Emergent Theme

Low Utility Case is the one that appears least prominently in the generation of the Emergent Theme

Strong Evidence means strong evidence available to support finding.

4.3.4 Co-operative Bank of Kenya

The analysis in Table 4.10 shows the emergent themes in Co-operative bank case, their relative importance and the contribution of the case in producing the theme.

Table 4. 10: Emergent theme in Co-operative Bank case

Description	Particulars	Status
Case Code	Coop	
Analyst's Synopsis		
Situational Constraints		
Uniqueness among other Cases:		Grew to dethrone Barclays Bank and Standard Chartered Bank from top 3 slots
Prominence of themes in case	Prominence of theme 1: Dynamic Capabilities	High
	Prominence of theme 2: Operations Adaptability	Moderate
	Prominence of theme 3: Skilled Workforce	High
	Prominence of theme 4: Decision making	Moderate
Utility of Case in developing themes	Utility of Case in developing theme 1	High
	Utility of Case in developing theme 2	Moderate
	Utility of Case in developing theme 3	High
	Utility of Case in developing theme 4	Moderate
Unique Contextual factors		
Findings/Evidence	1 BDA has been supported at strategy level	Strong
	2 Starting to invest in tools	Moderate
	3 Employed data scientist, strategists and engineers	Strong
	4 Decision making yet to be automated	Moderate

Key:

High Utility Case is the one that appears most prominently in generation of the Emergent Theme

Low Utility Case is the one that appears least prominently in the generation of the Emergent Theme

Strong Evidence means strong evidence available to support finding.

4.4 Cross-case analysis

The cross-case analysis section puts together the disparate case reports and identifying patterns in the data.

4.4.1 Cross-case comparison

Comparison among cases is made possible since the same set of questions are employed for the four cases. During data collection and analysis, both individual cases and multiple case compete for attention in what Stake (2006) refers to as the ‘case quintain dilemma’. This happens notwithstanding the fact that the single case being studied at a given time received more attention that the collection of cases. Giving more attention to the situation of an individual case rather than viewing a case as a way to generalize or represent other cases embodies the power of a case study design (Guba & Lincoln, 1985).

4.4.2 Cross-case synthesis

The overarching themes across the four cases are obtained through a reductive process where peculiarity of each case is progressively lost to pave way for most important categories. The list of all themes and their relative weights for each case is developed in table 4.11

When analyzing more than two cases, Yin (2009) specifically recommends use of cross-case synthesis because it is easier and also produces more robust results. Cross-case synthesis entails argumentative representation as opposed to numerical tallying. The aggregation of the most salient aspects from the four cases in table 4.7, table 4.8, table 4.9 and table 4.10 is presented in table 4.11.

Table 4. 11: Cross Case synthesis Nvivo output

Utility of Case/ Multiple case theme	**Case 1 BBK**	**Case 2 KCB**	**Case 3 EQTY**	**Case 4 COOP**
Theme 1: Dynamic Capabilities	H	M	H	H
Theme 2: Operations Adaptability	H	H	H	M
Theme 3: Skilled Workforce	M	H	H	H
Theme 4: Decision making	M	H	H	M
Theme 5: Big Data	M	M	M	M
Theme 6: Cognitive capability	M	L	M	L
Theme 7: Time Resource	M	M	M	L

Key: H=High utility M=Moderate Utility L=Low Utility

4.5 Research Findings

Dynamic capability emerged as an important finding from several respondents who articulated the need for training and learning. Many respondents acknowledged the value of BDA, but then expressed their inadequacy to operate in BDA environment. Some stated that their world view is different having been brought up in a generation where the current technologies were inexistent. There was evidence of cognitive biases in terms of anchoring where old ways of doing thinks impeded decision making.

There was evidence of BDA destabilizing team cohesion with a shift on how employees carried out their duties due to conflict between the old and new way of doing things. Most of the legacy systems did not have the capacity to analyze and process big data in a way that can facilitate quicker decisions. On the other hand, not many employees were versatile enough to operate the two systems, causing anxiety and distress. This led to emergence of 'silos' in the work place disrupting the cohesiveness of team work.

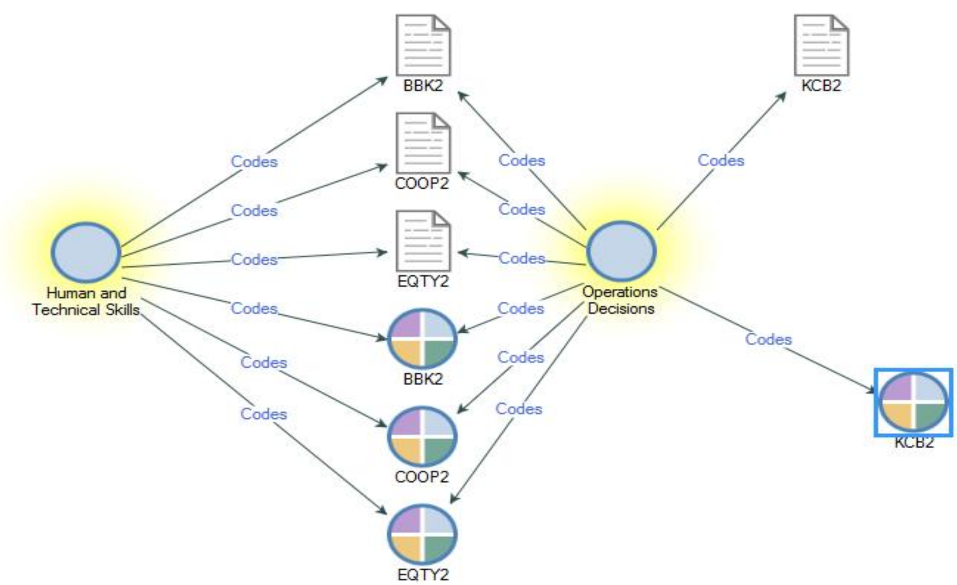
The uncertainty faced by the banks was quite evident with their desire to adapt their operations as quickly as possible so that they are not disrupted and left behind. In all cases, the strategic objectives to integrate BDA into their operations was given impetus from the banks' respective boards.

The challenge posed by BDA caused banks to respond by employing different strategies and workarounds. The data evidence showed that there had been culture change trainings where employees are taken through session to learn new ways of working. In addition, new hires were taken through a mandatory induction on ways of working.

The impact on operations structure change was an important finding in this study. The creation of position of Chief Data Officer was to help Chief Executives have direct access to most relevant and up to date information necessary in order to make decisions promptly. From the interviews, the role of Chief Data Officer in senior management was found to be support for decision making.

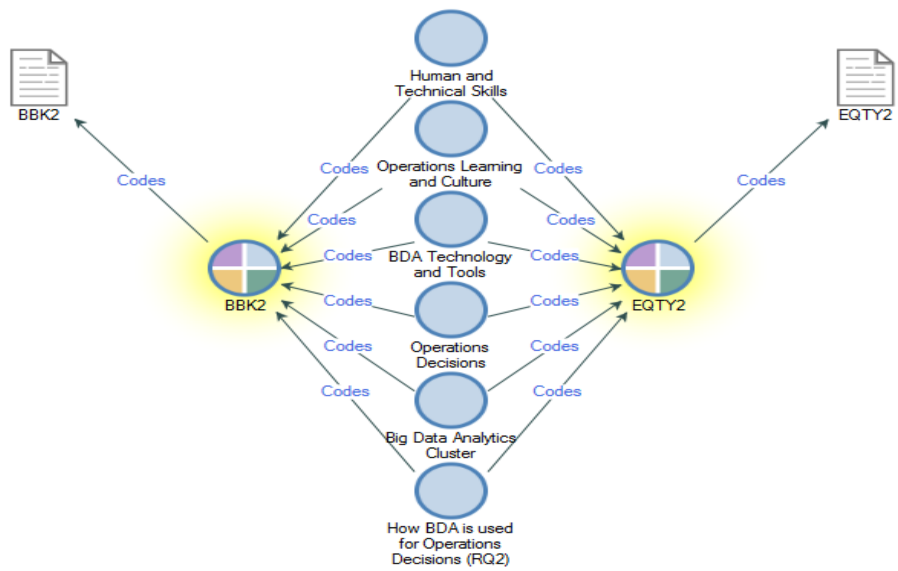
In summary, these findings indicate that BDA does not necessarily produce fast, adaptable and quality decisions. It is how BDA is integrated into the operations that determines the quality, speed and flexibility of decisions. Figure 4.5 presents comparison of cases output from Nvivo while figure 4.6 shows comparisons of nodes. In both figures, data is coded on the nodes based on the two research questions, RQ1 and RQ2.

Figure 4. 5: Comparison of cases



Source: Nvivo coding of open ended interviews

Figure 4. 6: Comparison of nodes



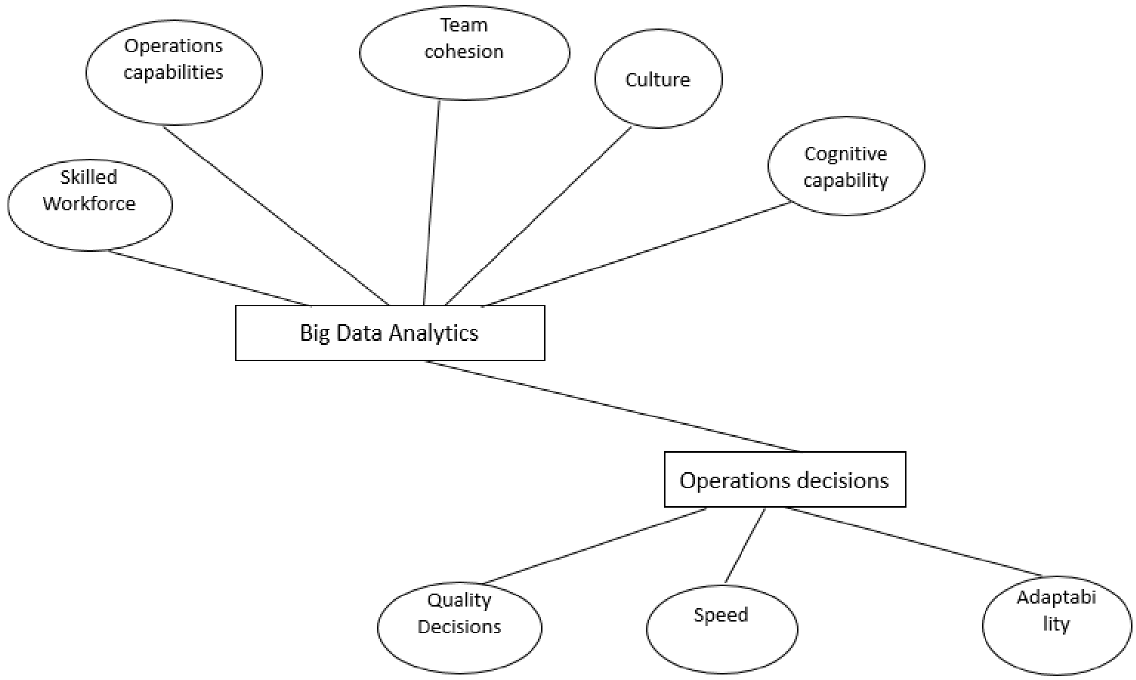
Source: Nvivo coding of open ended interviews

4.6 Emerging themes and New Conceptual Framework

The study findings are derived from themes in line with Merriam (2009) which emerge from the categorization of qualitatively coded data.

The analysis of data generated four global themes (dynamic capabilities, operations ambidexterity, skilled workforce and decision making) and eight organizing themes or sub-categories (data science, data analytics and business intelligence, retention of critical skills and hiring for talent, cognitive capabilities, team cohesion, culture and learning). This constitute the revised conceptual framework as shown in figure 4.7

Figure 4. 7: New Conceptual Framework



Source: Author, 2019

In this study, 32 quotations were identified from the skilled workforce global theme, 23 quotations from the culture and learning global theme and 17 quotations from the dynamic capabilities global theme. The most significant themes and sub-themes emerging from the description of cases and within case analysis are summarized in appendix A.1 and table 4.12.

Table 4. 12: Research Themes/Categories and Sub-themes

Global Theme	Organizing theme/Sub-theme	Sample Quotations from Filed Interviews
Dynamic Capabilities (17 quotations)	Data Science	"in the era of big data, we see opportunities to interact with our customers than never before. Customer communicate with us through the available digital channels and social media platforms. Paying attention to what they say has enabled us to know their different experiences.
	Data Analytics and business intelligence	"The first step in this quest has been the rolling out CaseWare IDEA Analytics System, a BDA tool the bank launched one..two years ago. We are investing in this technology because we can bet with big data to drive operational excellence"
Operations adaptability (23 quotations)	Culture	"our culture is the fabric that holds the bank and its stakeholders together. We have noble aspirations for people and society. This is what makes us Equity, ….it is who we are and it defines how we execute our strategy."
	Learning Capabilities	"The biggest barrier has got to do with the old folks. Doing stuff that makes them uncomfortable, different from what they are used to. The this is how we have always done mentality slows down decision-making. But all this is progressive, you cannot impose your habits on older people."
Skilled workforce (32 quotations)	Retention of critical skills	"This job requires skill and experience. There is so much data, in coming in different formats. At times you get overwhelmed, but the moment you learn how to make sense from the messiness, you are good to go. The key here is training and retaining the good people."
	Hiring for talent	"With great big data analytics tools, we can actually handle large volumes of data, you know it is easier to pick abnormal trends like fraudulent transaction. This is a pain in the neck. Now decisions can be rather faster, if you can flag an irregular transaction and act quickly."
Decision making	Cognitive capabilities	"…these people, blatantly ignore evidence from analytics and still go ahead to deny customers loans. You surely don't grow that way"
	Team cohesion	"…now they need to get the right people on board, not recycling the same old people. Even within the organization there are people who are eager to learn analytics skills…"

Source: The Coding Manual for Qualitative Researchers (Saldaña, 2009)

4.7 Discussion of Research Findings

This research study sought to establish if BDA is used for making operations decision within banks in Kenya and if so to what extent. Concerning the first research question, it was evident that banks in Kenya are starting to use BDA. For the second research question, the results show that while there are common similarities in use of BDA, the question of how BDA is employed in operations decision vary from one bank to the other.

First, building on KBV approach helped the researcher to find insight from the results. Integrating BDA into operations decisions was found to enhance the dynamic capabilities and operations learning that enabled the banks operations respond quickly to changes in external environment (Filatotchev & Nakajima, 2010). It has been argued in literature that some operations have more cognitive capabilities than others and this significantly influences the decisions (Helfat & Peteraf, 2015). However, the results from this study suggest that, as knowledge resource, BDA aids managerial decision making in different ways. In some instances, informants recognized the criticality of BDA as a knowledge resource, while in other cases informants did not see the efficacy of BDA if the cultures of the organizations in question had not been transformed.

Secondly, the KBV suggests that knowledge is a critical resource. However, from this study, it is not the amount of information per se that counts but how a manager tasked with decision making uses the data. This is in line with Filatotchev and Nakajima (2010) although it does not suggest the implication of too much data that firms cannot analyze. From the results, the transformation operations processes and culture was found to be necessary in improving operations decisions (Wamba et al., 2015). In some instances where these transformation had not taken place, the researcher found out a lot of inertia and old way of doing things. The speed of operations decisions depended a lot on the process which depends on capacity to handle time pressures.

The researcher expected to see BDA triggering changes in the banks' processes and capabilities to support operations decisions. While this is true, it was not obvious in most cases due to difficulty of seamless integration of BDA to existing systems that led to tension.

From this study, two surprising findings emerged when BDA is being integrated into operations: cognitive capabilities and team cohesion. The findings emerged as common themes to all the four cases. These two highlight critical themes that impact on dynamic capabilities that service operations seek to build.

It was found that the success or otherwise or BDA hinges on how cognitive capabilities and team cohesion are incorporated whenever BDA is integrated into operations. This has two implications. First, there needs to be real understanding BDA technology, not in the abstract sense as was observed. To derive value from BDA, it has to be known what type of data is to be collected, how it will be analyzed and how to interpret and apply insights to the business.

In addition, service operations would need to build their own capabilities at individual level to overcome cognitive limitations. Finally, to enhance team cohesion, operations need to seek new ways of working that cut across traditional structures and 'silos.'

CHAPTER FIVE: SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter presents the summary of study findings, conclusions, implications and recommendations for future research.

5.2 Study Summary

The purpose of this study was to explore how commercial banks in Kenya use Big Data Analytics to make their operations decisions. The study used a qualitative approach and multiple-case study of four established commercial banks. Primary data was collected using used semi-structured interviews while documents reviews was used to obtain secondary data for triangulation purposes.

Analysis of data began with case descriptions outlining the background context of the banks and then an in-depth exposition of how the firms use Big Data Analytics to make decisions. Thereafter the data was uploaded into Nvivo and an exploration conducted. First cycle coding and after first cycle coding was done to generate themes and categories for the two research questions (Saldaña, 2009). Finally, within-case analysis and cross-case comparison was conducted and results presented in Chapter 4.

5.3 Conclusions

In this study, the researcher set out to explore whether Big Data Analytics is used for making operations decisions and if so how. To carry out this research, a study of four banks domiciled in Kenya was undertaken with the view of discovering how decision making process are being transformed by the presence of Big Data Analytics.

The results showed unequivocally that banks in Kenya are beginning to adopt Big Data Analytics to make decisions. However, there is no one size fits all in terms of how BDA is used for operations decisions and different firms employ different approaches in integrating BDA into their operations. The approach employed were circumstance contingent and depend on the context, history, firm strategy and business models.

From the results, five research themes were generated which have big influence on how Big Data Analytics can be used for operations decisions. These themes are: operations capabilities, cognitive capability, skilled workforce team cohesion and culture. The management of these five was found to be critical to designing operations that can facilitate decisions that are of high quality, fast and adaptable.

5.4 Recommendations

This study is based on data gathered from interviews and archival sources. While this study proposes important insights into operations decision in Kenyan Banks, the findings are subject to the limitation of the study. First, being a qualitative case study, generalization of study findings is limited. However, generalizability was not the goal of the study, but rather an in-depth examination of a phenomena. The researcher is cognizant of the personal biases before, during and after qualitative interviews.

The findings present a snapshot of the issues and so it is recommended to examine varying impact of BDA on operations decision across many service operating firms. The research also reveals that decisions undertaken by a firm are influenced by firm context and type of business. Therefore, longitudinal research on different industries could enhance this research by highlighting how operations capabilities have evolved over time.

REFERENCES

Alushula, P. (2019, March 14). *Business Daily*. Retrieved from https://www.businessdailyafrica.com: https://www.businessdailyafrica.com/news/Data-analytics-drive-Barclays-Bank-loan-book-growth/539546-5025766-pvkglz/index.html

Amit, R., & Schoemaker, P. J. (1993). Strategic assets and organizational rent. *Strategic Management Journal*, 14(1), 33–46.

Anand, A., Wamba, F. S., & Sharma, S. (2013). The Effects of Firm IT Capabilities on Firm Performance: The Mediating effect of process Improvement. *24th Australasian Conference on Information Systems* (pp. 5-12). Melbourne, Australia: Australasian Conference on Information Systems.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 99-120.

Benders, J., & Van Nunen, J. (1981). A Linear Programming Based Decision Support System for location and Allocation Problems. *Informatie*, 693-703.

Bendoly, E. (2015). Managing and Mismanaging Process Constraints and Variability. In E. Bendoly, W. Wezel, & D. Bachrach, *The Handbook of Behavioral Operations Management* (pp. 33-35). Oxford, New York: Oxford University Press.

Blyler, M., & Coff, R. (2003). Dynamic capabilities, social capital, and rent appropriation: ties that split pies. *Strategic Management Journal*, 24(7), 677–686.

Bok, H., Kankanhalli, A., Raman, K., & Sambamurthy, V. (2012). Revisiting media choice: a behavioral decision-making perspective. *International Journal of e-Collaboration*, 8(3), 19–35.

Boudreau, J., Hopp, W., McClain, J. O., & Thomas, L. (2003). On the interface between operations and human resources management. *Manufacturing & Service Operations Management*, 179-202.

Bryman, A., Bell, E., Hirschsohn, P., Dos Santos, A., Du Toit, J., Masenge, A., . . . Wagner, C. (2014). *Research Methodology-Business and Management contexts*. Cape Town: Oxford University Press.

Bughin, J., Catlin, T., Hirt, M., & Willmott, P. (2018). *Why digital strategies fail*. New York: McKinsey Quarterly.

Camillus. (2008). Strategy as a wicked problem. *Harvard Business Review*, 17–29.

CBK. (2018). *Central Bank of Kenya Annual Report.* Nairobi: Central Bank of Kenya.

Charmaz, K. (2006). *Constructing Grounded Theory: A Practical Guide through Qualitative Analysis.* Thosand Oaks: Sage Publications.

Chen, H., Chiang, R. H., & Storey, V. C. (2012, 6 24). Business Intelligence and Analytics: From Big Data to Big Impact. *MIS Quarterly*, pp. 36(4): 1165-1188.

Chesbrough, H., & Rosenbloom, R. (2002). *The role of the business model in capturing value from innovation: evidence from Xerox Corporation's technology spin-off companies.* Norwalk, Connecticut: Industrial and Corporate Change.

Chiang, R. H., & Abbasi, A. S. (2016). Big Data Research in Information Systems: Toward an Inclusive Research Agenda. . *Journal of the Association for Information Systems,*, 17(2), i–xxxii.

Christensen, C. (1997). *The Innovator's Dilemma: When New technologies cause great firms to fail.* Boston: Harvard Business School Press.

Clark, K. B., & Baldwin, C. (2000). *Design Rules: The Rower of Modularity.* Cambridge, MA: MIT Press.

Clayton, C., & Raynor, M. (2003). *The Innovator's Solution.* Boston, MA: Harvard Business Press.

Cooper, R. (2010). *Robert's Rules of Innovation.* Hoboken, New Jersey: John Wiley & Sons, Inc.

Corbin, J., & Strauss, A. (2008). *Basics of qualitative research: Techniques and procedures for developing grounded theory.* Oxford, England: Sage Publications.

Corbin, J., & Strauss, A. (2008). *Basics of Qualitative Research: Techniques and Procedures of Developing Grounded Theory.* Sage Publications: Thousand Oaks, California.

Creswell, J. (2007). *Qualitative inquiry and research design: Choosing among five approaches 2nd Ed.* Thousand Oaks, CA: Sage Publications.

Creswell, J. (2018). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches.* Sage Publication: Thousand Oaks.

Crozier, R., Ranyard, R., & Svenson, O. (2002). *Decision Making: Cognitive Models and Explanations.* Routledge: Corwin Press.

Cytonn. (2018, December 16). *Cytonn Banking Sector Report*. Retrieved from https://cytonn.com: https://cytonn.com/uploads/downloads/q32018-banking-sector-report.pdf

Davenport, T. H. (2006). Competing on analytics. *Harvard Business Review*, 84: 98–107.

Deloitte. (2014). *Technology in the Mid-Market Perspectives and Priorities.* New York: Deloitte.

Edwards, W. (1961). Behavioral Decision Thoery. *Annual Review of Psychology* , 12(1): 473-498.

Eisenhardt, K. (1989). Research, Building Theories From Case Study. *Academy of Management. The Academy of Management Review*, 532-550.

Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big Data consumer analytics and the of marketing. *Journal of Business Research*, 69(2), 897–904.

Erickson, F. (1986). Qualitative methods in research on teaching. In M. Whittrock, *Handbook of research on teaching* (pp. 119-161). Old Tappan, NJ: Macmillan.

Filatotchev, I., & Nakajima, C. (2010). Internal and external corporate governance: An interface between an organization and its environment. *British Journal of Management*, 21(3), 591–606.

Gangadharan, G., & Swami, S. (2004). Business Intelligence Systems:Design and Implementation Strategies. *26th IEEE International Conference on Information Technology Interfaces* (pp. 139–144). Croatia.: International Conference on Information Technology Interfaces.

Gavetti, G. (2005). Cognition and hierarchy: rethinking the microfoundations. *of capabilities' development. Organization Science*, 16(6),599–617.

Gillon, Brynjolfsson, Griffin, J., Gupta, M., & Mithas. (2012). Panel–business analytics: radical shift or incremental change? *Proceedingsof the 32nd International Conference on Information Systems* (pp. 16–19). Orlando, Florida:: Association for Information.

Guba, E. G., & Lincoln, Y. S. (1994). *Competing paradigms in qualitative research. Handbook of qualitative research.* Oxford: Sage.

Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. *Information&Management*, 3-6.

Hajirezaie, M., & Husseini, S. M. (2009). Evaluating the Effectiveness of Strategic Decisions at Various Levels of Manufacturing Strategy: A Quantitative Method. *World Applied Sciences Journal*, 6 (2): 248-257.

Hartmann, P. M., Zaki, M., Feldmann, N., & Neely, A. (2014). *Big Data for Big Business?A Taxonomy of Data-driven Business Models used by Start-up Firms.* Cambridge, United Kingdom: Cambridge Service Alliance.

Helfat, C. E., & Peteraf, M. A. (2015). Managerial cognitive capabilities and the microfoundations of dynamic capabilities. *Strategic Management Journal*, 36(6), 831–850.

Henderson, & Clark. (1990, May 12). Architectural innovation: the reconfiguration of existing product technologies and the failure of existing firms. *Administrative Science Quarterly*, pp. 9–30.

Hickson, D. J., Miller, S. J., & Wilson, D. C. (2003). Planned or prioritized? Two options in managing the implementation of strategic decisions. *Journal of Management Studies*, 40(7), 1803–1836.

Hogarth, R. (1987). *Human judgement: an overview. In Judgement and Choice, pp 204–234.* Oxford, England: John Wiley and Sons.

iLabAfrica. (2019, February 13). *https://ilabafricastrathmore.wordpress.com/*. Retrieved from https://ilabafricastrathmore.wordpress.com/2019/02/11/equity-bank-and-ilabafrica-to-train-data-scientists/: https://ilabafricastrathmore.wordpress.com/2019/02/11/equity-bank-and-ilabafrica-to-train-data-scientists/

Isaksson, R., Johansson, P., & Fischer, K. (2010). Detecting supply chain innovation potential for sustainable development. *Journal of Business Ethics*, 97(3), 425-442.

Jeseke, M., Grüner, M., & Wei, F. (2013). *Big data in logistics: A DHL perspective on how to move beyond the hype.* Troisdorf, Germany: DHL Customer solutions & innovation.

Kahneman, D. (2013). *Thinking Fast and Slow*. New York: Farrar, Straus and Giroux.

Kahneman, D., Rosenfield, A. M., Gandhi, L., & Blaser, T. (2016). Inconsistent Decision Making is a Huge Hidden Cost for Many Companies. Here’s How to Overcome What we call ISE. *Harvard Business Review*, 10-12.

KBA. (2019, June 10). *Kenya Bankers Association*. Retrieved from https://www.kba.co.ke: https://www.kba.co.ke/downloads/State%20of%20Banking%20Report%20200618%20(web).pdf

Keen, P., & Morton, S. (1978). *Decision support systems, an organisational perspective*. Oxford: Addison Westley.

Kiron, D. (2013). Organizational Alignment is Key to Big Data Success. *MIT Sloan Management Review*, 40-42.

Kohli, R. (2007, July 20). Innovating to create IT-based new business opportunities at United Parcel Service. *MIS Quarterly Executive*, pp. 199–210.

Kumar, S. (2018). Understanding Different Issues of Unit of Analysis in a Business Research. *Journal of General Management Research*, 70-82.

LaValle, Lesser, E., Shockley, R., Hopkins, M., & Kruschwitz, N. (2011). Big Data, Analytics and the Path from Insight to Value. *MIT Sloan Management Review*, 2-13.

LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2011). Big Data, Analytics and the Path from Insight to Value. *MIT Sloan Management Review* , 52(2): 21-32.

LeCompte, M., & Preissle, J. (1993). *Ethnography and Qualitative Design in Educational Research.* London: Academic Press.

Lycett. (2013). Datafication: making sense of (Big) data in a complex world. *European Journal of Information Systems*, 22(4), 381–386.

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., & Roxburgh, C. &. (2011). *Big data: the next frontier for innovation, competition and productivity*. New York: McKinsey Global Institute.

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., & Byers, A. (2016, October 17). *Big data: the next frontier for innovation, competition, and productivity*. Retrieved from McKinsey Consulting: http://www.mckinsey.com/business-functions/digital-mckinsey/our-insights/big-data-the-next-frontier-for-innovation

March. (1994). *Limited rationality. In A Primer on Decision Making:How Decisions Happen. pp 1–55.* New York: Free Press.

March, J. (1978). Bounded Rationality, Ambiguity, and the Engineering of Choice. *The Bell Journal of Economics*, 9(2): 587-608.

McAfee, A., & Brynjolfsson, E. (2012). Big Data The Management Revolution. *Harvard Business Review*, 59-68.

McAfee, A., & Brynjolfsson, E. (2012). Big Data. The management revolution. *Harvard Buiness Review*, 90(10), 61–68.

McAfee, A., & Brynjolfsson, E. (2012). Big Data: The Management Revolution. *Harvard Business Review*, 5-9.

Meissner, P., & Wulf, T. (2014). Antecendents and Effects of Decision Comprehensiveness: The Role of Decision Quality and Perceived Uncertainty. *European Management Journal*, 32(4): 625-635.

Merriam, S. (2009). *Qualitative Research: A Guide to Design and Implementaion.* San Francisco, CA: Jossey-Bass.

Mikalef, P., Pappas, I., Krogstie, J., & Giannakos, M. (2017). Big data analytics capabilities: a systematic literature review and research agenda. *Information Systems and e-Business Management*, 1-32.

Miles, M., Huberman, M., & Saldana, J. (1994). *Qualitative Data Analysis: A Methods Sourcebook.* London, United Kingdom: Sage.

Milliken, F. J. (1987). Three types of perceived uncertainty about the environment:state, effect, and response uncertainty. . *Academy of Management Review*, 12(1),133–143.

Mithas, M., L., Earley, Murugesan, & Djavanshir. (2013). Leveraging big data and business analytics. *IEEE IT Professional*, 15(6), 18–20.

Muthui, M. (2019, January 14). *https://www.businessdailyafrica.com*. Retrieved from Business Daily Africa: https://www.businessdailyafrica.com/datahub/Kenya-banks-could-be-headed-for-zero-growth-this-year/3815418-4934810-o3owko/index.html

Nutt, P., & Wilson, D. (2010). *Handbook of Decision Making.* London: Wiley.

O'Neil, C. (2016). *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens democracy*. New York, NY: Crown.

Oriedo, T. (2019, January 23). *https://www.businessdailyafrica.com*. Retrieved from Business Daily Africa: https://www.businessdailyafrica.com/corporate/tech/Big-Data-analytics-at-heart-of-Fuliza-M-Pesa-success/4258474-4948176-ytejap/index.html

Paré, G. (2004). Investigating information systems with positivist case research. *The Communications of the Association for Information Systems*, 13(1), pp. 232-265.

Prahalad, C., & Hamel, G. (1990). The Core Competence of the Corporation. *Harvard Business Review*, 79-91.

Provost, F., & Fawcett, T. (2013, August 15). Data Science and its Relationship to Big Data and Data-Driven Decision Making. *Data Science and Big Data*, pp. 51-59.

Rotella, p. (2012, April 2). *Forbes*. Retrieved from http://www.forbes.com: http://www.forbes.com/sites/perryrotella/2012/04/02/is-data-the-new-oil

Rowe, F. (2005). Are decision support systems getting people to conform? The impact of work organisation and segmentation on user behaviour in a French Bank. *Journal of Information Technology* , 20(2), 103–116.

Saldaña, J. (2009). *The Coding Manual for Qualitative Researchers.* London: Sage Publications.

Sanchez, R., & Mahoney, J. T. (1996). Modularity, Flexibility and Knowledge Management in Product and Organization Design. *Strategic Management Journal 17* , 63-76.

Saunders, M. N. (2011). *Research methods for business students 5th Ed.* New Delhi: Pearson Education India.

Seuring, S. A. (2008). Assessing the rigor of case study research in supply chain management. . *Supply Chain Management: An International Journal,* , 13(2), 128-137.

Sharma, Reynolds, P., Scheepers, R., Seddon, P., & Shanks, G. (2010, 7 8). Business analytics and competitive advantage: A review and a research. *In Bridging the Socio-Technical Gap in DSS - Challenges for the Next Decade*, pp. 187–198.

Simon. (1947). *Administrative Behavior: A Study of Decision-Making Processes in Administrative Organization.* New York: Palgrave Macmillan.

Simon. (1956). Rational choice and the structure of the environment. *Psychological Review*, 63(2), 129–138.

Singer, J., & Vinson, N. G. (2002). Ethical issues in empirical studies of software engineering. *IEEE Transactions on Software Engineering* (pp. 28(12), 1171-1180). Boston: IEEE.

Skinner, W. (1974). The focused factory. *Harvard Business Review*, 113-121.

Slack, N., & Lewis, M. (2011). *Operations Strategy.* Edinburgh, England: Pearson Education Limited.

Solow, R. (1987). *We'd better watch out.* New York, NY: New York Times Book Review.

Stake, R. (2006). *Multiple Case Study Analysis.* New York: The Guilford Press.

Storey, V. C., Chen, H., & Chiang, R. H. (2012, June 24). Business Intelligence and Analytics: From Big Data to Big Impact. *MIS Quarterly*, pp. 1165-1188.

Strassmann, P. A. (1990). *The Business Value of Computers: An Executive's Guide,* . Boston: Information Economics Press.

Sutcliffe, K., & McNamara, G. (2001). Controlling Decision Making Practice in Organisations. *Organization Science*, 484–501.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18, 509–533.

Tversky, A., & Kahneman, D. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica,*, 263-291.

Vaus, D. d. (2005). *Research Design in Social Research.* London: Sage Publication.

Verschiedene. (2014). *Big Data: Opportunities and Challenges.* Helsinki: IEEE COMPUTATIONAL INTELLIGENCE MAGAZINE, XX(X), 60.

Victorino, L., Field, J., Buell, R., Dixon, M., Goldstein, S., & Menor, L. (2018). *Service Operation; What Next.* Utah: Management Faculty Publications.

Waller, M., & Fawcett, S. (2013). Data science, predictive analytics, and big data: a revolution that will transform supply chain and Management. *Journal of Business logistics*, 77-84.

Wamba, S., Akter, S., Gunasekaran, A., Dubey, R., & Childe, S. (2016). How to improve firm performance using big data analytics capability and business strategy alignment? *International Journal of Production Economics*, 182: 113-131.

Whittington, R., Cailluet, V., & Yakis-Douglas, B. (2011). Opening strategy: Evolution of a precarious profession. *British Journal of Management*, 22(3), 531–544.

Wieder, B., & Ossimitz, M.-L. (2015, October 19). The Impact of Business Intelligence on the Quality of Decision Making – a Mediation Model. *Procedia Computer Science*, pp. 1163-1171.

Winter, S. G. (2003). Understanding dynamic capabilities. *Strategic Management Journal*, 24(10), 991–995.

Yin, R. (2003). *Case Study Research.* London, United Kingdom: Sage.

Yu, S., & Yang, D. (2016). The Role of Big Data Analysis in New Product Development. *International Conference on Network and Information Systems for Computers (ICNISC)* (pp. 11-12). Wuhan, China: IEEE.

Zaslavsky, A., Perera, C., & Georgakopoulos, D. (2012). Sensing as a service and big data". *Proceedings of the international conference on advances in cloud computing (ACC)* (pp. 21-29). Bangalore, India: Computer Society of India.

APPENDIX 1: SEMI-STRUCTURED INTERVIEW GUIDE

1. Research Project Background

Informants to be briefed on project and its aims

2. Informant Background

How long in the organization

There current and previous roles

3. Big Data Analytics context (Researcher's Reflection and memoing)

Do different banks use of BDA differently? Any similarities?

Does size of the bank matter, big medium, small?

Does possession of big data (BD) provide competitive advantage or its use thereof (BDA)

How easy or difficult do employees find it to become 'tech savvy'. If difficult, how?

4. Extent of Big Data Analytics (BDA) use by the bank

Does your bank use Big Data Analytics? For how long?

When and what lead your company to adopt BDA? What system was used earlier?

What is unique with BDA technology? How is it similar to systems used earlier? How is it different?

What is your perspective on how the bank has transitioned/is transitioning to BDA? Do you feel the transition process has been a success? If not, why? Any challenges?

Which BDA technology tools do you use (these are analytics and visualization tools). Are they internal or outsourced?

Whenever you are making decision, does BDA make you look up to it more or look back to the old ways. Does it reduce use of gut feeling and hunches?

What do you do when evidence from data is contrary to conventional wisdom?

Big data is continuously coming in, at high velocity, in large volumes and in a variety of ways. What risk doe this pose to the bank's operation processes and strategy?

5. Uncertainty and Complexity of operations decisions

How does BDA change the chance of decisions going wrong? Increase or decrease?

Does BDA eliminate doubt and reduce uncertainties you may have in decision making?

Does BDA narrow down the options to be considered? Do you decide faster than before?

Does BDA reduce human intervention in operations processes? Doe this minimize errors and mistakes?

Does BDA reduce infightings among employees and teams. If so, how?

With BDA, how well do you related with other departments? How does it affect the time it takes to reach consensus?

How does BDA affect the number of consultative meetings? Does BDA boost confidence in your decisions?

How has use of BDA impacted the customer perception of service quality?

Are there errors that have arisen due to your total reliance on BDA, when it doesn't make intuitive sense?

How well do you know your customers with the support of BDA?

6. Operations decision making process

Does BDA speed up or slow down the time taken for you to reach a decision

Does BDA make the operations process more or less flexible?

Are there decisions which rely more/less on BDA than others. Give an example

In what ways have insights from BDA helped you to accomplish your task. Has it made you more effective and efficient?

Has BDA triggered demand and need for staff to be trained on data analytics to examine and analyze information? If so, how has it changed the operations processes.

How has BDA influenced culture of the organization (the way things get done)

7. Closing Remarks

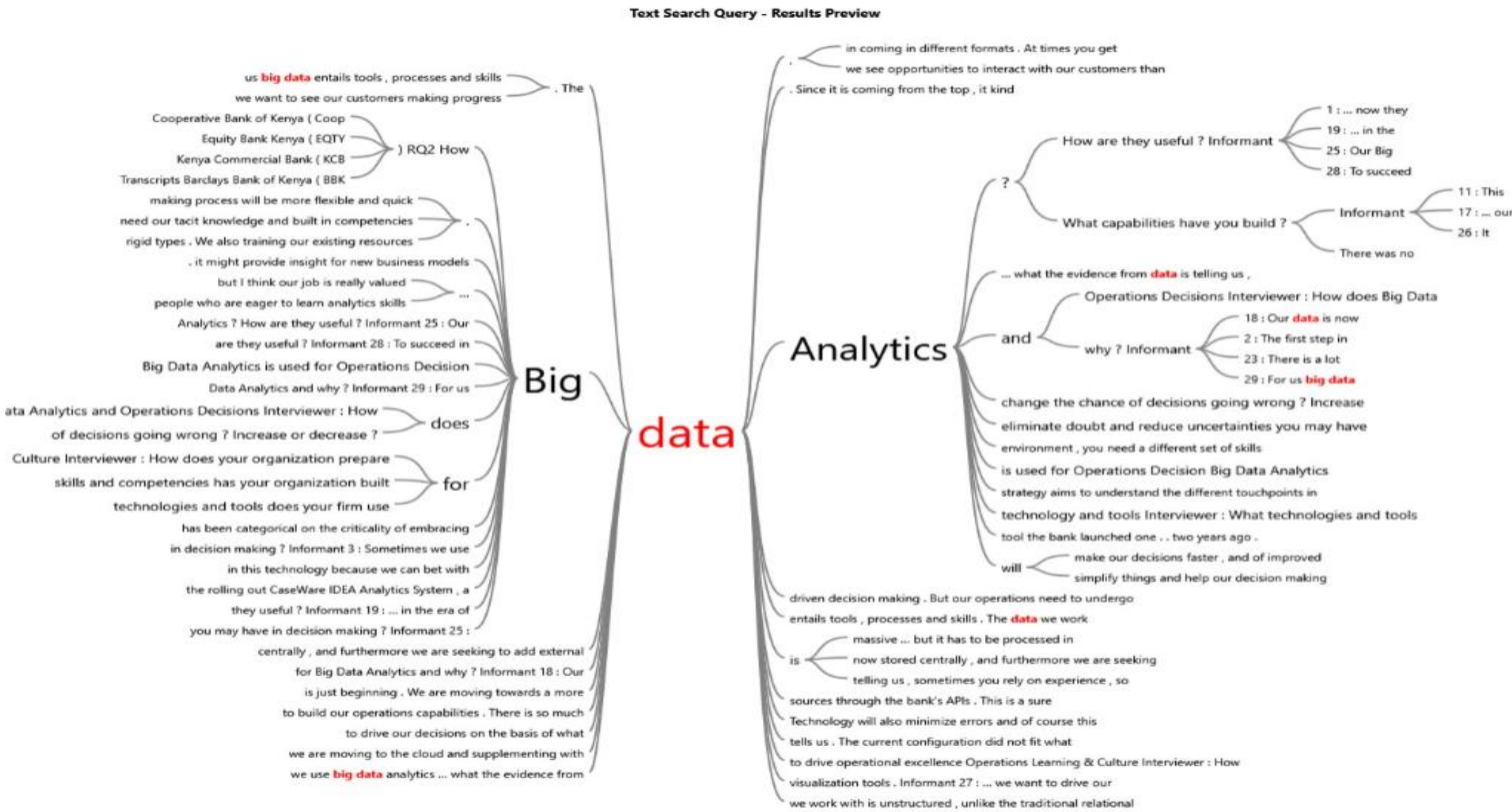
Which other bank do you know that have succeeded in or are in the process of making BDA transformations?

Who else can I contact?

Figure A. 1: Word frequency

Source: Nvivo Coding of primary data

Figure A. 2: Big Data Analytics Cluster Interview Responses Nvivo Summary



APPENDIX 2: LIST OF COMMERCIAL BANKS AND MICROFINANCE BANKS IN KENYA

Table A 1: List of Banks in Kenya

Rank	Name of Bank	Number of Branches	Category
1	KCB Bank Kenya Limited	199	Large/Tier 1
2	Equity Bank (Kenya) Limited	170	Large/Tier 1
3	Co-operative Bank of Kenya Limited	147	Large/Tier 1
4	Barclays Bank of Kenya Limited	107	Large/Tier 1
5	Diamond Trust Bank (K) Ltd.	70	Large/Tier 1
6	I & M Bank Ltd	42	Large/Tier 1
7	Standard Chartered Bank Kenya Limited	37	Large/Tier 1
8	Commercial Bank of Africa Limited	28	Large/Tier 1
9	Family Bank Limited	90	Medium/Tier 2
10	National Bank of Kenya Ltd	73	Medium/Tier 2
11	Chase Bank (K) Limited**	58	Medium/Tier 2
12	NIC Bank Kenya PLC	38	Medium/Tier 2
13	Bank of Africa Kenya Limited	30	Medium/Tier 2
14	Imperial Bank Ltd**	26	Medium/Tier 2
15	Stanbic Bank Kenya Limited	26	Medium/Tier 2
16	HFC Limited	26	Medium/Tier 2
17	Prime Bank Ltd	21	Medium/Tier 2
18	Ecobank Kenya Limited	18	Medium/Tier 2
19	Bank of Baroda (Kenya) Ltd	14	Medium/Tier 2
20	Bank of India	7	Medium/Tier 2
21	Citibank N.A Kenya	3	Medium/Tier 2
22	Sidian Bank Limited	41	Small/Tier 3
23	Transnational Bank Limited	28	Small/Tier 3
24	Jamii Bora Bank Ltd	27	Small/Tier 3
25	Consolidated Bank of Kenya Ltd	18	Small/Tier 3
25	Credit Bank Limited	18	Small/Tier 3
27	Gulf African Bank Limited	18	Small/Tier 3
28	First Community Bank Ltd	17	Small/Tier 3
29	African Banking Corporation Limited	13	Small/Tier 3
30	Spire Bank Ltd	13	Small/Tier 3

Table A 1 Contd.

Rank	Name of Bank	Number of Branches	Category
31	SBM Bank (Kenya) Ltd	11	Small/Tier 3
32	Charterhouse Bank Ltd*	10	Small/Tier 3
33	Guardian Bank Limited	10	Small/Tier 3
34	Guaranty Trust Bank (Kenya) Limited	9	Small/Tier 3
35	M Oriental Bank Limited	8	Small/Tier 3
36	Paramount Bank Limited	8	Small/Tier 3
37	Habib Bank AG Zurich	5	Small/Tier 3
38	Middle East Bank Kenya Limited	5	Small/Tier 3
39	DIB Bank Kenya Limited	4	Small/Tier 3
40	Mayfair Bank Limited	4	Small/Tier 3
41	Victoria Commercial Bank Limited	4	Small/Tier 3
42	Development Bank of Kenya Ltd.	3	Small/Tier 3
43	UBA Kenya Bank Limited	3	Small/Tier 3

*Under Statutory Management

** In Receivership

Table A 2: List of Microfinance Banks in Kenya

Rank	Name of Micro Finance Bank	Number of Branches
1	Faulu Microfinance Bank Limited	37
2	Kenya Women Microfinance Bank PLC	32
3	Rafiki Microfinance Bank Limited	17
4	SMEP Microfinance Bank Limited	7
5	Caritas Microfinance Bank Limited	5
6	Sumac Microfinance Bank Limited	5
7	Century Microfinance Bank Limited	3
8	Remu Microfinance Bank Limited	3
9	UWEZO Microfinance Bank Limited	3
10	Choice Microfinance Bank Limited	2
11	Daraja Microfinance Bank Limited	2
12	Maisha Microfinance Bank Limited	2
13	U & I Microfinance Bank Limited	2

Source: Central Bank of Kenya, Bank Supervision Report 2017/2018