BIG DATA ANALYTICS AND SUPPLY CHAIN PERFORMANCE OF NETWORK FACILITIES PROVIDERS IN KENYA

BY

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DECLARATION

I declare that this research project is my original work and has not been submitted for presentation in this or any other university.

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Signature……………….........   Date: ……………………….

This research project has been submitted for examination with our approval as the University supervisors.

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ABSTRACT

Big data analytics (BDA) has become a very important concept in light of the ever increasing generation of data in the world. BDA has various applications one of which is supply chain performance (SCP) through techniques such as demand forecasting, trend analysis and customer behaviour analysis among others. This research studied BDA and SCP of network facilities providers in Kenya. The study's objectives were; to identify to what degree network facilities providers in Kenya are using BDA in supply chain; to determine the relationship between BDA adoption and SCP of network facilities providers in Kenya and to ascertain challenges faced by network facilities providers in Kenya in adoption of BDA in their supply chain.The study used descriptive cross-sectional research design and collected primary data using web-based questionnaire which were administered via mail to the entire target population of 57 network facilities providers in Kenya. The number of responses received was 39 which formed a substantial portion of the populations and thus analysis was comprehensively done using descriptive statistics and multiple regression analysis. Results from the study suggest that network facilities providers in Kenya have adopted BDA in their supply chain to a moderate extent with descriptive analytics adopted the most. Further, it was found that there is a positive relationship between BDA and SCP though to a very low extent. BDA affects SCP attributes; reliability, agility and cost by 24.7%, 27.7% and 14.2% respectively. While the dimensions of BDA were jointly found to be good predictors of reliability and agility, they were statistically insignificant on cost. BDA was found to be time consuming and there was evidence that lack of top management commitment (TMC) and limited resources were the biggest challenges. Lack of expertise was the least experienced challenge among the network facilities providers. The research recommends more investment on powerful, faster and sophisticated computers and technologies to aid swift capturing, storing and processing of big data to solve the time consumption dimension of BDA. This can be done by top management's improved commitment and thus allocation of resource to the integration of BDA in SCM. The limitation of the study is that it adopted a simplistic multiple regression model to establish the association between BDA and SCP yet there are other variables that exist which affect this relationship and ought to be included in the analysis. Future research needs to improve this model to give it stronger explanatory power by including TMC as a mediating, mediated of intervening variable. Top management commitment comes out as a major challenge in this study and it therefore, needs to be explored further in light of the role of institutional pressure towards enhancing a firm's BDA adoption.

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DEDICATION

To my wife Mary, my children: Mike, Cindy, Prince and Marianna. To my parents – Commissioner Bonee and Dr. Ruth and to all my siblings.

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ABBREVIATIONS AND ACRONYMS

APICS	American Production and Inventory Control Society
BA	Business Analytics
BDA	Big Data Analytics
BDPA	Big Data and Predictive Analytics
BI	Business Intelligence
BSC	Balanced Score Card
CA	Communication Authority of Kenya
CBK	Central Bank of Kenya
GDP	Gross Domestic Product
GPS	Global Positioning System
ICT	Information and Communication Technology
IT	Information Technology
KNBS	Kenya National Bureau of Statistics
NASEM	National Academies of Sciences, Engineering, and Medicine
NFP	Network Facilities Provider
OP	Organization Performance
PEOU	Perceived Ease of Use
PLC	Public Limited Company
POS	Point-Of-Sale

PU	Perceived Usefulness
P2P	Person to Person
RBV	Resource Based View
RFID	Radio Frequency Identification Device
RBV	Resource Based View
SCC	Supply Chain Council
SCM	Supply Chain Management
SCP	Supply Chain Performance
SCOR	Supply Chain Operation Reference
SIM	Subscriber Identity Module
SMS	Short Messaging Service
SU	Strathmore University
TAM	Technology Acceptance Model
TOE	Technology Organization Environment
TRA	Theory of Reasoned Action
TUK	Technical University of Kenya

CHAPTER ONE: INTRODUCTION

1.1 Background of the Study

Big data is an emerging phenomenon that is currently influencing the society and continues to draw a lot of interest from technology enthusiasts, companies, governments and the public. Individuals and companies currently live in an age of data torrent, demonstrated by the ever-growing voluminous data generated from diverse sources (Hu, Wen, Chua & Li, 2014). According to Zhong, Huang, Lan, Dai, Chen and Zhang (2015) the supply chain industry accumulates such huge volumes of data gathered through tracking devices, sensors, radio frequency identification device (RFID), point –of-sale (POS), global positioning system (GPS), customer blogs, Facebook, call centres among others. The vast array of these data are normally manipulated through the aid of information technology (IT) techniques such as analytics, business intelligence insights among others (Wamba, Akter, Edwards, Chopin and Gnanzou, 2015), which presents avenues for improvement of current supply chain practices, superior inventory management and cost reduction (Christopher and Ryals, 2014), in turn, leading into increased revenues in the supply chain industry.

There is an exponentially increasing volumes of data that is generated and transmitted over the both wired and wireless technologies: the web, internet, satellite and radio communication. Cisco (2018) projects that in 2020 there will be a network of 50 billion devices connected to the internet. In Kenya, usage of data surged especially during the Covid-19 pandemic (Communications Authority of Kenya, 2020). The authority has attributed the progression to to the rising demand for online information. User of information are adopting virtual meetings and learning using video-conferencing following governments' directives for people to stay home and keep social distancing. Despite the increasing use and generation of data facilitated by network facilities providers, the huge data has not been given much attention yet, big data analytics technologies has made it possible to reveal great value behind such massive data. This study, therefore, seeks to explore how network facilities providers in Kenya are using BDA to improve supply chain (SC) performance.

This study is anchored on two theories, namely: Technology Acceptance Model (TAM) (Davis et al. 1989) and Resource Based View (RBV) (Barneys 1991). These two theories offer the most appropriate theoretical framework upon which this research will be anchored. To explain the degree to which network facilities providers have adopted big data analytics, Technology Acceptance Model was employed while RBV helped to illustrate how BDA capabilities can improve competitive advantage in SCM. This theory refers to how performance and competitive advantage can be achieved due to the possession of rare and valuable resources which other rival firms cannot imitate. The theory considered having BDA as a significant resource in the organization that helps in achieving its objectives.

1.1.1 Big Data Analytics

BDA is largely an evolution of business intelligence and business analytics. Davenport (2014) defines it as the assembling and analysis of huge sets of data enabled by extensively powerful computers monitoring a multiplicity of digital flow – from different sources – and uses complex algorithms to analyse them. Tachizawa, Alvarez-Gil and Montes-Sancho (2015) contend that big data analytics is analyzing vast volumes of unstructured data to discover otherwise unseen trends, indefinite relationships and other valuable knowledge. While big data has largely been defined in reference to the vastness of data storage, there are other vital characteristics popularly known as the 5V's of big data, namely: Veracity, Variety, Value, Velocity and Volume (Erl, Khattak & Buhler, 2016). Each of the 5V's has unique implication for big data analytics.

Variety represents the view that data is accumulated and produced from diverse origins, for example, mobile devices, sensors, online social networks, Internet of Things (IoT) among others, in semi-structured, unstructured and structured formats. Unstructured data is usually not organized structurally as would be convenient for analysis such as audio, text, videos and imagery. On the other hand, structured data is organized in strict standard format for analysis ordinarily stored in spreadsheets and databases that can run queries. With fully structured data on one extreme and unstructured data on the other, semi-structured data lies in between the continuum and normally, it lacks conformity to stringent criterions. Veracity refers to the level of trustworthiness and quality of data especially in view of the fact that data flows from many diverse sources such as social media platforms which inherently may contain some level of unreliability and uncertainty (Gandomi, 2015).

Value signifies the process of uncovering otherwise hidden revelations from voluminous data for purposes of making sound decisions (Gandomi, 2015). The other characteristic of big data is velocity, which is used to describe the rapidity of data generation and delivery, which can be synthesized in streamline, nearly real-time, in batch or real-time. (Assunção, 2015). According to Chen (2014) volume describes the vastness of data, which is believed to have increased in unprecedented proportion in human history such that it becomes a challenge to store.

1.1.2 Supply Chain Performance

SCM is the planning, organizing, directing and controlling of activities within a network that is involved in manufacturing and delivering goods and services to customers or end-users while supply chain performance is the assessment of both tangible such as cost and intangible elements such as flexibility of the supply chain management (Chang, Tsai & Che- Hsu, 2013).

The balanced score card (BSC) is one of the approaches that scholars have utilized to measure SCP. Halme (2010) posits that BSC consists of four major areas of measurement, namely, customer perspective – the value added to customers as measured by customers' estimation of quality, timely delivery, cost, service level among others; internal business perspective – processes used in production and delivery of products as measured by rate of wastages, defects rates, number of activities, and so on.; financial perspective - which measures financial success as indicated by among others, profit margins, return on investment and cash flows; finally, innovation and learning perspective which measures how the firm improves its core competencies, motivates, equips and trains its workforce.

Supply chain operation reference (SCOR) model (SCC, 1996) is also a distinguished supply chain performance measurement approach. The framework is organized around SCOR processes, SCOR best practices, SCOR performance metrics and supply chain skills – people. The model provides a strong linkage between the metrics and five supply chain management processes, namely; plan which overarches across the other four: source, make, deliver and return. According to APICS (2020) there are over 250 performance metrics categorized under five performance attributes as follows: Reliability – extent to which customers' demands such as quality; on-time, damage-free, complete delivery are achieved. Responsiveness – speed at which processes are performed and how fast supply chain fulfils customers' demands. Agility – capacity to respond to external changes in the market place to maintain or increase supply chain competitive advantage. Cost – the cost incurred in managing supply chain processes and finally, Assets – the ability to utilize supply chain assets efficiently in the delivery of customer demands. (Supply- Chain Council, 2010). This paper adopted the SCOR performance evaluation criteria, because, according to Ntabe et al. (2015) it is the most thorough SC appraisal framework and an ideal tool for aiding strategic decisions hence helps an organization achieve measurable and actionable outcomes.

1.1.3 Network Facilities Providers in Kenya

Network facilities providers (NFPs) own communication infrastructure such as cellular communication base stations, fibre optic cables, satellite earth stations, radio communication transmission equipment and broadcasting transmission towers and equipment. NFPs are the backbone of for content service, applications and networks. The Communications Authority of Kenya categorizes NFPs into tier 1, 2 and 3 as determined by resources owned/ controlled at national, regional and local levels respectively. Tier 1 NFPs comprise of 3 major players namely; Telkom Kenya Limited, Airtel Networks Limited and Safaricom PLC with the rest falling in the other two tiers. The sector provides services such as: data/internet services, fixed telephony services, mobile telephony services among others.

According to CA (2020), there are 52.2 million active mobile subscribers representing a mobile penetration rate of 116.1% with Safaricom PLC controlling 64.8% of these. Traditional fixed line service posted 19,848 subscribers while fixed Voice over Internet Protocol (VoIP) and fixed wireless technologies recorded 1,076 and 49,227 subscriptions respectively. By the end of quarter 1 of 2020, CA reports that, total wireless subscriptions (mobile data subscriptions, satellite data subscribers) stood at 38,937,033 while terrestrial wireless data recorded 82,403 subscribers; total fixed (wired) subscriptions [fixed fibre optic data subscribers, fixed cable modem subscribers, fixed DSL data subscribers (copper), other fixed data subscribers (e.g. radio)] registered 457,669 users. The Internet subscriptions/home data/ fibre-to-the-office stood at 541,600. The number of registered domains was 91,603. This telecommunication sector has 202,102 active mobile money transfer agents and 21.9 million customers subscribed to the money transfer services (CA, 2020). There has been 1.84 billion mobile money transfer transaction from person to person including withdrawals which are valued at Ksh 4.35 trillion (CBK, 2020). Mobile commerce transactions stood at 529.6 million with a value KSh.1.5 trillion. Mobile data subscription was recorded at 38.9 million (CA 2020)

Digitization of the world is greatly transforming the telecoms sector. The increasing need for flexibility, agility has triggered new ways of communication. In the 21st century, artificial intelligence has become a norm in the day to day communication and a major talking point by customers and companies (Call Centre Helper, 2020). With the growth of 5G technology, customers are increasingly getting enriched cellular experiences. There is also a rise in new markets due to the unprecedented increase in demand for novel network services though it comes with a fair share of challenges. Unsettling competition from sellers of technology and customer service management are thought to be the leading challenges expereinces by telecommunication companies.

1.2 Research Problem

Massive data is being generated exponentially in the world today as there is a surge in the number of internet websites, mobile network subscribers and online services. (Mohamed et al, 2018) which makes BDA a very significant concept in improving the competitiveness of an organization. Supply chain professionals are constantly pursuing more effective, efficient, agile and integrated supply chain yet they still struggle in handling voluminous data generated by the supply chain. This unprecedented explosion of vast data from various sources across the SC has necessitated demand to devise sophisticated techniques and technologies that can swiftly make sense of the huge data with high level of intelligence. (Darvazeh et al, 2020). In a study by Srinivasan and Swink (2018) it is argued that while there is a good understanding of BDA as relates to customer behaviours and intention, it remains less understood in its use for supply chain operational decisions.

Lack of ability is cited by Rowe and Pournader (2017) as the fundamental reason for not applying BDA techniques within the supply chain. Therefore, strengthening of BDA capabilities is thought of as a critical success factor for competitiveness of any SC (Tiwari et al, 2018). Communication is also changing among customers; VoIP and internet messaging are some of the cloud-based technologies that are changing the industry's landscape. Customers are becoming more sensitive to quality and on-time delivery thus the ability to monitor and make real-time decisions on call quality and traffic of data will give telecoms an edge hence better returns. (Call Centre Helper, 2020). However, according to Business Daily (2020) appreciation of big data analytics in Kenya is very low and its acceptance into business strategy is wanting since many of the companies are finding it a challenge to convert big data into meaningful insights and have little or no idea on the value they can derive from the insights.

A number of researches have been conducted on big data analytics and performance. Globally, Nwanga, Omwuka and Aibuni (2015) researched on how service to the customer and earning within Nigeria's mobile phone industry was impacted by big data analytics. The researchers found out that real-time analytics provided valuable insights that the providers relied on to meet individual customer demands, improve profits and reduce overall operational cost. Gunasekaran, Papadopoulos, Dubey, Wamba, Childe, Hazen and Akter (2017) researched adaptation of big data and predictive analytics (BDPA) on organization performance (OP) and SCP of technology and e-commerce firms, consulting firms and manufacturing companies in Pune, Hyderabad and Bangalore cities of India. The researchers' findings were that BDPA has potential to significantly reduce costs of running supply chain, improved agility, enhanced supplier relations, higher sales and planning capacity. Seetha, Patwa, Niranjan, Ranjan, Moorthy and Mehta (2018) studied impact of BDA on the SC of multinational companies in USA, Europe, Middle East, Australia and Asia and revealed that big data adoption was significantly positively related to operational efficiency, customer satisfaction and saving of cost as well as demand management.

Locally, Mugane (2018) reached the findings that the number of financial institutions effectively using BDA was still small (23%).The most popular big data technologies used by financial institutions were in-memory databases, artificial intelligence and prescriptive analytics. Overall, adoption of BDA was found to lead to competitive advantage of banks and fintech companies. Kiragu (2019) established that telecoms, telecommunications service providers, ICT providers and University of Nairobi's school of informatics have adopted BDA to a great extent (88%) and that most used business intelligence and predictive analytics. Kibe, Kwanya and Owano (2020) researched the impact of BDA on OP of Strathmore University (SU) and Technical University of Kenya (TUK) and revealed that BDA was positively correlated with innovativeness, productiveness, efficiency, creativeness and effectiveness in both institutions.

From the studies reviewed above, big data analytics methods has not been projected systematically and sequentially. Additionally there is no research found in Kenya which has explored BDA as a construct of supply chain performance. Contextually, none has specifically delved into NFP industry in Kenya in spite of its significance in the growth of the economy. It is against this background that this study sought to answer the following research questions: To what extent have network facilities providers in Kenya adopted big data analytics? What is the relationship between big data analytics and supply chain performance of network facilities providers in Kenya? What challenges do network facilities providers in Kenya face while implementing big data analytics?

1.3 Research Objectives

This study was guided by the following study objectives:

i. Identify to what extent network facilities providers in Kenya are using BDA in supply chain.
ii. To determine the relationship between BDA adoption and SCP of network facilities providers in Kenya.
iii. To establish challenges faced by network facilities providers in Kenya in adoption of BDA in their supply chain.

1.4 Value of the Study

This study is important to network facilities providers in that it provides them with valuable information so that they can integrate big data analytics as a strategy for superior performance and competitive advantage. It will also enable network facilities providers in Kenya to relate the value created because of linking BDA to the supply chain performances (SCP) in the firm. As a result, findings and recommendations from the study will help provide information that would be of use to stakeholders regarding the factors that could influence the success of BDA on SCP as well challenges encountered among network facilities providers.

Businesses in diverse industries can also profit from the results of this study since it may serve as a benchmark for adoption of BDA. It is believed that the findings of this study would be insightful to these businesses especially on how BDA adoption can be beneficial to their firms' SCP.

As academicians, the value of the research is to help understand how BDA adoption can have an influence on SCP of network facilities providers in Kenya. Academia may find the findings of this study useful, more especially for researchers who have interest in furthering research on BDA. Findings are anticipated to help build on existing knowledge in the subject domain.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

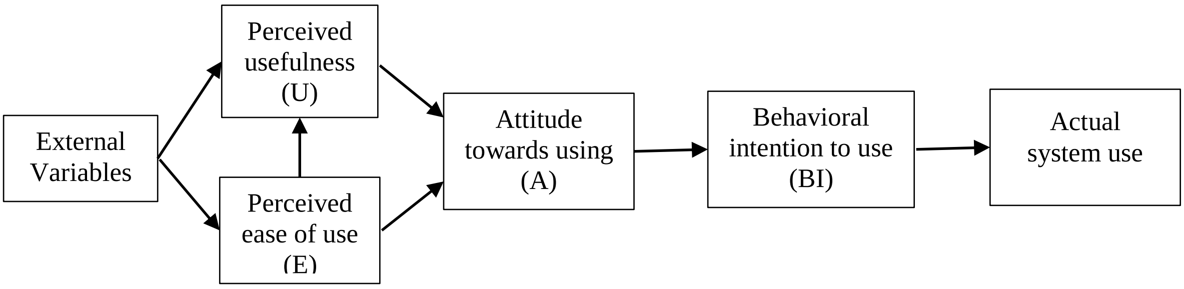
This chapter introduces the theoretical review of network facilities providers followed by the concept of big data analytics. It looks at what has been suggested by various authors and scholars regarding big data analytics from diverse perspectives. Therefore, the chapter encompasses the concept of big data analytics of network facilities providers. The chapter is concluded by looking at empirical review and the conceptual model.

2.2 Theoretical Literature Review

This section discusses a framework in which the theories relevant to the research are based. The study focuses on two most relevant theories, namely; TAM and RBV. These are discussed next.

2.2.1 Technology Acceptance Model

TAM in an information systems theory that is believed to be parsimonious and robust in explaining IT/IS adoption behavior and has been frequently employed by many scholars in various fields (Heili & Assar, 2009; Ramdani & Kawalek, 2008; Hao, 2013). It stemmed from theory of reasoned action (TRA) and it rationalizes the process of concurrence and adoption of technology by users. Two factors are proposed as being the most influential on users' decision as to when and how they embrace novel know-how. These are: the level to which persons consider a new technology would improve their job performance – perceived usefulness (PU) and the measure to which a person deems that use of new technology would be without much efforts – perceived ease of use (PEOU) (Davis,1989). However, TAM has been continuously upgraded to include other factors to help explain and predict the adoption of new technology apart from using only PU and PEOU. The following figure explains the TAM.



Source: Davis (1989)

This study is anchored on TAM from the viewpoint that BDA adoption may be hindered or enabled by employees/ management perception of its difficulty or ease of use. The hypothesized benefits of big data are considered attractive and convincing to potential users of the technology and would thus enhance the perception of its usefulness thereby improving BDA adoption in the network facilities providers supply chain.

2.2.2 Resource Based View

The RBV underscores that for a firm to achieve competitive advantage and superior performance, it heavily depends on its assets/resources. The two assumptions of RBT that Peteraf and Barney (2012) propose as a basis for evaluating competitive advantage include: the assumption that companies in the same industry may be varied in line of resources that they control, and secondly, that resource dissimilarity could continue over time if the assets to be used to execute organizations' strategic operations are not entirely movable from one firm to the other. The theory recognizes the internal operational processes as crucial components of the firm's assets for example using BDA in executing operations decisions such as demand forecasting. The organization will be able to evaluate the impact of the BDA on SC's competitive advantage and performance of the individual organization.

In this investigation, BDA is viewed as a technological practice that depends and augment's on the resources at the disposal of network facilities providers to enhance effectiveness and efficiency. The competitive advantage in the said scenario is exhibited by superior responsiveness, efficient utilization of assets, enhanced reliability, superior agility and cost efficiency. Big data analytics leads to better coordination and use of supply chain resources.

2.3 Approaches of Big Data Analytics

Organizations that adopt analytics must be appreciative of the various methods with which insights are achieved for better decision-making (Erl et al., 2016). Classification of data is one such criteria that aids understanding of the data. Davenport (2009) argues that all data needs to be aggregated and ask the following queries: "what has happened? Why it has happened? What will happen? And how to make the best of it?" These queries are representative of the four main analytics methods: descriptive, diagnostic, predictive and prescriptive respectively.

Descriptive analytics is a BDA method that gives insights to past or presently happening data. It summarizes and describes collected data in a manner that gives useful information to guide future actions (Marcelo, Vicente, Ladeira, & de Oliveira, 2018). According to Davenport

(2009) it asks, “what has happened?” An illustration of descriptive analytics is to make categorization of customers by their tastes and preferences.

After descriptive analytics, comes diagnostic analytics that attempts to unravel the cause of an occurrence. It utilizes past data historical data gauged against any other relevant data to explore avenues for establishing any identifiable patterns or relationships. It is valuable to firms as it provides extensive comprehension into a particular problem. Davenport (2009) posits that organizations should gather comprehensive data; failure of which diagnostic analytics may be pain stakingly slow as every individual problem would need separate analysis and detection.

Predictive analytics refer to the determination of the possibility of an event occurring. It concerns itself with the manipulation of data into substantial and actionable information. It answers the query, “what will happen?” (Davenport, 2009). Suppose an organization sells diverse commodities, predictive analytics assist to explore consumers expenditure patterns, product consumption habits among other behaviour to predict accurately what other product(s) they would buy/consume hence enabling cross selling and in turn improving profit per customer as well as better customer relationship. Predictive analytics utilizes sophisticated statistical tools and other empirical techniques to analyse historical and new data for the prediction of the future (Bonnes, 2014).

Prescriptive analytics analyses data by way of machine learning, business rules, mathematical science, simulation algorithm and optimization to not only predict probable future outcomes but recommends various decision options that best suits the prediction thereby answering the query “how to make the best of it?” It can be helpful in determination/ setting of product pricing or even selection of an advertising strategy to improve income. Davenport (2019) went further to add a sought of ‘what if’ analysis that is referred to as automated analytics. It answers the query, “what if we took the action?”

A taxonomy by NASEM (2017) grouped BDA as per the following stages: descriptive and exploratory, predictive and prescriptive. Other valid categorizations of BDA include one advanced by Jing, Yan and Pedrycz, (2019) who grouped BDA according to security data that incorporates machine learning, knowledge-based methods and statistical methods. On the other hand Cardinale, Guehis and Rukoz, (2017) described an all-purpose design for BDA approaches that allows categorization according to the type of database used, distributed parallel model and data storage layer.

Of the aforementioned approaches, the well-liked and favoured categorization of BDA is the Davenport's BDA classification (Davenport, 2009) because of the assimilation, systematization and harmony between the methods; therefore, it will be adopted in this study. BDA should begin with descriptive analytics to establish what has happened then to diagnostics analytics to ascertain why it has happened. Predictive analytics should follow to indicate probable future occurrence and finally prescriptive analytics to aid in the decision making support.

2.4 Empirical Literature Review

In this section, a review of relevant studies is discussed. Gunasekaran et al. (2017) researched the influence of BDPA integration on organization performance (OP) and supply chain performance (SCP). In the study, assimilation is theorized as a three step process namely acceptance, routinization and finally assimilation. It further identified connectedness and sharing of information as resources and sought to establish their influence on SCP and OP with top management commitment being the mediating variable. The research surveyed e-commerce and technology companies, manufacturing companies and consulting companies located in Bangalore, Hyderabad and Pune cities in India. It employed a cross-sectional survey that was sent via e-mail to a sample of 315 corporations drawn from Dun and Bradstreet database. The results from the study recommend that connectedness and sharing of information mediated by commitment of top management has a positive relationship to BDPA adoption, which has a positive relationship to BDPA integration as mediated by BDPA standardization, and positively related to SCP and OP.

Seetha et al. (2018) conducted a study centered on BDA and operational excellence in SP practices. The study surveyed respondents of multinational companies in USA, Europe, Middle East, Australia and Asia. The collected data was analyzed using structural equation modelling and findings prove that analytics, Internet of things (IoT), data science, vendor rating and demand management have effects on supply chain on matters cost saving, customer satisfaction, operational excellence and bridging communication discrepancies between supply chain management (SCM) and demand management. The researcher further asserts that firms which adopt big data technology can accumulate financial gain and value addition and that soon the industry would adopt BDA as a standard. Through the study, BDA and SCM are incorporated hence providing a modernistic explanation of the Supply Chain Operations Reference (SCOR).

Mugane (2019) conducted a study whose objectives were to determine the degree to which big data analytics assimilation amongst banks and fintech companies in Kenya, to establish the association between the adoption of BDA and competitive advantage and finally to establish the challenges and opportunities of adopting BDA. Descriptive research design was used. The population consisted of 42 commercial banks and 38 fintech companies in Kenya amongst whom a census survey was done. Data was captured using questionnaires and analysis was performed using means, frequencies, standard deviation and regression analysis. Multivariate regression technique was used to ascertain the nature of association between the adoption of BDA while 23.1% were effectively using the technology. The rest of the organizations were either planning to adopt or testing their data models. The study found that adoption of big data analytics leads to significant achievement of competitive advantage. It had also enabled the organizations that were effectively using BDA to come up with new products and enter new markets. It was also found that the organizations studied faced various challenges in the adoption of BDA, some of which were integration of legacy systems with new technologies and poor quality of data. Adoption of BDA presented the organization various opportunities which could be exploited some of which were improving customer service, fact-based decision making and operations management.

Karuga (2019) study pursued to examine the extent by which telecoms, telecommunication service providers, Information Communication Technology companies and service providers and a major institute of higher learning in Kenya had adopted big data analytics, the factors which influenced adoption process and the suitability of the model used to establish this adoption in their operations. The study employed a descriptive research design and semi structured questionnaires were used to collect data. Multivariate regression was applied to find out the significantly the independent variables affected adoption of BDA to drive decision making. The study found that BDA had been adopted to a great extent by these companies. Organizations used business intelligence and BDPA in their operations. The adoption of big data analytics was influenced by TOE factors. The degree of compatibility of big data analytics to the existing IT systems, top management support, size and structure of the organization and the intensity of the competition were identified as the factors with highest significant effect on BDA assimilation. Other factors such as the perception of the customer on their data privacy, the availability of data and international trends were also considered as important. Some of the challenges highlighted included inadequate legal framework, need for employee culture change and inadequate presence of skilled staff on big data analytics.

Kibe et al. (2020) researched on the impact of BDA on OP of two Kenyan universities, namely SU and TUK to enable an in-depth comprehension of the concept, the study took a mixed method research approach. Data collection was done via questionnaires. Both primary and secondary data were collected from ICT employees of SU and TUK; interviews were also conducted. Descriptive statistics was used to analyse and present the data. Findings suggest that BDA adoption is positively related to OP especially on productivity, innovativeness, effectiveness, creativeness and efficiency in both institutions. Whilst Strathmore University demonstrated that BDA adoption is positively related to competitiveness and profitability, TUK revealed that the two variables were negatively related. Overally, TUK showed there was a weak relationship between BDA adoption and organization performance while Strathmore University demonstrated a good influence between the dependant and independent variables.

2.5 Challenges of Big Data Adoption

The adoption of BDA is marred with several challenges such as, time consumption, according to Blackburn (2015), Predictive analytics initiative is characterized with being time taking seeing as it is involves various stages such as; development stage, testing stage and finally the adapting stage. Moreover, coordinating the activities of experts from divergent and varies mindsets can be a daunting task. Inadequacy of resources is another challenge facing BDA. The absence of resources in IT as well as capability to exchange information and data instantaneously amongst firms in a supply chain will culminate to irregularities. Dutta & Bose (2015), posit that cooperation and multifunctional formation of teams among different compeers in an organization has to be of utmost importance for realization of BDA. Seah, Hsich and Weng, (2010) asserts that Leadership plays a central part in favorable actualization of systems in BDA towards the management of supply chain. Security concerns and privacy issues also pose a challenge to BDA, Hu et al, (2014) warns that the use and application of BDA presents serious concerns on security, privacy, unethical use of Big Data this would lead to ineffective processing of data; and verily result to biased findings as stated by Tien (2012).

Other challenges to BDA are behavioral issues Big Data pays attention to correlation as opposed to causation that makes necessary human reasoning to offer solutions to big problems. Unclear ROI and vaguely defined benefits make stakeholders cautious about applying BDA (Richey Jr., Morgan, Lindsey-Hall & Adams, 2016; Sanders, 2016). Implementing full-scale BDA is highly dependent on the ‘‘downstream” workers who execute these task which presents a challenge to achieving financial benefits for these firms according to Davenport, Harris, De Long & Jacobson, (2001). According to Schoenherr and Speier-Pero

(2015) usage of predictive analytics on SCM is primarily hindered by the unavailability of skilled employees, lack of integration, and poor change management among others. The absence of experts in BDA is a significant matter among SC professionals according to Richey et al, (2016). Scaling up data is identified as a serious technical issue in the adoption of BDA according to Richey et al. (2016). After a particular period organisations often have get rid of their data so as to create space for newly generated data

Quality concerns related to data production processes are a challenge as well. This is especially because it is linked to the process of producing data, which is frequently put in comparison with product manufacturing processes (Hazen, Boone, Ezel & Jones-Farmer, 2014; Wang, Storey & Firth, 1995). Hazen et al (2014) asserted, low quality of data would impede the data analytics activities and affect decisions by the management. Shortcomings in procedures and techniques also pose a challenge to BDA as unavailability of quality data is not the sole challenge; low capacity of methods to exploit the huge volumes of data accordingly is a major problem. As relating to demand forecasting techniques for instance, ample attention is directed purely to endogenic and time-series variables for forecasting demand, and there is inadequate consideration for exogenic information sources and variables, this is according to Meixell and Wu (2001). Without doubt, this has deduced to development of improved data management abilities and methods for demand forecasting, thereby enhancing operations in supply chain.

2.6Summary of Literature Review

A summary of literature review is provided in table 2.1. It provides the scholar(s), focus of study, methodology, major findings, research gaps and how the gaps will be addressed in this study.

Table 2.1 Summary of Literature Review

Scholar(s)	Focus of Study	Methodology	Major findings	Research gaps	Address of Gaps
Nwanga, Omwuka and Aibuni (2015)	Effect of BDA to Nigeria mobile phone industry.	Exploratory research design	Big data analytics presents a lot of opportunities for the growth of telecommunications industry in Nigeria viz reduced operational cost, customer satisfaction and improved revenue	The study was Nigeria based thus could not represent mobile network providers in Kenya. It also does not specifically address BDA effect on SCP	Study done in Kenya. The dependent variable is SCP
Gunasekaran, Papadopoulos, Dubey, Wamba, Childe, Hazen and Akter (2017)	BDPA for SC and OP.	Cross-sectional survey. 315 e-commerce and technology, manufacturing and consulting companies in India	BDPA has potential to significantly reduce costs of running supply chain, improved agility, enhanced supplier relations, higher sales and planning capacity.	The study was Indian based thus could not represent mobile network operator in Kenya	Study done in Kenya.
Seetha, Patwa, Niranjan, Ranjan, Moorthy and Mehta (2018)	Impact of BDA on SCM	Descriptive survey approach. Multinational companies in USA, Europe, Middle East, Australia and Asia surveyed	analytics, Internet of things (IoT), data science, vendor rating and demand management have effects on supply chain on matters cost saving, customer satisfaction, operational excellence	The study did not systematically focus on BDA approaches as the independent variables	BDA methods approached systematically (descriptive, diagnostics, predictive and prescriptive analytics)

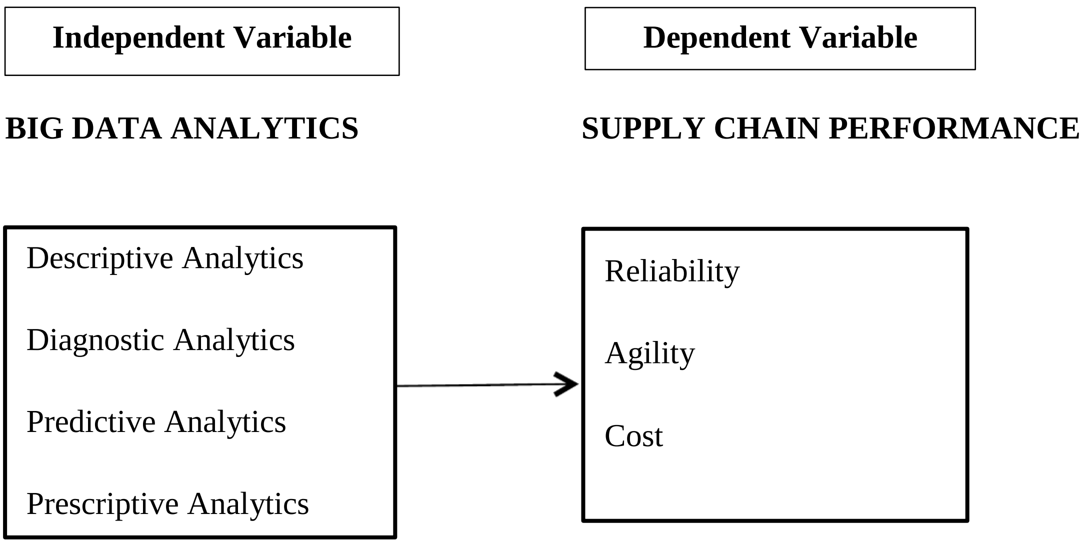
Mugane (2019)	BDA and competitive advantage of commercial banks and fintech companies in Kenya	Descriptive survey approach. 42 commercial banks and 38 fintechs surveyed	Big data analytics leads to significant achievement of competitive advantage	Context is commercial banks in Kenya. Did not address BDA effect on SCP	Context is NFPs in Kenya. Addresses BDA influence on SCP
Karuga (2019)	Adoption of BDA to drive decision making	Descriptive survey approach. Telcoms, Telecommunication compamies, ICT and UoN School of Computing were surveyed	The degree of IT systems compatibility, top management support, size and structure of the organization and the intensity of the competition had significant effect on the adoption of big data analytics	Context is telecommunication, telecoms, ICT companies and a learning institution in Kenya. Did not address BDA effect on SCP	Context is specific to NFPs. BDA is investigated explicitly in relation to SCP
Kibe, Kwanya and Owano (2020)	Relationship between BDA and OP of the TUK and SU in Kenya.	Selected Case Studies of TUK and SU. Descriptive statistics used to analyse.	BDA and OP are positively related especially on productivity, innovativeness, effectiveness, creativeness and efficiency	Does not address BDA effect on SC reliability, agility and cost. Context was case study of 2 learning institutions in Kenya	Research investigates influence of BDA on SC reliability, agility and cost

Source: Researcher (2020)

2.7 Conceptual Framework

In this study, the independent variable is big data analytics whose dimension are: diagnostic analytics, descriptive analytics, predictive analytics and predictive analytics while the dependent variable is supply chain performance which is operationalized by: reliability, agility and cost. A schematic diagram of the hypothesised relationship is provided in figure 2.1 below.

Figure 2.1: Conceptual Model



Source: Researcher (2020)

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Introduction

This chapter presents the research approach adopted in the investigation. The section looks into the research design, target population, the research instrument, data collection methods and data analysis procedures.

3.2 Research Design

This study adopted a cross-sectional research design. A cross-sectional survey enables researchers to observe and describe variables of interests of a research at a specific point in time without any form of manipulation (Kothari, 2004). The design was suitable for this research, as it aids the gathering of significant information on big data analytics in network facilities providers. Kibe et al (2020) successfully used this method in a study on association between BDA and OP of two Kenya Universities - TUK and SU.

3.3 Target Population

The target population of this study was the network facilities providers in Kenya. According to Communication Authority of Kenya (2018), there are a total of 57 network facilities providers in Kenya (appendix II). The study carried out a census due to the relatively low number of the target population.

3.4 Data Collection

The study used primary data which was collected via questionnaires. Questionnaire was the most preferred technique for collecting data as it allowed investigators to reach a large group of population and it was also economical. Additionally, provided that a questionnaire has high level of reliability, respondents would give closely comparable responses over and over again if a research was to be repeated severally. (Bryman & Bell, 2018; Saunders & Buckingham, 2017)

The questionnaires had four parts I, II, III and IV where each section aligned to respective study objectives. Part I; focused on collecting general information of the participant and the organization. Part II; enquired about information on the extent of BDA adoption by network facilities providers in Kenya. Part III; sought information on the effects of big data analytics on supply chain performance of network facilities providers in Kenya and Part IV; pursued information on challenges faced while implementing big data analytics. Data was collected by questions framed using the 5 point Likert scale format. The respondents were supply chain managers or their equivalents – one in every firm.

Web-based questionnaires were sent via email to the various managers and their assistants. This approach was preferred in light of the prevailing COVID-19 pandemic against which virtual interaction and social distancing was encouraged. The researcher was assisted by three data collectors to make calls, email reminders to follow up respondents as well as making limited physical contacts.

3.5 Data Analysis

Background information, objective one; extent network facilities providers in Kenya are using BDA in supply chain and objective three; challenges faced by network facilities providers in adoption of BDA in their supply chain was analyzed using descriptive statistics. To establish whether or not there is a relationship between BDA and SCP of network facilities providers, a regression analysis was used. The regression model is as follows: -

$$Y_1 = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \varepsilon$$

$$Y_2 = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \varepsilon$$

$$Y_3 = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \varepsilon$$

Where:

Y_1 = Reliability, Y_2 = Agility, Y_3 = Cost

$\boldsymbol{\alpha}$ = the Y intercept when x is zero or the constant

$\boldsymbol{\beta_{ij}}$ **=** Regression Coefficients

$\mathbf{X_1}$ = Descriptive Analytics

$\mathbf{X_2}$ = Diagnostic Analytics

$\mathbf{X_3}$= Predictive Analytics

$\mathbf{X_4}$= Prescriptive Analytics

$\boldsymbol{\varepsilon}$ = the error term

Table 3.1 gives a summary of data collection and the analysis method

Table 3.1: Summary of Data Collection and Analysis Method

Objective	**Questions**	**Data Analysis Method**
Background Information	Part I	Descriptive Statistics - – Means, frequencies, & percentages
Extent network facilities providers in Kenya are using BDA in supply chain	Part II	Descriptive Statistics – Means & standard deviation
Relationship between BDA adoption and supply chain performance	Part III	Inferential Statistics - Correlation & Regression Analysis
Challenges faced by network facilities providers in adoption of BDA in their supply chain	Part IV	Descriptive Statistics – Means & standard deviation

Source: Researcher (2020)

CHAPTER FOUR: DATA ANALYSIS, FINDINGS AND INTERPRETATION

4.1 Introduction

This chapter starts with data analysis, findings then finally interpretation. This section represents results on the data sought on BDA and SCP of NFPs in Kenya. The research had three objectives: to ascertain the level to which BDA have been employed in NFPs in Kenya, to determine the effect of BDA on SCP of NFPs in Kenya. The target study population for the study was supply chain managers or their equivalent in operations, procurement or marketing departments/

4.1.1. Response Rate

In this study, 57 questionnaires were distributed out of which 39 were fully filled and hence usable for the study. This translates to 68% response rate. Mugenda and Mugenda (2003) argues that a response of >60% is sufficient for comprehensive data analysis.

4.2 Demographic Information

The study sought to examine background information of the respondents in terms of job title, gender, working experience, level of education and age of the company in Kenya. The intended purpose for this information was to find out the relationship between information given and the general profile of the respondents.

4.2.1 Gender

The researcher sought to establish the composition of respondents' gender as represented in the companies. Table 4.2.1 below summarizes the results.

Table 4.2.1 Gender

Gender	Frequency	Percent
Male	24	62
Female	15	38
Total	39	100.0

Source: Research Data (2020)

The findings from table 4.2.1 above show that there was a gender discrepancy between male and female employees since male respondents were 63% and female respondents were 37%.

This indicates that more male employees occupy supply chain relates positions in NFPs more than female employees.

4.2.2 Education

The research required respondents to indicate what their highest level of education was. The results are summarized in table 4.2.2 as follows.

Table 4.2.2 Education

Education	Frequency	Percent
College Level	5	12
Undergraduate	17	44
Masters	17	44
Total	39	100.0

Source: Research Data (2020)

From the table 4.2.2 it can be seen that 12 % of the research participants had certificate and diploma qualifications, 44% of the respondents had undergraduate qualifications while 44% of the respondents had master's degree qualification. Hence, the respondents had adequate relevant education background and considered to be well placed to present reliable information as sought by the researcher.

4.2.3 Experience

The researcher wanted to establish the respondents' work experience in their respective companies; table 4.2.3 summarizes the responses that were provided.

Table 4.2.3 Work Experience

Experience	Frequency	Percent
1 to 5 years	20	51
6 to 10 years	16	41
over 10 years	3	8
Total	39	100.0

Source: Research Data (2020)

The results revealed that 51% of the research participants had worked in their respective companies for < 5 years, 41% had experience spanning 6-10 years and 8% had over 10 years' experience. This is evidence that the bulk of respondents had sufficient experience and thus considered to have adequate knowledge and understanding of their respective companies' with regard to what the researcher sought.

4.3 Adoption of big data analytics

Objective one of the study was to establish the degree of implementation of BDA in NFPs in Kenya. Descriptive statistics was carried out on all the BDA dimensions investigated by the study on a scale of 0-100 where 0-no extent at all and 100-very great extent. Table 4.3 below represent the results.

Table 4.3 Extent to which BDA has been implemented by NFPs

Descriptive Statistics		
BDA	**Mean**	**Std. Deviation**
Descriptive Analytics	72.9	16.63117
Diagnostic Analytics	65.0	16.74175
Predictive Analytics	67.9	16.64837
Prescriptive Analytics	67.5	20.59143

Source: Research Data (2020)

From the results of descriptive statistics on the extent of adoption of BDA, the results indicate that all the BDA dimensions have been implemented by NFPs in Kenya as indicated above. Descriptive analytics indicated a mean of 72.9, diagnostic analytics indicated a mean value of 65, predictive analytics indicated a mean value of 67.9 while prescriptive analytics indicated a mean value of 67.5. Hence, BDA has been implemented to a moderate extent in NFPs in Kenya. The results above, therefore, helps this study to resolve and agree that NFP's in Kenya have adopted BDA in their supply chain processes to a moderate extent.

4.3.1 Discussion

The first objective of this study was to establish the extent of implementation of BDA in NFPs in Kenya and its effect on SCP. The findings of the study show that to a moderate degree NFP's in Kenya have implemented BDA in their supply chain operations. This was indicated by the results whereby descriptive analysis carried out on each and every variable, indicated that all the four BDA approaches had mean values greater than 60 on a scale of 0-100 where 0 indicates not implemented, while 100 indicates fully. This is consistent with a study by Seetha et al (2018) who found out that multinational companies have adopted big data analytics as part of supply chain management. However, this findings are contrary to a study carried out by Barbosa et al (2018) who studies the use of BDA in managing supply chain resources in Latin America and established that the uptake of the practice is still low as pertaining supply chain.

4.4 Relationship between BDA with Reliability as Measure of SCP

The study's second objective was to uncover the outcome of implementation of BDA on reliability as a SCP measure in NFPs in Kenya. The study used multiple regression on all the supply chain performance measures. Table 4.4.1 summarizes the regression analysis while holding agility and cost constant below:

Table 4.4.1 Regression Coefficients on Reliability

Coefficients					
Model	Unstandardized Coefficients		Standardized Coefficients	Z Value	Sig.
	B	Std. Error	Beta		
(Constant)	4.747	1.320		3.596	0.001
Descriptive analytics	0.245	0.419	0.109	0.584	0.563
Diagnostic analytics	1.350	0.701	0.563	1.976	0.032
Predictive analytics	0.554	0.471	0.334	1.176	0.248
Prescriptive analytics	0.976	0.459	0.501	2.127	0.041

a. Dependent Variable: Reliability
b. Predictors: Diagnostic Analytics, Descriptive Analytics, Prescriptive Analytics, Predictive Analytics

$$Y=4.747+0.245X_1+1.350X_2+0.554X_3+0.976X_4$$

From the table above it can be seen that, descriptive analytics (t=0.584, p=0.563) and predictive analytics (t=1.176, p=0.248) are positively related to reliability but are statistically insignificant at 95% confidence level as (t=0.584<1.96; p=0.563>0.05) while (t=1.176<1.96;

p=0.248>0.05) respectively. Findings further suggest that there is a positive and statistically significant relationship between reliability and both diagnostics analytics (t=1.976, p=0.032) and prescriptive analytics (t=2.127, p=0.041) both meeting the test criteria at 0.05 significance level ($t \geq 1.96$, $p \leq 0.05$). The beta value $\beta_1 = 0.245$ indicates that a unit increase in descriptive analytics will result in 0.245 unit increase in reliability of the supply chain performance while $\beta_2 = 1.350$ implies that an increase in diagnostic analytics by one unit will cause an increase in SC reliability by 1.350 units. On the other hand, $\beta_3 = 0.554$ means that an increase in predictive analytics by one unit will cause a change in the reliability of SC by 0.554 units and lastly $\beta_4 = 0.976$ implies that any unit increase in prescriptive analytics will bring about a relate increase in 0.976 unit in the reliability of SC

4.4.2 Model Summary on Reliability

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.497[a]	0.247	0.158	1.323

a. Dependent Variable: Reliability
b. Predictors: Diagnostic Analytics, Descriptive Analytics, Prescriptive Analytics, Predictive Analytics

The research findings show in table 4.4.2 that R squared is 0.247 implying that 24.7% variation in reliability of the supply chain can be explained by variations in the predictor variables. There could be other variables that may also explain variations in reliability, these variable(s) comprise the remaining 75.3% of the unexplained variation in the model.

Table 4.4.3 ANOVA Table on Reliability

ANOVA[a]					
Model	**Sum of Squares**	**Df**	**Mean Square**	**F**	**p-value**
Regression	19.528	4	4.882	2.787	.042[b]
Residual	59.549	34	1.751		
Total	79.077	38			

a. Dependent Variable: Reliability

b. Predictors: Diagnostic Analytics, Descriptive Analytics, Prescriptive Analytics, Predictive Analytics

Table 4.4.3 gives results of whether the model was a good fit. As indicated in the table, the independent variables are good predictors of reliability as a performance attribute of supply chain. This is evidenced by p-value 0.042<0.05 and an F-calculated (2.787) greater than F-critical value (2.668) thus the overall model is statistically significant at 95% confidence level.

4.5 Effect of BDA with Agility as a Measure of SCP

The second objective of the study was to determine the effects of implementation of BDA on agility as a supply chain performance measure in NFPs in Kenya. The study used multiple regression on all the supply chain performance measures. The results on agility are as indicated in table 4.5.1below:

Table 4.5.1. Regression Coefficients on Agility

Coefficients[a]					
Model	Unstandardized Coefficients		Standardized Coefficients	Z Value	Sig.
	B	Std. Error	Beta		
(Constant)	1.413	1.899		0.744	0.462
Descriptive analytics	1.187	0.603	0.361	1.969	0.057
Diagnostic analytics	1.524	1.008	0.433	1.511	0.140
Predictive analytics	0.766	0.677	0.315	1.131	0.266
Prescriptive analytics	0.446	0.660	0.156	0.675	0.504

a. Dependent Variable: Agility
b. Predictors: Diagnostic Analytics, Descriptive Analytics, Prescriptive Analytics, Predictive Analytics

$$Y=1.413+1.187X_1+1.524X_2+0.766X_3+0.446X_4$$

The study established that there is a positive but statistically insignificant relationship between diagnostic analytics (t=1.511. p=0.14), predictive analytics (t=1.131, p=0.266), prescriptive analytics (t=0.675. p=0.504) and agility. The three predictor variables produced values (t<1.96, p>0.05). However, descriptive analytics produces statistically significant values (t=1.967, p=0.057) at least at 94% confidence level. From the model above, the constant 1.413

indicates that when all variables are zero-rated, agility will still perform at 1.13 units; β_1 = 1.187 implies that a unit increase in descriptive analytics will cause a related increase in agility of the SC by 1.187 units. The coefficient values β_2 means that an increase in diagnostics analytics by one unit will result in increase in agility of the SC by 1.524 units while the same unit increase in predictive analytics would cause a change in agility by 0.766 units. Finally, varying predictive analytics by one additional unit will bring about a positive change in SC agility by 0.446 units.

Table 4.5.2 Model Summary on Agility

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.526[a]	0.277	0.191	1.904

a. Dependent Variable: Agility
b. Predictors: Diagnostic Analytics, Descriptive Analytics, Prescriptive Analytics, Predictive Analytics

The research findings show in table 4.5.2 that R squared is 0.277 implying that 27.7% variation in agility of the supply chain can be explained by variations in the predictor variables. There could be other variables that may also explain variations in reliability, these variable(s) comprise the remaining 72.3% of the unexplained variation in the model.

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Table 4.5.3 ANOVA Table on Agility

ANOVA					
Model	**Sum of Squares**	**Df**	**Mean Square**	**F**	**Sig.**
Regression	47.106	4	11.776	3.249	.023[b]
Residual	123.253	34	3.625		
Total	170.359	38			

a. Dependent Variable: Agility
b. Predictors: Diagnostic Analytics, Descriptive Analytics, Prescriptive Analytics, Predictive Analytics

Table 4.5.2 gives results of whether the model was a good fit. As indicated in the table, the independent variables are good predictors of the reliability as a performance attribute of supply chain. This is evidenced by p-value 0.023<0.05 and an F-calculated (3.249) greater than F-critical value (2.668) thus the overall model is statistically significant at 95% confidence level.

4.6 Effect of BDA with Cost as a measure of SCP

The second objective of the study was to determine the effect of implementation of BDA on cost as operational performance measure in NFPs in Kenya. The study used multiple regression on all the operational performance measures. The results on reliability are as indicated in table 4.6.1 below:

Table 4.6.1 Regression Coefficients on Cost

Coefficients[a]					
Model	Unstandardized Coefficients		Standardized Coefficients	Z Value	Sig.
	B	Std. Error	Beta		
(Constant)	0.355	2.312		0.154	0.879
Descriptive analytics	0.432	0.734	0.118	0.589	0.560
Diagnostic analytics	1.809	1.228	0.460	1.473	0.150
Predictive analytics	0.372	0.824	0.137	0.451	0.655
Prescriptive analytics	0.831	0.804	0.260	1.034	0.308

a. Dependent Variable: Cost

b. Predictors: Diagnostic Analytics, Descriptive Analytics, Prescriptive Analytics, Predictive Analytics

$$Y=0.355+0.432X_1+1.809X_2+0.372X_3+0.831X_4$$

As exhibited in table 4.6.1, all the four predictor variables were analyzed against cost as a measure of SCP and returned values showing a positive relationship with cost though they were all statistically insignificant as follows: descriptive analytics (t=0.589, p=0.560), diagnostic analytics (t=1.473, p=0.15), predictive analytics (t=0.451, p=0.655) and prescriptive analytics (t=1.034, p= 0.308) all of which fail to satisfy the criteria ($t \geq 1.96$, $p \leq 0.05$). From the model above, the constant 0.355 means that even if all independent variables are equated to zero, the cost reduction in supply chain will be at 0.355 units. $\beta_1 = 0.432$ indicates that a unit increase in descriptive analytics will cause a resultant cost reduction in supply chain by 0.432 units while $\beta_2 = 1.809$ implies that if diagnostic analytics is increased by on unit, cost reduction in supply chain will change by 1.809 unit. Unit increase in each of predictive analytics and prescriptive analytics will cause a change in cost reduction of supply chain by 0.372 ($\beta_3 = 0.372$) and 0.831($\beta_4 = 0.831$) respectively.

Table 4.6.2 Model Summary on Cost

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.376[a]	0.142	0.041	2.31753

a. Dependent Variable: Cost
b. Predictors: Diagnostic Analytics, Descriptive Analytics, Prescriptive Analytics, Predictive Analytics

The research findings show in table 4.6.2 that R squared is 0.142 implying that 14.2% variation in agility of the supply chain can be explained by variations in the predictor variables. There could be other variables that may also explain variations in reliability, these variable(s) comprise the remaining 85.8% of the unexplained variation in the model

Table 4.6.3 ANOVA Table on Cost

ANOVA[a]					
Model	Sum of Squares	Df	Mean Square	F	Sig.
Regression	30.156	4	7.539	1.404	.254[b]
Residual	182.613	34	5.371		
Total	212.769	38			

a. Dependent Variable: Cost
b. Predictors: Diagnostic Analytics, Descriptive Analytics, Prescriptive Analytics, Predictive Analytics

Table 4.6.3 gives results of whether the model was a good fit. As indicated in the table, the independent variables are not good predictors of the cost of running the supply chain. This is evidenced by p-value 0.254>0.05 and an F-calculated (1.404) less than F-critical value (2.668) thus the overall model is statistically insignificant at 95% confidence level.

4.6.1 Discussion

The second objective of the study was to establish the effect of BDA on supply chain performance in NFP's in Kenya. The study used multiple regression analysis to analyze the effects of the various BDA approaches on supply chain performance in NFPs in Kenya. The multiple regression analysis established that 24.7% of reliability, 27.2% of agility, 14.2% of cost as supply chain performance indicators were affected by implementation of BDA in NFP's in Kenya. This is an indication that, though the NFPs have adopted BDA to moderate to great extent, the practice is yet to significantly impact on the supply chain performance. The models used on reliability and agility were statistically significant at 95% confidence level but was statistically insignificant for the cost as a performance attribute of supply chain.

The findings are consistent with the study carried out by Gunasekaran et al (2017) on BDPA for SCP and OP of technology and e-commerce companies among others located in India and found out that indeed BDA influences SCP to a low extent. Contrary to the finding, a study by Huisman (2018) across the retail sector in Netherland concluded that descriptive, predictive and prescriptive have an impact on SCM and business performance to a great extent.

4.7 Challenges faced in Implementation of BDA in NFPs in Kenya

Table 4.7 represent the results of challenges faced by NFPs in implementation of BDA.

Table 4.7 Challenges faced by NFPs in Implementation of BDA

Descriptive Statistics		
Challenges	**Mean**	**Std. Deviation**
Time consuming	2.56	1.094
Lack of top management support	2.50	1.155
Limited resources	2.31	0.704
Data security and privacy	2.31	1.302
Unclear benefits and ambiguity on return on investment	2.25	0.775
Data scalability (inadequate storage capacity)	2.19	0.834
Poor quality of data	2.0	1.033
Lack of data handling procedures	1.94	1.063
Lack of expertise among staff	1.94	0.929

Source: Research Data (2020)

The research found out that challenges were faced by NFPs to a moderate extent. The most faced challenge is time consuming nature of BDA (M=2.56) followed by lack of commitment and support by top management (M=2.5). Unclear benefits and ambiguity on return on investment, inadequate storage capacity and poor quality of data indicated means of 2.25, 2.19 and 2.0 respectively. Lack of resources and data security both followed (M=2.31) while the least challenges faced were lack of expertise among staff and data handling procedures both at M=1.94.

4.7.1 Discussion

The third objective was to ascertain the hurdles face by NFPs in the adoption of BDA Kenya and the findings indicate that NFP's in Kenya to a moderate extent face a number of challenges in the implementation of BDA like lack of tom management commitment, poor data quality, and inadequate storage capacity among others.

Organizations face barriers and challenges in implementing BDA which can either be internal or external to the organization. The finding of this study indicates that high cost associated with implementation of BDA, lack of top management commitment, time consumption and inadequate resources as the major challenges faced by NFPs in Kenya. This is consistent with a study by Blackburn et al (2015) on predictive analytics approach for demand forecasting in the process industry. The researchers found out that adoption of BDA is marred with several challenges such as, time consumption since analytics initiatives involves various stages such as; development stage, testing stage and finally the adapting stage. Moreover, coordinating the activities of experts from divergent and varies mindsets can be a daunting task.

Though this study identifies the time consumption dimension of BDA as the biggest challenge in implementation of the practice other studies such as Dutta & Bose (2015), who posit that cooperation and multifunctional formation of teams among different compeers in an organization has to be the biggest challenge for realization of BDA. Seah, Hsich and Weng, (2010) asserts that Leadership plays a paramount role for actualization of systems in BDA towards the management of supply chain.

CHAPTER FIVE: SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

The section starts with the summary of the study, proceeds to conclusions, recommendations and ends with limitations of the study. One of the objective of the study was to establish the level of BDA implementation in NFP's in Kenya. The other objectives were to investigate the relationship between BDA and SCP of NFP's in Kenya and lastly to determine the challenges faced by NFPs in implementation of BDA.

5.2 Summary

This study focused on BDA and SCP of NFPs in Kenya. The objectives of the study were: to establish the degree to which network facilities providers have adopted BDA in their SC; to find out the relationship between BDA and SCP of network facilities providers in Kenya and lastly to determine the challenges faced by NFPs in the adoption of BDA. The study carried out a census of all 57 network facilities operators in Kenya and used a descriptive cross-sectional research design. Data was collected using web-based google form questionnaires from supply chain managers, procurement managers and operations managers or their equivalents in various NFPs. All the questionnaires were sent through email and WhatsApp to specific managers. A total of 39 responses were received and were deemed fit for analysis. The respondent background information showed that we had more males that females occupying the targeted departments. The respondents had sufficient level of education and had served in the respective companies for substantial amount of time thus were in a good position to provide the data sought by the researcher.

To the extent NFPs have adopted BDA in their supply chain as measured by reliability, agility and cost, findings reveal it is to a moderate to large extent as indicated by means of three and above. This is pointer to the fact that NFPs have accepted and adopted BDA and are leveraging the benefits of its techniques to make supply chain decisions. The second objective sought to examine the relationship that exists between BDA and SCP of these NFPs. Results reveal that there BDA and SCP are positively related as indicated by positive coefficients produced by the studies multiple regression model. From the results, BDA dimensions have the greatest impact on agility (27.7%) followed by reliability (24.7%) and lastly, on cost (14.2%). These results indicate that BDA has little impact on the SCP of NFPs. Though they have adopted BDA to a moderate to large extent, evidence show that it is yet to have meaningful impact on SCP.

5.3 Conclusion

Big data analytics has been adopted by network facilities providers in their supply chain to a moderate extent. Of the different approaches of big data analytics, descriptive analytics has been embraced to a large extent followed by prescriptive and predictive analytic. Diagnostic analytics is the least adopted approach among NFPs. The study further found out that BDA has little impact on the SCP of NFPs. However, agility is the most impacted performance attribute of the supply chain followed by reliability. The study found a BDA impact level of only 14% on the cost of running supply chain operations.

Network facilities providers find big data analytics time consuming as it ranked highest among challenges faced in adoption of big data analytics. Lack of TMC is also a big challenge in the implementation of BDA. Interestingly, network service providers do not find lack of expertise as a challenge as would be argued by some scholars – it ranked least among the challenges.

5.4 Recommendations for Policy and Practice

Network facilities providers need to invest in more powerful computers and technologies so that they can capture, store and process big data analytics faster. This study reveals that time consumption of BDA was the biggest challenge among NFPs which understandably is so since they are generators of huge volumes of data as they form backbone of the entire infrastructure in the country that carries almost all data generated by mobile phones, internet website, radio transmission among other networks.

Lack of senior management commitment has also been cited as a major challenge thus it is incumbent upon them to take BDA seriously in light of the changing competitive business environment and offer leadership towards embracing BDA across various functions in the companies. In so doing, they will thus allocate more resources for upgrading of requisite BDA technologies. The results reveal that BDA's impact is not adequately felt in supply chain management, therefore, top management should deliberately channel focus and resources supply chain analytics and strive to make supply chain decisions as aided by insights from big data analytics.

5.5 Limitations of the Study

Despite the insights revealed by this study, some limitations exist: simplistic multiple regression model was adopted to establish the relationship between BDA and SCP yet there are other variables that exist which affect this relationship and ought to be included in the analysis. Likewise, the model assumed that the relationship between BDA and SCP in linear, which may not be the case. The model cannot reveal causation of the effects of BDA.Additionally, this study used a survey approach. Though it is a sound methodological approach, it may limit the extent of insights unveiled.

5.6 Suggestions for Further Research

Future research should considered in BDA with additional variable such as top management commitment and resources as mediating, mediated or intervening variables as part of the analysis model. This would be an improvement of this model and would have a stronger explanatory power. Top management commitment comes out as a major challenge in this study and it therefore need to be explored further in light of the role of institutional pressure towards enhancing a firms BDA. For such an approach, the institutional theory may play a key role. To establish deeper insights on the relationship between BDA and SCP, future research may be done using a mixed method approach, for example, using both a survey and semi-structure

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APPENDICES

Appendix I: Research Questionnaire

This questionnaire intends to gather data on the influence of big data analytics on the performance of supply chain of network facilities providers in Kenya. Kindly fill in the questionnaire. The purpose of this survey is strictly academics and any information availed shall be treated with the highest level confidentiality. You shall remain anonymous as far as your identity is concerned.

PART 1: GENERAL INFORMATION

1. What is your gender?

Male ☐ Female ☐

2. What is your highest level of education?

☐ O-Level ☐ A-Level

☐ College Level ☐ Graduate Level

☐ Post Graduate Level ☐ Any other (Specify) …………………..

3. How long have you been in this position?

☐ Less than 1 year ☐ 1 - 5 years

☐ 6 – 10 years ☐ Above 10 years

PART II: BIG DATA ANALYTICS ADOPTION

To what extent has your firm implemented the following Big Data* Analytics approaches? Tick as appropriate using the following Likert scale of 1-5 where: 1= Not at all; 2= Little Extent; 3= Moderate Extent; 4= Great Extent; 5=Very Great Extent

big data is all the data – whether or not categorized (eg sms-in activity, sms-out activity, call-in activity, call-out activity, internet traffic activity, social media activity, images, mobile money transactions, competitor pricing, customer locations, web logs, blogs & news etc) – present in your servers

	BIG DATA ANALYTICS	Respondents Rating				
		1	2	3	4	5
	Descriptive Analytics					
7.	My organization uses big data* to establish that products and service have reached customers on-time, in the right quality and right quantity					
8.	My organization uses big data* to monitor changes in the market place					
9.	Insight from big data* are used to quantify supply chain running costs (eg labour cost, material costs, transportation cost)					
	Diagnostic Analytics					
10.	Big data* is used by my organization to establish causes of any anomalies in the timely and quality delivery of products and services					
11.	Insights from big data* are used to establish the reasons for changes in the market place					
12.	Big data* analytics is used to detect reasons for negative variances of supply chain expenses (eg labour cost, material costs, transportation cost)					
	Predictive Analytics					
13.	Big data* helps my organization to determine when customers will need a product or service, in which quantity and of what quality					
14.	Big data* facilitates my organization to predict trends and changes in the marketplace					
15.	Insights from big data* helps my organization to forecast supply chain running costs (eg labour cost, material costs, transportation cost)					
	Prescriptive Analytics					
16.	Big data* helps my organization to determine the best way to deliver goods and services on time, in right quantity and right quality					
17.	Big data* insights guides the organization's response					

	to the changes in the market place					
18.	Big data* analytics leads my organization to determine the ideal costs of running supply chain (eg labour cost, material costs, transportation cost)					

PART III: SUPPLY CHAIN PERFORMANCE

To what extent has big data* adoption affected the following measures of supply chain performance? : Kindly indicate on a scale of negative ten (-10) to positive ten (10) where -10= totally deteriorated and +10 =totally improved it

	SUPPLY CHAIN PERFORMANCE INDICATOR	RATING
19.	Perfect order fulfilment	
20.	Capacity to respond to external changes in the market place to maintain or increase supply chain competitive advantage.	
21.	Ability to keep cost incurred in managing supply chain processes at minimum.	

PART IV: CHALLENGES OF BIG DATA ANALYTICS ADOPTION

To what extent does your organization face the following challenges when implementing big data* analytics? Tick as appropriate using the following Likert scale of 1-5 where: 1= Not at all; 2= Little Extent; 3= Moderate Extent; 4= Large Extent; 5=Very Large Extent

	CHALLENGES OF BIG DATA ANALYTICS ADOPTION	Respondents Rating				
		1	**2**	**3**	**4**	**5**
22.	Time consuming					
23.	Lack of expertise among staff					
24.	Limited resources					
25.	Data security and privacy					
26.	Lack of data handling procedures					
27.	Poor quality of data					
28.	Behavioral issues					
29.	Data scalability (inadequate storage capacity)					
30.	Lack of top management support					
31.	Unclear benefits and ambiguity on return on investment					

THANK YOU FOR PARTICIPATING IN THIS STUDY!

Appendix II: List of Network Facilities Providers in Kenya

	Licencee Name	Telephone Number(s)
1	AIRTEL NETWORKS KENYA LIMITED	+254734110019/+254734110000
2	SAFARICOM LIMITED	+254722003272/+254722005188/
3	TELKOM KENYA LIMITED	+25420 4952460/+25420343399
4	ALAN DICK & COMPANY (EAST AFRICA) LIMITED	+254722570112/+254203742821/+25420 3742821
5	BANDWIDTH AND CLOUD SERVICES GROUP LIMITED	+254202667249/+254702273535/+25471 1405460
6	BELL WESTERN LIMITED	4440169/+254722526777/
7	COMMCARRIER SATELLITE SERVICES LIMITED	+25420331739/+25420331741/+2547222 04567
8	FOURTH GENERATION NETWORKS LIMITED	+254203258252/+254203258000/+25472 2720720
9	FRONTIER OPTICAL NETWORKS LIMITED	+254728906769/+254203742859/+25473 6791003
10	GEO-NET COMMUNICATIONS LIMITED	+254716023785/+254722418148/202468 18
11	HARUN INTERNATIONAL LIMITED	2226327/3311183/
12	INTERNET SOLUTIONS KENYA LIMITED	+254203600405/+254733837356/+25472 2898867
13	IWAY AFRICA KENYA LIMITED	+254713601117/2972000/
14	JAMII TELECOMMUNICATIONS LIMITED	+254711054121/+254711054100/+25420 3975000
15	KENYA EDUCATION NETWORK	+254732150500/+254703044500/
16	KENYA ELECTRICITY TRANSMISSION COMPANY LIMITED	+254719018000/+254719189797/+25473 2128000
17	KENYA PIPELINE COMPANY LIMITED	+254722207678/+254202606500/
18	KENYA TOWERS LIMITED	+254178486174/+254178486174/
19	LIQUID TELECOMMUNICATIONS KENYA LIMITED	+254732199000/+254731091705/+25420 5000000

20	MOBILE TELEPHONE NETWORKS BUSINESS (K) LIMITED	+254207600001/+2542076000330/+254724739502
21	SEA SUBMARINE COMMUNICATIONS LIMITED	+254205133100/+27761220131/+254722540643
22	SIMBANET COM. KENYA LIMITED	+254734701501/+254202804030/+25420828758
23	THE KENYA POWER AND LIGHTING COMPANY LIMITED	+254732170170/+254703070707/
24	VODACOM BUSINESS (KENYA) LIMITED	+254202714815/+254716025745/+441133606060
25	WANANCHI GROUP KENYA LIMITED	+254719028777/+254732132777/+254787610195
26	WANANCHI TELECOM LIMITED	+25420 2804030/+254734701501/
27	WIAFRICA KENYA LIMITED	+254722748081/+254770640077/+254736044359
28	ABLE WIRELESS COMPANY LIMITED	+254202453048/+254735460073/
29	AMAZI GROUP LIMITED	+254722513656
30	AZANURU TECHNOLOGIES LIMITED	+254739839381/+254733272621/+254710656958
31	BALOZI DISTRIBUTED ANTENNAE SYSTEM LIMITED	+254202899000
32	BOMA WIRELESS COMPANY LIMITED	+254701439410/+254774075782/
33	CABLE ONE LIMITED	230657
34	COOLIGHT TECHNOLOGIES AFRICA LIMITED	+254722700980
35	DR. WIRELESS LIMITED	+254787524179/+254205236801/
36	EMBARQ LIMITED	+254202619800/+254725001010/+254735001010
37	EMERGING MARKETS COMMUNICATIONS (K) LIMITED	+254202733233/+254722207203/+254722207249
38	EQUATOR DATANET KENYA LIMITED	+254722297244
39	FIBERLINK LIMITED	+254725475364/+254202000500/+25420

		2000501
40	HIRANI TELECOMMUNICATION LIMITED	+254700123007
41	HORYAL SERVICES LIMITED	+254722382015
42	ICON WIRELESS LIMITED	+254727488003
43	INDUSTRIAL TECHNOLOGY TRADING COMPANY LIMITED	44400011
44	INTELLECT GROUP LIMITED	+254720552222/+254713039943/+254204442010
45	KLASS IMAGE LIMITED	+254722553992
46	MASABA SERVICES LIMITED	+254722701903
47	MY ISP LIMITED	+254789656023/+254203569999/
48	NETWORK INFRASTRUCTURE KENYA LIMITED	+254203258222
49	NEXT THING NETWORKS LIMITED	+254727339186/+254722989001/
50	POA INTERNET KENYA LIMITED	+254731445662/+254722757453/
51	SKY BROADBAND KENYA LIMITED	+254716247332
52	VALLEYPOINT TELECOMS LIMITED	+254202637156/+254789888588
53	BLUE STREAK HORIZONS NET LIMITED	
54	BRAND TECHNOLOGIES	+254726758854
55	CABLE TELEVISION NETWORK (MOMBASA) LIMITED	+254412221594/+254723332842/+254412222057
56	MAWINGU NETWORKS LIMITED	+254705100600/+254720787216/+254712205000
57	SYOKINET SOLUTIONS LIMITED	+254726815478/+254722603473/+254776370355

Source: CA (2018)