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ADOPTION OF BIG DATA ANALYTICS TO DRIVE DECISION MAKING

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DECLARATION

This research project is my original work and has not been presented to any other university for the award of a degree.

Signed ________________________________ Date ________________________________

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This research project has been submitted for examination towards fulfilment for the award of Master of Science in Information Technology Management with my approval as the university supervisor.

Signed ________________________________ Date ________________________________
Mr. Christopher A. Moturi

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ABSTRACT

The current business environment has been experiencing rapid change brought about by high intensity of competition, disruptive technologies, creativity, innovations and strategic marketing. To sustain competitiveness in the current uncertain environment, organization need to make accurate decisions regarding their market, operations and investment. This can be achieved by having evidence-based decision making approaches. Global companies have adopted big data analytics to facilitate evidence decision making. This 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. To accomplish the objectives of the study, a descriptive research design was employed by the study. The data was collected from telecoms, telecommunication service providers, Information Communication Technology companies and service providers. A major institute of higher learning was also part of the sample due to its rich ICT bias and presence of ICT innovation hub. Semi structured questionnaires were used. Data analysis was done using Statistical Package for the Social Sciences (SPSS) and presented using tables, charts and percentages. Multiple linear regression was applied to find out the significance of each variable towards adoption of big data analytics to drive decision making. The study found that big data analytics had been adopted to a great extent by this companies. Organizations used business intelligence, big data as well as predictive analytics in their operations. The adoption of big data analytics was influenced by technological, organizational and environmental 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 the adoption of big data analytics. 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. The limitation of the study was that data was mostly collected using online questionnaires hence people’s emotions and expressions could not be captured, however this was the most efficient way to reach a great number of respondents. It was recommended that the legal framework be made adequate to enable more organizations to adopt this technology, organizations also need to train their employees to acquire skills in big data analytics as well as establish networks with data driven companies.

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LIST OF ABBREVIATIONS

BDA-	Big Data Analytics
BI-	Business Intelligence
CSP-	Communications Service Providers
DOI-	Diffusion of Innovation
IoT-	Internet of things
ICT-	Information communications technologies
SPSS-	Statistical Package for the Social Sciences
TOE-	Technology, Organization, and Environment

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DEFINITION OF TERMS

Big Data: Extremely large data sets that may be analyzed computationally to reveal patterns, trends, and associations, especially relating to human behavior and interactions.

Big data analytics: Big data analytics is the process of examining large and varied data sets -- i.e., big data -- to uncover hidden patterns, unknown correlations, market trends, customer preferences and other useful information that can help organizations make more-informed business decisions.

Telecommunication: the transmission of signs, signals, messages, words, writings, images and sounds or information of any nature by wire, radio, optical or electromagnetic systems. Telecommunication occurs when the exchange of information between communication participants includes the use of technology.

Service Providers: A third party or outsourced supplier, including telecommunications service providers (TSPs), application service providers(ASPs), storage service providers (SSPs), and internet service providers (ISPs).

CHAPTER ONE
INTRODUCTION

1.1 Background

Big data as a term was introduced the very first time to the computing domain by Roger Magoulas from O'Reilly media in 2005 describing a large set of data which cannot be managed and processed by the old data management techniques because of its complexity and size (Ularu *et al*., 2012).

Big data exhibits four major characteristics namely; volume, velocity, variety and value. Volume is the huge quantity of data while velocity refers to the mobility of data streams, on the other hand variety denotes the relational and non-relational data obtained using different ways; for example when mobile networks are considered we obtain real time data. Value is the worth of the significance of big data applications, it has a scarceness value, uncertainty value and diversity (Mo & Li, 2015).

Additionally other dimensions of big data are veracity and variability. Veracity characterizes the unreliability of certain data sources. For example a person's sentiments on social media are ambiguous as they involve human conclusions(Gandomi & Haider, 2015).Variability on the other hand is the deviation in the data flow rates (Gandomi & Haider, 2015).

From Accenture Analytics a global analytics firm, big data is evidently delivering important value to users (Accenture, 2014). Bigger companies are more likely compared to others to regard big data as exceedingly significant and crucial to their digital strategy. (Accenture, 2014).Web data, purchase transactions records, social media data, click stream data, cell phone GPS signals and sensor data are major sources of Big Data (Singh *et al*., 2015).

Owing to their networks and the multiplying of smart devices, communications service providers (CSPs) have access to a lot of information about their customer's preferences, movements and behaviors. Big data is an extremely valuable asset for these companies. It places them in a key place to gain more customers and build new revenue streams opportunity (IBM, 2013).

Big data provides a cost effective vision to foster enrichment in making decisions in very key fields including healthcare, financial productivity and security (Hilbert, 2016).

In developing countries however, the limitations are privacy fears and the scarcity of human resource, deepened by extended structural shortages in infrastructure, economic resources and institutions (Hilbert, 2016).

Big data is beneficial when used to steer decision making otherwise if left in a vacuum it is worthless. Organizations therefore require effective procedures to change high volume of fast-moving and diverse data into important insight (Gandomi & Haider, 2015).

To see to it that this happens organizations need to apply both data management and data analytics. Here data management refers to the process and the technologies used to acquire, store and prepare data for analysis. On the other hand Analytics involves analyzing and acquiring intelligence from the big data. Analytics also unearths unseen trends, unknown relationships, marketplace tendencies, consumer likings and other valuable business insights, which leads to effective marketing, fresh opportunities for income, enhanced customer service, enriched working efficiency as well as competitive advantages among other benefits (Gandomi & Haider, 2015). Big Data analytics expects to understand what transpired, why it transpired and predict future happenings (Ularu *et al*., 2012).

McKinsey & Company an international consulting agency researched on how value was created by big data. A thorough research was carried out on different sectors as the U.S. healthcare, the EU public sector administration, U.S. retail, global manufacturing, and the global personal location data. The findings from the research were that big data could stimulate the economic role, advance the productivity as well as the competitiveness of enterprises as well as public sectors, and generate enormous benefits for customers. Creative and effective use of big data would result in improved efficiency and quality (Chen *et al*., 2014).

1.2 Problem Statement

Big data analytics has enabled the possibility to generate value from volumes of raw data allowing organizations to pursue incredible insights for effective decision making and quality of service. Organizations are however hesitant to adopt big data solutions due to several barriers including data storing and transmission, data scalability, quality of data, its complexity, appropriateness, how secure, how private, how much it can be trusted, data ownership, as well as transparency (Brohi *et al*., 2016)

The potential of data-driven decision making is currently being accepted globally, a lot of interest is being generated for the concept of big data. "Though the potential of big data is real there is presently a big gap between its potential and its realization" (Agrawal *et al*, 2012).This research seeks to assess the adoption of big data analytics for data driven decision making in telecoms, telecommunication service providers, Information Communication Technology companies and service providers as well as a major institute of higher learning in Kenya.

1.3 Objectives

To assess the adoption of Big Data Analytics for data driven decision making.

1. Identify to what extent telecoms and telecommunications service providers in Kenya have adopted big data analytics to drive decision making.
2. Identify the factors that influence the adoption of big data Analytics for data driven decision making.
3. Establish the suitability of the framework used to explore the adoption of Big Data Analytics for data driven decision making.

1.4 Significance of the study

Big data analytics and Business intelligence (BI) are becoming very important in both the academic as well as the commercial communities (Chen *et al.*, 2012).

This study is significant to all organizations that would like to do evidence based or data driven decision making, this includes telecom companies, banking sector, health sector, security, government and academia.

The study will help the organizations become familiar with issues that influence the adoption of big data analytics and help this organizations make informed decisions while adopting this technology.

1.5 Assumptions and limitations

The study was limited to telecoms, telecommunication service providers, Information Communication Technology companies and service providers and a major institute of higher learning. It was assumed that the companies chosen for the research would be willing to divulge information for the purpose of the research. The companies were only willing to divulge their information with proof that the information was used for research purposes only. A formal request was done to the to the HR department of the companies of study.

It was also assumed that the organizations studied had a similar organizational structure of which to a great extent was the case. Another assumption was that the data collected and analyzed could be used to rate the extent to which companies had adopted big data analytics to drive decision making.

CHAPTER TWO
LITERATURE REVIEW

2.1 Fundamentals of Big Data Analytics

With the speedy growth of data worldwide big data describes huge datasets. Chen *et al* (2012) introduced the background of big data and reviewed the different associated technologies which included cloud computing, internet of things, data centers as well as Hadoop. Their focus was on the value chain of big data which was data generation, acquisition of data, the storage of data as well as data analysis. Several representative applications of big data were examined and they included internet of things, enterprise management, medical applications, online social networks as well as smart grid.

The important issues of big data were identified as great need for a rigorous as well as full definition of big data, an operational model of big data, an official description of big data, as well as a theoretic system of data science. The discussions at the time were more of speculations than scientific research due to the fact that big data had not been officially and structurally defined and the existing models had not been strictly verified.

The paper concluded that with the arrival of internet of things, growth of mobile sensing technology, and development of data acquisition technology, persons became not only the users and the consumers of big data, but also became the creators and contributors as well. Peoples actions based on big data would be progressively concerned and surely cause huge changes of social activities within the future society.

2.2 Adoption of Big data Analytics

Gandomi & Haider (2015) highlighted the necessity of creating suitable as well as efficient analytical approaches to leverage enormous volumes of varied data which may be in unstructured text, in audio, as well as in video formats. The research paper supports the need to come up with new instruments to do predictive analytics for structured big data as well.

Micheni (2015) did a thorough study of the adoption of big data as a technological innovation, and also the adoption matters for big data, big data availability as well as its access. This research presented a literature review of academic literature, policy documents from international agencies as well as reports from industries, to enable the assessment of the diffusion as well as the adoption of big data innovation in developing countries. Google Scholar search was used for appropriate literature as well as the combinations of key words to obtain information on big data, analytics, developing countries, as well as diffusion of Innovations.

The research offered a theoretical framework for Innovations Diffusions in the study of Big Data innovation adoption in developing countries. In conclusion the study saw that Diffusion of innovations (DOI) could significantly speed up the adoption and use of Big Data. The research cited challenges faced by developing countries which limited the capability as well as the effective utilization of these technologies.

The study also concluded that the diffusion theory notions provided an effective machinery for policy leaders within developing countries to be able to maximize adoption of Big Data innovations, as well as inform policy implementers on ways of increasing the rates of Big Data adoption.

GalbRaith, (2014) research looked at firms that were at the leading edge and were taking advantage of the phenomenon of big data to develop big data analytics capabilities.

To GalbRaith, (2014) organizations that were enjoying the most success at the time were had used big data to progress their current business endeavors as well as come up with new opportunities. To put strategic importance on big data it requires the addition of digital capabilities to the present firm which include analytics. The change process brings about a shift in power to analytics experts as well as real or actual time decision making.

GalbRaith, (2014) discusses the issues that come with a shift of power as well as real-time decision making, and then describes how Nike Shoe Company came up with a digital sports division to take advantage of big data to build a completely new income stream. He then uses the Star Model™ framework to assess the impact of big data to an organizations design.

In this research challenges of big data are examined not only in the technical aspect but also in the organizational aspect and the need for shifting power from experienced and critical decision makers to data driven decision makers. For success, the organization requires to perform a shift in power to data specialists who create fresh perceptions from big data (GalbRaith, J. R., 2014). Resistance to big data will either be competence-enhancing or competence-destroying. GalbRaith, (2014), cited Procter & Gamble as using big data to enhance its competence. The firm P&G has employed data analytics since 1992, and tries all things that may increase its understanding of customer behavior. P&G therefore adopted the use of big data before most of the other firms.

The person who drives the big data initiatives is the CIO (Chief ICT Officer) and is supported by the CEO there is also a shift in hiring as more data scientists are hired.

P&G and Google have also exchanged worker where Google learns marketing and P&G benefits from Google's digital acumen.

With a real case study of P&G and Nike shoe Company. GalbRaith,(2014) has gone to show that top management support and especially from both CIO and CEO is an enabler of big data analytics adoption. Top management support also leads to employee empowerment and recruiting of the right resources. The study also shows that early adoption of big analytics gives the company competitive advantage.

2.3 Strategic use of big data to support decision making

Ndambo (2016) focused on big data as well as competitive advantage in insurance companies as well as banks in Nairobi, Kenya. He sort to establish the extent to which big data analytics was being used in this fields, determine the association of big data analytics and competitive advantage and also establish the challenges of big data analytics in commercial Banks and insurance companies in Nairobi.

A descriptive survey was employed for the purpose of data collection and it targeted commercial banks and insurance companies in Nairobi, Kenya. Out of the 42 Commercial banks and 49 insurance companies in Nairobi, a sample of 20 Commercial banks and 25 insurance companies were undertaken. The assumption was that the companies' used big data analytics. Data collection was done through structured questionnaires after which it was analyzed using percentages, frequencies, mean, as well as standard deviation and regression techniques. Findings were that companies in the financial industry specifically commercial banks and insurance firms had invested in data storage facilities and advanced tools in the area of business intelligence for reporting and analyzing consumer/ client behavior. These allowed the companies to anticipate consumer needs more effectively, in addition to optimizing their operations.

The challenges cited in the adoption of the technology were the issue of the volume of data and getting the right tool to analyze which would involve initial capital, there was also the challenge of not having trained personnel, data interpretation as well as the timeliness of the analysis.

Mogire *et al*., (2015) set out to research on big data and looked at the areas of its tactical use, predictive analytics, visual challenges, security challenges and paralysis by analysis. Research methodology was a literature review of different journals.

The review shows that organizations can benefit greatly from analyzing consumer data to be able to determine their inclinations thus improving marketing decision support.

The review saw the use of big data analytics in different aspects including; customer satisfaction, customer journey, supply chain risks, competitive advantage, pricing, discovery and experimenting, analytics in

The findings were that it was necessary to use the available data as well as technologies so as to come up with the new era of business applications that merge data driven methods and domain specific knowledge.

Ularu *et al.*, (2012) established that 100 Terabytes of data were updated daily via Facebook as well as a lot of other activities on social to this effect they estimated that a value of 35 Zettabytes of data would be generated yearly by the year 2020.

Today organizations have realized the significance of using more of data to enhance making of decisions for company strategies. This research intended to describe the notion of big data stressing the significance of its analytics, the research also showed how big data analytics would improve decision making in future.

The significance of big data and big data analytics is related with the fact the society we are in is informational and knowledge based. Information has a major role in economic, cultural and political stages. Knowledge on the other had creates a competitive advantage through appreciating the information and predicting the advancement of facts based on data

Each and every organization should look at collecting a lot of its data to back its decisions as well as obtain associations by analyzing data to drive decisions.

IBM views big data as having four aspects of Volume, Velocity, Variety and Veracity.

The significance of big data entails in its capacity to advance efficiency where the data used is large and of different types.

The challenges in big data include; proper analyzing as well as understanding of the big data, technical knowledge of the new technology, need for specialist and privacy and security.

To gain competitive advantage organizations need to take care of all the aspects and also to take keen interest in its own characteristics.

To get more customers and grow income amidst competition in Internet Service Provider (ISP) industry, the parties have to put in a lot of effort to improve their service management. Moturi & Mutungi (2013) explored the characteristics of customer usage as well as their preference by looking at monthly capacity usage and the price of bandwidth using data from an ISP in Kenya and proposed a Business Intelligence Model to assist ISPs develop effective service management strategies.

Ularu *et al* (2012) also looked at the big data analytics software Apache **Hadoop** an open source quickly growing platform used in big data. Hadoop allows distribution of large data sets across clusters of product servers.

The paper gives an understanding of big data concept and its importance it also proposes additional research on benefits of using big data analytics, in particular the software tool Hadoop. Organizational characteristics is key for a company to fully adopt big data analytics and gain competitive advantage.

Agrawal et al. (2012), in a white paper research, indicated that decisions that were earlier made through guess work or very well sort models of reality were now being based on data. Big data analytics dictates most perspectives within the social order together with; mobile facilities, trade manufacturing and financial services in life sciences and physical sciences. The prospects of big data is not only in research but also in education and health.

While the potential is real and significant, technical challenges remain. The research sort to establish the challenges being faced by industries in order to exploit big data.

The research looked at the five stages in the big data pipeline and also looked at the five challenges. The phases considered were; the acquisition and recording of data, extraction of information and cleaning, the integration, aggregation and representation of data, Query processing ,modeling and analysis of data, as well data interpretation.

Agrawal et al. (2012), cited Heterogeneity and incompleteness of data as the major challenges as well as scale, timeliness, privacy and human collaboration.

The conclusion of the research was that by improving the analysis of huge volumes of data there was the likelihood to make speedy steps in many scientific disciplines and improving the lucrativeness as well as success of enterprises.

This research white paper focused more on the technical challenges and did not look at other aspects of organization or environment challenges.

2.1 Technology adoption theories

Different technology adoption theories are used in adoption studies. To date researchers continue using the theories in their studies,theories such as; Technology Acceptance Model (TAM) (Davis 1986, Davis 1989, Davis *et al.* 1989), unified theory of acceptance and use of technology (UTAUT) (Venkatesh *et al.* 2003), theory of planned behavior (TPB) (Ajzen 1985, Ajzen 1991), DOI (Rogers 1995), and the TOE framework (Tornatzky and Fleischer 1990).

The Diffusion of Innovation (DOI) together with the Technology Organization and Environment theory (TOE) adoption theories are used at the firm's level.
The theories TBP,TAM and UTAUT are adoption theories that are used at the individual level.

2.1.1 Technology adoption model at firm level

Oliveira & Martins (2011) did a literature review on technology adoption theories at firm level. The review sort to fill the gap where very few reviews have been done on technology adoption models especially at firm level. The study discussed two known models that is the diffusion of innovation (DOI) theory, and the technology, organization, and environment (TOE) framework.
In DOI the key constructs to organizational innovativeness are; internal characteristics of organizational structure, external characteristics of the organization as well as individual characteristics.
On the other hand the TOE recognizes three aspects of an organizations context that are key for the process it uses to adopt as well as realize a technological innovation. This three aspects are; environmental context, technological context as well as organizational context.
An in-depth evaluation of the TOE framework was made, and studies that had used it as the only theory and the others that had combined it with others were analyzed. Studies were analyzed where TOE was combined with DOI, the institutional theory, as well as Iacovou, Benbasat, and Dexter model.
It was seen that the institutional theory helped in understanding the issues that influenced the adoption of inter-organizational systems (IOSs).The theory suggests that imitative, strong, and normative institutional pressures present in an institutionalized environment could affect the way an organization inclined towards an IT-based inter-organizational system.
The Iacovou, Benbasat, and Dexter model on the other hand analyses the features that influence organizations to adopt IT based innovations with regard to three contexts as external pressure, perceived benefits as well as organizational readiness.
Oliveira & Martins (2011) analyzed the models by looking at the experiential texts, as well as the variance amid dependent variables and independent variables.
In conclusion the study found that a great number of empirical studies came the two theories, DOI and TOE.
TOE had an advantage over DOI as it included the environment context not found in DOI, thus making it superior for intra-firm innovation adoption.

2.1.2 Diffusion of Innovation (DOI)

Rogers (2003) defines the innovation-diffusion process as "an uncertainty reduction process", the suggested attributes of innovations helping to reduce the uncertainty of an innovation include five features this are; complexity, compatibility, relative advantage, observability as well as trialability (Rogers, 2003).

Rogers (2003) highlighted the fact that views of an individual predicted the degree of adoption of a particular innovation.

DOI theory's main dependent construct is Implementation Success or Technology Adoption.

On the other hand the main independent constructs of the theory are; Compatibility of Technology, Complexity of Technology, Relative Advantage or the perceived need for technology.

The view in DOI is that innovation is conversed over certain channels over time and in particular social systems (Rogers 1995).

From the study individuals have varied degrees of readiness to adopt an innovation and also that the population that adopts an innovation have a normal distribution over time (Rogers 1995).

Further segmentation of the normal distribution separates the individuals in five classes of innovativeness as; innovators, early adopters, early majority, late majority, laggards (Rogers 1995).

According to Rogers (1995), "Innovativeness is associated with independent variables as external characteristics of the organization, individual characteristics as well as internal organizational structural characteristics".

Individual characteristics comprises the attitude of the manager or leader towards an innovation or change. Internal Characteristics of organizational structure is concerned with opinions where the level of concentration of power and control for relatively few individuals is called centralization. On the other hand Complexity relates to the level by which members of an organization have great knowledge and expertise in the technological innovation. A formalized organization on the other had is one with a degree to which it insists that its members have to follow certain rules and procedures. Further where the organization has available uncommitted staff to drive innovation is called Organizational slack while the "size" of the organization refers to the sum of employees within the firm.

External characteristics of an organization entails the directness or the openness of the firms systems.

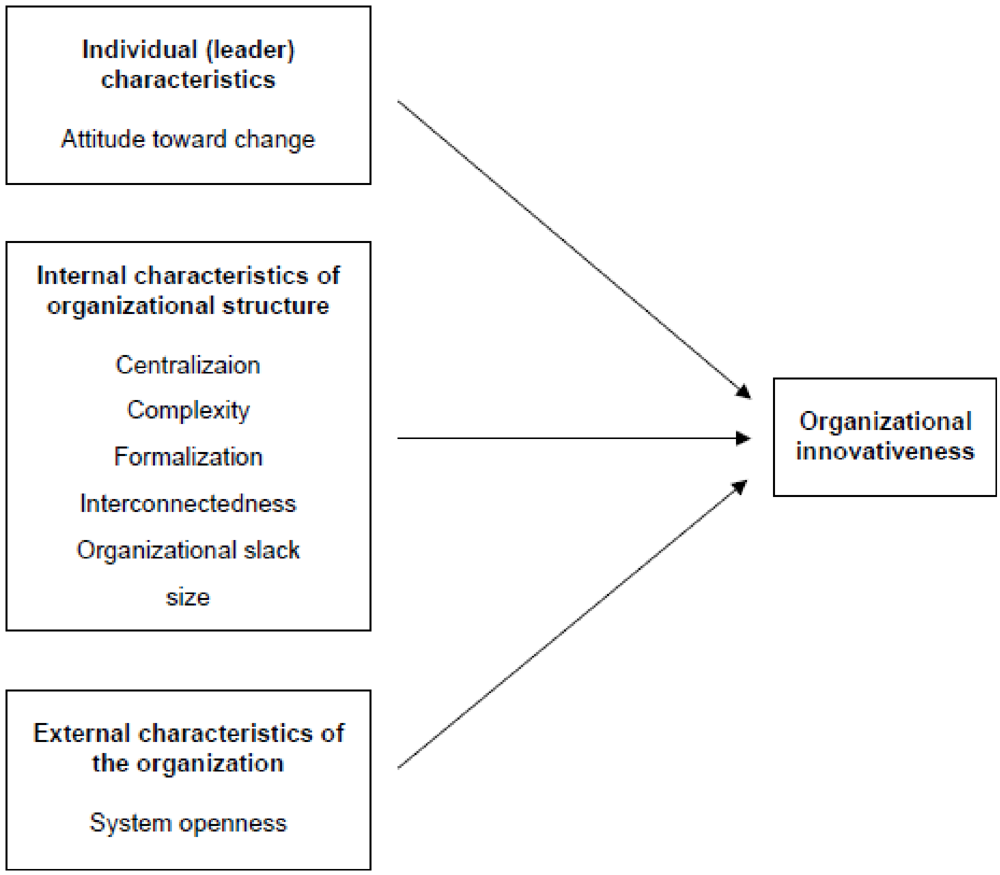

Figure 2.1: Diffusion of innovations (Rogers 1995)

The DOI theory has been modified to suite different research approaches and studies have shown that complexity, compatibility as well as relative advantage (perceived need) are significant precursors to the adoption of innovations (Bradford and Florin, 2003; Crum et. al., 1996).

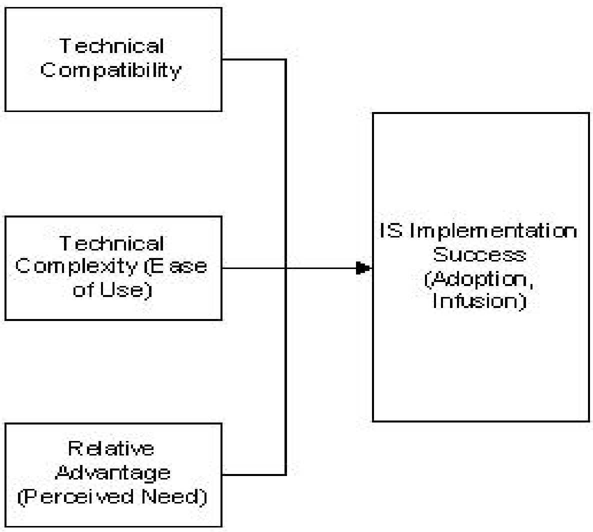

Figure 2.2: IS Diffusion variance model

Sources: Argawal and Prasad (1998) Cooper and Zmud (1990), Crum *et al* (1996)

2.2.3 TOE (Technology, organization, and environment) theory

TOE theory framework established in 1990 (Tornatzky and Fleischer 1990) brings out three contexts of a firm that affect the adoption and implementation of technological innovation within the organization. The three aspects are defined as; technological context, organizational context, and environmental context.

Technological context defines the internal as well as external technologies that apply to the organization. This comprises the present operations as well as the equipment internal to the organization (Starbuck 1976), and also the available technologies external to the organization. (Thompson 1967, Khandwalla 1970, Hage 1980).

Organizational Context on the other hand defines descriptive measures of an organization which includes size, scope, as well as managerial structure.

Environmental context looks at the ground within which an organization performs its operations including competitors and transactions with the government (Tornatzky and Fleischer 1990).

The main dependent variable for TOE theory is Technology Adoption (or Likelihood of Adoption, Intention to Adopt, and Extent of Adoption) (Tornatzky & Fleischer 1990).

Key independent variables of the theory are; Technological Context Organizational Context Environmental Context (Tornatzky & Fleischer 1990).

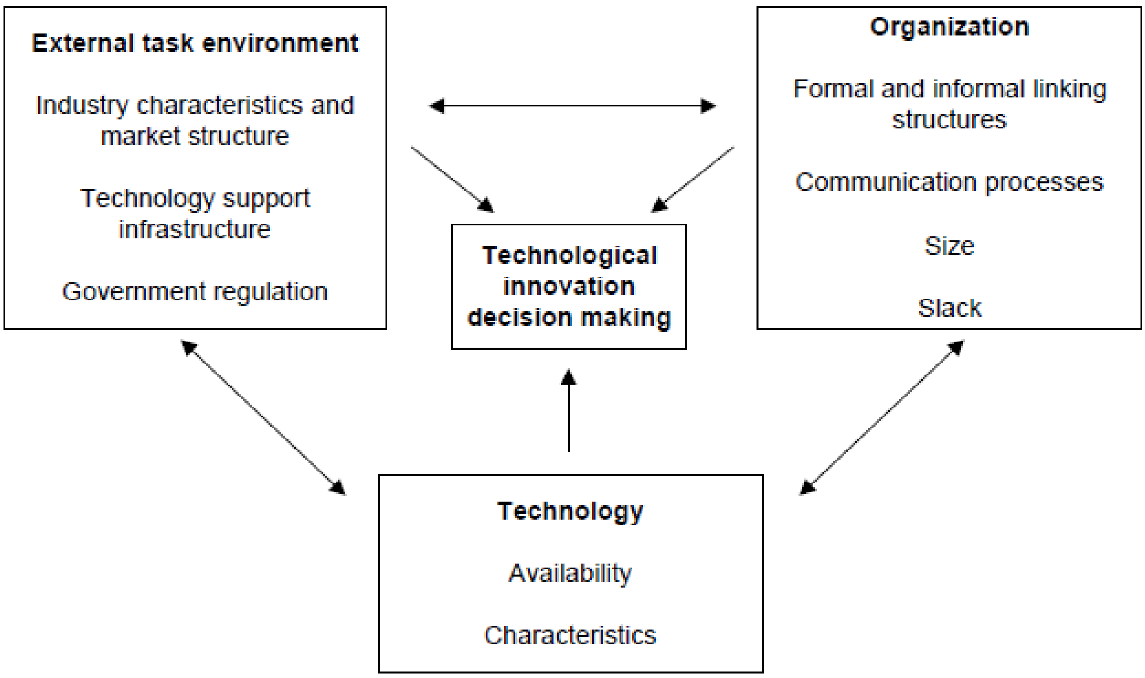

Figure 2.3: Technology, organization, and environment framework (Tornatzky and Fleischer 1990)

Wang *et al.* (2010) merged TOE and DOI frameworks to include variables as; relative advantage, complexity, and compatibility onto TOE framework.

In the research of Hoti, E. (2015) we see the combination of TOE and DOI to come up with the below elements as identified and adjusted by Hoti.

Table 2.1: Identified elements of the TOE framework

Technological	
1. Relative advantage	Degree to which an innovation is perceived as being better than the idea it supersedes
2. Compatibility	Degree to which an innovation is perceived as consistent with existing values, past experiences and adopter needs
3. Complexity	Degree to which an innovation is perceived as relatively difficult to understand and use
Organizational	
1. Top management support	Support of the top management (CEO) to the IS adoption initiative
2. Organizational readiness (size) cost/financial and technical resources)	Comparing to large businesses small businesses face ressource poverty and thus difficulties in innovation adaption. Ressource poverty manifests itself also in financial constraints and lack of professional expertise.
3. Information intensity and product characteristics	Degree to which information is present in the product or service of a business, reflects the level of information intensity of that product or service
4. Managerial time	Time required to plan and implement the new IS.
Environmental	
1. Industry pressure (competition)	Competition and high rivalry increases the likelihood of innovation adaption for the purpose of gaining competitive advantage
2. Government pressure/support	Government strategies or initiatives that encourage SMEs to adopt new IS.
3. Consumer readiness	Lack of customer readiness Influences the adoption process and is an inhibitor towards IS use

Source: Hoti, E. (2015)

2.4 Research Framework

A research framework is the frame or the structure of the study. From Literature review and theoretical review we decided to adopt the Technology-Organization-Environment (TOE) framework as it not only focusses on Technology and Organization but it also focuses on the environment. From the literature review we also noted that the specific elements within the three contexts of TOE were varying across different studies. For example Wang *et al.* (2010) added relative advantage, complexity, and compatibility from DOI to the TOE framework.

Hoti, (2015), also identified specific factor within the three contexts of TOE that are outlined in the literature review. With this background we identified independent variables on the TOE framework to be used for this study.

Technology Context: This refers to both the external and internal technologies that are pertinent to the organization. The independent variables defined here are: Relative Advantage, Technology Compatibility, and Technology Complexity.

Organization Context: Comprises of the structures both Formal and informal, Communication processes, Top management support, Size of the organization and Slack of resources. For the study we identified the below independent variables: Top management support, Size of the Organization

Environment context: The TOE Framework environment context consists of Industry characteristics (including competition) and market structure, Technology support infrastructure and Government regulation.

The identified variables were: Competition intensity, Regulatory requirements

2.5.1 Technology Context

Borgman *et al*, (2013), indicated that for an organization to adopt technology innovations the decisions are influenced by the present technology within the organization as well as the way the innovations suite the said present technologies.

The constructs defined for **technology context** are as below;

Relative Advantage: The level to which an innovation is observed to be superior than the idea it succeeds (Rogers,2003).Continued use of digital communications including use of mobile phone as well as the internet is generating opportunities to use big data in developing countries(Micheni, 2015).

In previous research relative advantage has been positively associated with the adoption of innovative technology **(**Borgman *et al* 2013).

H1.It is hypothesized that perceived relative advantage of big data analytics is positively related to the adoption of big data analytics.

Technology Compatibility: Is the level by which an innovation is thought to be constant with the current standards, previous capabilities and the needs of likely adopters (Rogers 2003).

Micheni(2015) in her research indicates that already we are in the data age and the ways of data generation are increasing undoubtedly, the technologies of analyzing the data are maturing and efforts to use the technologies to solve social problems are setting in.

H2.It is hypothesized that perceived compatibility is positively related to the Adoption of Big data.

Technology complexity: Is the level by which an innovation is thought to be comparatively hard to comprehend and to use (Rogers 2003).Rogers indicated that complexity was a significant hurdle for adoption of an innovation.

Big data presents quite a number of analytical problems owing to its huge size and complex as well as unstructured nature, this challenges demand the continual improvement of tools and expertise (Micheni, 2015).

H3. It is hypothesized that perceived complexity of using and understanding big data analytics is negatively related to the adoption of big data analytics.

2.10.2 Organization Context

Organizational context is the clear indications about the organization including size, scope as well as managerial support (Tornatzky & Fleischer 1990).The constructs defined for our research are:

Top Management Support: In their research Borgman et al, (2013) indicated that the support of senior management in an organization can positively aid the adoption of an innovation by enabling a conducive environment and providing of required resources. Through communicating a convincing dream for big data analytics top management can aid transformation, this can also be achieved through allocation of adequate resource and through facilitating training of the staff to have the technical skills required.

H4. It is hypothesized that top management support is positively associated with the adoption of big data analytics

Size of the Organization: Size of a firm is also significant for the adoption of technology innovations. Larger organizations may have more available resources accessible for use in pilot projects or in larger scale **(**Borgman *et al* 2013).For the adoption of big data large organizations are more likely to adopt as they are more likely to have the resources at hand.

H5. It is hypothesized that the size of the firm is positively related to the adoption of big data analytics.

2.5.3 Environment Context

Environmental context this is the ground for which the organization runs its operations and it includes the competitors, the industry, as well as the requirements of the government (Tornatzky & Fleischer 1990).

The constructs that will be considered in the case of our study are:

Competition Intensity: This is the degree by which the organization is affected by the competitors in the market. The higher the degree of competition will force a firm invest a lot in innovations resources **(**Borgman *et al* 2013).

Companies can use big data analytics to understand their customers better and therefore provide them with customized services causing them to have a competitive advantage over their competitors.

H6. It is hypothesized that competition intensity is positively related to the adoption of big data analytics by organizations.

Regulatory Requirements: This are requirements imposed by the government that could have positive or negative outcome on innovation. Through allowing for tax benefits through introduction of regulations that pushes organizations to adopt certain technology standards governments can support technology innovation **(**Borgman *et al* 2013).

Government can on the other hand can impose straining regulations. For example for the case of big data analytics the issue of data protection requirements need to be put into consideration for adoption.

H7. It is hypothesized that stricter regulatory requirements to an organization is negatively related to the adoption of big data analytics.

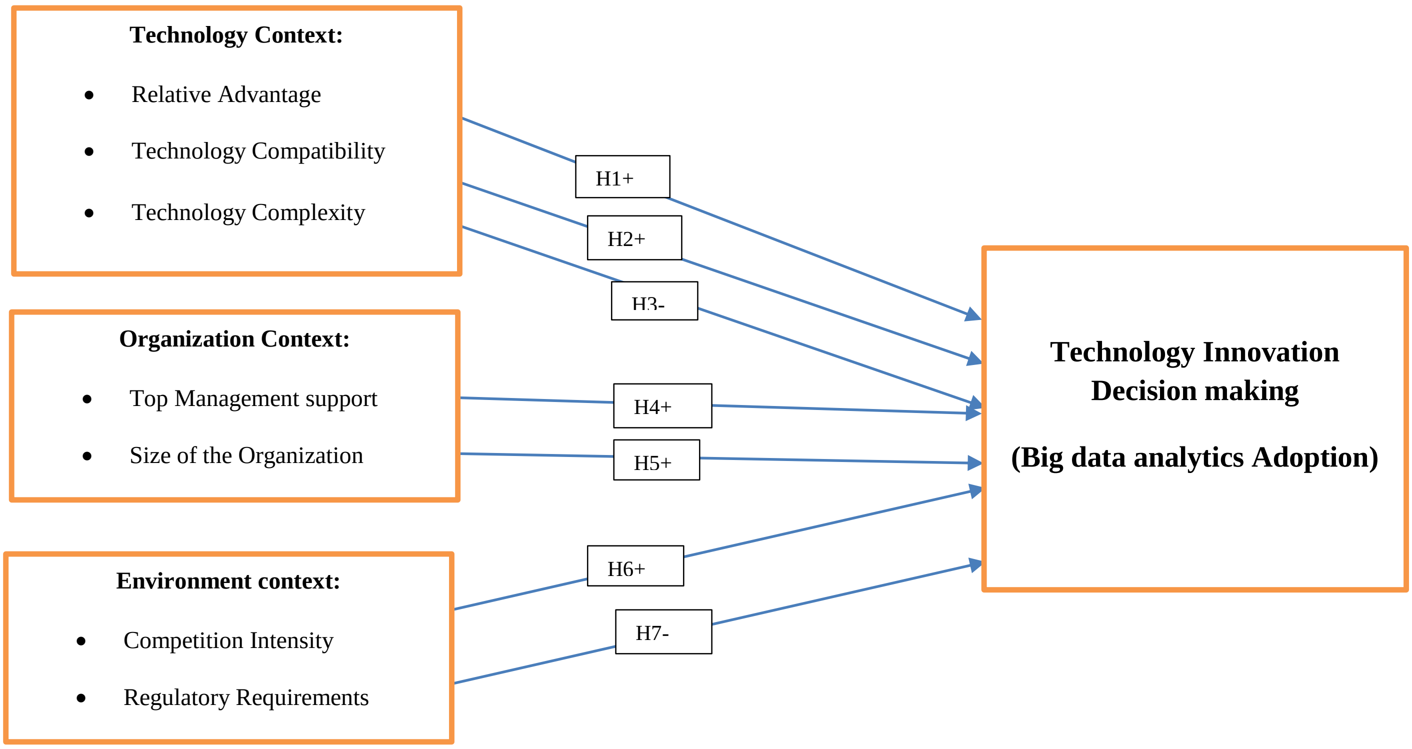

Figure 2.4: Research Framework

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter describes the philosophy that supports the research, the research approach, data collection as well as data analysis.

3.2 Research Philosophy

Research philosophy encompasses key assumptions on the way the researcher views the world. There are different underlying *philosophical paradigms.* A paradigm can be defined as a set of common assumptions or ways of thinking about some aspect of the world (Oates, 2015)

Research philosophy encompasses issues of ontology (reality), epistemology (knowledge) and axiology (ethics). Three different philosophical paradigms: positivism, interpretivism and critical research exist.

Positivism inspires what is called 'the scientific method. The scientific method assumes that the world is ordered and regular, not random and can be investigated objectively (Oates, 2015).The positivists paradigm is characterized by hypotheses, theories, objectivity, hypotheses testing, quantitative data analysis and generalization. The scientific method allows one to shape awareness by an iterative cycle. In a positivist research one formulates theory, derives hypothesis, tests hypothesis objectively, observe results, confirm or refute a hypothesis, accept, modify or reject theory.

For this study a positivist research approach and the philosophy of positivism is adopted.

A deductive process will be employed to test the hypotheses and theory adopted in the research framework.

3.3 Research Design

Different research designs exists, the study chose a descriptive survey with both qualitative and quantitative data.

A survey denotes the method of obtaining information concerning a phenomena that is being studied from all or a selected number of respondents within the area of study. In a survey, the researcher scrutinizes those phenomena which exist in the universe independent of his action (Kothari, C.R, 2004).

There are three basic types of case studies (Yin, 2003b) this are; exploratory, descriptive and explanatory.

An **exploratory study** is applied to describe the questions or hypothesis to be applied in succeeding study. Exploratory study brings out an understanding of research problem and is applied for instance where little literature is available about the topic of study and hence a real-life example has to be investigated.

A **descriptive study** on the other hand leads to a wealth of detailed analysis of a specific occurrence and its context.

An **explanatory study** is deeper than a descriptive study as it explains why events occurred the way they occurred or why certain outcomes came about.

3.4 Target Population

A population describes an entire group of individuals, events or objects having a common observable characteristic (Mugenda & Mugenda, 2012).

This research targeted people in the Technology and ICT departments in telecoms, telecommunication service providers, Information Communication Technology companies and service providers. A major institute of higher learning was also part of the sample due to its rich ICT bias and presence of ICT innovation hub.

The choice of the target group was guided by the fact that business intelligence and analytics (BI&A) and big data analytics had become unceasingly important both in the business communities and the academia (Chen et al 2012).

Respondents were Head of departments, Managers, Engineers, IT specialists and Subject matter experts in Strategy and innovation departments, technology support departments and ICT departments for case of academic institution.

3.3 Data Collection Method

The main source of data was primary quantitative data. This data was obtained through structured online questionnaires developed using google forms. This method of collection was selected as it was faster to reach out to the target group as they could access the questionnaire from their mobile phones and also easier to process collected data.

The guided interviews were done to department heads using same questionnaire that was administered to the rest of the target group.

The structured online questionnaires were sent out to technical team involved in analytics and planning and those in Strategy and innovations department.

3.4 Data Analysis

Data analysis involves looking at patterns in the data and drawing conclusions (Oates, 2005).

The study data that was gathered was largely quantitative in nature. Therefore, quantitative methods of data analysis were used. Quantitative data means data, or evidence based on numbers. (Oates, 2005).

Descriptive statistical techniques were used to summarize the data obtained using frequencies especially for nominal data, percentage, range and standard deviation for describing the distribution and mean for describing central tendencies.

Statistical Package for Social Sciences (SPSS) was used for data organization and analysis.

The analyzed data and the research results were presented in percentages, frequency tables as well as charts.

Multiple linear regression technique was used to test the research framework (TOE) for each of the three variables i.e. Technology, Organization and environment.

$Y = \alpha + \beta 1X1 + \beta 1X2 + \beta 1X3 + \beta 1X4 + \beta 1X5 + \beta 1X6 + \beta 1\ X7 + ẹ$

Where

Y=Big data analytics Adoption

α = Constant Term

β1= Beta coefficients

X1= Relative Advantage

X2=Technology Compatibility

X3=Technology Complexity

X4= Top Management support

X5= Size of the Organization

X6= Competition Intensity

X7= Regulatory Requirement

ẹ = Error

CHAPTER FOUR
RESULTS AND DISCUSSION

4.1 Introduction

This chapter is about data analysis and the findings of the research as presented in the research methodology. Data was collected from telecoms, telecommunication service providers, Information Communication Technology companies and service providers and a major institute of higher learning through google forms that were then downloaded to excel format for analysis. Only a few of the questionnaires were hand filled. The results are presented in tables and charts for simplicity.

4.1.1 Response Rate

A total of 100 respondents were targeted by this study. A total of 61 filled the questionnaire while 39 did not respond to the questionnaire. Therefore, the resulting response rate was 61%. Mugenda and Mugenda (2003) asserted that a response rate of 60% is good for a study.

4.2 Demographic Information

4.2.1 Age Bracket

The study shows that 51% of the respondents were aged between 20-35 years and a proportion of 46% aged between 36-45 years. The rest proportion of 3% consisted of respondents aged 46 years and above. The results shows that most of the respondents were young people who worked in analytics, strategy and innovations departments as technical experts. This could be associated with the fact that the young are technologically scurvy.

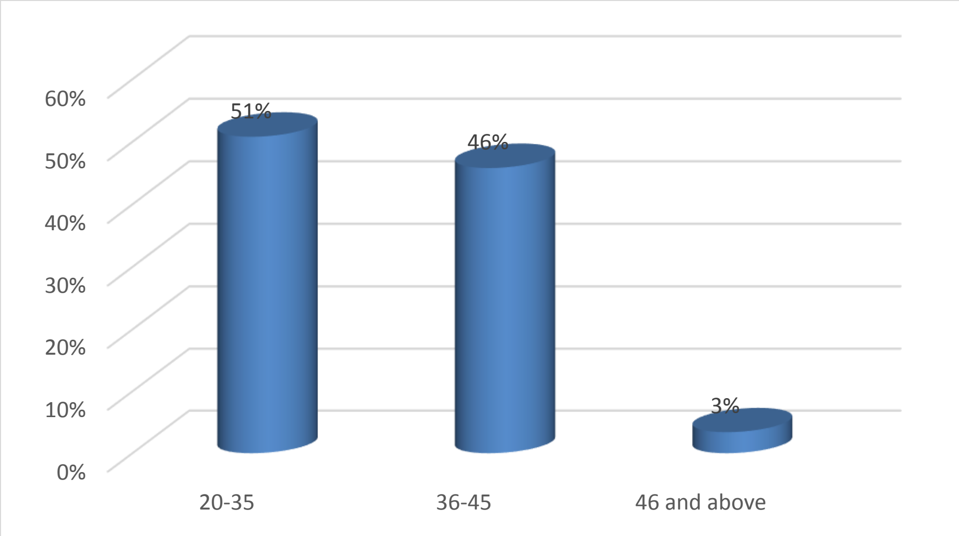

Figure 4.1: Age Bracket

4.2.2 Education Level

Figure 4.2 shows that 63% of the technical experts in the organizations sampled had degrees, 32% had masters and 3% had diplomas. This shows that the technical staff in the organizations were highly educated in their fields. Probably because the departments were technical in nature and could only have with qualified staff.

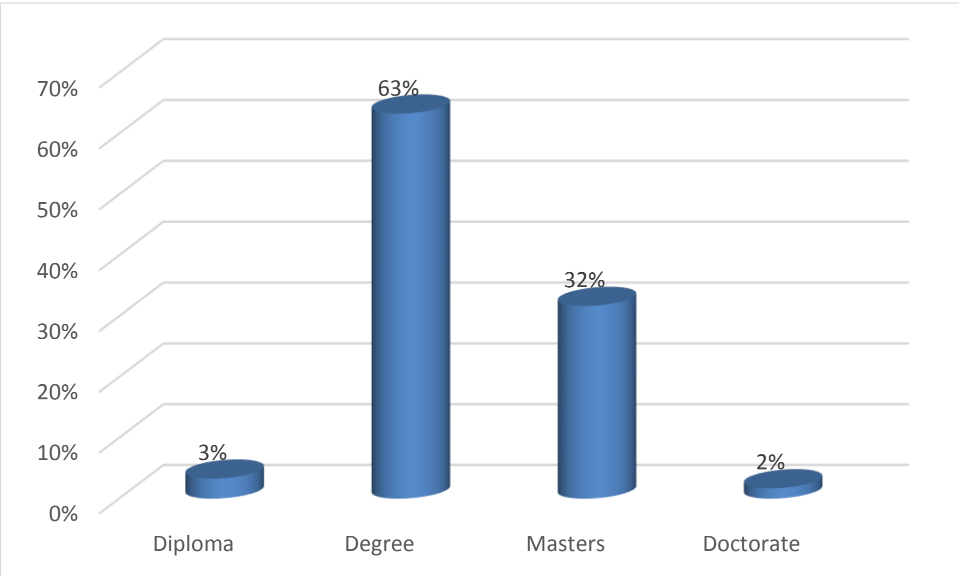

Figure 4.2: Education level

4.2.3 Position in the organization

A check on the designation of the respondent's shows that 33% were engineers, 29% were managers of the IT and data related departments, 17% were IT specialists and 9% experts in their specific roles. Others were head of departments and directors. The results shows that the strategy and innovations departments were highly staffed with experts in different fields and also that the respondents held both technical and managerial positions and thus could generate knowledge from the perspectives of the technical officers and also from manager's level.

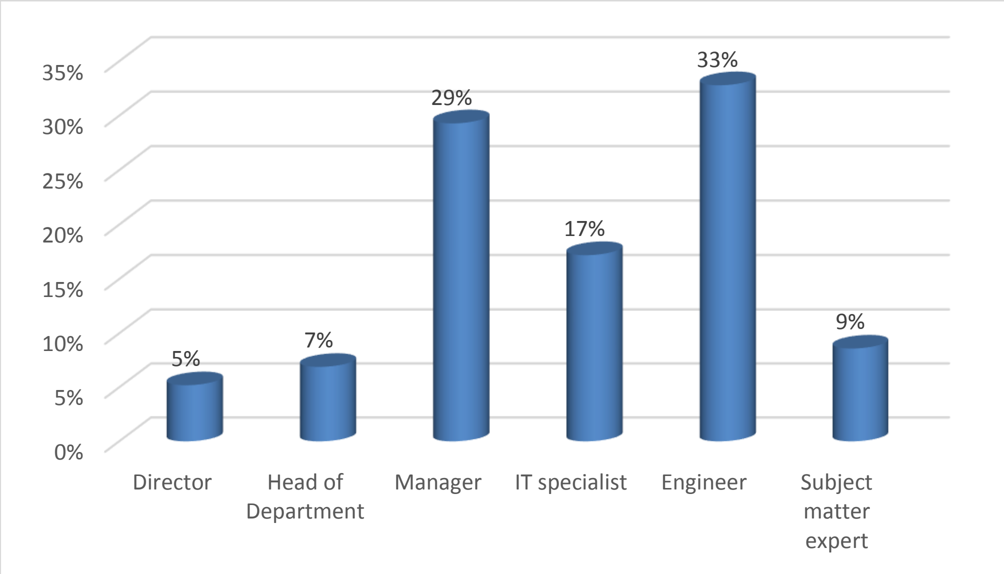

Figure 4.3: Position in the organization

4.2.4 Number of Employees in the Organization

Figure 4.4 shows that 56.9% of the organizations represented had more than 5, 000 employees, 15.5% had between 1, 000-5, 000 employees and 27.6% with a staff establishment of less than 1,000. The results implies that most of the organizations had large staff establishment reflecting stability and strength.

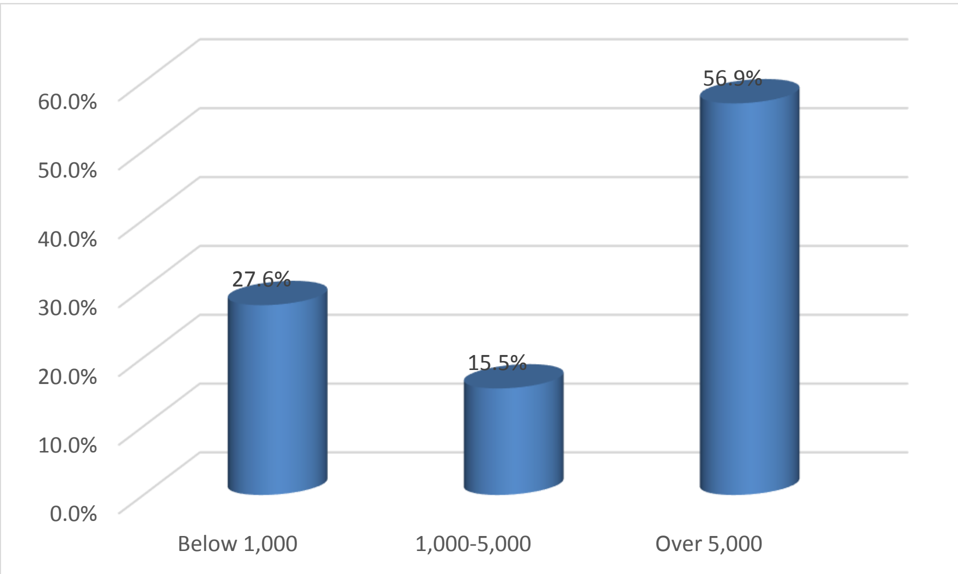

Figure 4.4: Number of Employees in the Organization

4.3 Adoption of Big Data Analytics

4.3.1 Duration the organization had used big data analytics

Figure 4.5 shows that 62% of the organizations had used big data analytics for less than five years, 15% had used it for 6-10 years and 12% between 11-20 years. A number of the studied organizations (12%) had not used big data analytics. This shows that 88% of the organizations sampled had used big data analytics and could provide reliable data on the use of big data and its usefulness in decision making.

The results indicated that different organizations used different data analytics technologies. Some indicated that they incorporated business intelligence big data and predictive analytics. Common technologies used included Hadoop, Allot clearsee and other customized BI systems. Others used Google analytics,Cloudera, MapR, Splunk, MongoDB, Hortonworks, Data Mediator Flytxt, Datalake, structural and relational databases, customized predictive analytics systems among others technologies.

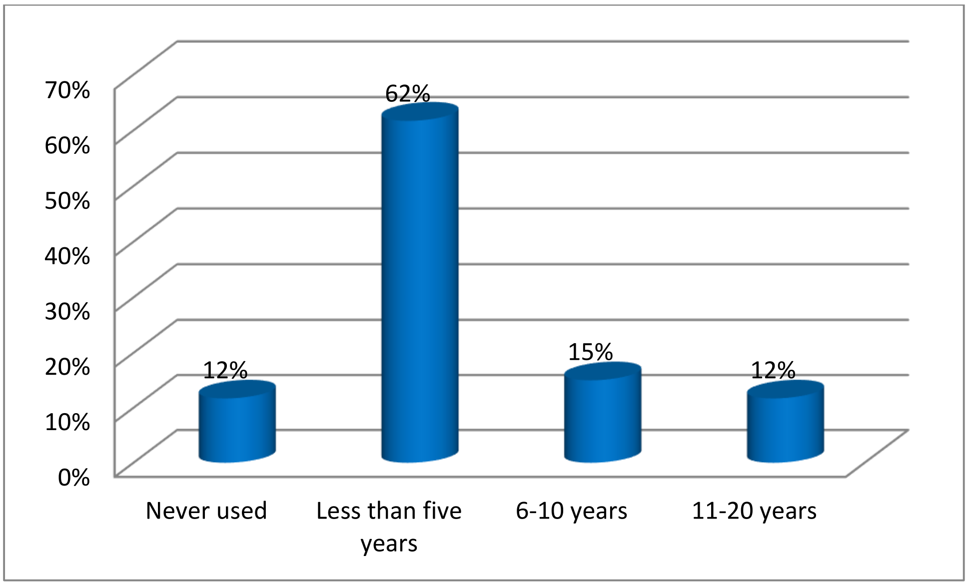

Figure 4.5: Duration the organization had used big data analytics

4.3.2 Extent of commitment to the use of the big data Analytics to drive decision making

Table 4.1 shows the extent and willingness with which organizations supported the adoption of big data analytics. From the results, 41% of the respondents affirmed that their organizations had commitment to adopt big data analytics systems to a very great extent. A proportion of 44% of the respondents indicated that top management in their organizations supported the adoption of big data analytics to a very great extent. Further, 36% of the respondents affirmed that their organizations allocated resources towards innovations such as big data to great extent.

The result shows some commitment and willingness and even support towards adoption of innovations and adoption of big data analytics in the organizations.

Table 4. 1 Extent of commitment to the use of the big data systems

	No extent	**Less extent**	**Moderate extent**	**Great extent**	**Very great extent**
Organization's commitment towards adoption of big data analytics to improve its business activities	2%	7%	21%	29%	41%
Extent of top management support towards the adoption of Big data analytics to drive decision making	5%	5%	11%	35%	44%
The extent of resource slack that used to drive innovation	7%	11%	30%	36%	16%

4.3.3 Extent of adoption of big data with respect to duration of use

One-way-ANOVA test was done to establish whether the extent of adoption of big data in decision making varied across firms with regard to the period they had used the big data system. The ANOVA test results in table 4.2 shows a p value of p=0.000 ($p<0.05$) implying that they were differences on adoption of big data across firms. A post hoc analysis was done to establish the nature of the variations.

Table 4.2: ANOVA Results- Duration and adoption

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	12.899	3	4.300	9.896	.000
Within Groups	24.330	56	.434		
Total	37.229	59			

Table 4.3 shows that the adoption (measured in terms of means) was less for the firms which had not adopted compared to those which had adopted the big data. Further, the post hoc shows that the extent of adoption for the firms which acquired big data more than 10 years ago was and those which acquired the system less than 5 years ago was 0.43565. Although the value was more for firms who acquired the system long ago, there was no significant difference between those who had used big data for less than 5 and those who had used it for more than 10 years (p=0.114). This shows that the extent of use and functionality was almost the same.

Table 4.3: Post Hoc Analysis-Duration and adoption

LSD						
(I) Duration the firm used the big data	(J) Duration the firm used the big data	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Never used	Less than five years	-1.27864*	.27168	.000	-1.8229	-.7344
	6-10 years	-1.48810*	.33218	.000	-2.1535	-.8227
	11-20 years	-1.71429*	.35233	.000	-2.4201	-1.0085
Less than five years	Never used	1.27864*	.27168	.000	.7344	1.8229
	6-10 years	-.20946	.24498	.396	-.7002	.2813
	11-20 years	-.43565	.27168	.114	-.9799	.1086
6-10 years	Never used	1.48810*	.33218	.000	.8227	2.1535
	Less than five years	.20946	.24498	.396	-.2813	.7002
	11-20 years	-.22619	.33218	.499	-.8916	.4392
11-20 years	Never used	1.71429*	.35233	.000	1.0085	2.4201
	Less than five years	.43565	.27168	.114	-.1086	.9799
	6-10 years	.22619	.33218	.499	-.4392	.8916

*. The mean difference is significant at the 0.05 level.

4.3.4 Extent of adoption of big data with respect to the size of the firm

Table 4.4 shows One-Way- ANOVA test which was done to determine whether there was variations on the extent of adoption of the big data across firms of different sizes. The size of the firm was given by the number of employees. The test sought to establish whether large firms had adopted big data more than smaller firms. The results shows that there existed significant differences in the extent of adoption of big data systems across firms of different sizes.

Table 4.4: ANOVA- Size and adoption

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	8.224	2	4.112	9.045	.000
Within Groups	25.006	55	.455		
Total	33.230	57			

Table 4.5 shows that the extent of adoption was small for small firms with less than 1,000 employees compared to those which had more employees. Column on mean differences (I-J) shows the values were negative implying that they were small than those of large firms. The p values were also less than 0.05 ($p<0.05$) implying that the differences in adoption was significant. The mean difference (I-J) between largest firms (over 5,000) and those with

between 1,000-5,000 was 0.00505 implying that largest firms adopted big data to a great extent compared to the large firms. The p value however was p=0.984 (p>0.05) implying that the difference in adoption was not statistically significant. Therefore, the results show that the intensity of adoption of the big data system was high for largest firms compared to small firms but it was insignificant between largest firms and the large firms.

Table 4.5: Post Hoc Analysis-Size and adoption

LSD

(I) Size of the firm	(J) Size of the firm	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Below 1,000	1,000-5,000	-.83854*	.28095	.004	-1.4016	-.2755
	Over 5,000	-.84359*	.20541	.000	-1.2552	-.4319
1,000-5,000	Below 1,000	.83854*	.28095	.004	.2755	1.4016
	Over 5,000	-.00505	.25356	.984	-.5132	.5031
Over 5,000	Below 1,000	.84359*	.20541	.000	.4319	1.2552
	1,000-5,000	.00505	.25356	.984	-.5031	.5132

*. The mean difference is significant at the 0.05 level.

4.4 Technological factors and adoption of big data analytics

This section discusses results on the technological factors and how they relate with the adoption of the big data analytics.

4.4.1 Relative Advantage

The adoption of big data analytics had some advantage over other data analysis software application. Table 4.6 shows that 66.7% of the respondents strongly agreed that adoption of big data analytics had helped their organization to serve their customers better and also by reducing cost of operation (55.4%). This shows that the adoption had some advantage over the rest of the systems on decision making.

Table 4.6: Relative Advantage

	Strongly disagree	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
Adoption of new technologies like big data analytics helps us serve our customers better.	1.8%	1.8%	3.5%	26.3%	66.7%
Adoption of data analytics to drive decision making reduces cost of operations for our organization	1.8%	3.6%	17.9%	21.4%	55.4%

4.4.2 Technology Compatibility

Adoption of big data analytics was also influenced by the compatibility of the existing technological framework with the big data analytics systems. From the results, 45.6% of the respondents strongly affirmed that their organizations were familiar with the opportunities and threats likely to arise out of big data analytics systems. Further most respondents (36.8%) strongly agreed that their organization possessed the needed infrastructure necessary for adoption of the big data analytics systems. Others (47.4%) agreed that their existing IT infrastructure could be easily upgraded to accommodate data analytics and data driven decision making. The result shows that organizations were aware of the existence and usefulness of the data driven decisions making approaches, had compatible IT infrastructure and easily upgradable systems to adopt big data analytics and such related software applications.

Table 4.7: Technology Compatibility

	Strongly disagree	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
Our organization is familiar with the opportunities and threats brought by data driven decisions	5.3%	1.8%	19.3%	28.1%	45.6%
Our organization currently possesses the infrastructure necessary to enable adoption of big data analytics to drive decision making	5.3%	14.0%	12.3%	31.6%	36.8%
Our current IT infrastructure can be easily upgraded to accommodate data analytics and data driven decision making	3.5%	3.5%	12.3%	33.3%	47.4%

4.4.3 Technology Complexity

The other factor examined was the technological complexity of the data analytics systems. From the results, 29.8% of the respondents strongly agreed and 21.1% agreed that that using big data analytics to drive decision making was easy. A further 59.6% of the respondents had strong conviction that big data driven decision would bring growth of revenues to the organizations.

Table 4.8: Technology Complexity

	Strongly disagree	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
The technology of big data analytics to drive decision making is easy to understand and adopt	8.8%	19.3%	21.1%	29.8%	21.1%
Big data analytics and data driven decision making will bring growth in our organization in terms of revenue	0.0%	3.5%	10.5%	26.3%	59.6%

4.4.4 Hypothesis Testing 1

The study had three hypotheses on the relationship between technological environment and adoption of big data analytics in decision making. The hypotheses were testing through a multiple linear regression at 95% level of confidence to establish any causal effect relationship between technological factors such as relative advantage, technological compatibility and technological complexity. The three hypotheses were stated as shown.

H1.It is hypothesized that perceived relative advantage of big data analytics is positively related to the adoption of big data analytics.

H2.It is hypothesized that perceived compatibility is positively related to the Adoption of Big data.

H3. It is hypothesized that perceived complexity of using and understanding big data analytics is negatively related to the adoption of big data analytics.

Table 4.9: Model Summary-Technological context

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.655	.429	.397	.59546
a. Predictors: (Constant), Relative Advantage, Technology. Complexity, Technology. Compatibility				

Table 4.9 shows the model summary of the multiple linear regression. The R value is 0.655 and the R square is 0.429. Thus, the correlation (r=0.655) between the three factors and the adoption of the big data was strong and positive. The R square value of 0.4269 means that the three technological factors account for 42.9% of the variation in the adoption of big data analytics in the organizations. The remaining 57.1% is accounted for by other factors which were not in this model. This shows that the three technological factors account for a substantial proportion of the adoption.

Table 4.10: ANOVA-Technological context

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	14.116	3	4.705	13.271	.000
	Residual	18.793	53	.355		
	Total	32.909	56			
a. Dependent Variable: Adoption						
b. Predictors: (Constant), Relative.advanatage, Technology.compatibility Technology.complexity,						

The ANOVA table shows the goodness of fit of the model and also establishes the significance of the relationship between the independent and the dependent variables. Table 4.10 shows a F statistic value of F (3,53)=13.271,p=0.000. This implies that at least one of the independent technological factors has a statistically significant effect on the adoption of the big data analytics. The actual effect of each of the three technological factors is shown on coefficient table 4.11.

Table 4.11: Coefficient –Technological context

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.167	.458		2.548	.014
	Relative advantage	.169	.116	.186	1.458	.151
	Technology Compatibility	.506	.105	.638	4.801	.000
	Technology Complexity	-.132	.122	-.152	-1.087	.282

Table 4.11 shows the coefficient or elasticities of the independent variables in the regression equation. The resulting regression equation is shown as

A=1.167+0.169RA+0.506TC-0.132TCL

Where A =the Adoption of big data analytics,

RA=is the relative advantage of the adoption,

TC=is the degree to which the big data is compatible with the existing technological infrastructure and

TL =is the degree of technological complexity.

The results indicate that the relative advantage (0.169) has a positive but insignificant influence ($p>0.05$) on the adoption of the big data analytics in decision making in the organizations implying the results could have been obtained by chance. The technological compatibility (0.506) had a positive significant influence ($p<0.05$) on the adoption of big data analytics in organizations. Lastly, the technological complexity (-0.132) had a negative but insignificant ($p>0.05$) influence on the adoption of big data analytics by organizations. The results indicate that the most influencing factor was the degree of compatibility with the existing IT systems. The effect of relative advantage and technological complexity were not confirmed. Thus the study fails to reject the second hypothesis (H_2) that perceived compatibility is positively related to the Adoption of Big data in organizations and rejects the first and the third hypothesis on the relative advantage and technological complexity.

4.5 Organizational factors and adoption of big data analytics

This section discusses the organizational factors and how such factors relate with the adoption of big data analytics.

4.5.1 Top Management Support

Table 4.12 shows that 41% of the respondents strongly affirmed that their organizations were committed to adopt big data analytics to improve their business activities. A proportion of 44% of the respondents indicated that top management in their organizations fully supported the idea of adopting big data analytics to drive decision making. For those organizations which had adopted and those which were in the process of adopting the analytics system, a proportion of 44% indicated that the process was led through strategies. The top management in most of the organizations (52%) were aware of the benefits of adopting the systems as tools of aiding in decision making. The results indicates that in most of the organizations whose strategy innovation staff participated in this study, the adoption of big data analytics was fully supported by the management and strategies shad been put in place to have the process done since they knew the benefits of such a system in their organizations.

Table 4.12: Top management support

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Our organization is committed to adopting big data analytics to improve its business activities	2%	7%	21%	29%	41%
Our organization's top management fully supports the adoption of Big data analytics to drive decision making	5%	5%	11%	35%	44%
The adoption of Big data analytics in our organization is strategy-led	7%	7%	14%	28%	44%
The top management in our organization is aware of benefits of adoption big data analytics to drive decision making	2%	5%	14%	27%	52%

4.5.2 Size and structure of the Organization

Table 4.13 shows that 30% of the respondents felt that the number of employees influenced the adoption of the big data analytics in their organizations.28% were unsure whether employees numbers could affect the process.in terms of resources, 36% of the respondents indicated that their organizations had resource slack for driving innovations such as big data although an equally big number could not state whether they had such type of resource envelope.32%

indicated that their organizations structure influenced technological adoption. The results further shows that 40% of the respondents agreed that their organization had good communication for clarifying business strategies and competent staff (38%) which could drive adoption of technology in their organization. The results points to a situation where the organizations had good structure, resources, good communication channels and competent staff which easily help the organizations in the process of adopting new innovations such as big data analytics in the organizations.

Table 4.13: Size of the Organization

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Our organization's size (the number of employees) influences the adoption of technology	4%	16%	28%	30%	23%
Our organization has resource slack that is used to drive innovation	7%	11%	30%	36%	16%
The organizational structure has no influence on technology adoption	23%	32%	30%	9%	7%
Communication in my organization is effective and hence enables me to understand the business strategy	5%	19%	12%	40%	23%
Our organization has competent staff that can drive the adoption of technology such as big data analytics.	4%	13%	11%	36%	38%

4.5.3 Hypothesis Testing 2

The two hypothesis made on organizational factor were tested.

H4. It is hypothesized that top management support is positively associated with the adoption of big data analytics

H5. It is hypothesized that the size and structure of the firm is positively related to the adoption of big data analytics.

The study adopted a multiple linear regression to test the hypothesis. The test was done with the assumptions of 95% level of confidence to test the linear relationship between the organizational environment and the adoption of big data analytics by organizations.

Table 4.14: Model Summary-organizational context

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.907	.822	.816	.32910
a. Predictors: (Constant), size and structure of organization, Top management support				

The value R was 0.907 and that of R Square was 0.822 implying that the correlation between the organizational factors and the adoption of the big data analytics was strong and positive. The R square value indicates that organizational factors account for 82.2% of the variation in adoption of big data analytics. The remaining 17.8% is accounted for by other factors which are not included in the model.

Table 4.15: ANOVA-Organizational Context

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	27.060	2	13.530	124.927	.000
	Residual	5.848	54	.108		
	Total	32.909	56			
a. Dependent Variable: Adoption						
b. Predictors: (Constant), size and structure of organization, Top management support						

The Analysis of Variance (ANOVA) shows the goodness of fit of the model and the significance of the relationship between the predictors and the predicted variable. In this case, the F statistics was F (2, 54) = 124.927, p=0.000. Therefore, the one of the two organizational factors had significant effect on the adoption of the big data analytics and thus the data fitted the model.

Table 4.16: Coefficients-Organizational context

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.204	.219		.930	.357
	Top management support	.536	.057	.690	9.326	.000
	Size and structure .of organization	.313	.078	.296	4.003	.000

Table 4.16 shows the values of the coefficients of the independent variables in the model. The p values (sig) in the table shows that top management support (0.000) and size and structure of the organization (0.000) were all less than 0.05 indicating that they both had statistically effect on the adoption of the big data analytics in the organizations. The regression equation was given as:

A=0.204+0.536TM+0.313SS

Where A=Adoption of the big data

TM=Top management support

SS=Size and Structure of the organizations

The results shows that organizational environment is very important for adoption of big data analytics. From the results absence of the top management support and size and structure of the organizational the adoption of the big data could not be realized (constant is insignificant p>0.05). The contribution of top management support was highly significant contributing to large percentage of success compared to that of size and structure. This shows that top management support and size and structure influence the adoption of the big data analytics in organizations. Thus, the study fails to reject the two alternative hypothesis that top management has a positive correlation with adoption of big data analytics and that size and structure of the organization positively influences the adoption of the big data analytics.

4.6 Environmental factors and adoption of big data analytics

This section presents findings on the environmental factors influencing the adoption of big data analytics.

4.6.1 Competition Intensity

Table 4.17 presents results on competition and how the intensity influences the adoption of big data analytics. The results shows that most of the respondents felt that measures put in place by the government to promote technology were unclear and that they were neutral about whether the government was committed on that. Most of the organizations (41%) strongly agreed that indicated that competition had influenced the adoption of big data analytics. a big number of the organizations (48%) held the belief that adoption of the big data analytics would help them to improve the market share of their organizations. The industry players also helped shape the adoption of big data analytics. The results shows that organizations competitors who had adopted big data were viewed more favorably by customers thus forcing them to think about adopting the same. A proportion of 38% of the respondents indicated that they had efficient technological support from their service providers and consultants to enable them adopt the big data systems for decision making. This shows that the actions of other industry players influenced the organizations decisions on adoption of big data analytics.

Table 4.17: Competition Intensity

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Government demonstrates a major commitment to promote technology adoption	11%	16%	32%	30%	11%
Competition has influenced our organization to adopt technology such as big data analytics	4%	7%	16%	32%	41%
Adoption of big data analytics to drive decision making will improve the market share of our organization	2%	2%	11%	38%	48%
Our competitors who have adopted data driven decision making technologies are viewed more favorably by customers	5%	5%	25%	25%	39%
We have efficient Technology Support from our service providers and consultants to enable us to adopt big data analytics and use its insights to make decisions.	5%	4%	20%	38%	34%

4.6.2 Regulatory Requirements

The other aspect of the operational environment was the government regulations. The respondents indicated that some government regulations would influence the adoption of the big data systems such as the taxation on software and hardware, IT adoption policies, licenses fees and technology restrictions, compliance requirements, data governance, sharing, protection and privacy legislations, cyber-crime legislations among others regulations.

The legal environment was unclear and incomprehensive on data management and adoption of IT systems. A considerable number of the IT technical experts indicate that the legal environment was not conducive for adoption of the big data systems in their organizations citing that such laws were inadequate and required improvement. To the respondents, the legal framework requires improvement to capture data owners privacy, the taxation was excessive and prohibitive, there was no ICT ethics elements, lack of laws governing infringement and lack of clear guidelines on adoption of new technologies. On the contrary some of the respondents felt the legal environment was conducive for adoption since the government was supporting adoption of ICT, there were structures to solve challenges on information sharing as well as absence of restrictions on data collection and storage.

The adoption and usefulness of big data analytics in the organizations could be influenced by other environmental factors such as mistrust due to data abuse, ability to utilize the data correctly, competition, efficiency of operations, cost of adoption, training, knowledge and skills, cultural change, organizational structures, customer willingness and buy in, employee perception, organizations strategies, existing IT infrastructure, internal organizational policies, rate of IT evolvement as well as user perception among other factors.

The adoption of big data in organization had far reaching positive implications. The respondents stated that such system facilitates accurate decision making, target marketing , better knowledge of the customers, cost savings, timely response to market dynamics, ability to pick customer demands hidden trends, quick decision making and ability to unlock new revenue streams due to accurate decision making.

The respondents also highlighted some potential risk associated with the adoption of the big data analytic systems such as likelihood of misusing the information, confidential data violation and information leakage, cyber-attacks, spikes and euphoria economic panic and sabotage can lead to wrong decision making and lack of customer touch due to limited interactions with the customers.

The study further examined the level of human capacity preparedness in adopting the big data analytics. The result shows that a number of companies had adequate staff capacity while others did not. The organizations without human capacity had several suggestions to equip staff with relevant experience such as offering training, other were setting digital academy's to support innovations, outsourcing the big data systems, investing in cultural perspectives for easy buy in and building self-driven learning.

4.6.3 Hypothesis Testing 3

The third factor considered in this study was the relationship between environmental factors and adoption of big data analytics in organizations. The study hypothesized that.

H6. It is hypothesized that competition intensity is positively related to the adoption of big data analytics by organizations.

H7. It is hypothesized that stricter regulatory requirements to an organization is negatively related to the adoption of big data analytics.

The above hypotheses on environmental factors and adoption of big data analytics were tested through a multiple linear regression test at 95%. This test was done to determine the linear relationship between the environmental factors and the adoption of big data analytics.

Table 4.18: Model Summary-Environmental context

Model		R		R Square	Adjusted R Square	Std. Error of the Estimate
1		.571		.326	.292	.66788

a. Predictors: (Constant), Competition intensity, Regulatory environment

The model summary table shows a R value of 0.571 and a R Square value of 0.326. The results implies that environmental factors and adoption of big data analytics had a positive correlation of 0.571 while the R Square value implies that environmental context accounted for 32.6 % of the variation in adoption of the big data analytics in the organizations.

Table 4.19: ANOVA-Environmental context

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8.633	2	4.317	9.678	.000
	Residual	17.842	40	.446		
	Total	26.476	42			

a. Dependent Variable: Adoption

b. Predictors: (Constant), Regulatory environment, Competition intensity

The ANOVA test results shows the level of statistical significance between the environmental factors and the adoption of big data analytics in the organizations. From the results, the resulting F statistics was $F(2,40)=9.678$, $p=0.000$ implying that at least one of the factors had a statistically significance influence on the adoption of the big data innovations in organizations.

Table 4.20: Coefficients-Environmental Context

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.263	.580		2.177	.035
	Competition Intensity	.637	.152	.544	4.179	.000
	Regulatory environment	-.353	.207	-.222	-1.707	.096

The results shows that the intensity of completion had a significant contribution towards adoption of the big data analytics in the organizations. The resulting regression equation of the model was:

$A=1.263+0.637CI-0.353RE$

Where A=adoption of big data analytics

CI=Competition intensity

RE=Regulatory Environment (conduciveness)

The value of the constant was significant ($p<0.035$) implying that without competition and regulatory framework, the organization would dedicate 1.2% resources and efforts towards adoption of the analytics systems. The influence of the intensity of competition was significant ($p<0.05$) and positive implying that increase in the intensity of the competition influenced more adoption of the big data analytics in the organizations. The linear relationship of the regulatory framework on the adoption of the big data was negative and insignificant ($p>0.05$). This shows that the legal framework had negative implications on the adoption but very negligible perhaps because the legal framework was not explicit and adequate enough. Thus, the study accepts the hypothesis that intensity of competition has a positive relationship with the adoption of the big data analytics and rejects the second hypothesis that regulatory environment had negative influence on the adoption of big data analytics in organizations.

4.7 Summary of the findings

This study was motivated by the need to establish the extent of adoption of big data analytics to drive decision making, factors influencing the adoption and identifying a model to guide adoption of big data analytics. Accenture (2014), indicated that big data delivers significant value to users. The respondents indicated that adoption of big data analytics was advantageous in a number of ways: accurate decision making, better knowledge of the market and customers, quick decision making and timely response to market dynamics. This agrees with Gandoni & Haider (2015) that big data is used to uncover hidden patterns leading to additional better ways of marketing, fresh revenue opportunities, enhanced customer service, enhanced operational efficiency as well competitive advantages and many other benefits.

Some potential risks associated with the innovations included breach of confidentiality, leakage of information, sabotage and wrong decision making in case of wrong data and inaccurate interpretation. The results concur with the views of Hilbert (2016) who argued big data risks in developing countries included privacy concerns and human resource scarcity, pending physical lacks in terms of infrastructure, financial resources and establishments.

The study found that 88% of the organizations had adopted big data analytics in their operations to guide decision making. Some adopted the analytics systems more than 10 years ago but majority (62%) adopted it less than 5 years ago. This is explained by the fact that it is new and emerging tool for decision making which is currently gaining prominence and usefulness. The common big data analytics technologies included Hadoop and Allot clearsee others used google analytics, while others had their own customized systems. The results indicates that most of the organizations had committed to fully adopt big data analytics in their operations with support from top management and dedicated resource envelop to drive innovations.

The results showed that adoption of big data analytics was influenced by technological factors and context of the organizations. These factors were both current and internal equipment

(Starbuck 1976) and external technologies (Hage, 1980).The degree of adoption would be considered with respect to the relative advantage the analytics has over the existing technologies such as its ability to help organizations serve customers better and cost effectives. The second technological factor was the ease of compatibility with the existing IT infrastructure. The study found that a number of organizations were familiar and had knowledge about the big data analytics systems, possessed compatible processes and equipment and were able upgrade their IT systems to new emerging big data solutions implying which made the process of adoption easier. The last technological aspect was the complexity of the big data systems. According to diffusion of technology theory as postulated by Rogers (2003), innovations in organizations highly depended on the relative advantage, compatibility and complexity of the innovations. The study found that the technology was not easy which posed a challenge in adoption of the analytics applications.

The regression test found that among the three technological factors, the compatibility of the big data innovations with the existing IT systems had the highest influence ($B=0.536, p<0.05$) when adopting big data innovations. The influence of relative advantage on the adoption was positive but was considered a weak factor. The complexity of the analytic systems affected the adoption process negatively. However, organizations did not consider the complexity element important but as having insignificant effect. The results shows that compatibility was the most influential technological factor affecting the adoption of big data analytics compared to relative advantage and complexity in contrast to the findings of Bradford and Florin (2003) who held that all the three factors were equally important for adoption of technology.

The results on the organizational factors and adoption of big data analytics showed that top management in organization provided the necessary support to the process. A proportion of 70% (29 agreed and 41% strongly agreed) of the organizations were committed to the process of adoption, had devised strategies to led adoption of the big data analytics and enjoyed top management support. Borgman et al, (2013) argued that support by the senior most management contributed to the adoption of innovations through the making of a conducive environment as well as the provision required resources. The findings on the size and structure of the organizations shows that the number of employees influenced the adoption of the technology. The study found that 56.9% of the organizations had more than 5, 000 staff members. A percentage of 52% (36% agreed and 16% strongly agreed) of the respondents affirmed that their organizations had resource envelope for such innovations with good structures, effective communication and competent staff who could drive adoption of new technologies such as big data analytics. The results shows that large organizations adopted big data due to their strength and big huge resource capacities which agreed with the Borgman *et al* (2013) that big organizations could easily adopt new innovations since they have resources to facilitate the process.

Regression test results showed that support from the top management, the size and the structure of organizations influenced the extent to which organizations had adopted big data analytics in the organizations. Full support from the management positively influenced the process of adoption as well as the size and structure of the organizations. The results concurred with the views of GalbRaith,(2014) that top management support and especially from both CIO and CEO is an enabler of big data analytics adoption.

Environmental factors examined showed that some competition and industry players influenced adoption of the big data analytics in organizations. The study found that there was no clear understanding of the government commitment towards adoption on technologies. The intensity of the competition influenced adoption of big data analytics since most of the organizations felt it would improve their market share in the market. Other players such as actions of the competitors would influence their decision to adopt the new technologies. The efficiency of the support systems and their consultants were also other aspect of interest considered while adopting big data analytics. The regulatory environment also influenced the extent of adoption of the big data analytics. The results shows that organizations considered government policies and regulations such as taxation on software and hardware systems, adoption policies, compliance requirements and data governance, sharing and protection laws when adopting innovations such as big data analytics. Although the existing legal framework was not prohibitive, it was inadequate as it left some grey areas such as legislations on data owner privacy, lack of guidelines on ICT ethics and clear framework on adoption of new technologies. The regression test found that the intensity of competition significantly affected the adoption of big data analytics in organizations and had a positive influence of the process of adoption. Borgman *et al* (2013) indicated that additional competition causes a firm to invest more resources to innovations. The regulatory environment had a negative effect on the adoption of the big data analytics although it was not an important factor considered by organizations when adopting big data analytics in their processes.

For fast adoption of big data analytics, several recommendations were suggested such as choosing open source with a leeway to vendor support, upgrading IT systems to match high speed of data processing and retrieval, having flexible pricing model, networking with technologically driven companies, creating awareness, trainings, dedicating adequate resources to technology innovations and by encouraging management support and buy in.

CHAPTER FIVE
CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter contains the achievements, conclusion and recommendations from the study.

5.2 Achievements

Objective 1: Identify to what extent organizations in Kenya have adopted big data analytics to drive decision making.

The extent of adoption was measured using the number of years that the company have used the technology and the commitment of the organization to adopt big data analytics to drive decision making. 62% of the respondents affirmed that their organization had used the technology for less than 5 years. Further 41% of the respondents affirmed that their organizations had commitment to adopt big data analytics to drive decision making to a very great extent. A proportion of 44% of the respondents indicated that top management in their organizations supported the adoption of big data analytics to a very great extent. Further, 36% of the respondents affirmed that their organizations allocated resources towards innovations such as big data to great extent. The result shows some commitment and willingness and even support towards adoption of innovations and adoption of big data analytics in the organizations.

Objective 2: Identify the factors that influence the adoption of big data Analytics to drive decision making.

The factors that influenced the adoption of big data analytics to drive decision making were identified to be technological, organizational and environmental. The most significant factors are compatibility of big data analytics to the organizations technology infrastructure, support from top management, the size and structure of the organizations and the intensity of competition. Adoption is quick where the technological infrastructure is compatible, the top management support the adoption, the organization is big in size and the structure is adaptive. Competition and the actions of other industry players also affect the adoption of big data analytics to drive decision making positively.

The adoption of the big data analytics to drive decision making is negatively affected by increased legislations, prohibitive and lack of legislations. The study noted that usefulness of big data analytics was also influenced by ability to use the data correctly, customer willingness, existing IT systems, employee's perceptions, cost of adoption and internal policies.

Objective 3: To establish the suitability of the framework used in exploring the adoption of Big Data Analytics to drive decision making.

The TOE framework was established as a suitable framework to explore the adoption of big data analytics to drive decision making. The study has found that some of the technological and environmental factors immensely influenced the adoption compared to others. Thus adoption of big data analytics was found to be a function of compatibility, size and structure, top management support and competition intensity. The resulting adoption model is thus as shown in figure 5.1.

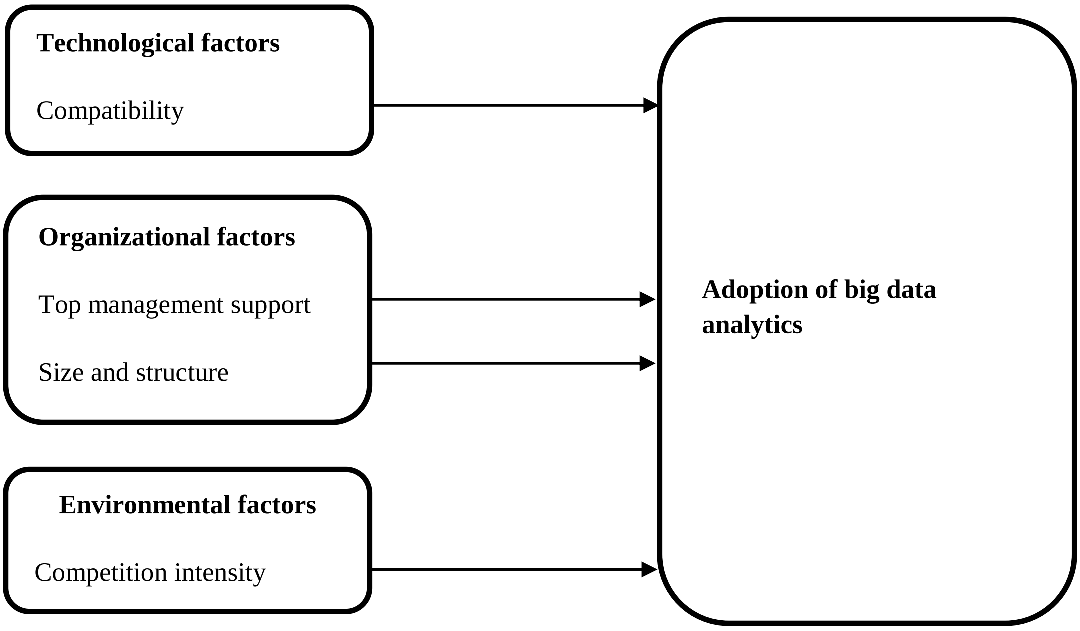

Figure 5.1: Big Data Analytics Adoption Model

5.3 Conclusion

The study notes that adoption of big data has a big potential to grow companies through accurate decision making, timely feedback and precise knowledge of the market which shapes marketing decisions. The technology has inherent risks such as likelihood of breach of confidentiality and leakage of information.

The big data analytics technology has been substantially adopted in some telecommunication organizations and institution of higher learning. The results shows that organizations which have not adopted the technology have committed to the process with full top management support and big resource allocation to facilitate the process of adoption. The common big data technologies are Hadoop and Allot clearsee.

The adoption of big data analytics is influenced by technological, organizational and environmental factors. The most significant factors are compatibility of the big data to the organizations systems, the degree of support from the management, the size and structure of the organizations and the intensity of competition. Adoption is therefore faster where organizations systems are compatible, the top management support the adoption, the organization is big in size hence slack resource for innovation and the structure is adaptive with adequate financial resources. The degree of competition including the actions of the industry players are also significant factors.

The adoption of the big data analytics is negatively influenced by the complexity of the systems and increased legislations, prohibitive and lack of legislations. The study noted that usefulness of big data systems in organizations was also influenced by ability to use the data correctly, customer willingness, existing IT systems, employee's perceptions, cost of adoption and internal policies.

5.4 Recommendations

The study recommends the following to facilitate adoption of the big data analytics in the organizations.

Adequate legal framework: The adoption of the big data analytics has potential risks which require adequate legislations to guide operations and use of the technology while safeguarding the privacy of the users and the customers.

Building staff capacity: there is need for organizations to train and build the capacity of staff to efficiently adopt the technology and use it to the advantage of the organizations.

Change of employee's perspective: The success of the adoption of the big data analytics would be quick and smooth with the positive perspective from the employees and the customers.

Building network with big data driven companies: This will facilitate cost effective adoption and exchange of skills as well as infrastructure for the adoption of the big data analytics in organizations.

5.5 Further Work

The study recommends studies to be carried out to establish that the tools being used for analytics are effective and useful. Further study on how new technologies including IoT and Artificial Intelligence are used for predictive, prescriptive and real-time decision making. There is also need to look at ways how collaboration with big data can be established between organizations that mine a lot of data and those that are in need of the data in order to derive mutual benefits.

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APPENDIX 1

QUESTIONARE

A Personal Data (Kindly tick ONE)

1) What is your age bracket?
   a) 20-35
   b) 36-45
   c) 46 and Above
2) What is your education level?
   a) Diploma
   b) Bachelors degree
   c) Masters degree
   d) Doctorate

3) Which position below do you hold in the organization?
   a) Director
   b) Head of department
   c) Manager
   d) I.T Specialist
   e) Engineer
   f) Subject Matter expert
   g) Other:(specify)--------------------

4) For how long has your organization used big data analytics to drive decision making?
   a) Never used
   b) Less than 5 years
   c) 6-10 years
   d) 11-20 years

5) What Data Analytics Technologies does your Organization use?

____

____

6) To what extent do you agree or disagree with the following views regarding your organizations technological context?

	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
Adoption of new technologies like big data analytics helps us serve our customers better.					
Adoption of big data analytics to drive decision making reduces cost of operations for our organization					
Our organization is familiar with the opportunities and threats brought about by big data driven decision making.					
Our organization possesses the infrastructure necessary to enable adoption of big data analytics to drive decision making.					
Our current IT infrastructure can be easily upgraded to accommodate big data analytics and data driven decision making.					
The Technology of Big data analytics to drive decision making is easy to understand and adopt.					
Big data analytics and data driven decision making will bring growth into our organization in terms of revenue.					

C Organizational Factors Affecting Adoption of Big data to drive decision making

7) How many employees does your organization have.
   a) below 1000
   b) 1000-5000
   c) Over 5000

8) To what extent do you agree or disagree with the following views regarding your organization’s internal context?

	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
Our organization is committed to adopting big data analytics to improve its business activities					
Our organization’s top management fully supports the adoption of Big data analytics to drive decision making					
The adoption of technology in my organization is strategy- led.					

The top management in our organization is aware of benefits of adopting big data analytics to drive decision making.					
Our organization's size (the number of employees) influences the adoption of technology					
Our organization has resource slack used in to drive innovation					
The organizational structure has no influence on technology adoption					
Communication in our organization is effective and hence enables me understand the business strategy					
Our organization has competent staff that can drive the adoption of technologies such as big data analytics.					

D Environmental Factors Affecting Technology adoption

9) To what extent do you agree or disagree with the following views regarding your organization's business and operational environment?

	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
Government demonstrates a major commitment to promote technology adoption					
Competition has influenced our organization to adopt technologies such as big data analytics					
Adoption of big data analytics to drive decision making will improve the market share of our organization					
Our competitors who have adopted data driven decision making technologies are viewed more favourably by customers.					
We have efficient technology support from our service providers and consultants to enable to adopt big data analytics and use its insights to make decisions					

10) What Government Regulations would mainly affect the adoption of big data analytics in your organization.--
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11) Is the legal environment conducive for the adoption of big data analytics?---------------
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12) Why do you think the legal environment is conducive or non-conducive?----------------
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13) In your view, what other environmental factors do you think can affect the adoption of big data analytics to drive decision making in your organization?-------------------------
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14) What would you recommend to ensure organizations are able to adopt new influential technologies such as big data analytics in their operations?--------------------------------
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15) What are the potential benefits of adoption of big data analytics to drive decision making?---
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16) What are the potential risks of adopting data analytics to drive decision making?-------
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